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INDEX

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ABSTRACT

This paper shows that oil price changes, measured as short-term futures returns, are a strong predictor of excess stock returns at short horizons. Ours is a leading variable for the business cycle and exhibits low persistence which avoids the fictitious long-horizon predictability associated to other predictors used in the literature. We compare our variable with the most popular predictors in a sample period that includes the recent financial crisis. Our results suggest that oil price changes are the only variable with forecasting power for stock returns. This significant predictive ability is robust against the inclusion of other variables and out-of-sample tests. We also study the cross-section of expected stock returns in a conditional CAPM framework based on oil price shocks. Our model displays high statistical significance and a better fit than all the conditional and unconditional models considered including the Fama-French three-factor model. From a practical perspective, ours is a high-frequency, observable variable that has the advantage of being readily available to market-timing investors.

Keywords: Return predictability, business cycle, crude oil, futures prices, asset pricing, conditional CAPM.

JEL Classification: G17, E44, Q43, E32, G12, G14.

I. Introduction

The predictability of stock returns is a controversial topic. Until recently, the prevailing view was that returns could be predicted at long horizons by the business cycle (Cochrane, 2005), although the evidence was largely concentrated on the use of financial variables as predictors. The evidence for long-horizon predictability was significantly stronger than for short horizons. But in recent years, several studies have questioned the existence of such stock return predictability. Boudoukh, Richardson, and Whitelaw (2008) show that the dominant findings in this literature are solely the consequence of the high persistence of the predictors. Also, Welch and Goyal (2008), who compare the out-of-sample predictive performance of a large number of popular predictors with the prevailing average excess stock return, find that none of these variables predicts equity premium at short horizons better than the historical average return.[1]

Despite this, defenders of predictability have continued working. Ang and Bekaert (2007) report evidence of predictability, at horizons of up to one year, using both the dividend-price ratio and the interest rate. Campbell and Thompson (2008), using a much longer sample, find that the out-of-sample forecasting power of several variables improves significantly when certain restrictions are imposed, and that trading on these predictors can lead to significant welfare benefits when compared to trading on the historical average return. Cochrane (2008) criticizes the existing tests for the dividend-price ratio and states that the null hypothesis of non-predictability of stock returns must be proposed along with its implication for the future growth of dividends. In other words, given that dividend-price ratio is stationary, the inexistence of predictability in the dividend growth guarantees that returns are predicted by that ratio.[2] More recently, Cooper and Priestley (2009) propose the output gap as a new forecasting variable for stock market returns. This variable is robust against the tests of Boudoukh, Richardson, and Whitelaw (2008) and Welch and Goyal (2008). Given that a persistent predictive variable, under the null hypothesis of non-predictability, will fictitiously exhibit forecasting power at long horizons, the current challenge is to propose a variable that predicts equity returns at short horizons and is robust against the new tests suggested in the literature.

This paper shows that unexpected changes in oil prices are a significant predictor excess stock market returns at short horizons and show a significantly better performance when compared to the standard predictors used in the literature. Moreover, our predictive variable has deep macroeconomic roots and allows us to connect the short-horizon predictability of equity returns with the business cycle.

This proposal is motivated by two lines of research: the relationship between GDP and oil prices and the response of equity returns to oil price shocks. Because stock return predictability has been detected at business-cycle frequencies, the first strand of literature justifies the relationship between oil prices and the macroeconomy. The second line of research, although less voluminous than the first, provides empirical evidence that past oil shocks have an impact on future equity returns.

Intuitively, there are sound reasons for believing that oil price leads the economic cycle, as nine of ten recessions in the United States since World War II have been preceded by an increase in oil prices (Hamilton, 2008). The relationship between GDP and oil prices begins with Hamilton (1983) and has evolved in several directions. These include the study of several transmission channels of oil shocks to the economy (Bernanke, 1983; Hamilton, 1988; Ferderer, 1996; Finn, 2000; Davis and Haltiwanger, 2001; Balke, Brown, and Yucel, 2002; Hamilton and Herrera, 2004; Huntington, 2007), analysis of the persistence of this relationship and non-linear shock measurements (Lee, Ni, and Ratti, 1995; Hooker, 1996; Hamilton, 1996; Hamilton, 2003), distinction between real and nominal impacts of oil prices (Cologni and Manera, 2008; Gronwald, 2008), and decomposition of supply and demand oil shocks (Kilian, 2008; Kilian, 2009).

Among studies that examine the impact of oil shocks on stock returns are Jones and Kaul (1996), who conclude that returns react rationally to oil price changes in the U.S. and Canada, but that there is an overreaction in the United Kingdom and Japan. Sadorsky (1999), Ciner (2001) and Park and Ratti (2008), using vector autoregression analysis, detect a significant impact of oil price shocks on equity returns. Driesprong, Jacobsen, and Maat (2008), in an industry-level study, find evidence of stock return predictability of monthly oil price changes in certain industries, consistent with an underreaction to oil shocks by investors. Kilian and Park (2009) study the different impacts of demand and supply shocks on equity returns. Their findings indicate that, overall, oil price shocks explain one-fifth of the long-term variation in equity returns. Nevertheless, and contrary to what is typically believed, the relative importance of demand shocks is much greater than that of supply shocks. Following a similar approach, Apergis and Miller (2009), using a sample of the G-7 countries and Australia, conclude that the effects of oil shocks, while statistically significant, generate a smaller economic impact on equity returns.

Oil price shocks are measured by short-term futures returns on crude oil contracts. Based on the macroeconomic literature (Hamilton and Herrera, 2004) and in-sample tests, four lags of this variable are used. The existence of negative Granger-causality of oil price shocks on both equity returns and production growth in a trivariate VAR confirms that oil shocks are a leading variable and are countercyclical. Therefore, increases in oil prices precede recessions and declines in excess stock returns.

To obtain a reliable inference from the predictive regressions, the tests consider covariance matrices of coefficients corrected for heteroscedasticity and autocorrelation that arise from the use of distributed lags and overlap of returns (Newey and West, 1987). Following Welch and Goyal (2008), we use bootstrap in order to address size distortions in the t-test for long horizons (Ang and Bekaert, 2007) and to make the correct inference from nested out-of-sample predictability tests (Clark and McCracken, 2005). At horizons of one to three quarters, the results of the in-sample regressions verify that oil price shocks exhibit predictive performance which is both statistically and economically significant. Moreover, it superior to the performance of all other variables considered (consumption-wealth ratio, price-dividend ratio, product gap and risk-free rate) with an $\bar{R}^2$ of 6%. This meaningful in-sample result was also detected in out-of-sample tests. Our variable exhibited the best R^2 out of sample, which was close to 1.2% at one quarter. For longer time horizons, however, no variable showed a significant predictive performance. To our knowledge, these results position oil price shocks as the best short-term forecasting variable today.

Our sample period is 1983Q2-2009Q4 and is restricted by the existence of crude oil futures prices. However, obtaining significant results in a sample period after the oil crisis in the 1970s is not an easy task since most variables lose their forecasting power within this period (see Welch and Goyal, 2008). Our variable also dominates recent predictors, like the output gap proposed by Cooper and Priestley (2009). Furthermore, oil price shocks have other virtues such as low persistence (they do not produce the pattern reported in Boudoukh, Richardson, and Whitelaw, 2008), they are directly observable (unlike variables such as consumption-wealth ratio and product gap, which must be estimated), they have no correlation with the predictive regression's disturbances (do not generate the bias analyzed in Stambaugh, 1999), they are a high frequency variable and are available at no cost. All of these characteristics are valued in the practice of portfolio management.

The rest of this paper is structured as follows. The next section presents our variable and its relationship to the business cycle and excess market returns. Section III contains the results from in-sample predictability at a quarterly horizon. Section IV reports the out-of-sample tests. Section V discusses the evidence of predictability at longer horizons. Section VI analyzes the impact of predictability in the cross-section of expected returns. Section VII concludes.

II. Oil price, the business cycle and excess market returns

This section presents our variable and establishes its relationship to the business cycle and excess stock market returns.

A. Oil price and the macroeconomy

As shown by Hamilton (2008), nine out of the last 10 recessions in the United States since World War II have been preceded by a rise in oil prices. This has not gone unnoticed by economists and has generated a substantial amount of research, particularly given the fact that oil consumption represents only 4% of GDP.[3] The study of the relationship between oil and the macroeconomy strengthens with the seminal work of Hamilton (1983). He uses Sims's (1980) bivariate VARs and six-variable VARs with quarterly data for the 1948-1980 period to show that oil prices strongly Granger-caused the GDP growth rate and the U.S. unemployment rate. According to his calculations, an increase in the oil price is followed by four successive quarters of lower GDP growth rates. Gisser and Goodwin (1986) confirm these findings and reject the existence of a structural break in this relationship as a result of the OPEC embargo in 1973. As shown by Ferderer (1996), the common transmission channels of oil price shocks to the real economy are: inflation, terms of trade (Huntington, 2007) and the capital utilization rate (Finn, 2000).[4]

Subsequent studies (Mork, 1989; Lee, Ni, and Ratti, 1995; Hooker, 1996; Hamilton, 2008), note a weakening of this relationship when data from 1980 onwards are included (which coincides with OPEC's loss of control of the oil market).[5] This turned attention towards non-linear relationships between the variables (Mork, 1989; Ferderer, 1996; Lee, Ni, and Ratti, 1995; Hamilton, 1996; Hamilton, 2003). This evidence required for new explanations to understand the asymmetric impact of oil on the economy. The common mechanisms are: monetary policy (Ferderer, 1996; Bernanke, Gertler, and Watson, 1997; Hamilton and Herrera, 2004; Balke, Brown, and Yucel, 2002; Leduc and Sill, 2004), imperfect intersectoral mobility of factors (Lee and Ni, 2002; Lilien, 1982; Hamilton, 1988; Davis and Haltiwanger, 2001), investment irreversibility (Bernanke, 1983; Dhawan and Jeske, 2008), wage rigidities (Lee, Ni, and Ratti, 1995), and interest rates (Balke, Brown, and Yucel, 2002).[6] Meanwhile, Hooker (1996) shows that none of the asymmetric specifications to date establishes a Granger-causal relationship in post-1973 data. Nevertheless, Carruth, Hooker, and Oswald (1998) document a strong and significant linear relationship between the U.S. rate of unemployent and oil prices.[7]

Jimenez-Rodriguez and Sanchez (2005) find significant empirical evidence of the effects of oil for the G-7 countries, Norway and the Eurozone overall. Jimenez-Rodriguez (2008) also reports similar findings, but for manufacturing production of six OECD member countries. Kliesen (2008) adds to the standard regression the variable CFNAI (Chicago Fed National Activity Index), which is the first principal component of 85 monthly indicators of real economic activity, and finds that oil has a significant impact on the U.S. macroeconomic performance. In addition, Cologni and Manera (2009) find a negative influence of oil shocks on GDP growth, although they reject the hypothesis that real GDP growth has no effect on oil prices. Kilian (2008) finds empirical evidence that exogenous oil supply shocks on output have caused significant impacts on the GDP of G-7 countries.[8] Cologni and Manera (2008) observe that oil price shocks affect only the GDP in Italy and in the U.S., albeit temporarily. For almost all of the countries in their sample, oil shocks affect inflation and nominal exchange rates. Gronwald (2008) concludes that only oil shocks that exceed a certain threshold affect the real sector of the economy, while “normal” positive shocks do generate significant nominal impacts.

Clearly, the abovementioned empirical evidence, though not free of debate, largely supports the existence of a significant relationship between oil price shocks and the business cycle in both economic and statistical terms. At the same time, these findings motivates the main question we address in this paper, which is: Given that oil price shocks precede changes in GDP, do they also have some predictive power for stock market returns?

B. Oil price and the financial market

Contrary to what has occurred with the relationship between oil shocks and the macroeconomy, the linkage between these shocks and the financial markets has received little attention.[9] For deeper analysis, Table I presents detailed information on the empirical studies reviewed in this section.

In a cross-country study on market efficiency, Jones and Kaul (1996) find that oil price shocks produce significant changes in stock returns and that in the U.S. and Canada this reaction is rational. On the other hand, they find an overreaction in the United Kingdom and Japan. Using daily data, Huang, Masulis, and Stoll (1996) find that oil futures returns have no correlation with stock returns, with the exception of oil company returns. Ciner (2001) tests for non-linear Granger-causality of futures returns on stock market returns, and unlike the evidence obtained by Huang, Masulis, and Stoll (1996), his results show a significant, non-linear relationship across the returns of both series. Using a VAR analysis with monthly data, Sadorsky (1999) finds that in the U.S. market the price of oil affects the financial market, but that the effect in the other direction is insignificant. He also finds that oil price shocks have an asymmetric effect on industrial production and real stock returns, with positive shocks having a greater impact than negative ones.

On the theoretical side, Wei (2003) builds a general equilibrium model to estimate the impact of an oil price shock on the value of a firm that faces investment irreversibility. His model predicts that an oil shock will have only a small impact. Consequently, he is unable to explain the massive decline in the stock market in 1974 after the oil shock of 1973.

Using data on stock indices and economic sectors of different countries, Driesprong, Jacobsen, and Maat (2008) find that oil prices have significant predictive power in developed economies, however, this is not valid for emerging countries. The underlying cause of this finding would be market inefficiency. In particular, they suggest an initial underestimation by agents of the impacts of the shock that is slowly corrected later. On the other hand, Park and Ratti (2008) find evidence that oil price shocks have a significant negative impact on real returns of several net importing countries, unlike what occurs in Norway, a net exporter, where the impact is positive. Moreover, in almost all of the countries considered in their sample, positive oil price shocks are quickly followed by increases in short-term interest rates. Evidence of asymmetric impact of oil shocks is only found for Norway and the United States. Also, an increase in oil price volatility significantly reduces real equity returns in many European countries.

Following Kilian (2009), Kilian and Park (2009) break down oil shocks into three classes: supply, aggregate demand and specific demand (or precautionary demand) shocks. According to their results, these shocks explain 6%, 5% and 11% of the long-term variation of real stock returns, respectively. They do not find a significant response of stock returns to oil supply shocks, a result that is consistent with Wei's (2003) model. However, they do find significant positive responses to global demand shocks and significant negative responses to precautionary demand shocks. Likewise, sector-level evidence suggests that the mechanism that transmits oil shocks to stock returns is through the demand for industrial products, and not, as widely believed, through the production costs of the firms. Apergis and Miller (2009) criticize the methodology used in Kilian (2009) and Kilian and Park (2009) due to the use of both stationary and non-stationary variables in their VAR specification. They differentiate the I(1) variables and carry out the same breakdown as Kilian (2009), but using only I(0) variables. Instead of including the equity returns in a same VAR, as in Kilian and Park (2009), Apergis and Miller (2009) use a second VAR with the three types of shocks and the stock market returns of each country. Using a sample composed of the G-7 Group and Australia, they conclude that the effects of oil shocks, although statistically significant, produce a minor impact on stock returns.

Several conclusions can be obtained from this literature review. As Table I shows, the use of oil spot prices has prevailed over the use of oil futures prices in the literature. Also, in contrast to most macroeconomic studies, the use of logarithmic oil returns has been predominant in the financial area. Finally, although this is clearly a highly relevant topic, the decomposition of oil price shocks is still in a very early methodological stage.

C. Stock returns and the business cycle

To better capture the aggregate impact of oil shocks and make our results more compatible with the macroeconomic evidence, here we use quarterly data. This also reduces the probability that our findings are contaminated by market inefficiencies as in Driesprong, Jacobsen, and Maat (2008), which are more particular to short horizons and should tend to disappear because agents have more time to adjust their expectations. Moreover, this allows us to include in the analysis the consumption-wealth ratio, a variable which is only available at a quarterly frequency (Lettau and Ludvigson, 2001a).

Our proxy for the stock market is the value-weighted CRSP index, from which we obtain the quarterly returns on the market portfolio (R_m). When using sample periods that start after 1983, we proxy the risk-free rate (R_f) with the 3-month constant-maturity treasury yields from the Federal Reserve Board of Governors. For longer sample periods we use the stock returns and the risk-free rate available from Ken French's web page, which contains data from September 1926. Stock returns are from the value-weighted CRSP index and the risk-free rate is from the 3-month Treasury bills from Ibbotson Associates.

Figure 1 shows the excess market returns from 1926Q3 to 2009Q4. The shaded areas represent the NBER (National Bureau of Economic Research) recession periods. The stock returns tend to be negative and grow during recessions, reaching peaks towards the end of each one. In fact, in our sample period the maximum return was reached by the end of the Great Depression of the 1930s. Nevertheless, this commonly cited contracyclical character of stock returns is evident only at the end of recessions; at the beginning of and during recessions, these returns are highly procyclical. For example, the minimum in the sample period was also reached during the Great Depression. In addition, expansions are characterized on average by positive returns, although they are less volatile than those generated during recessions.

NBER's business cycle dates enable the sample to be divided into the four stages: expansion, peak, recession and trough. Table II shows the first two conditional sample moments for the excess stock returns. As can be seen in the table, the most frequent stage of the economy is expansion, and during this phase of the cycle the average return is positive (2.9%) and greater than its historical average (2.0%). On the contrary, during the recession stage the average excess return on the market has a similar magnitude as it does during the expansion stage, but with the opposite sign (-3.0%) and almost twice the volatility. Finally, during the peaks (troughs), expectations about the state of the economy are negative (positive) and therefore, excess stock returns are highly negative (positive) in these stages.

Stock market returns vary considerably with the business cycle, and therefore should be predictable through leading variables that anticipate the cycle. This is consistent with Welch and

Goyal (2008), who instead of proposing the absence of predictability, conclude the following: "... our article suggests only that the profession has yet to find some variable that has meaningful and robust empirical equity premium forecasting power ...".

D. Measuring oil price shocks

Considering the evidence mentioned above, it seems natural to propose oil price shocks as a leading variable with the potential to forecast stock market returns. However, to maximize its predictive power, it is essential to consider only unanticipated changes in the oil price. Although direct oil spot returns have been a widely used variable in the literature (see Table I), they are excluded as a measure of oil shocks, because they contain some components that are clearly anticipated by market participants, such as the interest rate and the convenience yield.[10] To address this drawback it is possible to estimate unexpected oil changes with a model for spot price dynamics, as in Bachmeier (2008) and Nandha and Faff (2008), among others; however, this procedure still has disadvantages in that it depends on the model specification and the information set used by the econometrician to estimate the conditional mean may not coincide with that of the market. Indeed, unexpected oil price changes can only be captured with an objective and precise estimate of the expected spot price in the future.

We measure unexpected oil price shocks by short-term futures returns on crude oil. Using Fama and French's (1987) methodology and cointegration tests, Switzer and El-Khoury (2007) show that oil futures prices have significant predictive power for future spot prices. Moreover, Ma (1989) and Kumar (1992) confirm that futures prices, in addition to being unbiased predictors of spot prices, exceed the predictive capacity of a random walk and a wide variety of models. This evidence suggests that unexpected changes in oil prices are correctly captured by our proposed variable.[11] Therefore, we assume that quarterly unexpected oil shocks are proxied by oil futures returns, i.e.,

$$\Delta f(t) \equiv f^1(t) - f^4(t-3) \approx s(t) - \mathbb{E}_{t-3}\left[s(t)\right] \tag{1}$$

where $s(t)$ is the log oil spot price and $f^\tau(t)$ is the log oil futures price of a contract that matures in τ months.

Data on oil futures prices are from NYMEX, which began trading these contracts in March 1983.

Therefore, our sample period is from 1983Q2 to 2009Q4. Figure 1 presents our variable and the other predictors that are used for comparison purposes. The figure confirms that recessions are preceded by positive oil shocks, while during recessions these shocks are rapidly reversed. The great variability of the oil shocks is clear evidence of their predictive potential. Another visual characteristic is the low persistence of the series, which prevents it from being subject to the critiques of existing predictive variables. This also implies that the traditional asymptotic inference is not invalidated for our variable. The optimal number of lags of our variable to be considered in this study was determined using the Akaike Information Criterion (AIC) in Ordinary Least Squares (OLS) regressions of the excess stock market return on lagged oil shocks. In this study we consider four lags of our variable, because this number minimizes the AIC (see Table III). Interestingly, the number of lags coincides with that obtained in the macroeconomic literature (see Hamilton, 2003 andHamilton, 2008).

E. Oil price, the business cycle and stock returns

To show evidence of the relationship among the oil price, the business cycle and excess stock returns, we study the joint dynamics of these variables using a vector autoregression analysis with four lags. Following Cooper and Priestley (2009), we use the total Industrial Production Index (IP) from the Fed as a measure of output and a proxy for the business cycle. Table IV shows the maximum likelihood estimates for the VAR(4) model. As is common in macroeconomic series, industrial production growth rate ($\Delta\%IP$) is the easiest series to predict (its R^2 is 51%) and its own lags have useful information for forecasting its future values. On the other hand, the predictive power of the excess stock return ($R_m - R_f$) on $\Delta\%IP$ is a clear signal that the financial market correctly anticipates future economic growth. Moreover, in our sample the Granger-causality of oil shocks (Δf) on economic growth is also verified, evidence that is in line with the macroeconomic studies mentioned before.

The table also shows that for the excess stock returns, the lack of significance of its own lags is a clear sign of the efficiency of the equity market and that the findings of Driesprong, Jacobsen, and Maat (2008) are not seen in quarterly horizons.[12] There is also evidence of inverse causality with the industrial production growth rate, which is probably the consequence of an adjustment process of previous expectations about actual economic growth. Furthermore, and as expected, oil shocks demonstrate a significant predictive power for excess stock returns, which will be explored in greater depth in the following sections. Finally, the results reveal that oil shocks cannot be predicted with any of the lagged variables, which is evidence that our measure for oil shocks effectively captures unanticipated changes in this variable.[13]

III. Short-horizon predictability of stock returns

This section and the following ones contain an analysis and testing of the predictive power of oil price shocks for stock returns. In particular, this section focuses on the in-sample predictability of stock returns at a quarterly horizon.

The predictive performance of our variable will be evaluated and compared to the performance of the following variables: the risk-free rate (Campbell, 1987), the log dividend-price ratio (Fama and French, 1988), the consumption-wealth ratio (Lettau and Ludvigson, 2001a), and the output gap (Cooper and Priestley, 2009).

As described in Section C, the risk-free rate (R_f) is proxied by the 3-month constant maturity Treasury yields from the Fed. The log dividend-price ratio ($d - p$) was calculated from the value-weighted CRSP index using the methodology described in Ang and Bekaert (2007). The consumption-wealth ratio (cay) and its individual components are from Martin Lettau's web page and sampled at a quarterly frequency. The output gap (gap) is constructed using the total Industrial Production Index. Although Cooper and Priestley (2009) define four methods for calculating the output gap, the main one is the quadratic version of gap (based on its greater correlation with procyclical variables), which we also use here.[14] The output gap is estimated with data from 1948Q1 to replicate the series from Cooper and Priestley (2009). The variables $cay(t)$ and $gap(t)$ are assumed to be known at the start of time $t + 1$, and therefore can be used to forecast excess stock returns. We omit any complication due to the look-ahead bias in these variables and the normal delay in the publication and subsequent revisions of these and other macroeconomic series.

Table V presents the main statistics of the predictive variables, while Figure 2 provides the graphical evidence. As expected, the upper panel of Table V shows that the variables R_f, cay and gap exhibit less volatility than excess return ($R_m - R_f$), while the contrary is verified for our variable (Δf) and $d - p$. Unlike the existing predictor variables, Δf shows very low persistence; in fact, its first-order serial correlation is similar to that of $R_m - R_f$. The lower panel of Table V shows that the intratemporal correlation of our variable with the excess stock return is very low, rejecting Δf as a possible pricing factor.[15] Another important characteristic of our variable is its low correlation with other predictive variables, which suggests that Δf contains business cycle information not captured by the existing predictors. On the contrary, the existing variables show high levels of correlation (in absolute terms) among themselves, revealing the presence of redundant information.

Next we turn our attention to evaluating the predictive performance of our variable and the other variables considered here. We begin with the evidence of in-sample predictability at a quarterly horizon, for which we estimate the following regression:

$$R_m(t) - R_f(t) = \alpha + \beta' X(t-1) + \varepsilon(t) \tag{2}$$

where $X(t-1)$ is a vector of known predictors at $t-1$ and β its associated coefficient vector. It should be emphasized that $X(t-1)$ can include one variable, several variables or several lags of the same variable.

Table VI shows the OLS results of equation (2). We report asymptotic t-stats and Wald tests that correct for serial correlation and heteroscedasticity using Newey and West (1987).[16] The columns present the results for each predictor variable. The results indicate that our variable has the best predictive performance with an $\bar{R}^2$ of 6%. The Wald test corresponds to the null hypothesis that all the coefficients in equation (2) are zero, except the constant. This statistic is highly significant (p-value of 2%). The annual cumulative impact of our variable, calculated from the sum of the coefficients corresponding to the four lags of Δf, is also economically significant. To see this, consider a one-time increase in Δf of one standard deviation (19.5% in our sample, see Table V). This change leads to a 2.1% decrease in expected quarterly excess returns on the value-weighted CRSP index (19.5% $\times$ (-0.106) = -2.1%), which is equivalent to 29.6% (2.1% / 7.0% = 29.6%) of the historical average annual excess return.[17]

The dynamics of the distributed lags can be explained with aggregate demand shocks (see Kilian and Park (2009)). A positive shock to the global demand for industrial commodities produces both a direct positive impact and an indirect negative one in the financial market. The direct impact is manifested in an increase in the oil price and an increase in economic growth with a consequent positive stock return. Increased economic growth pushes the oil price even higher, and thus indirectly affects in a negative way the expected economic growth and expected stock returns in the future. The final impact will depend on the relative magnitudes of both impacts.[18] The direct impact is initially stronger, which explains the positive significant effect of the first lag of Δf. Later, the indirect impact begins to gather strength and cause negative repercussions, although not of sufficient magnitude to cancel out the initial positive impact (see the sign and low significance of the following two lags). One year after the unexpected aggregate demand shock, the indirect effect becomes dominant; in other words, the high price of oil causes a deceleration in the economy. This is manifested by the negative and significant coefficient of $\Delta f(t-4)$ which is also responsible for the cumulative negative impact reported.

The third column in Table VI shows the results for the interest rate as a predictor. This variable has the worst predictive performance in our sample, with $\bar{R}^2$ of -0.01. Contrary to the findings of previous studies (Campbell, 1987), the coefficient that accompanies this variable is positive, although not significant. This poor performance is associated with the low volatility of this variable in our sample. Its standard deviation is 0.006 (see Table V), a value well below the 0.032 reported by Ang and Bekaert (2007) for 1935Q2-2001Q4. The last three columns contain the results for the $d-p$, *cay* and *gap* variables. All of these have intuitive signs, although their coefficients (in absolute value) are lower than those reported in previous studies (see Ang and Bekaert, 2007; Lettau and Ludvigson, 2001a and Cooper and Priestley, 2009; respectively).[19] Moreover, the R^2 statistic for these variables (all about 2%) suggest that they have similarly poor predictive power, although *cay*'s coefficient is significant while the other two are not.

The regressions in Table VI show that the oil shocks have significant in-sample forecasting power. We now see whether our variable is robust to the inclusion of the other predictors considered here. To evaluate this, we estimate the following extended predictive regression:

$$R_m(t) - R_f(t) = \alpha + \sum_{j=1}^{4} \beta_j \Delta f(t-j) + \theta' Z(t-1) + \epsilon(t) \tag{3}$$

where $Z(t-1)$ is a vector of predictor variables and θ its associated coefficients vector. Thus, with the inclusion of $Z(t-1)$ in the regression, lack of robustness in the predictive power of our variable should be reflected in changes in sign and/or loss of significance in the coefficients that accompany the lags of oil shocks.

The results of the estimation of equation (3) are presented in Table VII. The last row contains the p-value of an asymptotic Wald test for the combined null hypothesis that all the coefficients associated with the lags of our variable are zero. The columns show the results of including each of the other variables in the predictive regression of Δf, while the inclusion of all of them is considered in the last column. First, given the low correlation of our variable with the others, the forecasting power of our variable remains intact. According to the Wald test for the coefficients of Δf, in all of the estimates these coefficients maintain their combined, unaltered significance. In addition, their signs and individual significance remain the same, and they are roughly the same size. Second, consistent with previous results, the greatest increase in predictive power is reached when our variable is used in combination with *cay*, obtaining an $\bar{R}^2$ of 8%. Third, contrary to what occurs with the oil shock coefficients, the results of the last column provide evidence of great instability in the predictive power of the other variables. None of these are significant. The coefficients of R_f and *gap* experience changes in sign and those of $d - p$ and *cay* vary dramatically in size. Of course, this evidence is consistent with the high correlation between these variables reported in Table V.

In summary, this section demonstrated that our variable has significant and robust in-sample forecasting power for stock returns. Out-of-sample predictability, also at a quarterly horizon, is considered in the next section.

IV. Out-of-sample predictability of stock returns

In-sample predictive performance is essential for establishing the existence of predictability. However, as noted by Welch and Goyal (2008), in order for a predictor variable to be used by an investor, it must also demonstrate good out-of-sample predictive performance. That is, a predictive variable must be able to forecast excess returns reasonably well with information available at the time of the forecast, which is not guaranteed by the in-sample tests of equations (2) and (3), as the coefficients are estimated using the full sample of available observations.

Welch and Goyal (2008) conclude that it is very difficult to find variables with short-horizon out-of-sample forecasting power that outperforms the average excess return in a recent sample period. In fact, when considering the sub-period from 1965 to 2005, they only find variables that outperform the prevailing historical average return at a five-year horizon. Although the out-of-sample predictive performance can be increased by imposing certain restrictions, as shown in Campbell and Thompson (2008), here we choose to keep the simplicity and linearity of the predictive model. Despite the poor in-sample predictive power of the other variables, we also test their out-of-sample performance.

In order to contribute to this discussion, we compare forecasts from nested linear models to determine whether each variable has predictive content for stock returns. The prevailing historical average of excess stock returns is used as a benchmark. Therefore, we define the following benchmark and competing models:

$$\text{benchmark:} \qquad R_m(t+1) - R_f(t+1) = \alpha_1 + u_1(t+1) \tag{4}$$

$$\text{competing:} \qquad R_m(t+1) - R_f(t+1) = \alpha_2 + \beta' X(t) + u_2(t+1) \tag{5}$$

where the coefficients α_1, α_2 and β are estimated recursively. The sample of size T is divided into in-sample and out-of-sample portions. R is defined as the minimum number of observations used for estimating the coefficients and $P \equiv T - R$ denotes the maximum number of one-step-ahead predictions. Thus, forecasts of $R_m(t+1) - R_f(t+1)$, $t = R, \ldots, T-1$, are generated recursively using the two linear models in equations (4) and (5), where all coefficients are re-estimated with new observations as forecasting moves forward through time.

The estimated forecast errors for the benchmark and competing models are denoted by:

$$\text{benchmark:} \qquad \hat{u}_1(t+1) = [R_m(t+1) - R_f(t+1)] - \hat{\alpha}_1(t) \tag{6}$$

$$\text{competing:} \qquad \hat{u}_2(t+1) = [R_m(t+1) - R_f(t+1)] - \hat{\alpha}_2(t) - \hat{\beta}(t)' X(t) \tag{7}$$

for $t = R, \ldots, T-1$ and the coefficients $\hat{\alpha}_1(t)$, $\hat{\alpha}_2(t)$ and $\hat{\beta}(t)$ are estimated with data through period $1, \ldots, t$. Then, one-step-ahead forecasts from the competing model can be compared to forecasts from the benchmark model (that is, a restricted version of the competing model) by using statistics based on the time series $\hat{u}_1(t+1)$ and $\hat{u}_2(t+1)$.

Our assessment of out-of-sample predictability involves three metrics. The first is the forecast encompassing test of Clark and McCracken (2001). Based on a composite forecast from both models, an encompassing test verifies whether the competing forecasts incorporate any useful information absent in the benchmark forecasts. To clarify how the test works, we follow Harvey, Leybourne, and Newbold (1998) and specify a regression of the excess stock return on a weighted average of forecasted values from the benchmark and competing models:

$$R_m(t+1) - R_f(t+1) = (1-\lambda)\left[\alpha_1\right] + \lambda\left[\alpha_2 + \beta' X(t)\right] + \nu(t+1) \tag{8}$$

where $0 \leq \lambda \leq 1$ and $\nu(t+1)$ is a error term. Substituting both forecasts from equations (4) and (5) yields:

$$u_1(t+1) = \lambda\left[u_1(t+1) - u_2(t+1)\right] + \nu(t+1) \tag{9}$$

Then, as λ is also the coefficient of the regression model in equation (9):

$$\lambda = \frac{\mathbb{C}ov\left[u_1(t+1), u_1(t+1) - u_2(t+1)\right]}{\mathbb{V}ar\left[u_1(t+1) - u_2(t+1)\right]} \tag{10}$$

Thus, the combined forecast will have a smaller expected squared error than the benchmark model forecast unless the covariance between $u_1(t+1)$ and $u_1(t+1) - u_2(t+1)$ is zero (i.e., $\lambda = 0$). This way, Clark and McCracken's (2001) test contrasts the null hypothesis that $\lambda \leq 0$ and is given by:

$$\text{ENC-NEW} = P\frac{\sum_{t=R}^{T-1}\left(\hat{u}_1(t+1)^2 - \hat{u}_1(t+1)\hat{u}_2(t+1)\right)}{\sum_{t=R}^{T-1}\hat{u}_2(t+1)^2} \tag{11}$$

Under the null hypothesis that the benchmark model encompasses the competing model, the covariance between series $u_1(t+1)$ and $u_1(t+1) - u_2(t+1)$ will be less than or equal to zero. Under the alternative that the competing model contains added information, the covariance should be positive. Hence, the encompassing test presented above is one-sided. Clark and McCracken (2001) demonstrate that the limiting distribution of ENC-NEW is not normal when the forecasts are nested under the null and they provide asymptotic critical values for this statistic.

The second test used here is the one developed by McCracken (2007). This test, unlike the one proposed by Diebold and Mariano (1995) in the context of non-nested models, allows for comparison of predictive accuracy between nested models. In particular, we use it to test for equality of the mean squared forecasting errors (MSE) from the benchmark and competing models, which is given by:

$$\text{MSE-F} = P\frac{\sum_{t=R}^{T-1}\left(\hat{u}_1(t+1)^2 - \hat{u}_2(t+1)^2\right)}{\sum_{t=R}^{T-1}\hat{u}_2(t+1)^2} = P\left[\frac{\text{MSE}_1 - \text{MSE}_2}{\text{MSE}_2}\right] \tag{12}$$

where $\text{MSE}_j = \sum_{t=R}^{T-1}\hat{u}_j(t+1)^2/P;\ j = 1, 2$. Based upon the value of this statistic the null of equal MSE is either rejected or not rejected. McCracken (2007) shows that when the two models are nested the alternative is one-sided, rather than two-sided. Moreover, since the asymptotic distribution of MSE-F under the null is nonstandard, tables of asymptotically valid critical values are provided in McCracken (2007).

Clark and McCracken (2001) use simulations to examine the small-sample properties of the ENC-NEW and MSE-F tests. They report that although both tests have good sample size properties, the ENC-NEW test is clearly the more powerful out-of-sample test of predictive ability. While this evidence indicates that the inference from the ENC-NEW test is more reliable, Welch and Goyal (2008) highlight an important problem of encompassing tests in general. The ENC-NEW test uses the entire out-of-sample test to estimate the parameter λ, but an investor trying to use a combined forecast to predict $R_m(t+1) - R_f(t+1)$ will only have the information available up to t to calculate the combination coefficient λ. Thus, although it does not have the best small-sample properties, the MSE-F test is the only one which enables testing of out-of-sample predictive power under the same conditions that an investor faces in reality.

Our final measure of out-of-sample forecasting performance is the out-of-sample R^2, R^2_{OS}. This statistic is the analog to in-sample R^2 and was proposed by Campbell and Thompson (2008). In terms of our notation it is computed as:

$$R^2_{OS} = 1 - \frac{\sum_{t=R}^{T-1}\hat{u}_2(t+1)^2}{\sum_{t=R}^{T-1}\hat{u}_1(t+1)^2} = \frac{\text{MSE}_1 - \text{MSE}_2}{\text{MSE}_1} = \frac{\text{MSE-F}}{P}\left(\frac{\text{MSE}_2}{\text{MSE}_1}\right) \tag{13}$$

As can be seen from equation (13), if R^2_{OS} is positive then the competing model has a lower MSE than the benchmark model. Also, as shown in the last equality, the R^2_{OS} is not a statistic that provides new information with respect to the other tests, since it is merely a scaled-up version of the MSE-F statistic.[20] That is, predictor variables with greater MSE-F will also exhibit greater R^2_{OS}. Then, this could also be considered a test of equal MSE, assuming that it has an asymptotic distribution.[21]

In general, when performing out-of-sample tests in a small sample, there is a trade-off with the number of in-sample observations that is hard to resolve. On the one hand, the objective is to use a relatively large in-sample proportion of the sample (R/T), so that the out-of-sample forecasts are done with estimates which are as similar as possible to those obtained with the full sample. But at the same time, as suggested by the results of Inoue and Kilian (2005), the out-of-sample proportion (P/T) must be large enough to prevent significant differences in power between the in-sample and out-of-sample tests. Thus, to achieve a reasonable level of power without producing excessive forecasting errors at the beginning of the out-of-sample sub-period, the optimal choice should be around $\pi = P/R = 1$. However, to make our test more rigorous, we choose 1997Q4, which is when the Asian crisis hit the U.S. economy, as the starting point for the out-of-sample sub-period. That is, given that our adjusted (for lags) sample encompasses the period 1984Q2-2009Q4, our choice implies the following sample portions: $R = 54$, $P = 49$ and $\pi = 0.91$.

As mentioned above, in the context of one-step ahead forecasts, Clark and McCracken (2001) and McCracken (2007) provide asymptotic critical values for the ENC-NEW and MSE-F statistics, respectively. These critical values depend on two parameters: $\pi = P/R$ and $K_2 - 1$, the number of variables included in $X(t)$. Because the tables with the critical values for these nonstandard tests do not contain the particular value of π chosen by us, we follow Clark and McCracken (2005) and obtain these values with an inference technique based on bootstrapping. In addition, based on the bootstrapped time series, we obtain the empirical distribution of the R^2_{OS} statistic and critical values for the tests in the next section. In particular, we use a parametric bootstrap (Berkowitz and Kilian, 2000) and our algorithm has five steps, which we briefly describe below:[22]

1. We estimate a bivariate VAR for the excess stock return, $R_m(t) - R_f(t)$, and the variables in $X(t)$ under the null hypothesis of nonpredictability. The model is estimated with OLS and using the full sample. The excess return is modeled according to equation (4) and for the variables in $X(t)$ the optimal number of lags of $R_m(t) - R_f(t)$ and $X(t)$ were chosen with the AIC criterion.

2. The coefficients of the VAR were adjusted for the small-sample bias using Kilian's (1998) procedure with 10,000 bootstrap draws.

3. We bootstrapped 999 time series for the excess stock return and the variables in $X(t)$ by drawing from the rescaled sample residuals with replacement (Berkowitz and Kilian, 2000)

using the adjusted VAR coefficients and initial observations selected by sampling from actual data (Stine, 1987).

4. Each artificial bivariate time series is used to estimate the benchmark and competing models (equations (4) and (5)) in a recursive way. Forecasting errors are calculated according to equations (6) and (7) and using the sample portions described above. The ENC-NEW, MSE-F and R^2_{OS} statistics were calculated based on these estimated forecasting errors with equations (11), (12) and (13).

5. For each statistic, critical values are simply computed as percentiles of the corresponding empirical distribution. The p-values are calculated using the standard method.

The results of the out-of-sample tests are presented in Table VIII. All of the tests coincide in that our variable is the only one with out-of-sample forecasting power for the excess stock returns at a 10% significance level.[23] Although the *cay* variable is marginally significant according to the ENC-NEW test (its bootstrapped p-value is 10.3%), as explained above, the only test that measures forecasting power under the effective conditions faced by a potential investor is the MSE-F test. Our variable (Δf) has the highest and most significant R^2_{OS} among all of the variables considered; however, the size of this statistic is only 1.2%. The table also shows that given the wide differences between the bootstrapped and asymptotic critical values, controlling for considerations of small sample and differences in the relative out-of-sample portion (i.e., π) is essential for a reliable inference, especially when highly persistent predictor variables are used. Also, as expected, as a consequence of the close relationship between the MSE-F and the R^2_{OS} statistics, the inference using the bootstrap method produces the same results for both tests.

Finally, the low R^2_{OS} for all the predictors is evidence that out-of-sample forecasting of stock returns has become an increasingly difficult challenge in recent times (one of the main points emphasized by Welch and Goyal (2008)). The forecasting ability of a predictor variable depends exclusively on its capacity to successfully summarize the conditioning information used by the market participants, which has become increasingly complex. For example, unlike what was found in previous studies, Ludvigson and Ng (2007) provide evidence that changing stock market volatility is not confined only to high-frequency data. This implies that at a quarterly horizon, even in periods of expansion or recession, it is possible to observe substantial changes in the volatility of equity premium.

V. Long-horizon predictability of stock returns

This section examines the in-sample predictability of stock returns at longer horizons. The evidence presented below is based on the following long-horizon regression:

$$R_m^h(t+h) - R_f^h(t+h) = \alpha_h + \beta_h' X(t) + \varepsilon^h(t+h) \tag{14}$$

where $R_i^h(t+h) = \prod_{j=1}^{h}\left(1 + R_i^1(t+j)\right) - 1$ is the h-period return for asset $i = m, f$ and $R_i^1(t+j)$ is the respective one-period return from time $t+j-1$ to $t+j$.

The evidence of long-run predictability has been the subject of a great deal of criticism. Some of the main problems with long-horizon regressions are the following:

1. Serial correlation in residuals induced by the overlap of observations.
2. Long-horizon regressions use the data inefficiently and provide spurious forecasts about the dynamics of variables, especially for non-exogenous predictor variables (Campbell, 1991).
3. By aggregating returns, long-horizon regressions invalidate the inference from standard asymptotic methods (Valkanov, 2003).
4. For persistent predictor variables, OLS coefficient estimates and R^2 are roughly proportional to the horizon under the null hypothesis of nonpredictability (Boudoukh, Richardson, and Whitelaw, 2008).

According to Boudoukh, Richardson, and Whitelaw (2008) long-horizon regressions are misleading for persistent variables. That is, long-horizon regressions associated with the variables R_f, $d-p$, *cay* and *gap* cannot show anything different to what was shown in Section III due to their high persistence (see Table V); in other words, these variables do not have predictive power for stock returns. If significant forecasting power appears on longer horizons, this is simply, according to Valkanov (2003), because our methodology for the hypothesis testing is incorrect. On the other hand, given the almost null persistence of our variable, the Δf shocks are absolutely short-lived. Therefore, by construction, at the most our variable could have forecasting power for stock returns over a one-year horizon.

Hence, given the results obtained for the other variables and the expectations for ours, we prefer to favor the simplicity of long-horizon regressions. Following Kilian (1999), we adapted the bootstrap algorithm described in the previous section to support the inference from the long-horizon regressions presented here. In addition, to evaluate the impact of the findings in Boudoukh, Richardson, and Whitelaw (2008) on the results for persistent predictor variables, we report both expected regression coefficient and the R^2 statistic at the hth horizon conditional on their one-period counterpart, under the null of nonpredictability. These are given by the following equations:

$$\mathbb{E}\left[\hat{\beta}_h|\hat{\beta}_1 = \hat{\beta}_1^*\right] = \left(1 + \frac{\rho\left(1-\rho^{h-1}\right)}{1-\rho}\right)\hat{\beta}_1^* \tag{15}$$

$$\mathbb{E}\left[R_h^2|R_1^2 = R_1^{2*}\right] = \frac{\left(1 + \frac{\rho\left(1-\rho^{h-1}\right)}{1-\rho}\right)^2}{h} R_1^{2*} \tag{16}$$

where $\hat{\beta}_1^*$ is the actual estimate of the regression coefficient in equation (14) for $h = 1$, ρ is the first-order serial correlation coefficient of the predictor variable and R_1^{2*} is the actual estimate of the R^2 statistic for $h = 1$, also from equation (14).

Our analysis covers return horizons up to five years (h = 20). For each horizon we consider the same number of observations and the same sample period 1984Q1-2004Q4 (i.e., 84 observations for each horizon). Table IX presents the OLS estimates of equation (14) for $h = 3, 4, 8, 12, 16, 20$. We report bootstrapped p-values for t-stats and Wald tests that correct for serial correlation and heteroscedasticity using Newey and West (1987). Because of overlapping observations, we increase lag length for the Newey-West estimator by $h - 1$.[24] The results show that our variable has significant forecasting power for stock returns up to a horizon of three quarters. For $h = 3$ the signs of the coefficients associated with Δf lags are the same as those for $h = 1$, the $\bar{R}^2$ is 7% and the bootstrapped p-value for the test that all coefficients for oil lags are zero is 0.02. At longer horizons, as expected, there is no evidence of predictability with our variable.

Regarding the other variables, Table IX shows that at the 10% significance level, none of the variables demonstrates forecasting power for stock returns at long horizons. The *cay* variable is marginally significant at a five-year horizon; however, given the absence of predictive ability at other horizons, it is very likely that this result can be explained by the look-ahead bias. The variable R_f has so little forecasting power that despite its high persistence, it does not exhibit the pattern predicted by Boudoukh, Richardson, and Whitelaw (2008). Instead, its regression coefficient changes sign through horizons and its $\bar{R}^2$ is always negative. Finally, the other persistent predictor variables ($d-p$, cay and gap) effectively follow the pattern predicted by Boudoukh, Richardson, and Whitelaw (2008). That is, both regression coefficients and R^2 are always (in absolute value) growing with the horizon. In fact, from horizons of one quarter to 20 quarters, the correlation between the estimated regression coefficients and those calculated from equation (15) are 0.97, 0.94 and 0.97 for $d-p$, cay and gap, respectively, whereas the correlation between the estimated R^2s and those calculated from equation (16) are 0.94, 0.80 and 0.97 for $d-p$, cay and gap, respectively. Hence, these results underscore the skepticism with which the evidence of predictability with highly persistent variables should always be viewed.

VI. Implications for the cross-section of expected returns

In this section we study the cross-sectional implications of our variable. Unlike traditional or unconditional asset pricing models which assume that stock returns are independent and identically distributed over time, conditional asset pricing models provide flexibility for pricing assets differently through time.[25] According to the latter models, the price of stock i, $P_i(t)$, is determined by the following equilibrium condition:

$$P_i(t) = \mathbb{E}\left[M(t+1) \cdot X_i(t+1) | I(t)\right] \tag{17}$$

where $M(t+1)$ is the stochastic discount factor or pricing kernel, $X_i(t+1) = P_i(t+1) + D_i(t+1)$ is the payoff of stock i and $I(t)$ is the agent's information set at time t.

Given that $I(t)$ is unknown to the econometrician, the model in equation (17) is implemented using a narrower information set, $\Omega(t) \subset I(t)$. Thus, if the model in (17) holds conditioned on a subset $\Omega(t)$ of the information set $I(t)$, then it necessarily holds conditioned on $I(t)$. This result implies that evidence in favor of the asset pricing model conditioned on $I(t)$ is obtained if the model conditioned on $\Omega(t)$ is not rejected. Moreover, when working with stationary variables it is common to divide by $P_i(t)$ and express the model in equation (17) as:[26]

$$1 = \mathbb{E}\left[M(t+1) \cdot (1 + R_i(t+1))\, |\Omega(t)\right] \tag{18}$$

According to Cochrane (1996), it is possible to include the effects of conditioning information by scaling the returns or the factors by instruments. Several authors have tested models with linear pricing kernels and variable sensitivities to the risk factors. Thus, they propose conditioning variables and employing them as instruments in scaled factor models, and subsequently analyzing the unconditional implications of these models. The standard in this modeling is to use linear pricing kernels of the following type:[27]

$$M(t+1) = b' \left(\tilde{F}(t+1) \otimes \tilde{z}(t) \right) = b^0(t) + \sum_{j=1}^{J} b^j(t) F^j(t+1) \tag{19}$$

where $\tilde{F}(t+1) = [1\ F(t+1)']'$, $F(t+1)$ is a column vector of J risk factors, $\tilde{z}(t) = [1\ z(t)']'$, $z(t) \in \Omega(t)$ is a column vector of L conditioning variables and $b = \left[b^{0\prime}\ b^{1\prime} \cdots b^{J\prime} \right]'$ where $b^j = \left[b^j_0\ b^j_1 \cdots b^j_L \right]'$ is a column vector of $L+1$ parameters and $b^j(t) = b^{j\prime}\tilde{z}(t)$. This model has typically been calculated for a vector of N returns, $R(t+1)$, with one factor ($J = 1$) and one conditioning variable ($L = 1$); in other words:

$$1_N = \mathbb{E}\left[\left(b^0(t) + b^1(t) F(t+1) \right) \cdot \left(1_N + R(t+1) \right) \right] \tag{20}$$

where $b^i(t) = b^i_0 + b^i_1 z(t);\ i = 0, 1$ and 1_N is a vector of ones with size $N \times 1$. In general, studies on conditional asset pricing comprise two empirical stages. The first stage is to show that the proposed conditioning variable has forecasting power for excess market returns. Variables that could potentially be part of $\Omega(t)$ are those with the ability to alert investors about future movement of returns. Hence, variables with proven forecasting power for market returns are natural candidates. The second stage is to estimate equation (20) and present evidence of adjustment in the cross-section of expected stock returns.[28] Thus, given the predictive ability of the conditioning variable and the functional form of the pricing kernel, the cross-sectional adjustment is exclusively determined by considerations of empirical design and the risk factors used. The most commonly used risk factors are the aggregate market return, $R_m(t+1)$, and real per-capita consumption growth rate, $\Delta c(t+1)$, that corresponds to the conditional version of the CAPM (Sharpe, 1964) and CCAPM (Breeden and Litzenberger, 1978), respectively.[29]

A wide range of conditioning variables have been used for the conditional models like the one in equation (20). For example, Lettau and Ludvigson (2001b) propose CAPM and CCAPM models conditioned on the *cay* variable. Lustig and Van Nieuwerburgh (2005) derive a conditional CCAPM on the housing collateral ratio (ratio of housing wealth to human wealth). Santos and Veronesi (2006) present a conditional CAPM on the labor income to consumption ratio (fraction of consumption funded by labor income). In these studies the evidence of predictability is only an intermediate step that enables the authors to fulfill the first requisite needed for the existence of a conditional asset pricing model, or in other words, that the equity risk premium is variable. Then, given that the predictability condition is satisfied, there should be a conditional model that correctly values the cross-section of returns using the proposed predictor. Therefore, papers on conditional asset pricing have a broader purpose because they include time-series and cross-sectional tests.

However, despite the clear relationship between predictability, time-varying risk premium and conditional asset pricing models, there is an important methodological asymmetry between studies on predictability and those on conditional asset pricing. Except for Lettau and Ludvigson (2001a) and Lettau and Ludvigson (2001b), papers on predictability have only sought to prove that the equity risk premium is variable and do not consider cross-section tests. On the other hand, studies on conditional asset pricing, such as Lustig and Van Nieuwerburgh (2005) and Santos and Veronesi (2006) only present evidence of in-sample predictability and generally lack the empirical rigor of the predictability studies.[30]

In our opinion, if a variable exhibits significant forecasting power for stock market returns, there should be a conditioning asset pricing model on that variable with significant predictive power for the cross-section of expected stock returns. For this reason and for greater robustness, we offer empirical evidence of adjustment in the cross-section of expected returns through CAPM and CCAPM models conditioned on our variable. In addition, the empirical performance of our conditional models is compared to the performance of the same models conditioned on the other predictor variables considered in the previous sections, as well as the following unconditional models: CAPM, CCAPM and the three-factor model of Fama and French (1993) (FF three-factor).[31]

The absence of arbitrage opportunities is clearly a consequence of a positive pricing kernel, i.e., $M(t+1) > 0$. However, empirical evidence reported in Nagel and Singleton (2011) reveals that the $M(t+1)$ implied by the estimates from equation (20) frequently takes large negative values. To address this problem, here we impose a restriction of non-negativeness by using an exponential pricing kernel of the following form:

$$M(t+1) = \exp\left(b^0(t) + b^1(t)F(t+1)\right) \tag{21}$$

where $b^i(t) = b^i_0 + b^i_1 z_1(t) + \ldots + b^i_L z_L(t);\ i = 0, 1$ and $F(t+1)$ is the risk factor (i.e., $F(t+1)$ is $R_m(t+1)$ for the conditional CAPM and $\Delta c(t+1)$ for conditional CCAPM). In addition, it is important to highlight that we allow for more than one conditioning variable, in particular, we use $L = 4$ for our models whereas $L = 1$ for conditional models on other variables. We work with the following pricing equation:

$$1_N = \mathbb{E}\left[\exp\left(b^0(t) + b^1(t)F(t+1)\right) \cdot (1_N + R(t+1))\right] \tag{22}$$

As noted by Lewellen, Nagel, and Shanken (2010), conditional asset pricing models present serious problems in pricing a risk-free portfolio. Although they report high R^2 in the cross-section, this is typically achieved at the expense of estimated intercepts that are substantially greater than their theoretical values (i.e., the risk free rate). To address this, we follow Nagel and Singleton (2011) and include the risk-free portfolio as an extra asset in our study. We consider the orthogonality relationship between a risk-free rate and the pricing kernel, $M(t+1)$, represented by the following moment restriction:[32]

$$0 = \mathbb{E}\left[M(t+1) - \frac{1}{1 + R_f(t+1)}\right] \tag{23}$$

In addition, we use the beta representation of equation (22) to produce the unconditional expressions for the expected risk-free return and the expected return of asset i given by:

$$\begin{aligned} \mathbb{E}\left[R_f(t+1)\right] &= \frac{1}{\mathbb{E}\left[M(t+1)\right]} - 1 && (24) \\ \mathbb{E}\left[R_i(t+1)\right] &= \mathbb{E}\left[R_f(t+1)\right] - \mathbb{E}\left[1 + R_f(t+1)\right] \mathbb{C}ov\left[M(t+1), R_i(t+1)\right] && (25) \end{aligned}$$

where in equation (24) we are assuming that the risk-free asset is unconditionally orthogonal to $M(t+1)$ (i.e., the risk-free asset is a zero-beta asset). Equations (24) and (25) can be used to assess the fit of an estimated model to the cross-section of average returns.

For the cross-sectional tests we use the standard 25 portfolio of Fama and French (1993) ordered by size and book-to-market, in addition to the risk-free portfolio, therefore $N = 26$. These series as well as the SMB (small minus big) and HML (high minus low) factors from the FF three-factor model are available from Ken French's web page. The real per-capita consumption series was constructed using data from the Bureau of Economic Analysis. Specifically, we construct our quarterly series from nominal consumption of nondurables and services, seasonally adjusted, per capita (NIPA Table 7.1). Real consumption was calculated by deflating the nominal series by the PCE (personal consumption expenditures) price index, 2005=100 (NIPA Table 2.3.4).

Tables X, XI and XII present the results of the estimation by the Generalized Method of Moments (GMM) for the moment conditions in equations (22) and (23). We report the asymptotic t-stats, and the Wald and J_T tests based on the covariance matrices of pricing errors corrected for heteroscedasticity and serial correlation using the Newey-West estimator. We use the identity weighting matrix for all estimates, based on the following reasons. First, we do not have theoretical arguments for giving more or less importance to a particular portfolio. Second, the number of moment conditions ($N = 26$) is large relative to our sample size ($T = 103$), so this choice avoids dealing with estimates that depend on unstable and near singular error covariance matrices. The root of mean square errors (RMSE) is used to measure the fit of an estimated model to the cross-section of average returns. In addition, Figures 3 to 15 plot the fitted expected returns for the 26 portfolios against their realized average returns. The 25 portfolios, sorted by size and book-to-market ratio, are labeled with two digits. The first digit refers to the size quintile (1 indicating the smallest firms, 5 the largest), and the second digit refers to book-to-market quintile (1 indicating the portfolio with the lowest book-to-market ratio, 5 with the highest).

Table X and Figures 3 to 5 show the results for the unconditional CAPM, CCAPM and FF three-factor models. The J_T tests do not reject any conditional or unconditional model, so our inference is based solely on the t-stats and Wald tests. The latter tests the hypothesis that all coefficients except the constant are zero. According to the Wald test, no model is significant at the 5% level; nevertheless, the FF three-factor model presents the best cross-sectional adjustment (RMSE=0.55%).

Table XI and Figures 6 to 10 present the results for the conditional CAPM models. A Wald test for the null hypothesis that conditional (C)CAPM model does not improve the adjustment relative to the unconditional (C)CAPM model is included in the *P-value Wald CAPM* row (i.e., it tests whether the additional coefficients in the conditional (C)CAPM model are zero). The table shows that the CAPM conditional on Δf exhibit by far the best forecasting power for the cross-section of expected returns (RMSE=0.34%); moreover, in accordance with both Wald tests, it is the only significant one at the 5% level. The risk factor $R_m(t)$ is significant throughout the interaction term only with $\Delta f(t-4)$. This implies that an oil shock accompanied by a subsequent decline in market return

($\Delta f(t-4) \cdot R_m(t) < 0$) causes a drop in future portfolio returns. This effect strongly suggests that our variable also has forecasting power for returns on more disaggregated stock portfolios. Finally, CAPM models conditioned on $d-p$ and *gap* slightly outperform the FF three-factor model, but none of these models is statistically significant.

Table XII and Figures 11 to 15 display the outcomes for conditional CAPM models. Based on these outcomes, we note that the CCAPM conditional on Δf is the only one that outperforms the FF three-factor model; however, it is not significant at the 5% level. Also, the CCAPM model conditioned on R_f is statistically significant but is outperformed by several conditional and unconditional models (RMSE=0.60%).

In summary, the conditional CAPM on our variable has significant predictive power for the cross-section of expected stock returns and has a better fit than all unconditional and conditional models considered here.

VII. Conclusions

Although the predictability of stock market returns has been associated with the business cycle, the evidence that supports this relationship is far from being conclusive. Moreover, when the sample is extended to include the period of the subprime crisis, none of the popular predictors exhibit forecasting power for stock returns. In this paper, we show that such a relationship exists.

We find that unexpected oil price changes, a non-persistent variable with deep macroeconomic roots, have significant forecasting power for stock returns at short horizons. Our variable, proxied by futures returns on crude oil, shows statistically and economically significant predictive power for stock returns at horizons from one to three quarters. Its predictive power outperforms those of the risk-free rate, the dividend-price ratio, the consumption-wealth ratio and the output gap, with quarterly $\bar{R}^2$ between 6% and 7%. This result is robust against the inclusion of other variables and out-of-sample tests. However, at longer horizons, none of the variables displays significant forecasting ability. Our results also validate the recent findings of Boudoukh, Richardson, and Whitelaw (2008) that unstable results in previous studies in this literature are due to the high persistence of the predictors used.

Furthermore, the following evidence protects our results against potential data-snooping biases. First, the relationship between the business cycle and oil price shocks has been studies since 1983 and since then, a large quantity of macroeconomic theory and evidence has supported this relationship. Second, several empirical studies in finance with different data and methodologies have found that stock returns are affected by past oil shocks. Third, our variable also shows significant forecasting power for the cross-section of expected returns. This was demonstrated using a conditional CAPM model on oil price shocks, which shows high statistical significance and better adjustment to all conditional and unconditional models considered, including the Fama and French (1993) three-factor model.

Finally, from a practical perspective, unlike variables based on macroeconomic series, such as the consumption-wealth ratio and the output gap, our variable can be directly observed and is available on a daily basis at no cost. These characteristics make use of our variable by potential investors highly feasible.

References

Ang, Andrew, and Geert Bekaert, 2007, Stock return predictability: Is it there?, *Review of Financial Studies* 20, 651–707.

Apergis, Nicholas, and Stephen M. Miller, 2009, Do structural oil-market shocks affect stock prices?, *Energy Economics* 31, 569 – 575.

Bachmeier, Lance, 2008, Monetary policy and the transmission of oil shocks, *Journal of Macroeconomics* 30, 1738 – 1755.

Balke, Nathan S., Stephen P.A. Brown, and Mine K. Yucel, 2002, Oil price shocks and the u.s. economy: Where does the asymmetry originate?, *Energy Joumal* 23, 27–52.

Berkowitz, Jeremy, and Lutz Kilian, 2000, Recent developments in bootstrapping time series, *Econometric Reviews* 19, 1–48.

Bernanke, Ben S., 1983, Irreversibility, uncertainty, and cyclical investment, *The Quarterly Journal of Economics* 98, pp. 85–106.

——— , Mark Gertler, and Mark W. Watson, 1997, Systematic monetary policy and the effects of oil price shocks, *Brookings Papers on Economic Activity* 1997, 91–157.

Boudoukh, Jacob, Matthew Richardson, and Robert F. Whitelaw, 2008, The myth of long-horizon predictability, *Review of Financial Studies* 21, 1577–1605.

Breeden, Douglas T., and Robert H. Litzenberger, 1978, Prices of state-contingent claims implicit in option prices, *Journal of Business* 51, 621–651.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373 – 399.

——— , 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157–179.

——— , and Samuel B. Thompson, 2008, Predicting excess stock returns out of sample: Can anything beat the historical average?, *Review of Financial Studies* 21, 1509–1531.

Carruth, Alan A., Mark A. Hooker, and Andrew J. Oswald, 1998, Unemployment equilibria and input prices: Theory and evidence from the united states, *Review of Economics and Statistics* 80, 621–628.

Ciner, Cetin, 2001, Energy shocks and financial markets: Nonlinear linkages, *Studies in Nonlinear Dynamics and Econometrics* 5, 203–212.

Clark, Todd E., and Michael W. McCracken, 2001, Tests of equal forecast accuracy and encompassing for nested models, *Journal of Econometrics* 105, 85 – 110.

——— , 2005, Evaluating direct multistep forecasts, *Econometric Reviews* 24, 369–404.

Cochrane, John H., 1996, A cross-sectional test of an investment-based asset pricing model, *Journal of Political Economy* 104, 572–621.

——— , 2005, *Asset Pricing* (Princeton University Press).

——— , 2008, The dog that did not bark: A defense of return predictability, *Review of Financial Studies* 21, 1533–1575.

Cologni, Alessandro, and Matteo Manera, 2008, Oil prices, inflation and interest rates in a structural cointegrated var model for the g-7 countries, *Energy Economics* 30, 856 – 888.

——— , 2009, The asymmetric effects of oil shocks on output growth: A markov-switching analysis for the g-7 countries, *Economic Modelling* 26, 1 – 29.

Cooper, Ilan, and Richard Priestley, 2009, Time-varying risk premiums and the output gap, *Review of Financial Studies* 22, 2801–2833.

Davis, Steven J., and John Haltiwanger, 2001, Sectoral job creation and destruction responses to oil price changes, *Journal of Monetary Economics* 48, 465 – 512.

Dhawan, Rajeev, and Karsten Jeske, 2008, Energy price shocks and the macroeconomy: The role of consumer durables, *Journal of Money, Credit and Banking* 40, 1357–1377.

Diebold, Francis X., and Roberto S. Mariano, 1995, Comparing predictive accuracy, *Journal of Business & Economic Statistics* 13, pp. 253–263.

Driesprong, Gerben, Ben Jacobsen, and Benjamin Maat, 2008, Striking oil: Another puzzle?, *Journal of Financial Economics* 89, 307 – 327.

Fama, Eugene F., and Kenneth R. French, 1987, Commodity futures prices: Some evidence on forecast power, premiums, and the theory of storage, *Journal of Business* 60, 55–73.

——— , 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3–25.

——— , 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Ferderer, J. Peter, 1996, Oil price volatility and the macroeconomy, *Journal of Macroeconomics* 18, 1–26.

Finn, Mary G., 2000, Perfect competition and the effects of energy price increases on economic activity, *Journal of Money, Credit and Banking* 32, 400–416.

Gisser, Micha, and Thomas H. Goodwin, 1986, Crude oil and the macroeconomy: Tests of some popular notions: Note, *Journal of Money, Credit and Banking* 18, pp. 95–103.

Gronwald, Marc, 2008, Large oil shocks and the us economy: Infrequent incidents with large effects, *Energy Journal* 29, 151–171.

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

——— , 1988, A neoclassical model of unemployment and the business cycle, *Journal of Political Economy* 96, 593–617.

——— , 1996, This is what happened to the oil price-macroeconomy relationship, *Journal of Monetary Economics* 38, 215 – 220.

——— , 2003, What is an oil shock?, *Journal of Econometrics* 113, 363–398.

——— , 2008, oil and the macroeconomy, in Steven N. Durlauf, and Lawrence E. Blume, ed.: *The New Palgrave Dictionary of Economics* (Palgrave Macmillan: Basingstoke).

——— , and Ana Maria Herrera, 2004, Comment: Oil shocks and aggregate macroeconomic behavior: The role of monetary policy, *Journal of Money, Credit and Banking* 36, 265–286.

Harvey, David I., Stephen J. Leybourne, and Paul Newbold, 1998, Tests for forecast encompassing, *Journal of Business & Economic Statistics* 16, pp. 254–259.

Hooker, Mark A., 1996, What happened to the oil price-macroeconomy relationship?, *Journal of Monetary Economics* 38, 195 – 213.

Huang, Roger D., Ronald W. Masulis, and Hans R. Stoll, 1996, Energy shocks and financial markets, *Journal of Futures Markets* 16, 1–27.

Huntington, Hillard G., 2007, Oil shocks and real u.s. income, *Energy Joumal* 28, 31–46.

Inoue, Atsushi, and Lutz Kilian, 2005, In-sample or out-of-sample tests of predictability: Which one should we use?, *Econometric Reviews* 23, 371–402.

Jimenez-Rodriguez, Rebeca, 2008, The impact of oil price shocks: Evidence from the industries of six oecd countries, *Energy Economics* 30, 3095 – 3108 Technological Change and the Environment.

——— , and Marcelo Sanchez, 2005, Oil price shocks and real gdp growth: Empirical evidence for some oecd countries, *Applied Economics* 37, 201–228.

Jones, Charles M., and Gautam Kaul, 1996, Oil and the stock markets, *Journal of Finance* 51, 463–491.

Kilian, Lutz, 1998, Small-sample confidence intervals for impulse response functions, *The Review of Economics and Statistics* 80, pp. 218–230.

——— , 1999, Exchange rates and monetary fundamentals: What do we learn from long-horizon regressions?, *Journal of Applied Econometrics* 14, pp. 491–510.

——— , 2008, A comparison of the effects of exogenous oil supply shocks on output and inflation in the g7 countries, *Journal of the European Economic Association* 6, 78–121.

——— , 2009, Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market, *American Economic Review* 99, 1053–1069.

——— , and Cheolbeom Park, 2009, The impact of oil price shocks on the u.s. stock market*, *International Economic Review* 50, 1267–1287.

Kliesen, Kevin L., 2008, Oil and the u.s. macroeconomy: An update and a simple forecasting exercise, *Federal Reserve Bank of St. Louis Review* 90, 505–516.

Kumar, Manmohan S., 1992, The forecasting accuracy of crude oil futures prices, *Staff Papers - International Monetary Fund* 39, pp. 432–461.

Leduc, Sylvain, and Keith Sill, 2004, A quantitative analysis of oil-price shocks, systematic monetary policy, and economic downturns, *Journal of Monetary Economics* 51, 781–808.

Lee, Kiseok, and Shawn Ni, 2002, On the dynamic effects of oil price shocks: A study using industry level data, *Journal of Monetary Economics* 49, 823–852.

——— , and Ronald A. Ratti, 1995, Oil shocks and the macroeconomy: The role of price variability, *Energy Journal* 16, 39–56.

Lettau, Martin, and Sydney C. Ludvigson, 2001a, Consumption, aggregate wealth, and expected stock returns, *Journal of Finance* 56, 815–849.

——— , 2001b, Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying, *Journal of Political Economy* 109, 1238–1287.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175 – 194.

Lilien, David M., 1982, Sectoral shifts and cyclical unemployment, *Journal of Political Economy* 90, pp. 777–793.

Ludvigson, Sydney C., and Serena Ng, 2007, The empirical risk-return relation: A factor analysis approach, *Journal of Financial Economics* 83, 171–222.

Lustig, Hanno N., and Stijn G. Van Nieuwerburgh, 2005, Housing collateral, consumption insurance, and risk premia: An empirical perspective., *Journal of Finance* 60, 1167–1219.

Ma, Cindy W., 1989, Forecasting efficiency of energy futures prices, *Journal of Futures Markets* 9, 393–419.

McCracken, Michael W., 2007, Asymptotics for out of sample tests of granger causality, *Journal of Econometrics* 140, 719 – 752.

Mork, Knut Anton, 1989, Oil and the macroeconomy when prices go up and down: An extension of hamilton's results, *Journal of Political Economy* 97, 740–744.

Nagel, Stefan, and Kenneth J. Singleton, 2011, Estimation and evaluation of conditional asset pricing models, *The Journal of Finance* 66, 873–909.

Nandha, Mohan, and Robert Faff, 2008, Does oil move equity prices? a global view, *Energy Economics* 30, 986–997.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, pp. 703–708.

———, 1994, Automatic lag selection in covariance matrix estimation, *The Review of Economic Studies* 61, pp. 631–653.

Park, Jungwook, and Ronald A. Ratti, 2008, Oil price shocks and stock markets in the u.s. and 13 european countries, *Energy Economics* 30, 2587 – 2608.

Sadorsky, Perry, 1999, Oil price shocks and stock market activity, *Energy Economics* 21, 449–469.

Santos, Tano, and Pietro Veronesi, 2006, Labor income and predictable stock returns, *Review of Financial Studies* 19, 1–44.

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

Sims, Christopher A., 1980, Macroeconomics and reality, *Econometrica* 48, pp. 1–48.

Stambaugh, Robert F., 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Stine, Robert A., 1987, Estimating properties of autoregressive forecasts, *Journal of the American Statistical Association* 82, pp. 1072–1078.

Switzer, Lorne N., and Mario El-Khoury, 2007, Extreme volatility, speculative efficiency, and the hedging effectiveness of the oil futures markets, *Journal of Futures Markets* 27, 61–84.

Valkanov, Rossen, 2003, Long-horizon regressions: Theoretical results and applications, *Journal of Financial Economics* 68, 201–232.

Wei, Chao, 2003, Energy, the stock market, and the putty-clay investment model, *American Economic Review* 93, 311–323.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

Table I
Literature on financial markets and oil prices

The table provides information on studies on financial markets and oil prices. The variables used are: Δf: log returns on oil futures prices; Δs: log returns on nominal spot prices; Δs_r: log returns on real spot prices; Sop: oil prices scaled by volatility, unexpected changes in oil prices (Lee, Ni, and Ratti, 1995); $Nopi$: net oil price increases (Hamilton, 1996; Hamilton, 2003); Vol: rolling volatility of oil price changes; $x^+ = max(0, x)$; $x^- = min(0, x)$.

Paper	Subject	Frequency	Data		
			Stock market	Oil	
				Series	Variable
Huang, Masulis, and Stoll (1996)	Joint dynamics	Daily	S&P 500, industrial portfolios, oil companies	Heating and crude oil futures	Δf
Jones and Kaul (1996)	Market efficiency	Quarterly	Real country indexes	PPI oil and related products	Δs
Sadorsky (1999)	Joint dynamics	Monthly	S&P 500/CPI	PPI fuels/CPI	Δs_r, Δs_r^+, Δs_r^-, Sop, Sop^+, Sop^-
Ciner (2001)	Joint dynamics	Daily	S&P 500	Heating and crude oil futures	Δf
Driesprong, Jacobsen, and Maat (2008)	Predictability	Monthly	Country indexes, sector indexes	Brent, WTI, Dubai, Arab Light, Brent futures, Oil futures	Δs, Δf
Park and Ratti (2008)	Joint dynamics	Monthly	Real country indexes	Brent/PPI all commodities	Δs_r, Sop, $Nopi$, Δs_r^+, Δs_r^-, Sop^+, Sop^-, Vol
Kilian and Park (2009)	Oil demand and supply shocks	Monthly	Real CRSP value weighted, industry portfolios	EIA refiner acquisition cost/CPI	Δs_r
Apergis and Miller (2009)	Oil demand and supply shocks	Monthly	Real country indexes	EIA Refiner Acquisition Cost/CPI	Δs_r

Table II
Stock market returns and the business cycle

Conditional excess stock returns for the sample period 1926Q3 to 2009Q4. Classification of states based on NBER Business Cycle Dates.

State	Frequency	Average excess return	Standard deviation of excess returns
Expansion	252	2.9	9.1
Peak	15	-5.5	8.1
Recession	52	-3.0	17.3
Trough	15	12.3	10.0
Total	334	2.0	11.3

Table III
Optimal lags of oil price shocks

OLS regressions of excess stock returns on lags of oil price shocks, 1983Q2-2009Q4. All estimations use full sample and include a constant.

Lags of oil price shocks	AIC
0	-4.884
1	-4.891
2	-4.867
3	-4.846
4	-4.893
5	-4.870
6	-4.844
7	-4.824
8	-4.803

Table IV
VAR estimation results, 1983Q2-2009Q4

Maximum likelihood estimates of the VAR(4) model for the rate of growth of industrial production ($\Delta\%IP(t)$), excess stock market returns ($R_m(t) - R_f(t)$) and log returns on crude oil futures ($\Delta f(t)$). Asymptotic t-stat in parentheses. Granger causality was tested using the asymptotic Wald test. The *All* row at the bottom of the table refers to all coefficients except the constant.

	$\Delta\%IP(t)$	$R_m(t) - R_f(t)$	$\Delta f(t)$
Constant	0.000	0.011	0.020
	(0.45)	(1.20)	(0.88)
$\Delta\%IP(t-1)$	0.276	0.956	-0.205
	(3.04)	(1.25)	(-0.11)
$\Delta\%IP(t-2)$	-0.027	-0.852	0.404
	(-0.26)	(-0.99)	(0.19)
$\Delta\%IP(t-3)$	-0.113	-1.215	0.460
	(-1.10)	(-1.40)	(0.22)
$\Delta\%IP(t-4)$	0.347	2.327	-1.194
	(3.70)	(2.93)	(-0.62)
$R_m(t-1) - R_f(t-1)$	0.061	0.038	0.269
	(5.59)	(0.41)	(1.19)
$R_m(t-2) - R_f(t-2)$	0.030	-0.069	0.191
	(2.52)	(-0.68)	(0.77)
$R_m(t-3) - R_f(t-3)$	0.005	-0.038	0.268
	(0.42)	(-0.37)	(1.07)
$R_m(t-4) - R_f(t-4)$	0.026	0.019	-0.087
	(2.12)	(0.19)	(-0.35)
$\Delta f(t-1)$	0.010	0.065	0.035
	(2.09)	(1.59)	(0.35)
$\Delta f(t-2)$	-0.006	-0.044	-0.183
	(-1.22)	(-1.04)	(-1.79)
$\Delta f(t-3)$	-0.012	-0.004	0.027
	(-2.35)	(-0.10)	(0.26)
$\Delta f(t-4)$	-0.005	-0.119	-0.057
	(-1.00)	(-2.74)	(-0.54)
R^2	0.51	0.18	0.06
$\bar{R}^2$	0.44	0.07	-0.06
P-value Granger causality test			
All	0.00	0.03	0.85
$\Delta\%IP$	0.00	0.04	0.98
$R_m - R_f$	0.00	0.94	0.53
Δf	0.01	0.04	0.49

Table V
Statistics for 1983Q2-2009Q4

Statistics for the excess stock return and the main predicts used in this study. Autocorrelation is the first-order serial correlation.

	$R_m - R_f$	Δf	R_f	$d-p$	cay	gap
Average	0.016	0.021	0.012	-3.781	0.005	-0.014
Standard deviation	0.087	0.195	0.006	0.386	0.019	0.063
Autocorrelation	0.031	0.031	0.972	0.974	0.910	0.977

	Correlation matrix					
	$R_m - R_f$	Δf	R_f	$d-p$	cay	gap
$R_m - R_f$	1.000					
Δf	-0.039	1.000				
R_f	0.006	-0.035	1.000			
$d-p$	0.139	-0.101	0.524	1.000		
cay	-0.108	-0.100	0.348	0.472	1.000	
gap	-0.121	0.111	-0.210	-0.847	-0.601	1.000

Table VI
Predictive regressions for excess stock returns, 1983Q2-2009Q4

OLS regressions for excess stock returns on the predictor variables in the first row. All tests are based on covariance matrices of coefficients corrected for heteroscedasticity and serial correlation using Newey and West (1987). Lag length in the Newey-West estimator is floor $\left[4 \cdot (T/100)^{2/9}\right]$, where floor$[x]$ denotes the integer part of x (Newey and West, 1994). Asymptotic t-stat in parentheses. At the bottom of the table, the p-value is for asymptotic Wald test and *All* refers to all coefficients except the constant.

	Δf	R_f	$d-p$	cay	gap
Constant	0.019	0.013	0.154	0.014	0.015
	(2.59)	(0.55)	(2.04)	(1.52)	(1.66)
$\Delta f(t-1)$	0.068				
	(1.95)				
$\Delta f(t-2)$	-0.035				
	(-0.53)				
$\Delta f(t-3)$	-0.024				
	(-0.48)				
$\Delta f(t-4)$	-0.115				
	(-2.68)				
$R_f(t)$		0.403			
		(0.25)			
$d(t-1)-p(t-1)$			0.036		
			(1.75)		
$cay(t-1)$				0.729	
				(2.09)	
$gap(t-1)$					-0.219
					(-1.58)
R^2	0.10	0.00	0.02	0.02	0.02
$\bar{R}^2$	0.06	-0.01	0.01	0.01	0.02
P-value Wald All	0.02	0.80	0.08	0.04	0.11

Table VII
Predictive regressions: Additional controls, 1983Q2-2009Q4

OLS regressions for excess stock returns on the predictor variables in the first row. All tests are based on covariance matrices of coefficients corrected for heteroscedasticity and serial correlation using Newey and West (1987). Lag length in the Newey-West estimator is floor $\left[4 \cdot (T/100)^{2/9}\right]$, where floor$[x]$ denotes the integer part of x (Newey and West, 1994). Asymptotic t-stat in parentheses. At the bottom of the table, the p-value is for asymptotic Wald test, *All* refers to all coefficients except the constant and Δf refers to the coefficients associated with the four lags of that variable.

	Δf & R_f	Δf & $d-p$	Δf & cay	Δf & gap	Δf & All
Constant	0.012	0.140	0.015	0.017	0.269
	(0.57)	(2.02)	(1.81)	(2.01)	(1.03)
$\Delta f(t-1)$	0.067	0.075	0.075	0.076	0.078
	(1.96)	(2.13)	(2.07)	(2.20)	(1.87)
$\Delta f(t-2)$	-0.036	-0.026	-0.029	-0.025	-0.028
	(-0.53)	(-0.41)	(-0.47)	(-0.38)	(-0.47)
$\Delta f(t-3)$	-0.026	-0.017	-0.023	-0.013	-0.026
	(-0.49)	(-0.33)	(-0.45)	(-0.26)	(-0.53)
$\Delta f(t-4)$	-0.116	-0.108	-0.114	-0.105	-0.117
	(-2.72)	(-2.50)	(-2.67)	(-2.33)	(-2.54)
$R_f(t)$	0.650				-1.708
	(0.45)				(-0.64)
$d(t-1) - p(t-1)$		0.032			0.061
		(1.68)			(1.01)
$cay(t-1)$			0.784		0.985
			(2.00)		(1.78)
$gap(t-1)$				-0.172	0.303
				(-1.50)	(0.93)
R^2	0.10	0.11	0.12	0.11	0.14
$\bar{R}^2$	0.05	0.07	0.08	0.06	0.06
P-value Wald All	0.02	0.00	0.00	0.00	0.00
P-value Wald Δf	0.01	0.01	0.01	0.02	0.02

Table VIII
Out-of-sample predictability tests, 1983Q2-2009Q4

Out-of-sample tests of stock return predictability. Each column reports the results using the predictor from the first row. Out-of-sample period is from 1997Q4 to 2009Q4. ENC-NEW, MSE-F and R^2_{OS} statistics are described in equations (11), (12) and (13). Asymptotic critical values for ENC-NEW test are from Table 1 in Clark and McCracken (2001) using $\pi = 1.0$. Asymptotic critical values for MSE-F test are from Table 4 in McCracken (2007) using $\pi = 1.0$. Bootstrapped p-values and critical values are based on the methodology of Clark and McCracken (2005).

	Δf	R_f	$d-p$	cay	gap
ENC-NEW					
Sample value	2.218	-0.555	0.202	1.630	0.063
0.10 Asymptotic critical value	2.169	0.984	0.984	0.984	0.984
0.05 Asymptotic critical value	3.007	1.584	1.584	1.584	1.584
Bootstrapped p-value	0.077	0.791	0.278	0.103	0.505
0.10 Bootstrapped critical value	1.939	1.325	1.325	1.653	2.163
0.05 Bootstrapped critical value	2.970	2.033	2.276	2.559	3.294
MSE-F					
Sample value	0.603	-1.287	-0.034	0.261	-0.750
0.10 Asymptotic critical value	0.545	0.751	0.751	0.751	0.751
0.05 Asymptotic critical value	1.809	1.548	1.548	1.548	1.548
Bootstrapped p-value	0.081	0.655	0.172	0.197	0.463
0.10 Bootstrapped critical value	0.443	0.789	0.431	1.335	1.816
0.05 Bootstrapped critical value	1.420	1.860	1.268	2.237	3.006
R^2_{OS}					
Sample value	0.012	-0.027	-0.001	0.005	-0.016
Bootstrapped p-value	0.081	0.655	0.172	0.197	0.463
0.10 Bootstrapped critical value	0.009	0.016	0.009	0.027	0.036
0.05 Bootstrapped critical value	0.028	0.037	0.025	0.044	0.058

Table IX
Long-horizon predictability, 1983Q2-2009Q4

OLS regressions of $R_m^h(t+h) - R_f^h(t+h)$ on the predictor variables using the same number of observations. All tests are based on covariance matrices of coefficients corrected for heteroscedasticity and serial correlation (Newey and West, 1987)). Lag length in the Newey-West estimator is floor $\left[4 \cdot (T/100)^{2/9}\right] + (h-1)$, where floor$[x]$ denotes the integer part of x. Bootstrapped p-values for t-stats in parentheses. $\mathbb{E}[\hat{\beta}_h|\hat{\beta}_1 = \hat{\beta}_1^*]$ and $\mathbb{E}[R_h^2|R_1^2 = R_1^{2*}]$ are described in equations (15) and (16), respectively. *P-value Wald All* is the bootstrapped p-value for the asymptotic Wald test that all coefficients except the constant are zero.

	Forecast horizon in quarters (h)					
	$h=3$	$h=4$	$h=8$	$h=12$	$h=16$	$h=20$
$\Delta f(t)$	0.153	0.019	-0.019	0.105	0.112	-0.143
	(0.01)	(0.44)	(0.45)	(0.33)	(0.35)	(0.28)
$\Delta f(t-1)$	-0.051	-0.057	-0.057	0.029	-0.147	-0.323
	(0.27)	(0.31)	(0.39)	(0.47)	(0.30)	(0.18)
$\Delta f(t-2)$	-0.081	-0.142	-0.128	-0.105	-0.051	-0.380
	(0.24)	(0.18)	(0.28)	(0.35)	(0.42)	(0.14)
$\Delta f(t-3)$	-0.208	-0.146	-0.154	-0.119	-0.138	-0.432
	(0.05)	(0.14)	(0.21)	(0.31)	(0.30)	(0.08)
R^2	0.12	0.05	0.02	0.01	0.01	0.04
$\bar{R}^2$	0.07	0.00	-0.03	-0.04	-0.04	0.00
P-value Wald All	0.02	0.58	0.82	0.75	0.71	0.45
$R_f(t+1)$	0.682	0.926	1.129	-0.084	-3.804	5.304
	(0.39)	(0.38)	(0.38)	(0.57)	(0.47)	(0.34)
$\mathbb{E}[\hat{\beta}_h\|\hat{\beta}_1 = \hat{\beta}_1^*]$	-0.125	-0.165	-0.317	-0.456	-0.585	-0.702
R^2	0.00	0.00	0.00	0.00	0.00	0.00
$\mathbb{E}\left[R_h^2\|R_1^2 = R_1^{2*}\right]$	0.00	0.00	0.00	0.00	0.00	0.00
$\bar{R}^2$	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
P-value Wald All	0.87	0.87	0.90	0.99	0.78	0.85
$d(t) - p(t)$	0.083	0.111	0.220	0.324	0.440	0.672
	(0.13)	(0.14)	(0.18)	(0.18)	(0.18)	(0.14)
$\mathbb{E}[\hat{\beta}_h\|\hat{\beta}_1 = \hat{\beta}_1^*]$	0.078	0.102	0.190	0.266	0.331	0.388
R^2	0.06	0.08	0.13	0.14	0.17	0.25
$\mathbb{E}\left[R_h^2\|R_1^2 = R_1^{2*}\right]$	0.05	0.06	0.10	0.14	0.16	0.17
$\bar{R}^2$	0.04	0.06	0.12	0.13	0.16	0.24
P-value Wald All	0.28	0.29	0.36	0.36	0.36	0.28
$cay(t)$	2.501	3.436	7.493	12.588	18.904	25.065
	(0.26)	(0.28)	(0.30)	(0.36)	(0.25)	(0.10)
$\mathbb{E}[\hat{\beta}_h\|\hat{\beta}_1 = \hat{\beta}_1^*]$	2.867	3.662	6.212	7.986	9.222	10.083
R^2	0.07	0.10	0.21	0.30	0.44	0.49
$\mathbb{E}\left[R_h^2\|R_1^2 = R_1^{2*}\right]$	0.09	0.11	0.16	0.17	0.17	0.17
$\bar{R}^2$	0.06	0.09	0.20	0.30	0.43	0.48
P-value Wald All	0.27	0.30	0.32	0.39	0.26	0.11
$gap(t)$	-0.444	-0.578	-1.548	-2.635	-4.161	-5.938
	(0.60)	(0.62)	(0.54)	(0.45)	(0.33)	(0.25)
$\mathbb{E}[\hat{\beta}_h\|\hat{\beta}_1 = \hat{\beta}_1^*]$	-0.345	-0.454	-0.862	-1.229	-1.558	-1.853
R^2	0.04	0.05	0.14	0.21	0.34	0.43
$\mathbb{E}\left[R_h^2\|R_1^2 = R_1^{2*}\right]$	0.02	0.03	0.05	0.07	0.08	0.09
$\bar{R}^2$	0.02	0.03	0.13	0.20	0.33	0.43
P-value Wald All	0.64	0.66	0.57	0.47	0.34	0.26

Table X
Unconditional asset pricing models, 1983Q2-2009Q4

GMM estimates of pricing kernel coefficients for the unconditional models. The models are estimated using returns on the Fama and French's (1993) portfolios and a risk-free portfolio ($N = 26$). The identity-weighting matrix is used in all estimates. All tests are based on covariance matrices of errors corrected for heteroscedasticity and serial correlation (Newey and West, 1987). Lag length in the Newey-West estimator is floor $\left[4 \cdot (T/100)^{2/9}\right]$, where floor$[x]$ denotes the integer part of x. Asymptotic t-stat in parentheses. At the bottom of the table, we report the p-value for J_T test of the null that all pricing errors are zero. *P-value Wald All* is the p-value for the asymptotic Wald test that all coefficients except the constant are zero. *RMSE* is the root of mean square errors and measures the fit of the estimated model to the cross-section of average returns.

	CAPM	CCAPM	FF three-factor
Constant	-0.027	0.506	0.022
	(-0.66)	(1.31)	(0.60)
$R_m(t)$	-0.139		
	(-0.11)		
$\Delta c(t)$		-121.603	
		(-1.21)	
$R_m(t) - R_f(t)$			-2.058
			(-1.25)
$SMB(t)$			0.259
			(0.09)
$HML(t)$			-3.986
			(-1.80)
P-value J_T	0.44	0.43	0.32
P-value Wald All	0.91	0.23	0.28
RMSE	0.78%	0.74%	0.55%

Table XI
Conditional CAPM models, 1983Q2-2009Q4

GMM estimates of pricing kernel coefficients for the conditional CAPM models on variables are in the first row. The models are estimated using returns on Fama and French's (1993) 25 portfolios and the risk-free asset ($N = 26$). The identity-weighting matrix is used in all estimates. All tests are based on covariance matrices of errors corrected for heteroscedasticity and serial correlation. Lag length in the Newey-West estimator is floor $\left[4 \cdot (T/100)^{2/9}\right]$, where floor$[x]$ denotes the integer part of x. Asymptotic t-stat in parentheses. At the bottom of table, we report the p-value for J_T test of the null that all pricing errors are zero. P-values presented are for asymptotic Wald tests. *All* means all coefficients except the constant. *CAPM* means the coefficients that are not in the unconditional CAPM model. *RMSE* is the root of mean square errors and measures the adjustment of an estimated model to the cross-section of average returns.

	Δf	R_f	$d-p$	cay	gap
Constant	-1.262	0.266	1.962	-0.413	0.007
	(-2.61)	(0.41)	(0.38)	(-0.75)	(0.09)
$\Delta f(t-1)$	-2.744				
	(-2.18)				
$\Delta f(t-2)$	-3.239				
	(-2.68)				
$\Delta f(t-3)$	-1.387				
	(-0.46)				
$\Delta f(t-4)$	6.932				
	(3.07)				
$R_f(t)$		-39.419			
		(-0.66)			
$d(t-1)-p(t-1)$			0.520		
			(0.38)		
$cay(t-1)$				42.908	
				(1.13)	
$gap(t-1)$					0.283
					(0.03)
$R_m(t)$	1.157	-7.826	-59.513	1.602	-1.634
	(0.59)	(-1.42)	(-1.96)	(0.44)	(-0.96)
$\Delta f(t-1) \cdot R_m(t)$	-20.573				
	(-1.21)				
$\Delta f(t-2) \cdot R_m(t)$	-17.374				
	(-1.63)				
$\Delta f(t-3) \cdot R_m(t)$	11.929				
	(0.54)				
$\Delta f(t-4) \cdot R_m(t)$	-63.751				
	(-2.92)				
$R_f(t) \cdot R_m(t)$		785.090			
		(1.42)			
$(d(t-1)-p(t-1)) \cdot R_m(t)$			-15.186		
			(-1.90)		
$cay(t-1) \cdot R_m(t)$				-251.228	
				(-0.95)	
$gap(t-1) \cdot R_m(t)$					89.443
					(1.79)
P-value J_T	0.07	0.32	0.33	0.33	0.35
P-value Wald All	0.00	0.46	0.19	0.45	0.25
P-value Wald CAPM	0.00	0.33	0.15	0.52	0.16
RMSE	0.34%	0.67%	0.53%	0.72%	0.53%

Table XII
Conditional CCAPM models, 1983Q2-2009Q4

GMM estimates of pricing kernel coefficients for the conditional CCAPM models on variables are in the first row. The models are estimated using returns on Fama and French's (1993) 25 portfolios and the risk-free asset ($N = 26$). The identity-weighting matrix is used in all estimates. All tests are based on covariance matrices of errors corrected for heteroscedasticity and serial correlation. Lag length in the Newey-West estimator is floor $\left[4 \cdot (T/100)^{2/9}\right]$, where floor$[x]$ denotes the integer part of x. Asymptotic t-stat in parentheses. At the bottom of table, we report the p-value for J_T test of the null that all pricing errors are zero. P-values presented are for asymptotic Wald tests. *All* means all coefficients except the constant. *CCAPM* means the coefficients that are not in the unconditional CCAPM model. *RMSE* is the root of mean square errors and measures the adjustment of an estimated model to the cross-section of average returns.

	Δf	R_f	$d-p$	cay	gap
Constant	0.811	1.033	1.877	0.375	0.485
	(2.25)	(1.48)	(0.44)	(0.86)	(1.50)
$\Delta f(t-1)$	-0.483				
	(-0.38)				
$\Delta f(t-2)$	-1.858				
	(-2.15)				
$\Delta f(t-3)$	0.384				
	(0.29)				
$\Delta f(t-4)$	-0.407				
	(-0.17)				
$R_f(t)$		-186.224			
		(-2.18)			
$d(t-1)-p(t-1)$			0.364		
			(0.32)		
$cay(t-1)$				19.948	
				(0.76)	
$gap(t-1)$					-0.253
					(-0.04)
$\Delta c(t)$	-308.738	-320.549	-390.098	-160.464	-144.812
	(-2.77)	(-1.83)	(-0.41)	(-1.57)	(-1.51)
$\Delta f(t-1) \cdot \Delta c(t)$	116.051				
	(0.35)				
$\Delta f(t-2) \cdot \Delta c(t)$	-134.842				
	(-0.59)				
$\Delta f(t-3) \cdot \Delta c(t)$	343.002				
	(1.09)				
$\Delta f(t-4) \cdot \Delta c(t)$	651.304				
	(1.46)				
$R_f(t) \cdot \Delta c(t)$		34600.413			
		(2.88)			
$(d(t-1)-p(t-1)) \cdot \Delta c(t)$			-68.620		
			(-0.27)		
$cay(t-1) \cdot \Delta c(t)$				1269.334	
				(0.34)	
$gap(t-1) \cdot \Delta c(t)$					1302.922
					(1.05)
P-value J_T	0.08	0.34	0.33	0.32	0.34
P-value Wald All	0.10	0.03	0.44	0.33	0.47
P-value Wald CCAPM	0.24	0.01	0.93	0.74	0.54
RMSE	0.48%	0.60%	0.73%	0.69%	0.68%

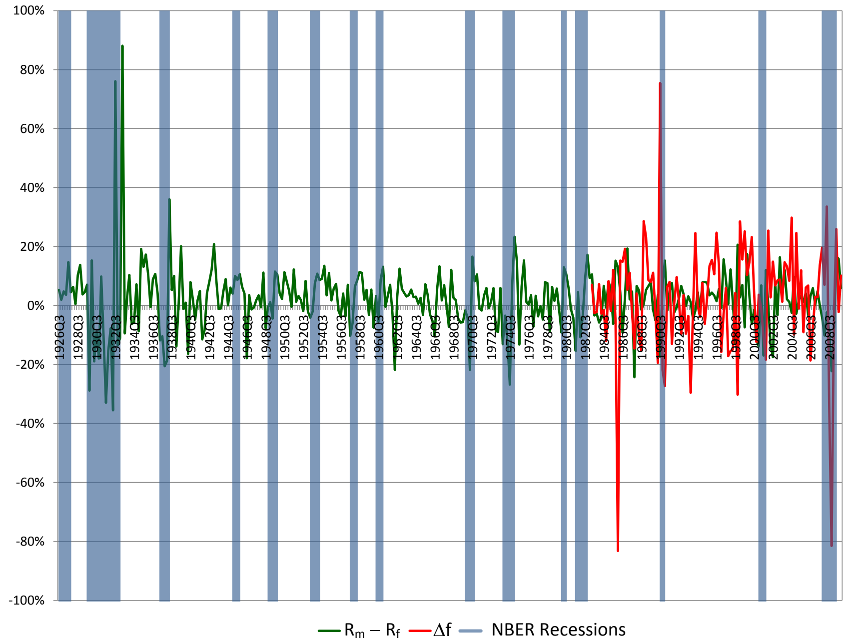

Figure 1. Excess stock market returns, oil shocks and the business cycle, 1926Q3-2009Q4.

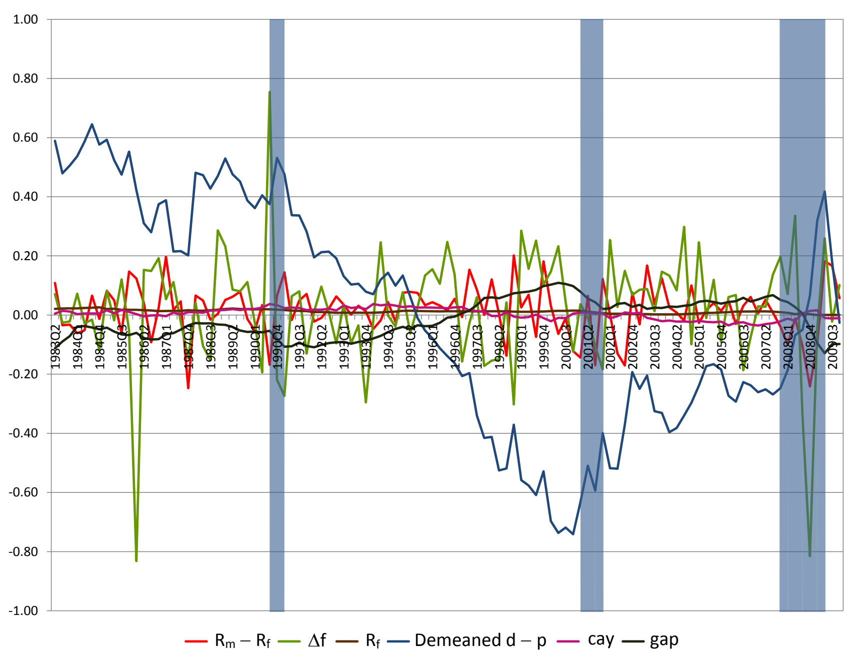

Figure 2. Excess stock market returns and predictor variables, 1983Q2-2009Q4.

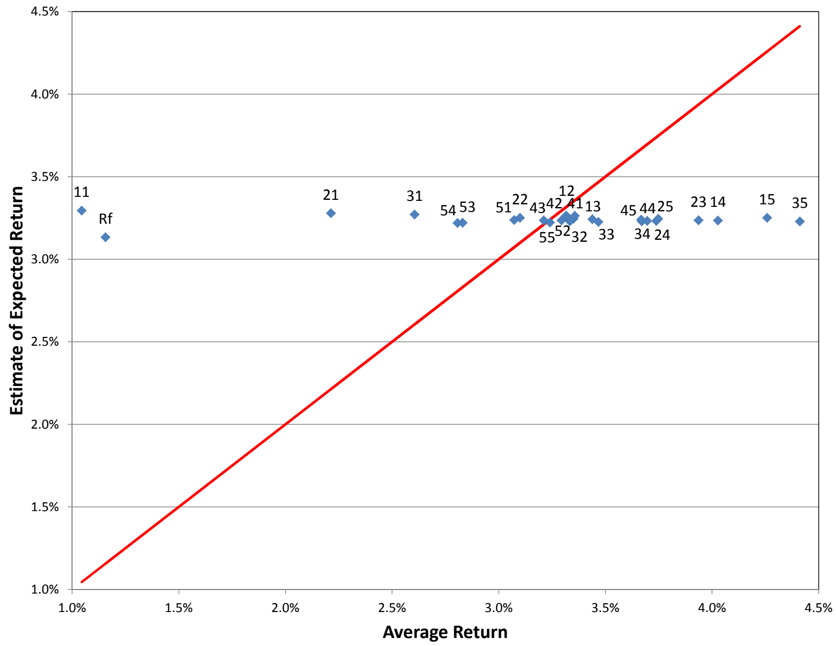

Figure 3. Realized vs. expected returns by CAPM: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

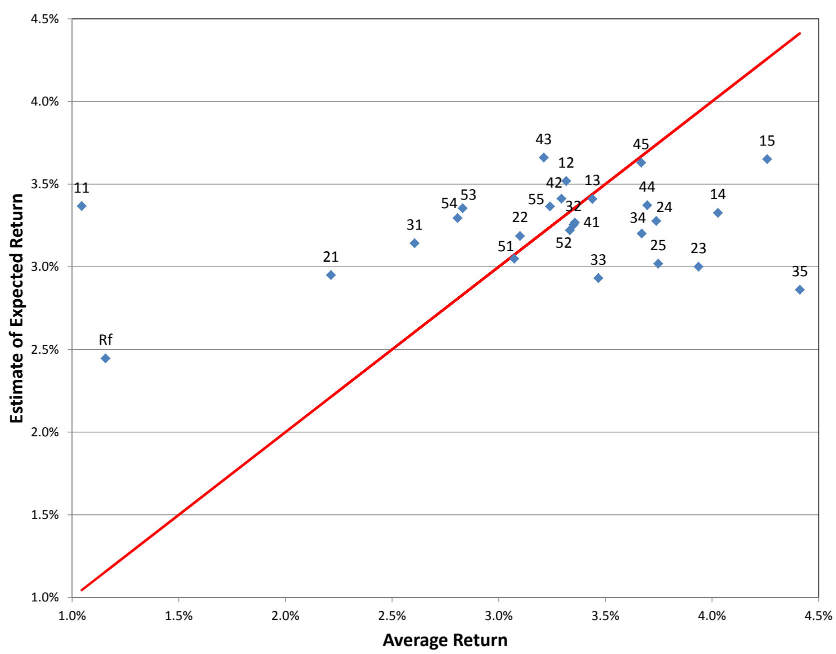

Figure 4. Realized vs. expected returns by CCAPM: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

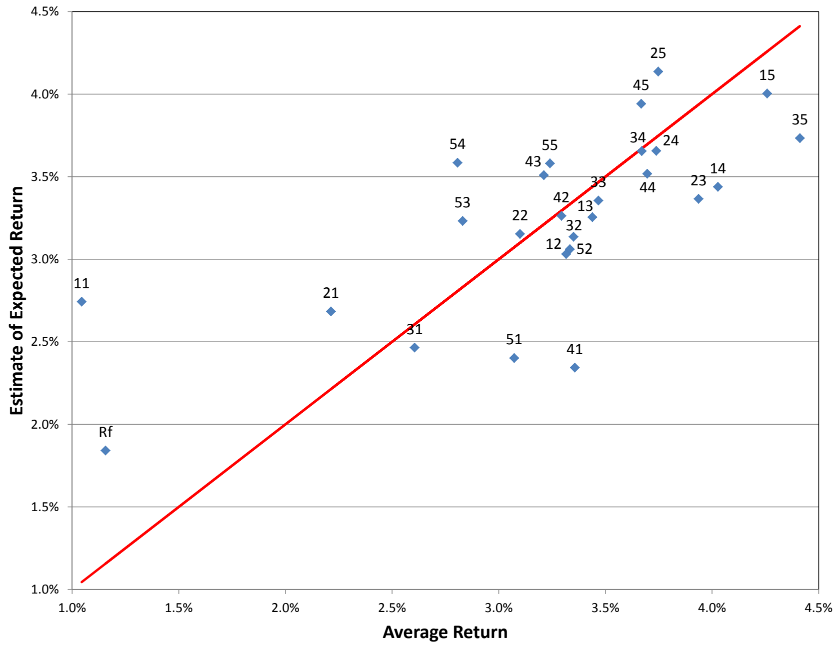

Figure 5. Realized vs. expected returns by FF three-factor: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

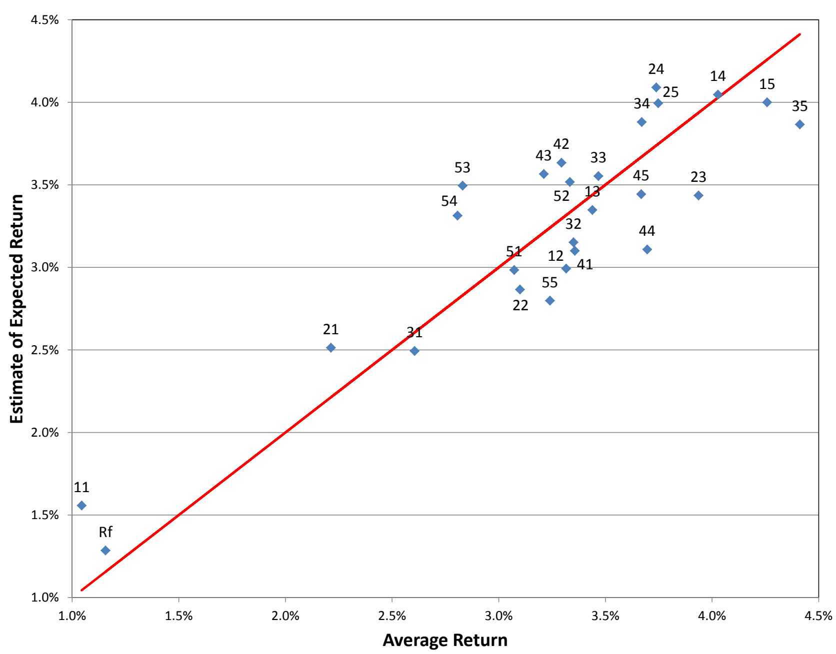

Figure 6. Realized vs. expected returns by CAPM conditioned on Δf: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

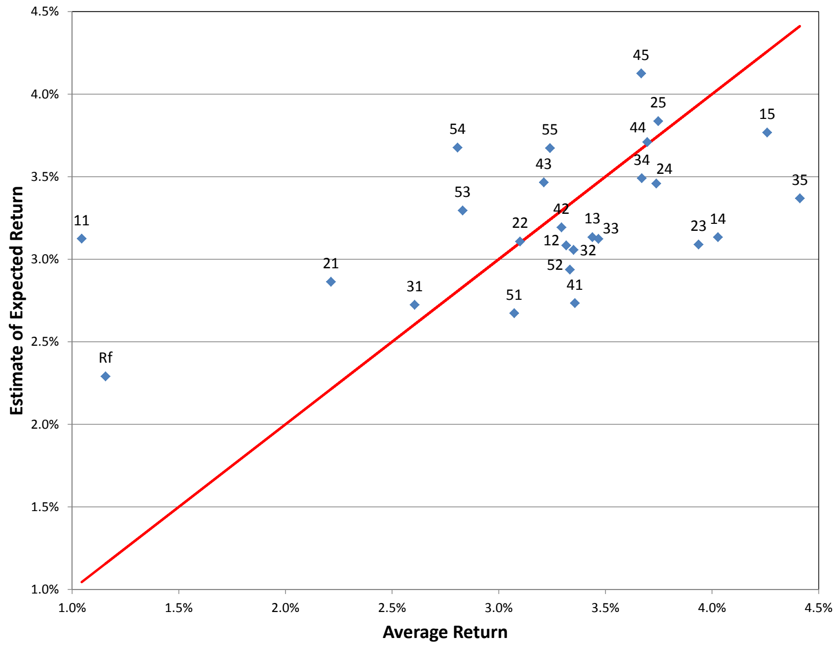

Figure 7. Realized vs. expected returns by CAPM conditioned on R_f: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

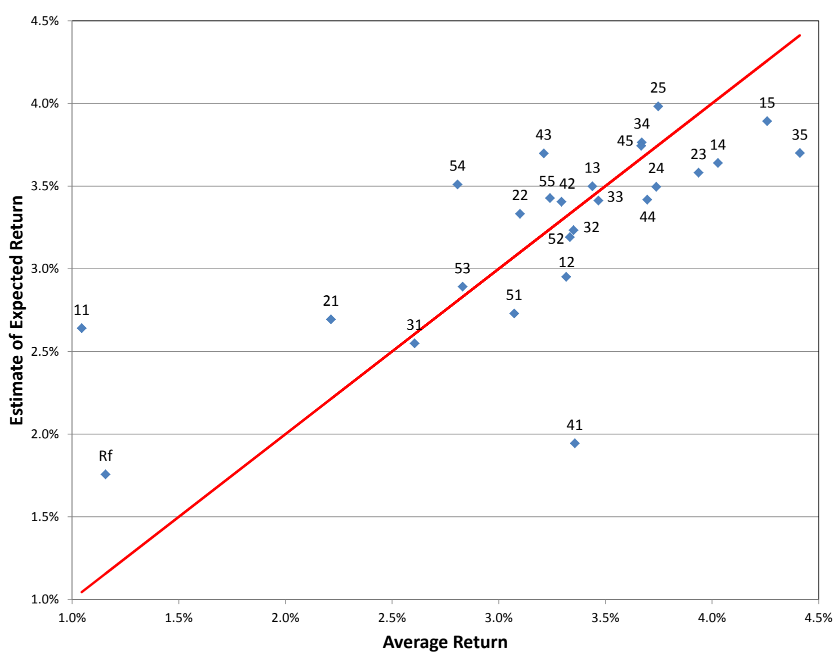

Figure 8. Realized vs. expected returns by CAPM conditioned on $d-p$: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

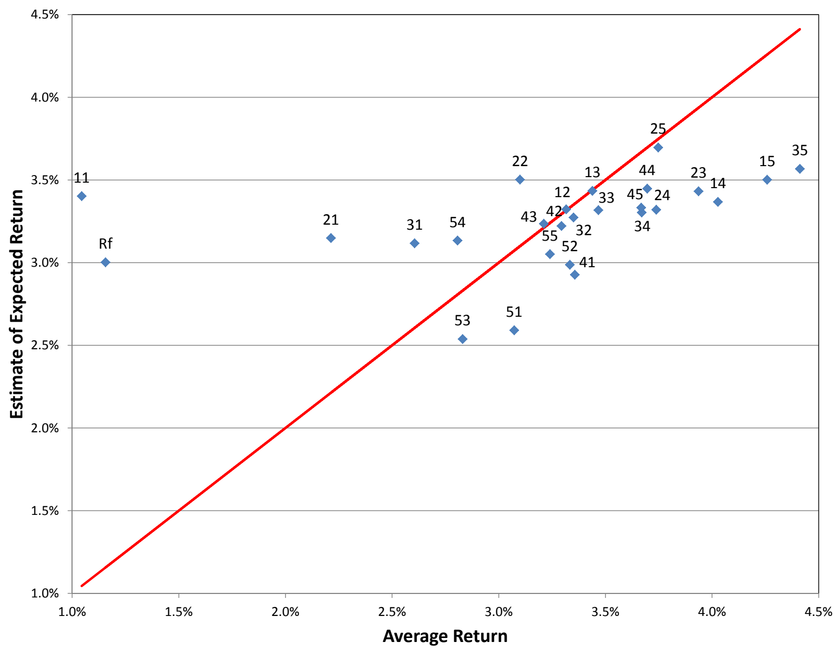

Figure 9. Realized vs. expected returns by CAPM conditioned on *cay*: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

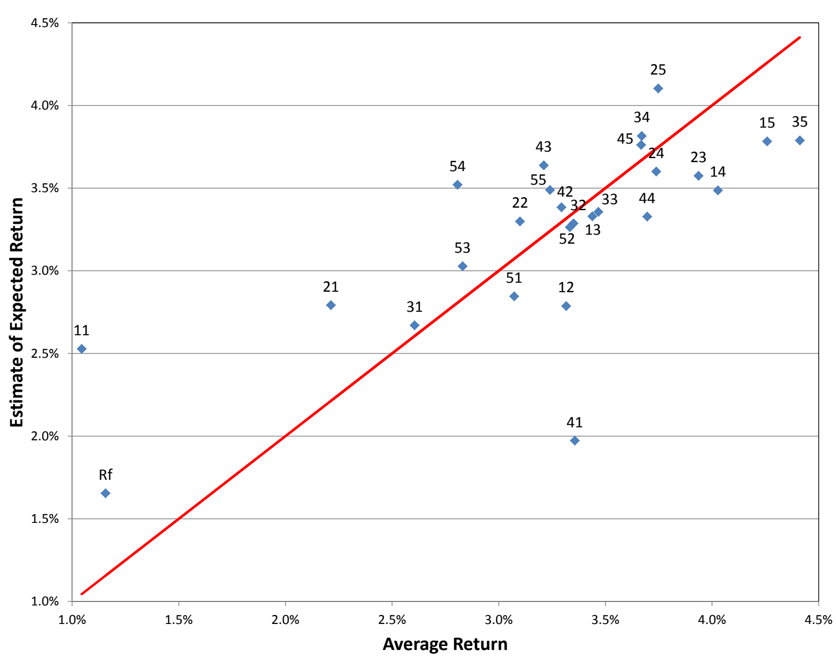

Figure 10. Realized vs. expected returns by CAPM conditioned on *gap*: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

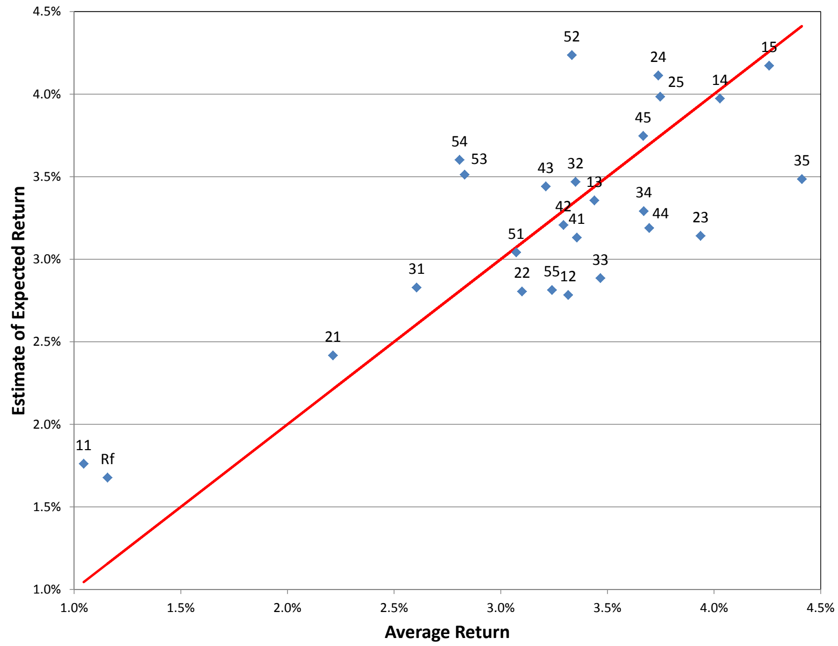

Figure 11. Realized vs. expected returns by CCAPM conditioned on Δf: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

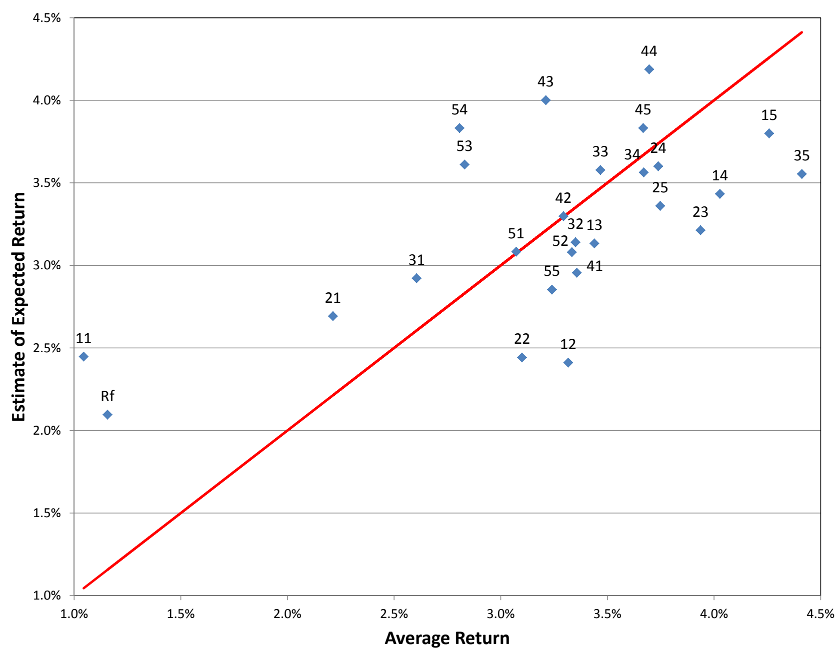

Figure 12. Realized vs. expected returns by CCAPM conditioned on R_f: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

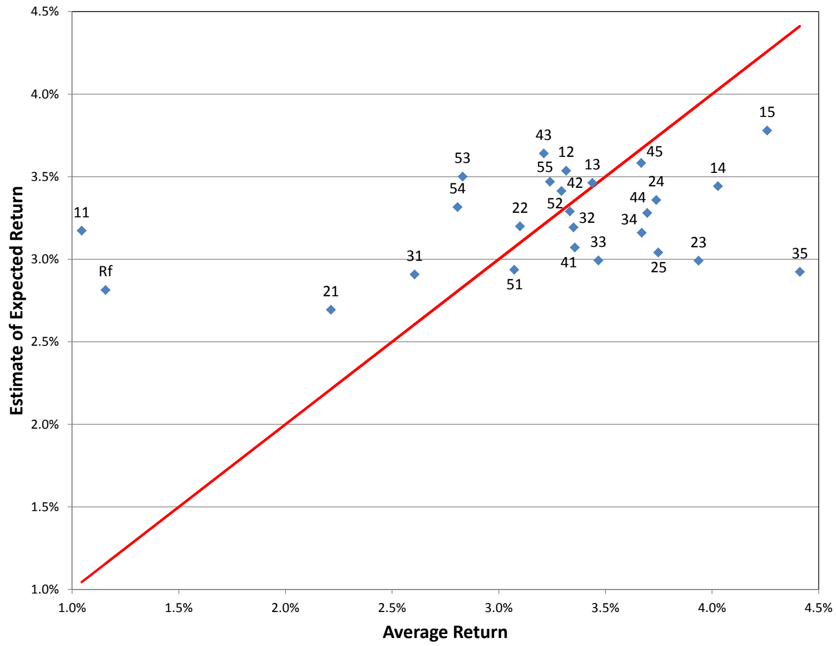

Figure 13. Realized vs. expected returns by CCAPM conditioned on $d - p$: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

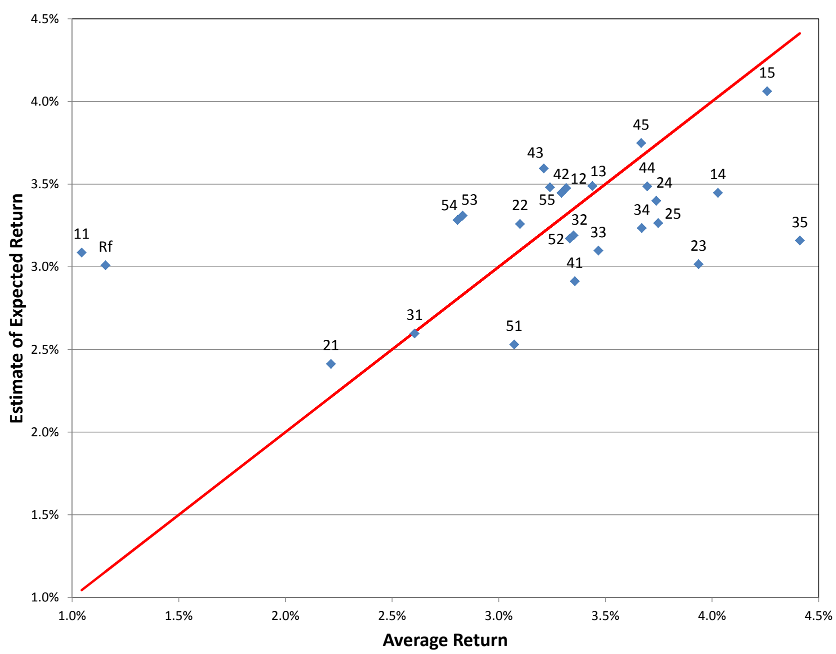

Figure 14. Realized vs. expected returns by CCAPM conditioned on cay: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.

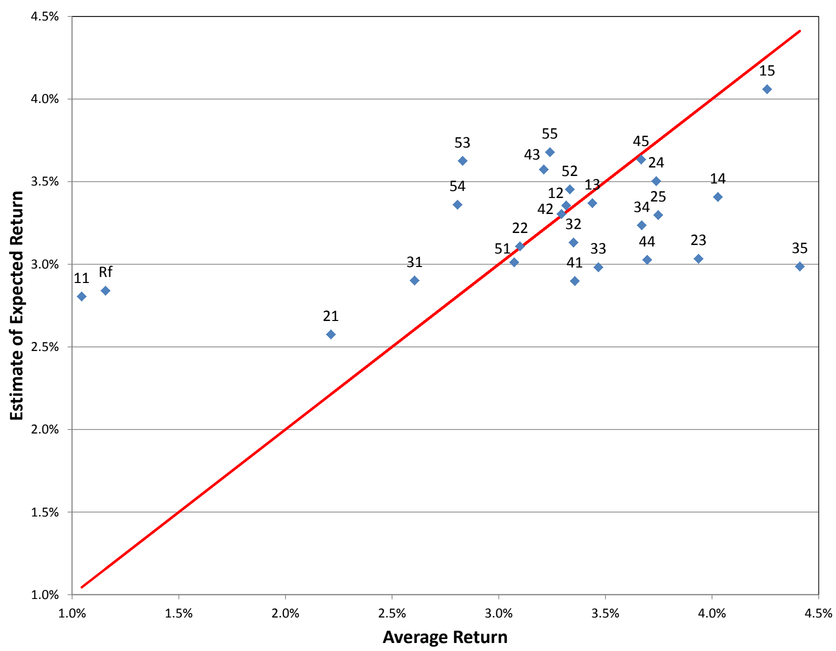

Figure 15. Realized vs. expected returns by CCAPM conditioned on *gap*: 25 Fama-French portfolios and a risk-free portfolio, 1983Q2-2009Q4.