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The Impact of Vertical Integration and Horizontal Diversification on the Value of Energy Firms

Abstract

We analyze the long-run return performance of 27 value-weighted equity portfolios based on a classification of the US energy sector that follows traditional industrial organization categories. When adjusted to market and fuel risks, portfolio returns show that both vertical integration and horizontal diversification failed to produce shareholder value during the 1990-2003 period. This confirms the theoretical predictions of both financial economics and industrial organization and shows that the wave of corporate restructuring that has interested US energy industries over the last decade may have occurred at a net cost to firm shareholders.

Keywords: abnormal return, agency cost, agency theory, beta estimation, conglomerate, cumulated excess return, diversifiable risk, downstream, economy of scale, economy of scope, excess return, Fama-French methodology, fitted return, fuel diversification, fuel risk, Henry-Hub, high-minus-low portfolio, horizontal diversification, in-sample estimation, market beta, market portfolio, market risk, merger, midstream, multi-factor risk model, natural gas industry, oil industry, outliers, out-of-sample estimation, perquisite, portfolio diversification, power industry, production stage, pure player, return distribution, risk-adjusted return, risk-free rate, rolling regression, security market line, shareholder diversification, shareholder value, small-minus-big portfolio, standard industrial classification, synergy, systematic risk, takeover, theory of the firm, transaction cost, upstream, utility, utility regulation, value chain, value-weighted equity portfolios, vertical integration, West-Texas intermediate.

Economic theory posits both positive and negative impacts of horizontal diversification of firm value. It also maintains that vertical integration produces value, when firms internalize functions which may not be adequately performed in the market. Nonetheless, there is large empirical evidence indicating that horizontal diversification across multiple activities is generally harmful to stock value, while vertical integration has at best mixed effects. For instance, Lang and Stulz (1993), Berger and Ofek (1995) and Servaes (1996) show the presence of a discount in the value of diversified firms with respect to single business companies in various industries. Likewise, in an era of growing commoditization, the theoretical rationale of vertical integration is increasingly challenged by the possibility of outsourcing various stages of firm value chains. And both facts seem to be significant throughout time and across countries.

Is this the case also in the energy sector? To answer this question, two separate aspects should be taken into account. The first has to do with the relative scarcity of industry-based literature on the value of fuel diversification and vertical integration in the energy sector. Mainstream research seems to have little interest in the financial value of these strategies; hence some novel empirical analyses may be useful. The second aspect regards some evident idiosyncrasies of the industry. There are proven complementarities in the production of various fuels (for example, between oil and natural gas in their extraction) or in the transformation of a primary source of energy into a secondary source (as Hunt (2002) illustrates in the cogeneration of power and steam). Therefore, it could be hypothesized that the energy sector enjoys some special conditions, for which both horizontal diversification and vertical integration possibly have inherent value.

In this chapter, we measure the financial value of these conducts by focusing on the equity return of a large sample of energy listings in the United States. Using daily portfolio returns, adjusted by systematic and fuel risks, we find scarce evidence to support the value-creating character of both phenomena. While our analysis shows some limited value linked to vertical integration, there seems to be a significant diversification discount across various US energy industries. This confirms previous empirical findings in other industries and seems to refute the specificities of the energy business. The claimed synergies stemming from vertical and horizontal expansions do not easily materialize and this may attest both to the inferior ability of firms, with respect to equity markets, to allocate capital internally among various businesses and to the negative effect of agency costs on equity value when firm executives engage in vertical expansion.

The remainder of the chapter is organized as follows. Section 11.2 briefly summarizes the existing empirical literature on horizontal and vertical expansion. Section 11.3 illustrates the econometric methodology through which we determine the risk-adjusted performance of energy equities. Section 11.4 describes the dataset of equity returns under investigation. Section 11.5 presents our results which, for clarity, are separately discussed in distinct sub-sections. Finally, in Section 11.6, we draw some inferences from the econometric findings which are presented in Section 11.5.

§ 11.2 - Literature Background

11.2.1 – Vertical Integration

In his classic contribution, Coase (1937) sets the foundation of the theory of the firm. Corporations and markets are alternative choices with respect to production organization, and transaction costs are the cornerstone. Corporations vertically expand until the marginal cost of internalizing production equals the marginal cost of outsourcing it in the market. For instance, when buyers incur sunk costs to manage repeated transactions, they develop an incentive to (upward) internalize suppliers into their firm, so as to avoid potential losses linked to the latter's opportunism. Similarly, sellers are inclined to downward internalize distribution when exposed to potential losses because of high concentration among their customers.

By leveraging on this general rationale, various authors have further discussed the factual consistency of firm expansion. Bain (1956, 1959) points out that vertical integration, like the integration of separate activities along a value chain, reflects the creation of market power. Tirole (1988) sees it as a profitable response to the cost of contiguous monopolies (Tirole 1988). Others think it may facilitate price discrimination (Perry, 1978) or it can be used to raise rivals' costs by increasing their costs of entry in the industry (Aghion and Bolton 1987, Ordover, Salop and Saloner 1990, Hart and Tirole 1990). Finally, Stigler (1951) advances a life-cycle theory arguing that, in an infant industry, vertical integration is more likely because the demand for specialized inputs is too small to support their independent production. In general, contractual incompleteness, combined with asset specificity, complexity and uncertainty, play a central role in driving transaction costs and in the increase of the probability that opportunistic behaviour may plague market relations (Carlton, 1979). So, as Joskow (1998a) points out, 'T*here is clearly no shortage of theories identifying potential incentives for vertical integration.*'

With this abundance of hypotheses, empirical studies have obviously thrived and have attempted to assess the factual importance of various factors as principal drivers of transaction costs. Most industrial organization surveys are product-based and focus on single products or services. Among them, studies deal with automobile components: (Klein, Crawford and Alchian 1978, Klein 2000, 2002, Monteverde and Teece 1982, Walker and Weber 1984, Langois and Robertson 1989); with coal: (Joskow 1985, 1987, 1988b, 1990, Kerkvliet 1991); with aerospace systems: (Masten 1984); with aluminium (Stukey 1983, Hennart 1988); with chemicals: (Lieberman 1991); with timber: (Globerman and Schwindt 1986)); with carbonated beverages: (Muris, Scheffman and Spiller 1992);with pulp and paper: (Ohanian 1994); with property-liability insurance: (Regan, 1997). In all these studies, the evidence significantly supports the role of transaction costs in driving vertical integration.[1]

[1] To illustrate a few among them, Monteverde and Teece (1982) and Masten (1984) link transaction costs to proxies for asset specificity, such as worker-specific knowledge and production component complexity. Klein (1988) shows that specific human capital in the form of technical knowledge is a major determinant for the decision to integrate vertically. Masten, Meehan, and Snyder (1989) enlarge

At the industry level, it appears that vertical integration is valuable when asset specificity combined with market concentration (in downward or upward production stages) raise expected transaction costs and provide a strong incentive to internalizing contractual relations.

11.2.2 – Horizontal Diversification

Horizontal diversification consists, instead, of corporate expansion into more than one industry across businesses not necessarily related to each other. With respect to vertical integration, the theoretical grounding behind horizontal diversification is less clear-cut. In particular, two partially competing explanations are at work.

On the one hand, industrial organization suggests that, because of commonalities in technology or economies of scale, firms may profit from synergies through the allocation of internally generated cash flows across different businesses (Williamson, 1975). By diversifying internally, firms can, in fact, expand without bearing the risk of paying the transaction costs linked to the exploitation of synergies in a contractual fashion. As a result, diversification usually occurs throughout related industries, although conglomerates at times claim that expansion across unrelated businesses may equally provide substantial synergies from non industry-specific economies of scale and scope.

On the other hand, financial economics points out that firms should not attempt to do internally what their shareholders can more efficiently accomplish in the capital market. If shareholder value maximization is the objective of the firm, diversification operated by mixing equity portfolios can provide shareholders with many of the benefits linked to horizontal diversification as a strategy (such as reducing business risk and taking advantage of new investment opportunity), at virtually no cost.

As Jensen and Meckling (1976) point out, the decision to internally expand a firm has, in fact, an explicit cost for shareholders, since it is often conditioned by a divergence of interest between firm managers and shareholders that is greater than potential profits justified by synergies. Shareholders indeed do not have the possibility of perfectly monitoring managers, so managers may choose to expand to appropriate value for themselves (in the form of perquisites). Therefore, by appointing executives and giving them the power of managing, shareholders often incur a different type of transaction cost—an *agency cost*—which, ultimately, may partially or completely offset the benefits of synergies and destroy shareholder value.

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the discourse to more production factors and compare the relative importance of relationship-specific human and physical capital, arguing their importance as an incentive to vertically integrate. Hennart (1988) uses the number of actual and potential trading partners to compare the extent of upstream vertical integration in the aluminium and tin industries (the greater their number, the smaller the sunk investments and the smaller the uncertainty associated with the transaction). Finally, Caves and Bradburd (1988) construct an index of forward vertical integration for a sample of 83 US manufacturing industries. They confirm Bain and Tirole and find that vertical integration rises with growing concentration in supplying and buying industries. They also show that vertical integration rises with spending on R&D and with capital-to-labour ratios.

Given this theoretical contrast, empirical work has here a thornier problem to deal with and, accordingly, its findings may be more debatable. However, the current availability of an extensive dataset on stock prices and their fine statistical basis has increasingly given the lead to financial research in this field. As distinguished from industrial organization research, these studies focus on the market as a whole and not on single industries.

Three studies provide a broad overview of the general effect of horizontal diversification and do not leave much doubt about its financial consequences. Morck, Schleifer, and Vishny (1990) show that acquiring firms, engaged in takeovers, experience negative returns as an immediate value adjustment to their future expected performance, when they announce unrelated acquisitions; while Lang and Stulz (1994) and Berger and Ofek (1995) find that, in most cases, diversified firms trade at a discount relative to a portfolio of single-segment firms in the same industries.

The hypothesis here is that diversification causes conglomerate firms to *ex-post* generate a different stream of cash flows than they would have as single-segment firms. Numerous studies indeed confirm this and, specifically, show that horizontal expansion often results in lower firm performance because of various agency problems. For instance, these include incompetent or irrational managers, competent but self-interested managers, wasteful spending in general and wasteful investment in poorly performing divisions in particular and, finally, the inability of the internal economy of the firm to correctly signal to managers good investment opportunities.[2]

§§§

To summarize and conclude this review, it appears that horizontal diversification vis-à-vis vertical integration seems to be unable to produce the value that it could theoretically create, particularly when unrelated activities are considered. This, nonetheless, may still be untrue in the case of certain energy activities—as indicated in the introduction—which, because of technological and business commonality, could actually liberate synergies when integrated. Moreover, as the energy sector is also characterized by high asset specificity and high industrial concentration, it could also represent a good empirical playground for factually observing the positive effect of vertical integration. The following sections, accordingly, are dedicated to the verification of this hypothesis.

§ 11.3 – Methodology

Tracking the value creation of vertical integration and horizontal diversification among energy firms requires establishing whether these strategies pay off for shareholders when they are discretionally undertaken by firm executives. To do this, it is first

[2] See, for example, the contributions of Comment and Jarrell (1993), Servaes (1996), Lamont (1997), Scharfstein and Stein (1997), Scharfstein (1998), Dennis and Sarin (1997), and Rajan, Servaes, and Zingales (1999).

necessary to form different equity portfolios that separate energy firm stocks in two dimensions:

1) the fuel/energy that firms produce and/or trade—namely, oil, natural gas, power, coal and their combinations;
2) the vertical stage of business in which firms are involved—customarily defined in the energy business as *upstream*, *midstream* or *downstream* activities, and their integrations.

In this manner, it is possible to separately observe the value performance of –

A) portfolios of pure players—that is, firms engaged in a single productive stage of one type of energy;
B) portfolios of horizontally diversified firms—that is, companies involved in the production/trade of two or more types of energy, whether involving one or more stages of production;
C) portfolios of vertically integrated firms—that is, companies involved in the integrated production of a single type of energy across two or more stages of their value chain,

by measuring their risk-adjusted returns over a sufficiently long time window.

The analysis of portfolio returns is preferable to the investigation of individual firm returns, since portfolios, by pooling more equities in a single asset, yield returns less affected by firm specificities and statistical disturbances. Here, we exploit this property extensively, while maintaining the ability of portfolios to single out firm strategies, by drawing the aggregation rationale directly from the industrial organization literature. As a result, we can avoid the traditional Standard Industrial Classification (SIC) through which census authorities separate firms according to their activities—a form of classification often used in financial studies of this type—and, thus, eliminate the risk of forming portfolios according to a taxonomy which is somewhat irrelevant for the purpose of this study.

A preliminary aggregation is presented in Table 11.1. As the scheme illustrates, pure-player *basic* portfolios, which pool single-fuel and single-segment firms, are first identified.[3]

[3] Note that certain pure-player portfolios that could theoretically be identified, but would not have actual meaning in the business practice, have been preventively discarded Specifically, this regards the 'oil midstream portfolio', collapsed into the 'oil upstream portfolio', and all coal portfolios which are collapsed into a single portfolio because all US coal firms are vertically integrated.

Table 11.1 – Basic Portfolios

<table>
<tr><td rowspan="2"></td><td rowspan="2">Tranformation Stage</td><td>OIL</td><td>NATURAL GAS</td><td>POWER</td><td>COAL</td></tr>
<tr><td>O</td><td>G</td><td>P</td><td>C</td></tr>
<tr><td>Generation/Upstream</td><td>UP - U</td><td rowspan="2">OU</td><td>GU</td><td>PU</td><td rowspan="3">CO</td></tr>
<tr><td>Transmission/Transport</td><td>MID - M</td><td>GM</td><td>PM</td></tr>
<tr><td>Distribution/Retail</td><td>DOWN - D</td><td>OD</td><td>GD</td><td>PD</td></tr>
</table>

However, these preliminary nine basic portfolios do not manage to include all firms in the sector. For instance, firms engaged in the extraction and distribution of oil—oil integrated firms—need to be tracked by a portfolio which results from the unification of OU and OD portfolios. As a consequence, starting from portfolios in Table 11.1, we identify 13 other *integrated* portfolios that complete the initial taxonomy and provide a list of 22 basic and integrated portfolios presented in Table 11.2 below.

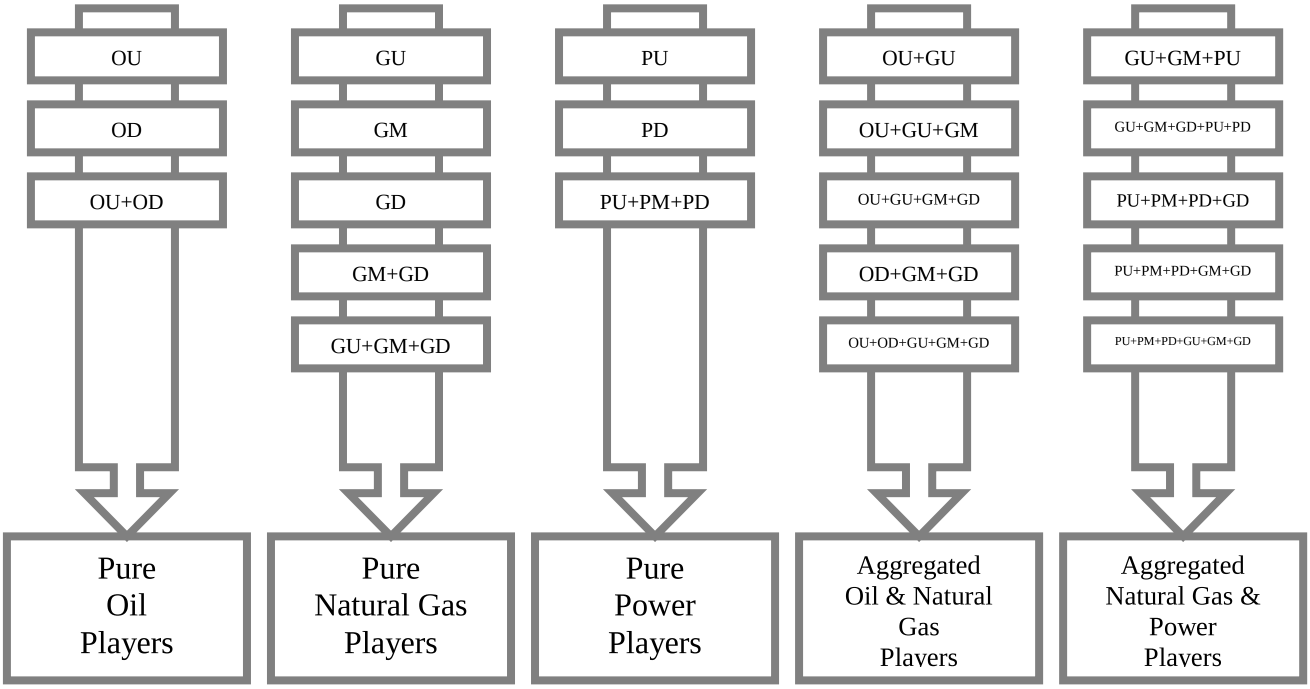
Table 11.2 – Basic and Integrated Portfolios

No.	Portfolios	Portfolio Codes	Firms
1	Oil upstream	OU	11
2	Oil up-downstream	OU+OD	3
3	Gas integrated and oil up-downstream	OU+OD+GU+GM+GD	17
4	Oil and gas upstream	OU+GU	330
5	Oil upstream and gas up – midstream	OU+GU+GM	8
6	Gas integrated and oil upstream	OU+GU+GM+GD	3
7	Oil downstream	OD	35
8	Gas mid-downstream and oil downstream	OD+GM+GD	7
9	Gas upstream	GU	6
10	Gas integrated	GU+GM+GD	5
11	Gas integrated and power up-downstream	GU+GM+GD+PU+PD	1
12	Gas up-midstream and power upstream	GU+GM+PU	1
13	Gas midstream	GM	11
14	Gas mid-downstream	GM+GD	39
15	Gas downstream	GD	39
16	Power upstream	PU	6
17	Power integrated	PU+PM+PD	77
18	Power and gas integrated	PU+PM+PD+GU+GM+GD	4
19	Power integrated and gas mid-downstream	PU+PM+PD+GM+GD	59
20	Power integrated and gas downstream	PU+PM+PD+GD	6
21	Power downstream	PD	3
22	Coal	CO	10

These 22 portfolios include 681 energy equities listed in the US according to the breakdown shown above and cover the entire set of activities observed in the sector.

In order to further mimic the diversification strategies that are discussed in the industrial literature, we subsequently proceed to the consolidation of a few among them and obtain five *aggregated* portfolios which are presented below. Figure 11.1 gives a specific depiction of how this aggregation takes place. Its rationale in connection with the horizontal possibilities of fuel diversification in the energy sector is self-evident.

Figure 11.1 – Industrial Strategies of the Energy Sector: Aggregated Portfolios



Daily returns on each of the 27 portfolios identified so far are then determined by summing daily individual firm returns weighted by firm daily market capitalization. *Value-weighted* portfolio returns, therefore, give an economically focused and normalized measure of performance, but also a rather gross measure. Portfolio weighted returns are, in fact, just an absolute measure of value creation. They track the change in the value of a portfolio of energy firms for an unspecified shareholder, but do not correct this change by considering the various types of risk that may be of interest for an investor who buys and holds energy stocks in the long term, nor by considering his ability to diversify his holdings through portfolio management.[4]

Instead *risk-adjusted* portfolio returns can better track a correct measure of performance, since they correct absolute performance by risk. But in order to determine them, it is necessary to identify various types of risk factors (typologies of risk exposures) that are of relevance for an unspecified investor in energy equities. Specifically, two broad categories of exposure appear here to be significant.

[4] In other words, simple portfolio returns do not take into account both (1) the risks that shareholders in energy firms bear by holding a certain type of equity and (2) their ability to hedge against these risks through portfolio diversification by buying other (possibly more risk-insulating) stocks and mixing them with their energy equities. For an introductory, yet rigorous, treatise on portfolio diversification as a risk-hedging practice in finance, see Copeland and Weston (2005).

1) On the one hand, as financial theory suggests, measuring the relative covariance of energy portfolio returns with market-wide weighted portfolio returns (determined across all main US equity bourses) provides a measure of the *systematic* risk borne by energy equities. Systematic risk is the risk of herding with market trends. Hence, it may be seen as the possibility that energy equities may simply fail to protect their holders from the risk of plummeting, when the whole market is in a bearish phase.

2) On the other hand, measuring the relative covariance of energy portfolio returns with daily fuel price returns (determined using fuel prices registered in US commodity markets) provides a measure of the *fuel* risks that affect energy equities. Energy firms do, in fact, produce and trade fuels, so they consistently maintain a large part of their assets in fuels and their derivates. The possibility that these firms' stocks may simply follow commodity market trends and fail to insulate their holders from the danger of losing value when fuel prices diminish is thus material.

Using portfolio absolute returns and various risk measures tracking the types of exposure just mentioned, we determine risk-adjusted returns by two complementary approaches which are elucidated in the following two sub-sections.[5]

11.3.1 – Fama-French Approach

First, we employ the well-known Fama and French (1993, 1996) approach in order to econometrically link our firm portfolio returns to three explanatory factors (which are all modelled as US market-wide portfolios). These three factors (as calculated by CRSP, see next section) are, respectively:

1) the daily weighted return of the US market-wide portfolio (Factor 1);
2) the daily time series of two special types of average portfolio returns, constructed from six benchmark portfolios, which divide US firms according to their value size and their market-to-book ratios (Factor 2 and 3).[6]

The first of the latter two series (Factor 2) is the average daily return difference between the yield of small value firms and large value firms (*small-minus-large*—SML, a measure of size risk). The second of the latter two series (Factor 3) is the daily return

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[5] Note that relying on daily returns to construct medium-to-long-run performance analyses may expose risk-adjusted return measurements to the danger of accounting for daily shocks, such as firm and industry news or market events, which may be economically irrelevant with respect to the purpose of this study. Nonetheless, we prefer to employ daily observations, at the cost of some econometric accuracy, since we precisely intend, in addition, to track portfolio risk-adjusted returns with respect to the ability of energy firm shareholders to diversify fuel price risk, which may be daily relevant. As is better explained below, this implies regressing portfolio returns on oil and natural gas daily prices. It, therefore, makes inferences clearer at the cost of some loss of econometric precision.

[6] Hence, whether firms have high or low value or whether they have high or low value growth.

difference between the returns of high growth firms and low growth firms (high-minus-low—HML, a measure of growth risk).[7]

Using this method, we estimate an econometric specification of the type,

$$R_{it} = \beta_i^1 M_t + \beta_i^2 SMB_t + \beta_i^3 HML_t + \varepsilon_t \,. \qquad [11.1]$$

All daily returns fed to each of the four time series on both sides of equation [11.1] are determined as *excess-returns*. Excess-returns are defined as daily returns in excess of the daily yield on US treasury bonds, which represents an approximation of the risk-free investment rate, R_{ft}, (the yield that an investor receives for holding a risk-less financial asset that pays compensation over time with certainty or, in other words, the time value of money). Therefore, portfolio returns R_{it} on the left side of [11.1] are precisely excess-returns determined as, $R_{it} = R_{it}^* - R_{ft}$, where R_{it}^* are total portfolio weighted-returns determined on day t for each of the 27 portfolios presented above (thus, with i=(1, 2, …, 27)). As such, R_{it} solely measure the compensation that an investor receives for bearing a risky asset in the form of an energy equity portfolio.[8] Likewise, M_t, SMB_t and HML_t are the part of the daily return, on each of the portfolios chosen as a risk factor, that exceeds the risk-free rate. Betas, β_i^1, β_i^2, β_i^3, are then regression coefficients (that is, factor sensitivities). Finally, ε_t is an error term.

In equation [11.1], the first regression coefficient—the market beta, β_i^1—represents the most relevant piece of information, since it tracks the systematic risk borne by an energy portfolio in its widest specification. Because of the partial correlation between all explanatory factors, its estimation is here adjusted by the presence of the other two return factors (SMB_t and HML_t) and gives a synthetic measure of the sensitivity of an energy portfolio to market risk.[9] Therefore, measuring how much an energy portfolio yields in a given time window, and subsequently weighting such return performance by its market beta, provides the risk-adjusted measurement of return that we need.

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[7] We refer the reader to the financial literature on multifactor return models for a complete explanation of the rationale of this econometric methodology.

[8] Note that, in [11.1], there is no term for an intercept. Using excess-returns indeed implies eliminating the intercept from this linear specification. In [11.1] the intercept would in fact represent a portfolio return observed when all regressors on the right side equal zero. Since regressors here represent risk factors, this observed return would be the one associated with the absence of risk. But as we already deducted this return (R_f) from all the time series in [11.1], we can constrain the estimation to the absence of an intercept.

[9] Observe that, for instance, in a bivariate regression model estimated with ordinary least squares of the general type, $y_t = b_x x_t + b_z z_t$, where y_t is a dependent variable and x_t and z_t are explanatory variables, the regression coefficients, b_x and b_z, measure the sensitivity of y_t to changes in the value of each regressor. Here, b_x, the coefficient between y_t and x_t, has a value which is not only a function of the covariance between them, but also a function of the covariance between x_t and z_t. Therefore, unless x_t and z_t are perfectly orthogonal to each other—and that would occur when x_t and z_t include only pair-wise independent observations, so their vector multiplication yields zero (a situation that with risk factors specified as in [11.1] can be *a priori* excluded in an empirical study of our type)—the estimation of $b_{x,}$ given the presence of $z_{t,}$ yields a better assessment of the elasticity of y_t with respect to x_t than in a simple univariate regression. This result is generalized and confirmed, in the multivariate case, by the Frish-Waugh theorem.

But equation [11.1] lends itself to further utilization. Note that it is rather simplistic to imagine that the portfolio sensitivity to risk factors (β_i^1, β_i^2, β_i^3) remains stable over long periods of time. It is indeed conceivable that, as time passes, energy firms modify their technology as well as their management regime and, thus, experience changes in their ability to protect investors from market (and other) risks. This implies that a single estimation of [11.1] on a given dataset, over the entire time window of the time series that it comprises, may not be the best methodological choice, since it constrains the estimation of β_i^1, β_i^2 and β_i^3 to single values. A better approach is thus to employ *rolling regressions*.

Let us suppose that we have a large dataset of past observations between today (t) and a remote earlier date ($t-m$).[10] Given the large number of available observations, it is possible to preliminarily estimate our model over an early part of the entire dataset (that is, between $t-m$ and $t-n$, with $t-n$ being a later date than $t-m$), beginning from the oldest observation. This first estimation assesses the preliminary explanatory role of our three factors for energy firm returns. Once this has been done, the (*in-sample*) estimated model can then be used to determine what the (*out-of-sample*) return on an energy portfolio should have been on the first day after the estimation interval ($t-n+1$). This is done by plugging into the three factor terms their return for that day, and by using previously estimated beta values. This *fitted* (that is, predicted) return can then be compared with the actual return observed on that first day after the estimation interval. The difference between that day's actual and fitted returns yields a second type of *excess-return* estimation (not only in excess of the risk free rate, but also in excess of what an investor's compensation should be, given the risk factor considered in the estimation), a datum that measures whether the energy portfolio has abnormally yielded more or less than expected. Repeating this procedure every subsequent day (that is, estimating a daily regression between $t-n+2$ and t) permits building a time series of abnormal returns for each energy portfolio. The evolution of these excess-returns over time provides, in turn, some relevant information on the dynamic behaviour (by the factors considered) of the risk-adjusted performance of energy portfolios.[11] One complication in this procedure is the need to establish how many observations should enter in the estimation window of each daily regression (namely, what should be the value of $m-n$). Predetermined rules are not available, but a consistent approach is to

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[10] That is, along the time interval ($t-m$, $t-m+1$, …, $t-1$, t).

[11] More formally, we divide the entire time window of available observations ($t-m$, $t-m+1$, …, $t-n-1$, $t-n$, $t-n+1$ …, $t-1$, t) into two intervals: (1) an estimation interval ($t-m$, $t-m+1$, …, $t-n-1$, $t-n$) and (2) a prediction interval ($t-n+1$, …, $t-1$, t). The first step uses the interval ($t-m$, $t-m+1$, …, $t-n-1$, $t-n$) to determine the fitted portfolio return for day $t-n+1$. Rolling the estimation of one day allows for updating the information that enters the estimation interval. The second step, therefore, uses the interval ($t-m+1$, …, $t-n+1$) to predict the fitted portfolio return for day ($t-n+2$). This iterated *in-sample-out-of-sample* procedure (rolling regression) is then repeated until the estimation interval (whose length is fixed) is rolled up to the next to the last observation ($t-1$), so as to predict the fitted return on the last available day in the dataset (t). A time series of fitted returns over the interval ($t-n+1$, …, t) obtains. The difference between actual returns and fitted returns over the same interval yields a time series of positive or negative excess returns (that is, in excess of the risk factors considered in [11.2]).

choose the estimation length that minimizes the average absolute value of excess returns, since this implies minimizing the out-of-sample error of the model.

11.3.2 – Multi-Factor Approach

As mentioned above, energy firms are naturally invested in the underlying fuels they produce or trade. This suggests that equity portfolio returns may significantly covariate with fuel prices. We observe that in a de-segmented market like the US, informed investors holding energy firm equities have the ability to diversify their portfolios by directly investing in fuels, which are tradable commodities. Therefore, we assume that energy equities should compensate investors and produce positive risk-adjusted returns, not only to the extent that they offer protection against market risks, but also if they protect unbiased investors from fuel price risks and provide a good alternative to investments. Therefore, to the extent that energy firm portfolios significantly respond to fuel price oscillations, it is possible to integrate equation [11.1] with additional return factors tracking fuel risks.

Let us convert daily fuel prices into daily fuel excess returns by using the statement,

$$R_{jt} = \frac{\left(P_{jt} - P_{jt-1}\right)}{P_{jt-1}} - R_{ft} \qquad [11.2]$$

where R_{jt} is a daily excess return on the *j*-th fuel on day *t*, P_{jt} is the *j*-th fuel price on the same day. Different time series of returns on *J* fuels can now be used as return factors and equation [11.1] can be integrated as follows,

$$R_{it} = \beta_i^1 M_t + \beta_i^2 SMB_t + \beta_i^3 HML_t + \sum_{j=1}^{J} \gamma^j R_{jt} + \varepsilon_t \,. \qquad [11.3]$$

In equation [11.3] gammas now represent portfolio return sensitivities to daily fuel returns. This model can then be employed in the same manner as described in the previous subsection for the classic Fama-French three factor model. Hence, risk-adjusted (by market and fuel risk) performance and excess-returns on various energy portfolios can be measured.

11.3.3 – Estimation

Consider first that the most straightforward approach to estimate [11.1] and [11.3] is to use ordinary least squares (OLS) over the entire available time window. This would yield a single value for all regression coefficients (β_i and γ_i) in the equations. But, given the long period of time involved in the estimation, these OLS parameters would likely suffer from two limitations. (1) They would be highly sensitive to several outlying observations that plague longitudinal datasets, as a result of market crises and unanticipated events. (2) They would not be able to track changes in the sensitivity of

equity portfolios to risk factors (that is, changes in β_i and γ_i) and would just average them out in a conditional mean.[12]
Compared to OLS[13], several estimation methods may provide some improvements when long-term market betas need be measured. For instance, *robust* estimation, *generalized autoregressive conditional heteroskedastic* (GARCH) models and *Bayesian* methods may, in various ways, take care of outliers, but only partially address the problem of temporal changes in the assessment of factor regression coefficients.[14]

In this study, we hold temporal modifications of return sensitivity to risk factors in great importance and, as described in Subsection 11.3.1, we take care of their impact in a direct fashion. Therefore, instead of relying on a single estimation that uses all observations in the time series to improve the determination of regression coefficients, we prefer to observe their evolution over time through rolling regressions. Note, that since this entails estimating a multiple set of regressions, each of them could make use of one of the methodologies just described and could theoretically address both the problem of bias and volatility of regression coefficients. However, since we allow the number of observations that enter the estimation window of each rolling regression to vary and optimize the number according to the daily *out-of-sample* predictive ability of *in-sample* estimations, we deem that—given the reduced length of the estimation window and the large number of regressions involved in this study—using a different approach than OLS represents a very minor improvement at the cost of some significant information on coefficient volatility.

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[12] For a complete treatise of beta estimation in longitudinal studies, see Marafin *et al.* (2006).

[13] Which, as an estimation method, is by construction quadratically penalized by the presence of outliers.

[14] More specifically, *robust* estimation methods may perform better, as far as the first problem is concerned, since they weight observations in the dataset differently and reduce the importance of outlying observations. By relying on median estimators (instead of quadratic mean estimators like OLS) or by reducing the relative importance of extreme observations in the dataset, these methods may thus achieve coefficient determinations which are somewhat more resistant to the presence of large negative and positive returns in the datasets. *Generalized autoregressive conditional heteroskedastic* (GARCH) models, by expressly factoring in the variance of errors in the estimation, can alternatively address the same problem in a more direct fashion. With this approach, regression coefficients can, in fact, be determined by expressly taking into account market crises and sclerotic investment behaviour as well as the effect that these phenomena have on the concentration of large return oscillations in small periods of time (large variance followed by small variance), over the entire dataset. Finally, *Bayesian* estimations, by assuming that estimated regression coefficients can be drawn from a certain statistical population (the so-called *posterior* distribution), can improve their estimation with respect to some bias that OLS coefficients may have, by functionally relating this distribution to a separate distribution (the *prior* distribution) that represents the population of true regression coefficients. With this approach, material improvements are available, to the extent that parameters describing the distribution of true regression coefficients (the prior distribution) can be inferred from historical information that is different from that contained in the dataset. However, if such information is not available, prior distribution parameters are drawn from the return dataset. This implies that estimated Bayesian regression coefficients tend to more closely converge to the OLS coefficients, the greater the volatilities of β_i and γ_i.

§ 11.4 – Data

Stock data used in this study are collected in the form of daily returns from the Center for Research in Security Price (CRPS). Our dataset comprises 14 years of daily observations (from 1990 through 2003) for 681 energy firms listed in the US equity markets. Sampled firms encompass four energy industries: oil, gas, power and coal.

The business nature of firms here considered is preliminarily assessed using CRSP industrial segments. However, recent studies have shown that CRSP industrial segments may suffer from some limitations.[15] For this reason, we control CRSP information on all firms and individually match them to one of the 22 structural portfolios presented above by analyzing their core business. Our analysis is based on: (1) business information directly released by the firm; (2) business news information as archived by Lexis-Nexis and Factiva; and (3) CRSP industrial segments, when no other source of information is available.

Apart from aggregated portfolios, the attribution of a firm to the 22 basic and integrated portfolios in Table 11.2 is univocal; a firm that is inserted in one portfolio is not included in any other. Our portfolio taxonomy is maintained stable throughout the time window considered in the study. This implies that, over time, new firm listings and firm de-listings modify two measures, namely: (1) the number of firms tracked by each portfolio and (2) the total market value of each portfolio. Since we customarily determine portfolio returns as the weighted average of the singular daily returns on each listing, using market capitalization as a weight,[16] we do not keep track of delisting returns unless they are specifically tracked by CRSP. As a result, this may introduce some bias in our measure of portfolio performance.[17] However, given the large pool of tracked data and the relative concentration of energy industries, firm de-listings, which generally apply to small businesses, have limited overall effects on our estimations.

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[15] CRSP segments follow SIC codes as specified by the US Bureau of Census.

[16] Formally, given a set of K firms included in the i-th portfolio, each daily portfolio return R_{it} results from,

$$R_{it} = \sum_{k=1}^{K} R_{kt} w_{kt} \text{ with } w_{kt} = \frac{v_{kt}}{\sum_{k=1}^{K} v_{kt}}.$$

In the equation above, v_{kt} and R_{kt} are, respectively, the daily market value and the daily return of each firm included in the portfolio.

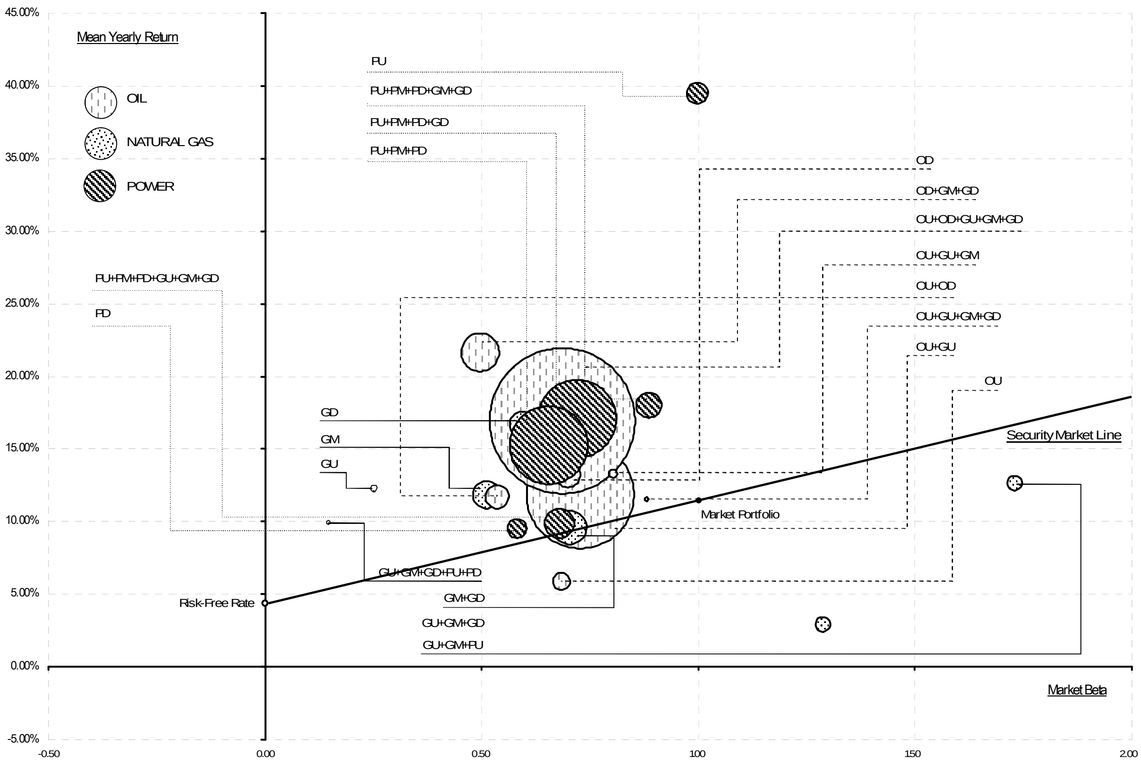
[17] Not keeping track of de-listing returns is tantamount to assuming that an investor holding a portfolio is able to anticipate a de-listing on its previous day and simultaneously sell off the interested security. In fact, daily returns are determined as relative increases in the share price of a listing over its previous day's price. Hence, new listings have an impact on portfolio returns that are first verified on the second day of their listings, while de-listings (which may generate a -100 per cent daily return) do not impact portfolio returns since they do not have market capitalization on the day of their de-listing. This assumption evidently contradicts the informational asymmetry that most investors bear in real equity markets and biases the calculation of portfolio returns. CRSP provides correcting information to account for this. However, this information may be partially incomplete. See Shumway (1997) for an extensive treatment of the problem.

As far as fuels are concerned, we use data as provided by the Energy Information Agency (EIA) of the US government. We employ three different series. (1) Oil prices are given by the West Texas Intermediate (WTI) FOB daily index. (2) Natural gas prices are given by Henry Hub wellhead daily observations. (3) Power prices are instead tracked in the form of monthly observations (since daily observations are unavailable) of the US state-mean industrial cost (¢/KWh) deflated by the aggregate US consumer cost index.

§ 11.5 – Results

Observing the historical return performance of all equity portfolios presented in Section 11.2 reveals different stylized facts. These appear both along the vertical (production stages) and horizontal (fuel) dimensions. We shall discuss them separately. However, before doing that, a few general aspects concerning the entire sector should be mentioned.

Figure 11.2 – Portfolio Positioning and Value in the Mean-Return/Market Beta Space



First, it should be observed that the largest investments in energy equities concern oil firms. In Figure 11.2, portfolios are plotted as pies in a Cartesian space where market betas, β_i^1, are measured along the *x*-axis, while the *y*-axis measures mean yearly observed portfolio returns. In this and the following figures, unless otherwise specified, β_i^1 are determined by estimating equation [11.1] through OLS over the entire dataset. Their statistical significance is, therefore, reduced. However, their values—hence the horizontal positioning of portfolios—approximate mean values determined from estimations conducted with rolling regressions (Table 11.3 at the end of this chapter summarizes OLS estimation values and statistics). Pies are then scaled according to the total market capitalization of each portfolio on 31 December 2003. Different patterns are attributed to different fuels: vertical marks to portfolios including oil or predominately oil firms (Portfolios from 1 through 8 in Table 11.2), dots to portfolios of purely or predominately natural gas firms (Portfolios from 9 through 15) and diagonal lines to portfolios of purely or predominately power firms (Portfolios from 16 through 22).

The two largest portfolios are those which include vertically and horizontally integrated oil and natural gas firms (Portfolio 3) and integrated upstream oil and natural gas firms (Portfolio 2). Specifically, Portfolio 3 includes all of the largest global oil and gas companies (such as Exxon-Mobil, for instance). From the graph it is evident how oil pies outsize and sometimes completely cover all the others. Utility portfolios are hardly comparable to oil portfolios, while natural gas portfolios are striking for their overall irrelevance by value in the US economy.

Note that the Cartesian space is crossed by an upward sloped thick line called Security Market Line (SML). This line connects two points: the observed risk-free yearly rate over the 1990-03 period (equal to 4.38 per cent), as determined by CRSP, using yields on US government debt and associated to the beta = 0 position on the *x*-axis, with the mean yearly return yielded by the overall US equity market portfolio (equal to 11.46 per cent), as determined by CRSP, including all dividends paid by all US listed firms over the same time period, and associated to the beta = 1 position[18]. According to financial theory, the SML can be seen as the plot of all possible combinations of market risk (betas on the *x*-axis) and associated compensation for holding an asset (returns on the *y*-axis) that an unbiased equity investor can obtain by diversifying his portfolio across all available securities in the US market (by mixing risky assets with governmental securities).[19] Therefore, the space north-west of the SML represents an area of positive excess-risk-adjusted-returns, since it contains return-risk combinations that yield more to investors than what they would normally obtain through portfolio diversification (that is, by diversifying their equity portfolios across available securities in the market). By the same token, the space south-east of the SML represents an area of negative excess-risk-adjusted-returns.

Here two general aspects are of interest. On the one hand, the large majority of energy portfolios have market beta, β_i^1, less than one. Therefore, they shield investors from systematic risk better than holding the entire market portfolio would do. On the other hand, owning equity in an energy business is substantially better than just investing in the market portfolio, in government bonds, or in any combination of the two. In fact, most portfolios fall above the SML. Only drilling oil in isolation (Portfolio 1) and

[18] In Figure 2 as well as in all figures that follow, all yields are expressed in yearly terms.

[19] Identifying the SML in a mean return/market beta Cartesian space instead of doing it in a mean return/standard deviation of return setting, is not very customary. We specifically draw on the analysis of Cochrane (1999) and adhere to his interpretation of Lintner’s capital asset pricing model because of its immediateness and graphical clarity.

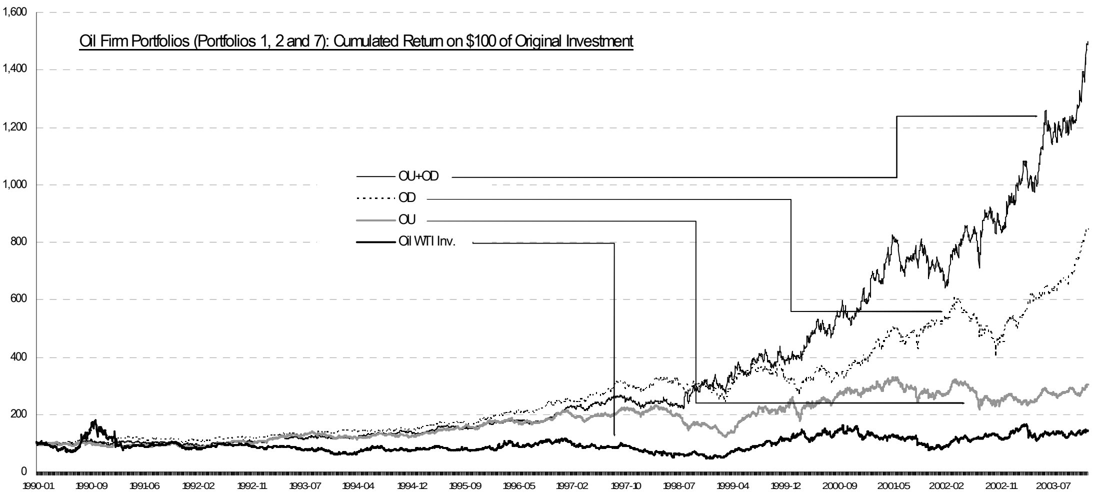
integrating the various production stages in the natural gas industry (Portfolios 10 and 12) yield less than what portfolio diversification would return to investors. It is difficult to determine which of the industries, oil or power, is the better of the two, although it seems that pure power generation creates tremendous value for stockholders (Portfolio 16).

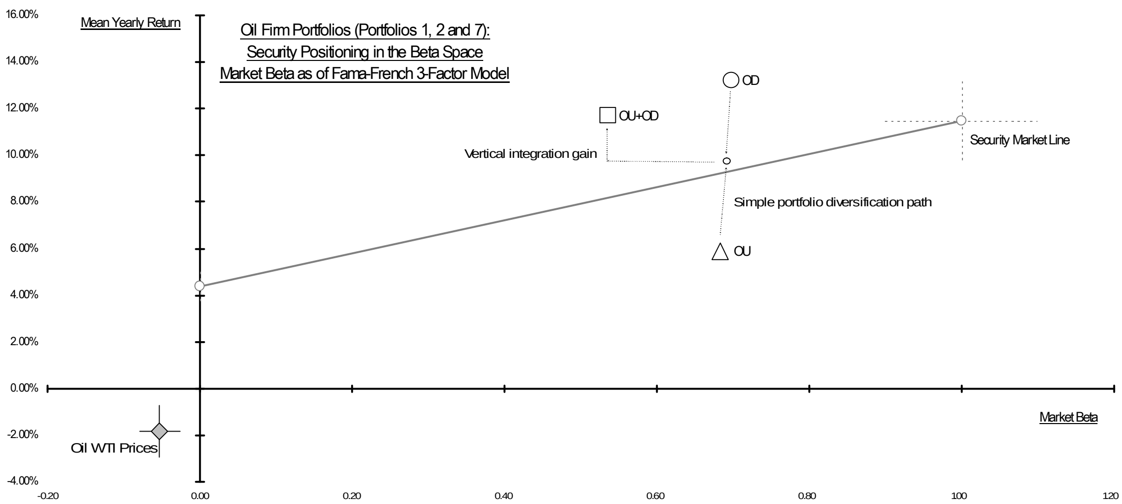
11.5.1 – Value Performance along the Vertical Dimension

11.5.1.1 – Oil Industry

Vertical integration in the oil industry produces good absolute value performance. Figure 11.3 shows the evolution of \$100 originally invested in oil upstream, downstream and integrated upstream and downstream activities, as well as in oil as a commodity. The integrated firm portfolio clearly outperforms all other portfolios as well as the underlying commodity.

Figure 11.3 & 11.4 – Vertically Integrated vs. Non-Integrated Oil Portfolios





This performance, however, changes when adjusted returns instead of portfolio values are considered. In Figure 11.4, it is evident how, on a market risk basis, upstream activities yield much less than downstream businesses (the first plot above the SML, while the second fall below). Replicating vertical integration through portfolio diversification implies to replicate Portfolio 2 (OU+OD) by simply mixing assets included in Portfolio 1 (OU) and 7 (OD). If one mixes equities with comparable value, this is tantamount to obtaining a mimicking portfolio that would position between the plotting of each single-segment portfolio (since portfolio returns and market betas are linear quantities with respect to the return and risk of the equities they include). Here, we observe that vertically integrated activities (Portfolio 2) do better than simply averaging the performance of single segment portfolios, as they position above and to the right of the virtual equally-weighted mimicking portfolio. However, vertical integration does not manage to create risk adjusted returns more than downstream businesses do in isolation (Portfolio 2 indeed plots at a distance above the SML which is slightly less than the one of Portfolio 7). If one then focuses on fuel price risk (Figure 11.3), it is also evident that, although two out of three oil portfolios (with the exception of upstream activities) dominate portfolio diversification, their values appear to significantly correlate with oil prices, a fact which may suggest some flaws in their price-hedging properties and which is further discussed later in this Section.[20]

11.5.1.2 – Natural Gas Industry

Vertical integration in natural gas businesses, compared to the oil industry, does not produce comparable absolute value performance. Figure 11.5 shows the increase of $100 of original investment in the upstream only, downstream only, midstream only, integrated natural gas portfolios, as well as in natural gas as a simple commodity. Integrated natural gas concerns create less or, at most, equal value, as compared to pure players. Portfolio 10 is then particularly inefficient and manages to create less value than investing in natural gas prices in isolation.

This negative result is significantly confirmed in terms of risk adjusted returns. In Figure 11.6, integrated gas companies are either on or below the SML, while single-stage businesses are always well above the market-wide portfolio diversification boundary. As far as fuel price risks are concerned (Figure 11.5), the correlation of natural gas portfolio values with natural gas prices is then less evident than in the case of oil businesses. This may suggest some better ability of natural gas firms to insulate stockholders from price exposures.

[20] Note that our analysis stops at the end of 2003 and does not include recent oil price history, with daily observations well above $50 per barrel and increasing values for oil equities.

Figure 11.5 - Vertically Integrated vs. Non-Integrated Natural Gas Portfolios: Portfolio Values

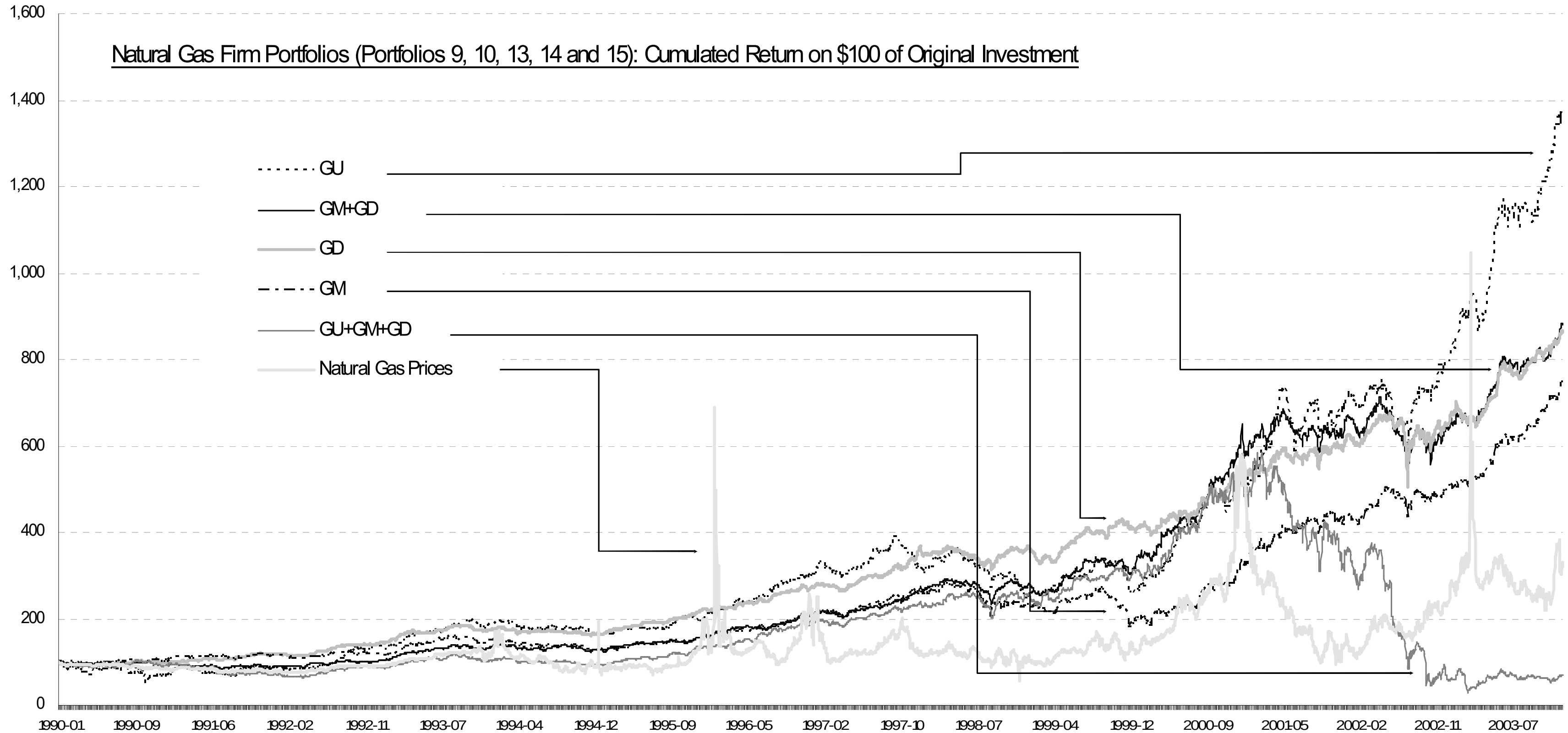
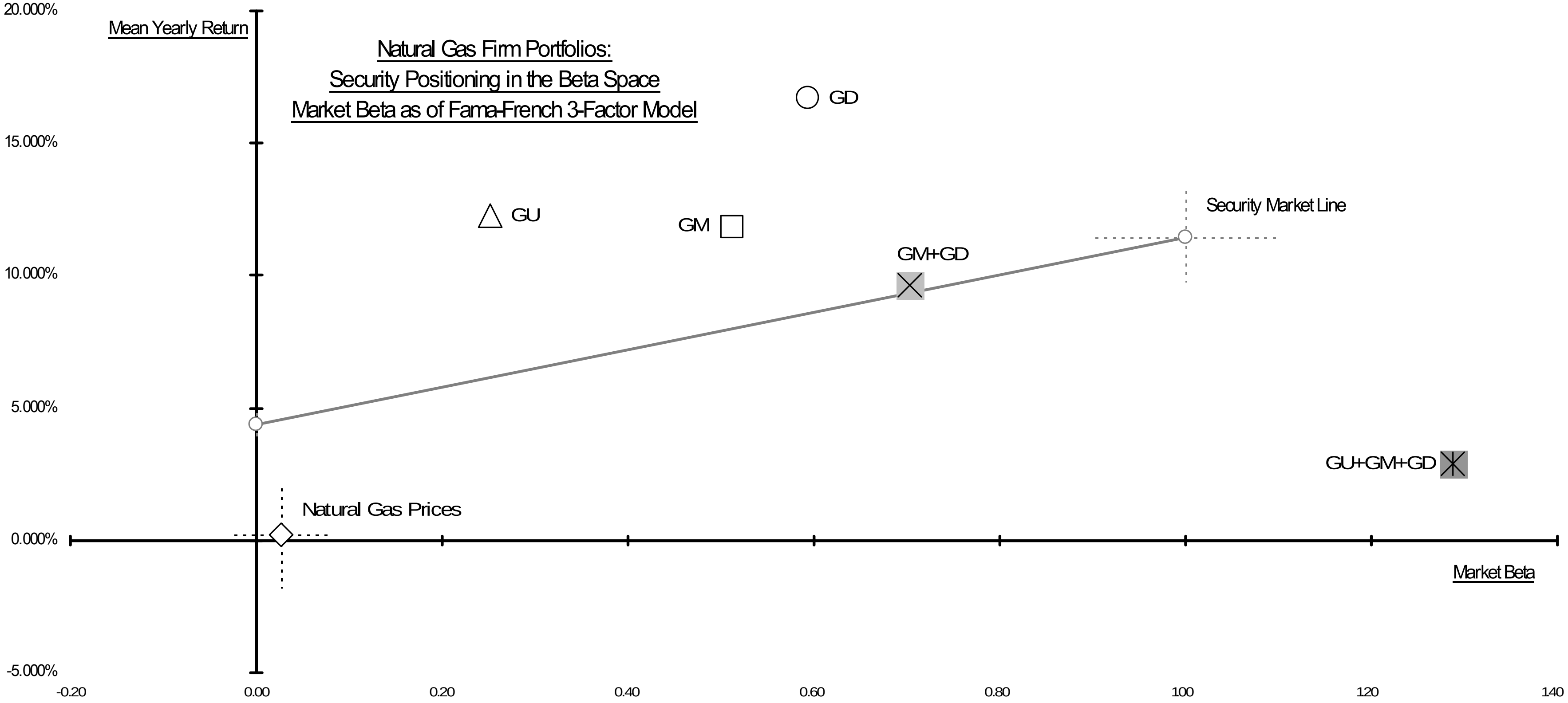


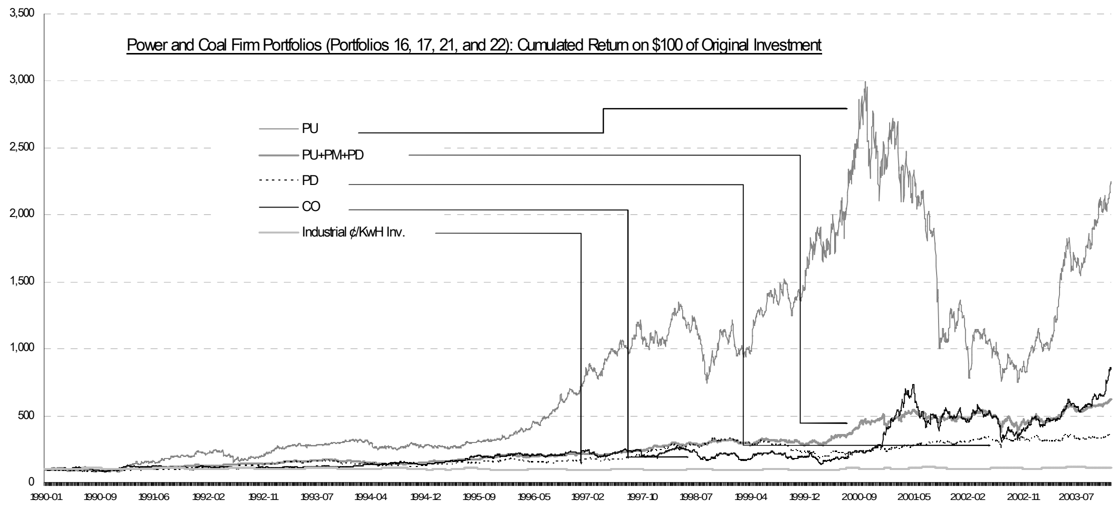
Figure 11.6 - Vertically Integrated vs. Non-Integrated Natural Gas Portfolios: Risk-Adjusted Returns

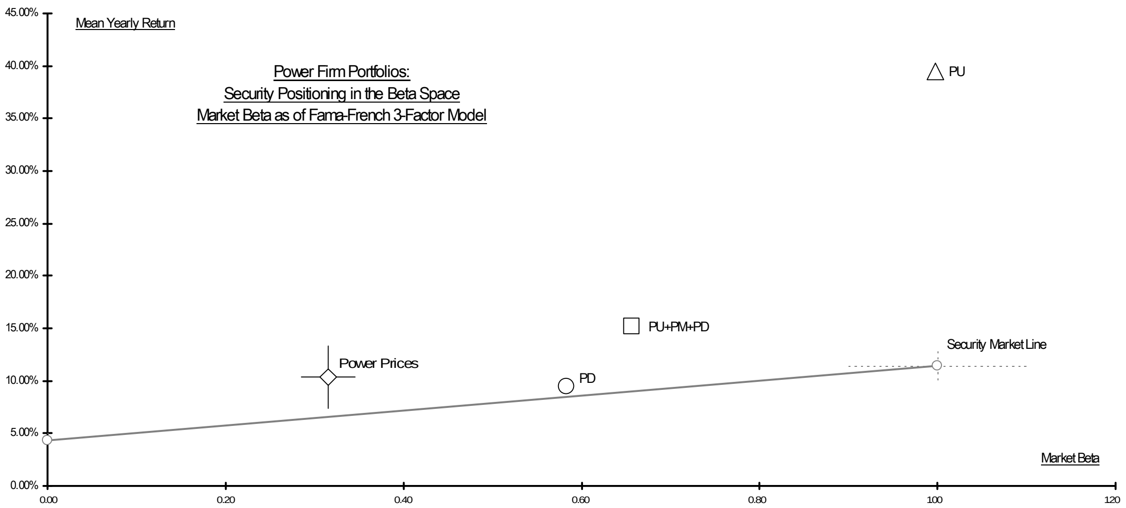


11.5.1.3 – Power Industry

Vertical integration in the power industry, similarly, has little power. Figure 11.7 shows that $100 of original investment in upstream activities not only produces much more value than the same amount of money invested in downstream businesses, but also more than investments in integrated activities. For shareholders, synergies from controlling the entire value chain in the industry seem, therefore, to be almost irrelevant and they would be better off concentrating their holdings in specialized generation firms (Portfolio 16). This is however true only throughout the 1997-01 period, since, after the beginning of 2001, the value performance of upstream businesses has significantly diminished.

Figure 11.7 & 11.8 – Vertically Integrated vs. Non-Integrated Power Portfolios





Unlike the other two industries examined so far, the performance of vertical integration among power firms slightly improves when risk-adjusted returns are considered. All power portfolios fall above the SML in Figure 11.8 and vertical integration seems to acceptably compare to pure portfolio diversification. Integrated companies yield, in fact, more than pure downstream firms. They dominate the SML and are closer to their theoretical mean positioning between the highest performers (Portfolio 16) and the lowest performers (Portfolio 21) than in any other case concerning integrated businesses examined so far. In substance, downstream businesses expose stockholders to very little risk, but yield irrelevant excess-returns, whereas upstream firms are still the most rewarding (their distance north-west of the SML is the largest among all energy portfolios), but require stockholders to bear very significant systematic risk (their beta positioning is most to the right). This finding seems to match the regulatory structure of the US power industry where downstream activities have been traditionally regulated, while upstream activities have been partially opened to competition since 1998 and may justify the apparent effect of vertical integration on risk-adjusted returns. In Figure 11.7 we also present the value performance of the integrated coal portfolio. In the US power industry, coal represents half of the total generation capacity (according to the EIA). Since we do not have daily power prices and daily coal prices, the coal portfolio may provide a proxy for a preliminary fuel price risk analysis. From a graphic analysis, it is evident how power firm portfolios (particularly generators) significantly correlate with the coal portfolio, from 2000 onwards. As in the case of oil firm portfolios, this may imply a partial inability of power firms to insulate their shareholders from underlying price dynamics. This issue is also further addressed later in this section.

11.5.2 – Value Performance along the Horizontal Dimension

11.5.2.1 – Oil with Natural Gas

Figure 11.9 shows the cumulated return for $100 of original investment in pure player portfolios vs. the absolute performance of an equal investment in diversified firm portfolios. The absolute value creation of most diversified businesses is lower than that of fuel concentrated activities. Only in one case (Portfolio 8) do diversified ongoing concerns outperform pure players and this occurs when firms specialize in downstream activities.

The same facts are confirmed when risk is considered. In Figure 11.10, pure and diversified firm portfolios are plotted in the market beta space (statistics for the OLS estimation of equation [11.1] on aggregated portfolios are provided in Table 11.4). It is evident how horizontal diversification between oil and gas does not significantly create value, even in terms of risk-adjusted returns. First, all diversified portfolios fall to the right of pure players portfolios. It appears that firms load risk when they diversify between fuels. Second, while all portfolios dominate the SML, in no case do diversified firms do better than pure natural gas players. Only Portfolio 3, the one which includes large oil and natural gas majors, manages to outperform pure oil players. This may be evidence of a stabilization effect that large oil companies seem to enjoy in risk-adjusted terms and could suggest that business diversification pays off only to the extent that firms have sufficient size and business expertise to fully profit from it.

Figure 11.9 – Horizontal Diversification between Oil and Natural Gas: Portfolio Values

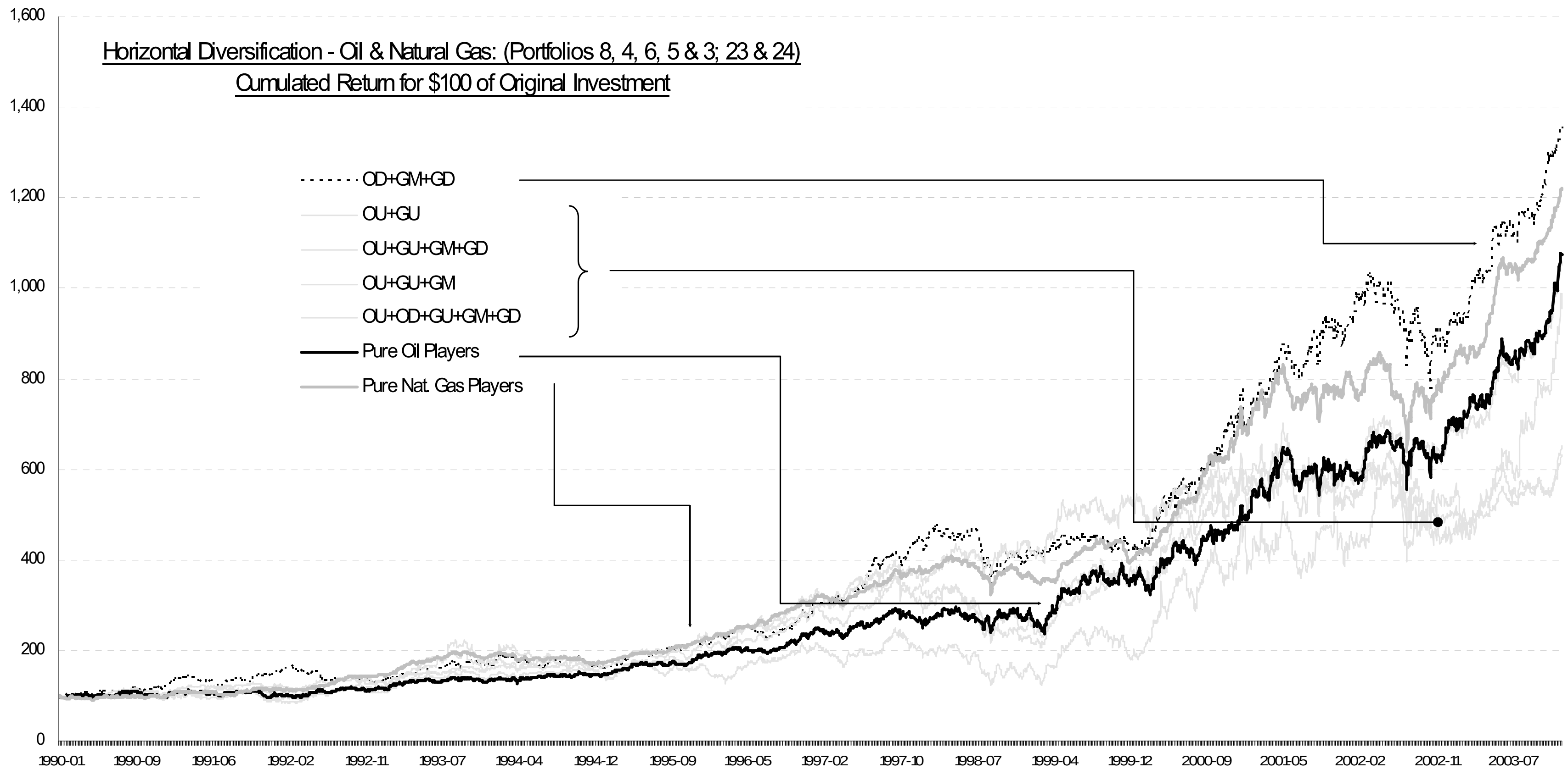
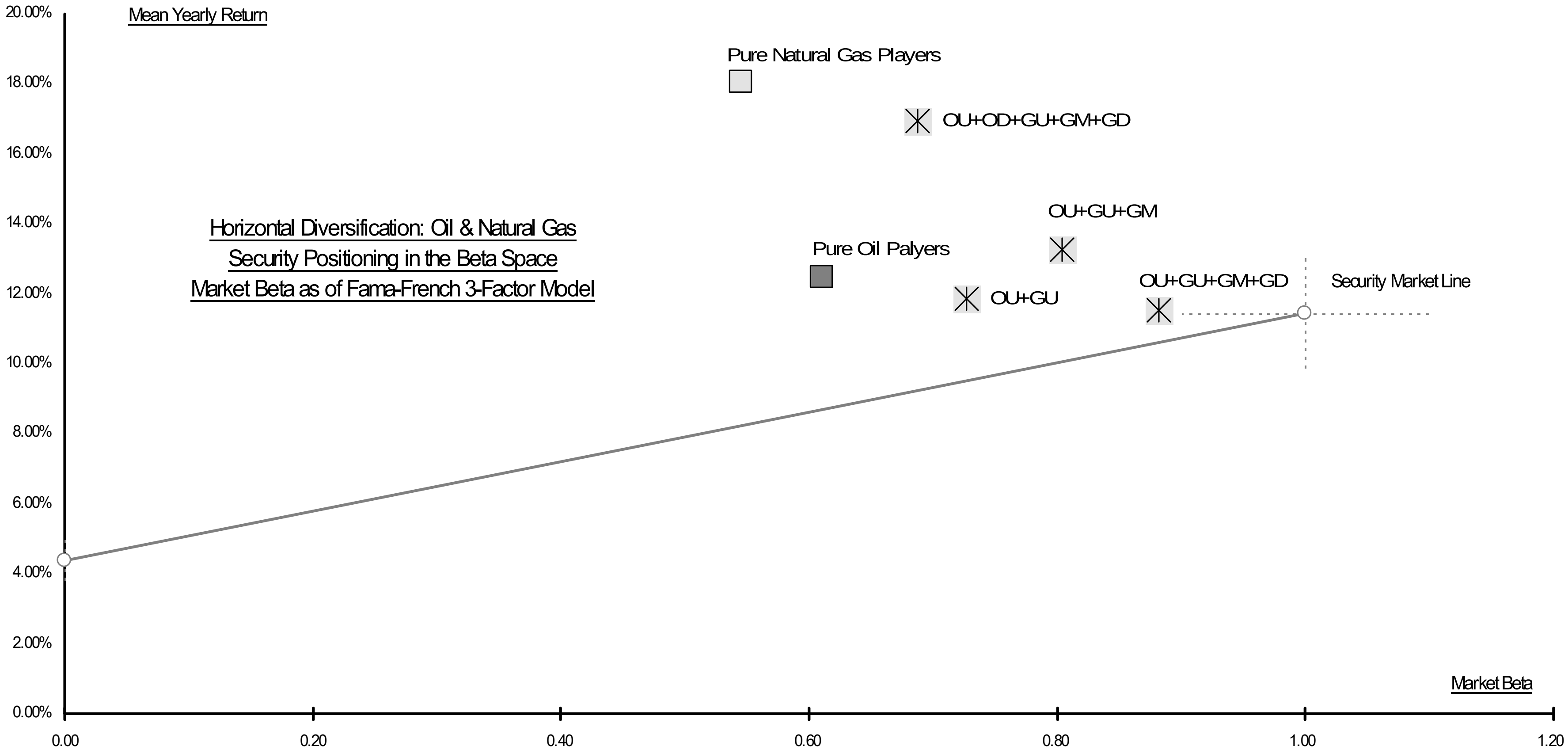


Figure 11.10 – Horizontal Diversification between Oil and Natural Gas: Risk-Adjusted Returns



11.5.2.3 – Natural Gas with Power

What is observed for diversification between oil and natural gas is even more confirmed when power utilities diversify into natural gas. Figure 11.11 and 11.12 show these facts. The first graph shows how, in all cases, diversified businesses produce less absolute cumulated value than pure players. Diversification in upstream activities (Portfolio 12) outperforms other portfolios for a while, but fails to maintains a constant result in the long run (notice however that this portfolio, like Portfolio 11, includes only one firm, Williams Cos.; thus it has low statistical significance).

The poor performance of horizontal diversification in risk-adjusted terms is even more compelling. Diversifying across energies is bad news for shareholders. The vertical distance between pure player portfolios and the SML dominates all other cases, with power production being the best type of investment. Only Portfolio 11 apparently reduces systematic risk in a significant way[21].

In Figure 11.13, all the evidence on horizontal diversification is summarized in a single graph. To avoid low significance, only aggregated portfolios (from 23 through 27) are considered here. Results do not significantly change. The arrows highlight the return-risk effect of diversification. While the summation of oil and natural gas increases the performance of the former, it does not really create value through synergies in terms of better positioning above the SML (diversified oil and natural gas firms yield slightly more than natural gas firms, but for significantly more risk); diversification between power and natural gas appears to be value destroying. Diversified utilities plot both below pure power players and natural gas firms. Their horizontal integration does not significantly protect investors from market risk; on the contrary it pushes equities towards the SML.

[21] However, Portfolio 11 is the other diversified portfolio that suffers from low significance, as it includes only one firm, Keyspan Energy Corp., which was de-listed in 1998 as the result of a merger. Its beta estimation, therefore, is not conducted over the same time-window as the other portfolios.

Figure 11.11 – Horizontal Diversification between Natural Gas and Power: Portfolio Values

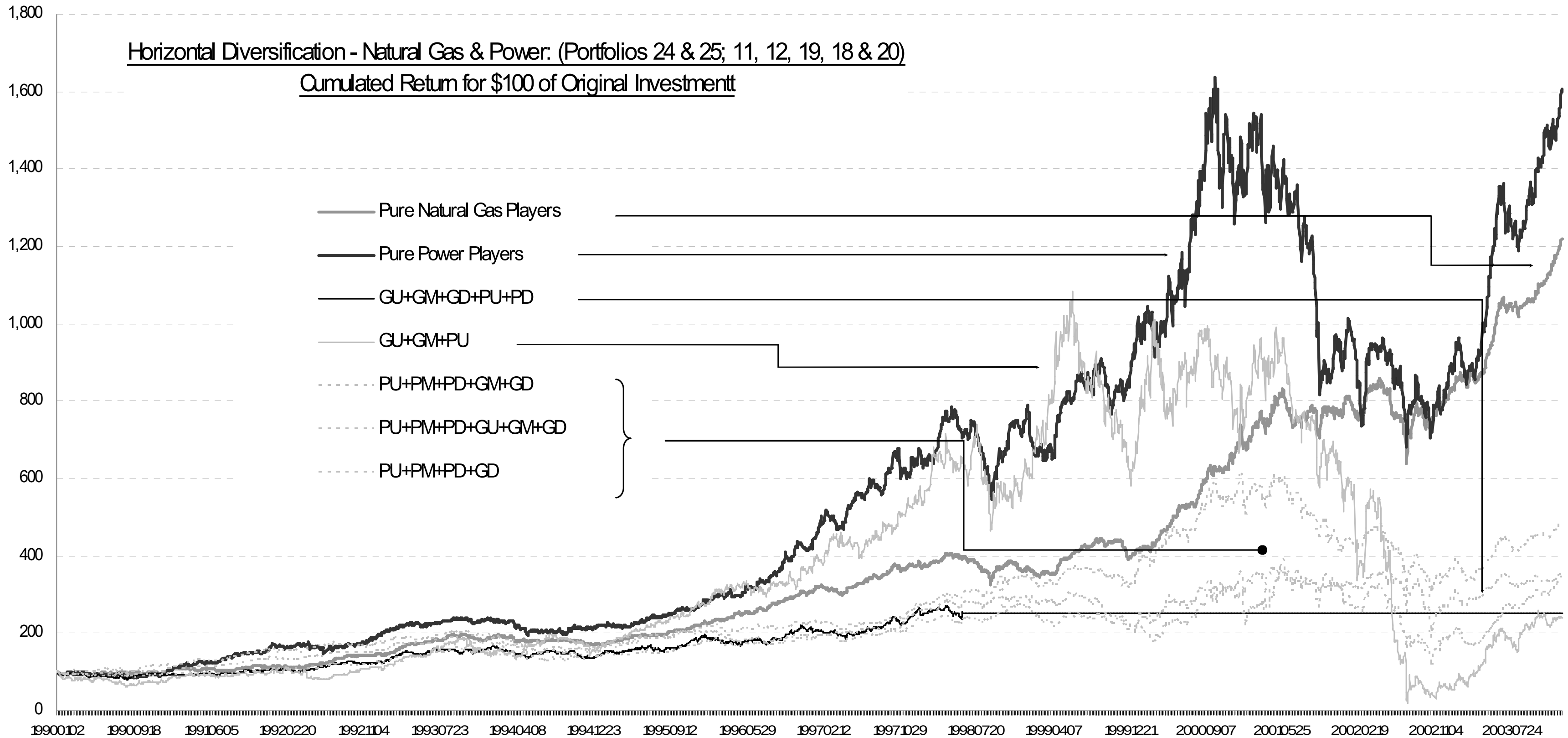


Figure 11.12 – Horizontal Diversification between Natural Gas and Power: Risk-Adjusted Returns

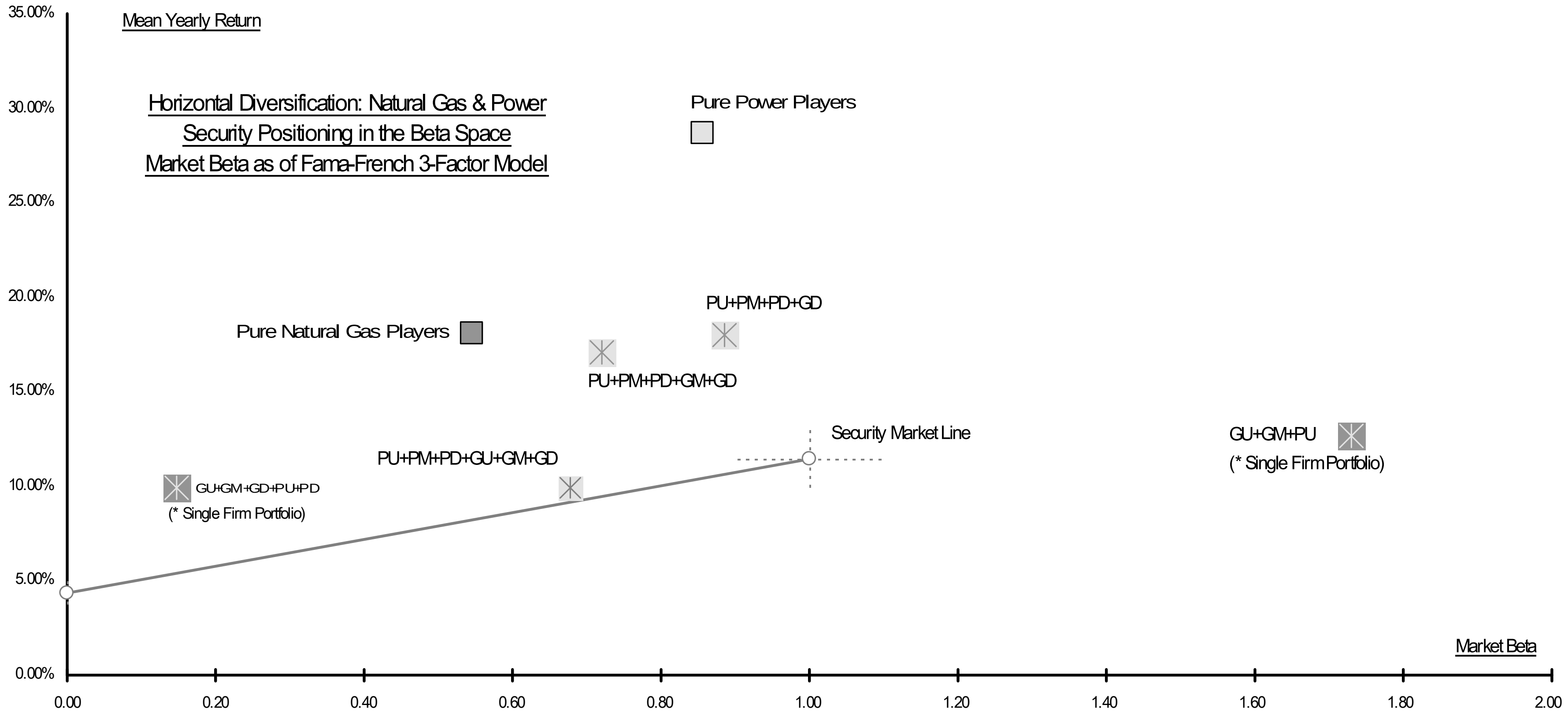
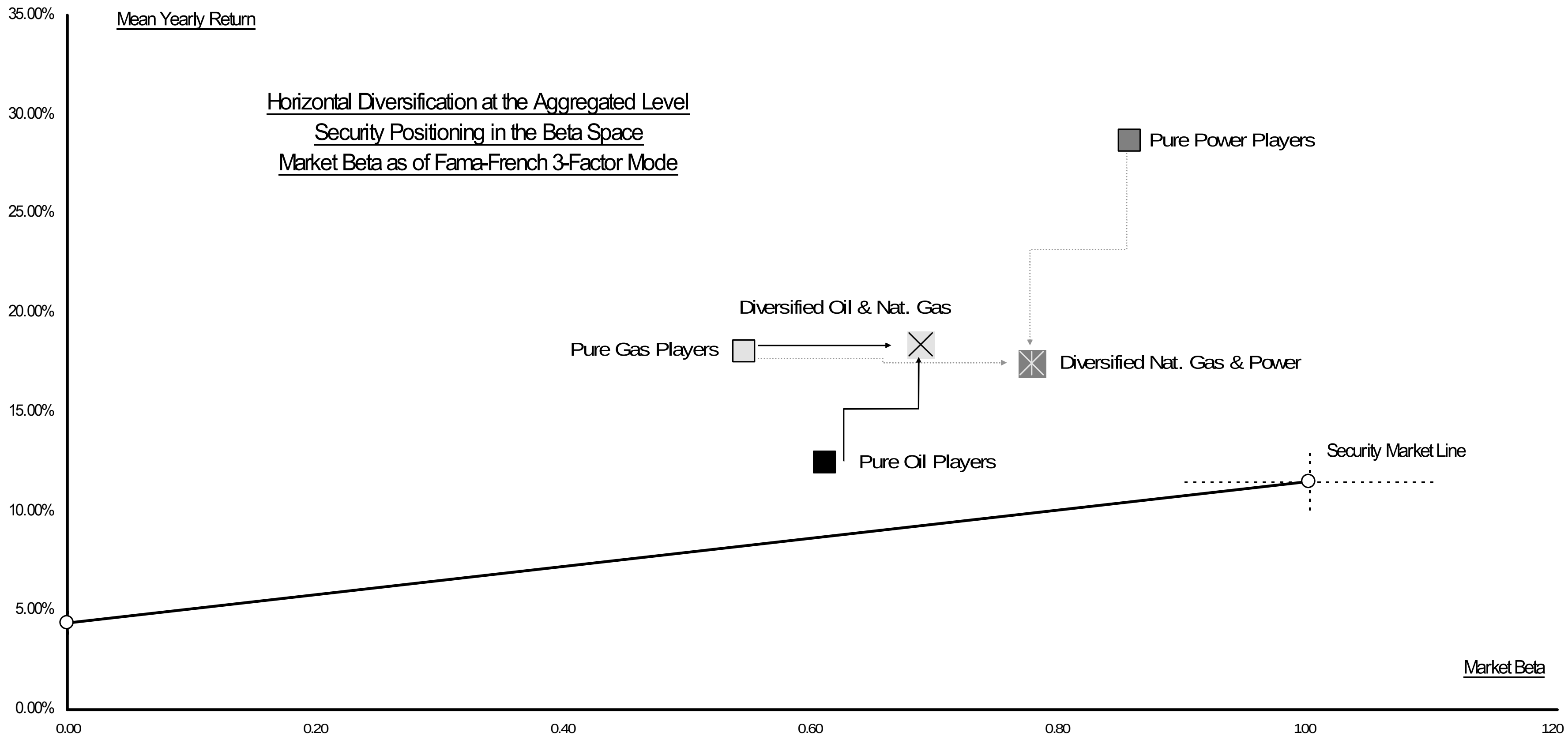


Figure 11.13 – Horizontal Diversification: All Fuels, Aggregated Portfolios.



11.5.4 – Value Performance Considering Market and Fuel Risks

As explained in Section 11.3, a more thorough assessment of the risk-adjusted performance of energy portfolios requires considering fuel in addition to market risks. In order to better track changes in the strategies of firms, we should then consider the information that running rolling regressions may provide. Therefore, we present in this subsection the results obtained by rolling daily regressions between 1992 and 2003 using OLS as the estimation procedure for equation [11.2]. For simplicity and better statistical significance, all results presented in this subsection are relative to aggregated portfolios only. Since fuel risk is then particularly significant with respect to equity investors' ability to diversify into different fuels, we focus here on the horizontal dimension, where fuel diversification is accomplished within firms.

Equation [11.2] considers all market regressors of the Fama-French specification [11.1] plus various fuel price time series, as additional regressors. Table 11.5 provides estimation statistics of equation [11.2] for all observations. Daily power price time series obtained from monthly EIA time series are never significant and, accordingly, are discarded as a regressor. Oil and natural gas prices are only insignificant in the case of the Pure Power Players Portfolio. The analysis conducted with Fama-French regressors presented in the previous subsection can thus be considered to be more representative for this latter type of firm.[22]

Rolling regressions require us, then, to specify their estimation windows. Using the Pure Oil Players Portfolio (Portfolio 23) as a reference, we use mean excess-returns obtained by rolling regressions of [11.2] over the entire dataset (1990-03) with various estimation window lengths (from ten to 1,000 observations) as a criterion of choice. Mean excess-returns are first negative and then positive and equate to zero when the estimation window length is between 470 and 480 observations (slightly less than two years of trading data). Therefore, we present here results obtained with an estimation window of 478 observations, a length that implies the possibility of using rolling regressions to draw inferences only between 1992 and 2003. Table 11.6 summarizes the estimation statistics for 3025 daily regressions run over this time interval.

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[22] Note that this model specification is robust with respect to serial correlation, which is not significantly detected on estimation errors. Residuals are also relatively well behaved in terms of their normality. Their skewness and kurtosis are contained between zero and one and five and six, respectively, in all cases, except for the case of Pure Power Players (for which, it has been already signaled that equation [11.2] is not the best specification). However, the Jarque-Bera statistics reject normality in all estimations. This is most likely the result of outlying observations which confer heteroskedasticity to the dataset. White heteroskedasticity tests indeed find that OLS estimation errors are driven by some or all of the squared regressors in [11.2], for all portfolios. In the presence of heteroskedasticity, the biggest drawback of OLS estimation is the significance and value of regression coefficients. Given the purpose of this study, we test if regression coefficients are significant and, in the case of market betas, have significantly different values, running a GARCH(1,1) specification on different sub-windows of the entire dataset. In all cases, except for the case of Pure Power Players, regression coefficients are significant. GARCH estimated market beta values converge to the OLS values at the second decimal. Therefore, we do not reject the significance of OLS results.

Figure 11.14 – Horizontal Diversification: Mean Rolling Regressions Results

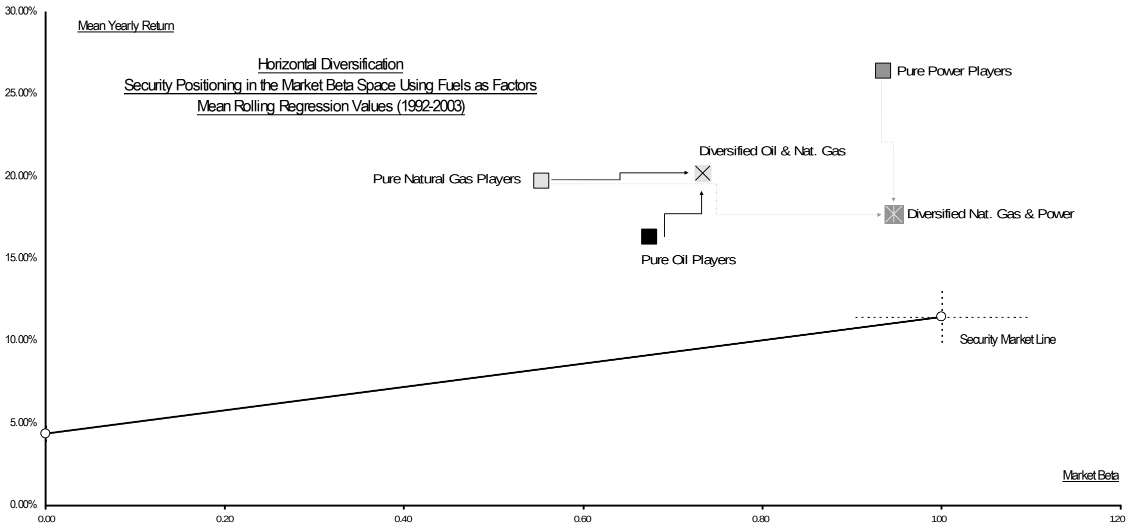
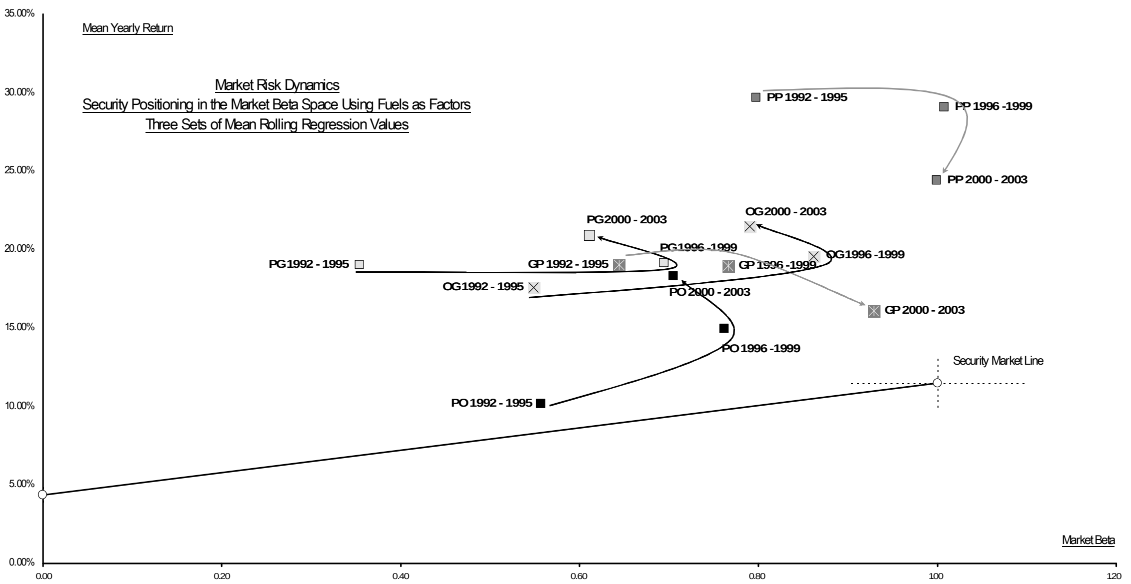


Figure 11.14 shows the effect of diversifying between fuels. The similarity with Figure 11.13 is patent and no new fact is put in evidence. Considering fuel prices as regressors does not significantly change the value of market betas. The only appreciable difference is that, using equation [11.2], the integration between natural gas and power results is to be performed with a relatively more significant increase in market risk than with a simple Fama-French estimation (Portfolio 27 falls further to the right). It appears to be confirmed, therefore, that, even with respect to fuel risks, energy firms fail to bestow value on shareholders by diversifying.

Figure 11.15 – Market Risk Dynamics



Rolling regressions allow us, then, to track modifications in market risk as a result of firms' longitudinal efforts to adapt business strategies to their evolving environment. Figure 11.15 shows how mean yearly returns, coupled with market betas, have moved portfolio positioning during the 1992-03 period. Three time windows of four years are analyzed: 1992-95, 1996-99 and 2000-03. Two separate aspects clearly emerge.

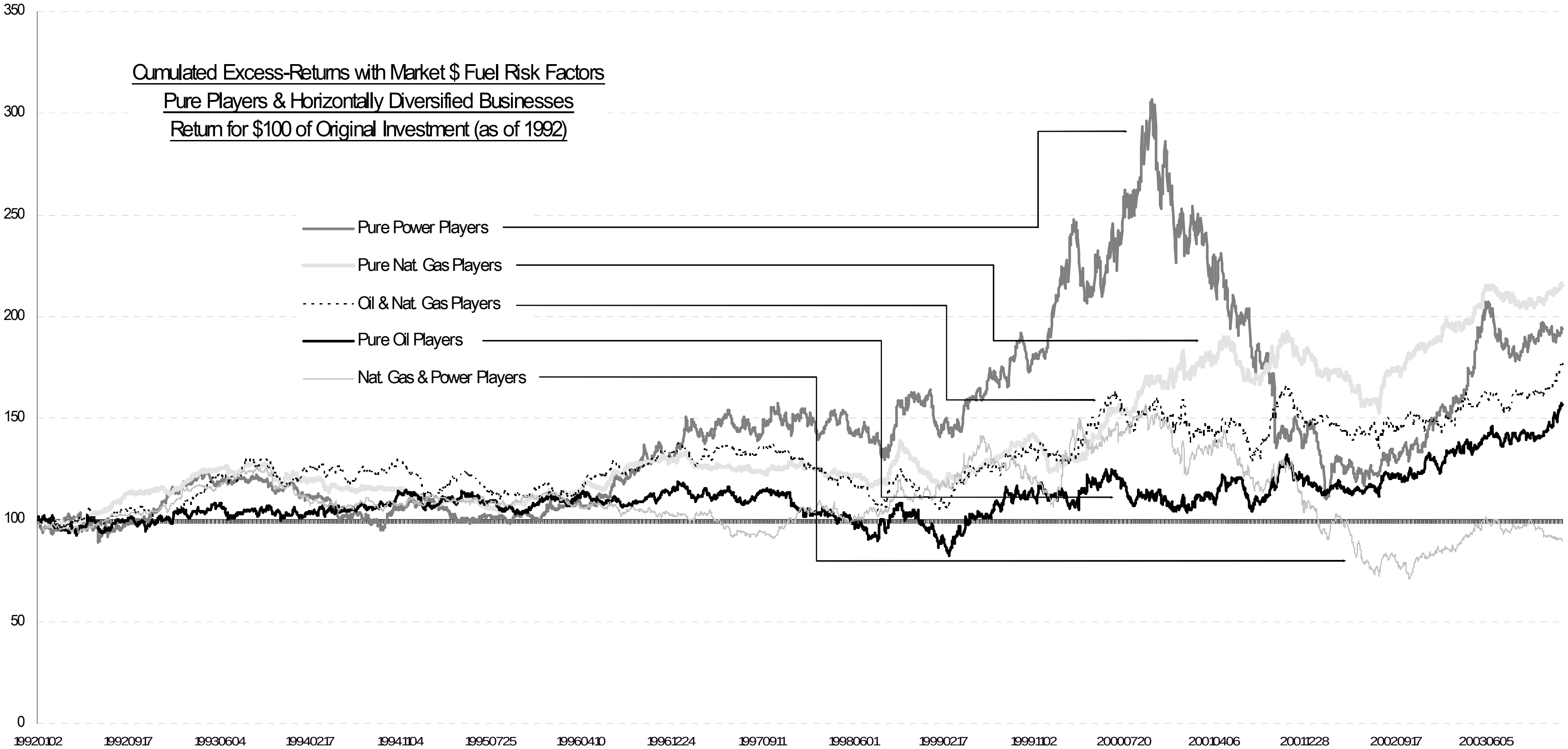
1) All firms have increasingly become vulnerable to systematic risk during the passage from the first to the second set of four years. Both solid black and grey arrows in the figure show that portfolios have progressively shifted to the right, while maintaining similar vertical height. Only pure oil firms (PO) appear to have improved performance as they were increasing risk and, thus, represent the only equity portfolio which has increased its risk-adjusted performance (its vertical distance from the SML) during the first eight years.

2) Equity portfolios made up of pure power players (PP) and diversified natural gas and power utilities (GP)—grey arrows—have consistently diminished their return performance throughout the entire 12 years, while all other types of firm—black arrows—after a first negative period, seem to have positively corrected their performance.

Here the story seems to be one of fuel prices. Power related portfolios appear to be conditioned by the effect of liberalization. Since, in deflated terms, mean power prices have diminished in the US (see EIA statistics reported in Table 11.7), the opening of the industry to competition has increasingly exposed them to market trends and their risk, while integration into natural gas has failed to produce the synergies that were expected, particularly in terms of risk diversification (the GP portfolio is the one showing the largest shift to the right during the second of the two time periods). On the other hand, after a first negative period, oil and natural gas firms have probably benefited from a moderate increase in industrial commodity prices (the oil price boom of the last two years is excluded from this study) and the full effect of their restructuring that took place during the second part of the nineties.

Finally, by using rolling regressions, it is also possible to determine out-of-sample excess-returns as explained in Section 11.3. These returns can be modelled as the yield that an investor would enjoy if he were to be compensated daily for buying and holding equities, given the exposures that equation [11.2] tracks in the form of market and fuel risk factors. Such a yield represents, therefore, a positive or a negative additional compensation that investors receive. As usual, we gauge the value evolution of $100 invested in each aggregated portfolio at this excess yield. Figure 11.16 shows results and a daily break-down (throughout the 1992-03 period), of the market and fuel risk-adjusted performance of aggregated energy equity portfolios shown in Figure 11.15.

Figure 11.16 – Cumulated Excess Returns



With the partial exception of diversified natural gas and power activities and (less so) pure oil businesses, investing in energy seems to be a good choice on a daily basis. At least four cycles seem to be identifiable: 1992-94, 1996-98, 1999-01 and 2002-03. During these periods, portfolio values have bulged, following first increasing then contracting underlying general stock and energy trends. With respect to the analysis in Figure 11.15, integration between oil and natural gas seems to yield some better synergic results, particularly in the 1996-98 triennium. On the other hand, integration between natural gas and power appears even more to be driven by the tremendous performance of pure power firms and always yields less than simple portfolio diversification by shareholders would yield. Finally, it even fails to rebound when pure power equities peak again during the 2002-03 period and ends up below the positive cumulated excess-return region.

§ 11.6 – Conclusions

In this study we investigate the ability of vertical integration and horizontal diversification to create value for US energy firm shareholders. Our results are mixed and appear to partially confirm the postulations of industrial organization, as far as the first type of corporate strategy is concerned, and of financial economics, with respect to fuel diversification.

On the one hand, vertical integration within energy portfolios seems to produce little risk-adjusted return performance for all types of energy firms. For industrial organization theory, this may, perhaps, indicate that asset specificity and the possibility of opportunistic behaviour across various stages of production are not a sufficient cause to release material synergies as a result of upstream or downstream integration. Across the various types of energy, this is all the more true for the natural gas industry, a type of activity which, as a result of vertical integration, has experienced the worst results in the time window considered. Only power utilities seem to partially escape this reality, possibly because of their ability to create value by being integrated upstream into generation—a relatively small industry (see Figure 11.2) that, in isolation, has experienced the best equity performance among all energy portfolios. US antitrust authorities, both in their praxis and their periodical reports, treat energy industries as relatively non-concentrated. Accordingly, they have largely permitted the significant wave of corporate restructuring through mergers and acquisitions that reshaped the US energy sector during the last decade. Given the linkage between concentration and opportunistic behaviour (see Subsection 11.2.1), industrial structure may, therefore, be at the origin of the contained performance of vertical integration in the sector. *A fortiori*, this may also suggest that firm management might promote vertical integration beyond its strict transactional cost rationale, admittedly showing that corporate expansion decisions could be grounded in motivations unrelated to firm value maximization.

This last remark becomes still more evident when results of horizontal diversification are considered. Whether including or excluding fuel risk as a return factor, in no case does diversifying across energies, through corporate expansion, outperform simple shareholders' portfolio diversification. Figure 11.13 and 11.14 show, with little uncertainty, that firm horizontal strategies fail to produce value for shareholders, while Figure 11.15 illustrates that, even if some partial mitigation of this fact were to be observed during the 2000-04 period, it would most likely be due to a general amelioration of the overall performance of oil and natural gas industries that interested both diversified and pure players (pure power players and diversified portfolios including power, on the other hand, continued and even deepened their decline in the period considered), rather than to better synergies. Such evidence, perhaps disappointing with respect to the theoretical value of economies of scope, plainly confirms contemporary corporate financial theory, while not refuting the explanatory power of transaction cost economics. The residual loss in equity value associated with corporate expansion (a transaction cost) probably out-weighs the possible synergic value of unrelated mergers and acquisitions. Clearly, we do not empirically test here if this is effectively explained by failures in the agency relationship between firm managers and their shareholders, although this seems to be suggested by our results.

Table 11.3 – Equation [11.1]: OLS Statistics, Full Dataset – Basic & Integrated Portfolios

No.	Portfolios	B_i^1	B_i^2	β_i^3	R^2	F
1	OU	0.684	0.099	0.659	0.153	212.944
2	OU+OD	0.536	-0.204	0.477	0.109	144.550
3	OU+OD+GU+GM+GD	0.688	-0.392	0.497	0.284	466.902
4	OU+GU	0.727	0.232	0.661	0.218	327.402
5	OU+GU+GM	0.804	0.005	0.676	0.190	276.079
6	OU+GU+GM+GD	0.882	0.681	0.870	0.101	132.696
7	OD	0.698	-0.052	0.602	0.225	342.254
8	OD+GM+GD	0.497	0.214	0.454	0.097	126.561
9	GU	0.252	0.267	0.231	0.007	8.189
10	GU+GM+GD	1.288	0.202	1.325	0.142	195.065
11	GU+GM+GD+PU+PD	0.147	-0.002	0.113	0.022	26.947
12	GU+GM+PU	1.731	0.386	1.363	0.129	174.430
13	GM	0.512	0.163	0.456	0.141	193.879
14	GM+GD	0.704	0.150	0.613	0.364	672.696
15	GD	0.594	0.164	0.495	0.365	676.022
16	PU	0.998	0.355	0.665	0.129	174.810
17	PU+PM+PD	0.656	-0.257	0.782	0.382	727.710
18	PU+PM+PD+GU+GM+GD	0.678	-0.213	0.916	0.281	460.216
19	PU+PM+PD+GM+GD	0.721	-0.153	0.773	0.346	621.653
20	PU+PM+PD+GD	0.886	-0.174	1.049	0.228	346.607
21	PD	0.583	-0.477	0.707	0.244	378.642
22	CO	0.953	0.085	0.690	0.173	246.093

Table 11.4 – Equation [11.1]: OLS Statistics, Entire Dataset – Aggregated Portfolios

No.	Portfolios	β_i^1	β_i^2	β_i^3	R^2	F
23	Pure Oil Players	0.610635493	-0.07738109	0.549148708	0.206926475	306.9255272
24	Pure Gas Players	0.544807523	0.15276079	0.492217746	0.276660068	449.9191127
25	Pure Power Players	0.856008198	0.067612305	0.670805375	0.223461798	338.5095044
26	Oil & Natural Gas	0.686801506	0.109486071	0.603567433	0.286834067	473.1191696
27	Natural Gas & Power	0.776890559	-0.01845229	0.696130998	0.309650626	527.6347988

Table 11.5 – Equation [11.2]: OLS Statistics, Entire Dataset – Aggregated Portfolios

Pure Oil Players				
Variable	Coefficient	St. Error	t-Statistic	Prob.
M_t	0.64888	0.022375	29.00021	0
SMB_t	-0.058661	0.030675	-1.912321	0.0559
HML_t	0.599412	0.037827	15.84598	0
Oil Prices	0.111269	0.006083	18.2929	0
Natural Gas Prices	0.009888	0.002601	3.801241	0.0001
R^2		0.283417		
Adjusted R^2		0.282604		
Pure Natural Gas Players				
Variable	Coefficient	St. Error	t-Statistic	Prob.
M_t	0.567829	0.015403	36.86406	0
SMB_t	0.172334	0.021117	8.160857	0
HML_t	0.530634	0.026041	20.37691	0
Oil Prices	0.030491	0.004187	7.281642	0
Natural Gas Prices	0.009147	0.001791	5.107992	0
R^2		0.302599		
Adjusted R^2		0.301808		
Pure Power Players				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
M_t	0.890003	0.030144	29.52469	0
SMB_t	0.121083	0.041326	2.929915	0.0034
HML_t	0.730614	0.050962	14.33636	0
Oil Prices	0.006163	0.008195	0.752128	0.452
Natural Gas Prices	-0.00243	0.003504	-0.69342	0.4881
R^2		0.228136		
Adjusted R^2		0.22726		
Diversified Oil & Natural Gas				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
M_t	0.7202	0.019017	37.87057	0
SMB_t	0.132095	0.026072	5.066574	0
HML_t	0.65001	0.032151	20.21743	0
Oil Prices	0.078211	0.00517	15.12834	0
Natural Gas Prices	0.011721	0.002211	5.301777	0
R^2		0.343786		
Adjusted R^2		0.343041		
Diversified Natural Gas & Power				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
M_t	0.7202	0.019017	37.87057	0
SMB_t	0.132095	0.026072	5.066574	0
HML_t	0.65001	0.032151	20.21743	0
Oil Prices	0.078211	0.00517	15.12834	0
Natural Gas Prices	0.011721	0.002211	5.301777	0
R^2		0.343786		
Adjusted R^2		0.343041		

Table 11.6 – Rolling Regressions: Estimation Statistics, Equation [11.2]

Pure Oil Players				
Variable	Mean R^2	Mean F	Mean Coefficient	Mean t-Statistic
M_t	0.326756	47.78727	0.674499	10.02243
SMB_t			-0.0249	-0.23938
HML_t			0.512348	4.670318
Oil Prices			0.119628	6.690151
Natural Gas Prices			0.062815	1.832097
Pure Natural Gas Players				
Variable	Mean R^2	Mean F	Mean Coefficient	Mean t-Statistic
M_t	0.375016	61.82351	0.553433	13.73188
SMB_t			0.233349	4.497297
HML_t			0.450891	6.859716
Oil Prices			0.02198	2.003611
Natural Gas Prices			0.103771	3.416432
Pure Power Players				
Variable	Mean R^2	Mean F	Mean Coefficient	Mean t-Statistic
M_t	0.239628	30.94384	0.935163	10.40324
SMB_t			0.148713	1.260548
HML_t			0.637687	4.309876
Oil Prices			-0.00468	-0.1785
Natural Gas Prices			0.007417	-0.13609
Diversified Oil & Natural Gas				
Variable	Mean R^2	Mean F	Mean Coefficient	Mean t-Statistic
M_t	0.366653	60.73669	0.733627	12.88214
SMB_t			0.212098	2.849652
HML_t			0.540424	5.780866
Oil Prices			0.07715	5.074656
Natural Gas Prices			0.058541	2.813889
Diversified Natural Gas & Power				
Variable	Mean R^2	Mean F	Mean Coefficient	Mean t-Statistic
M_t	0.355421	55.53761	0.779397	12.80209
SMB_t			-0.01209	-0.43301
HML_t			0.649565	6.357107
Oil Prices			0.015822	0.692453
Natural Gas Prices			0.022738	1.193331

Table 11.7 – Fuel Prices and Industrial Markups, US EIA Statistics

Electricity Prices (Deflated $.00/KWh)				Natural Gas Prices (Deflated $ per Mcf)		
Year	Commercial Consumers	Residential Consumers	% Spread	Wellhead Price	Commercial Consumers	Residential Consumers
1990	7.047375593	4.268310326	65.11%	1.527245542	4.265341134	5.499433507
1991	7.051422587	4.237024342	66.42%	1.428617548	4.166740285	5.44993845
1992	6.97287305	4.102743143	69.96%	1.471288569	4.098943432	5.331032609
1993	6.895602523	4.014345659	71.77%	1.679413475	4.343834359	5.526947674
1994	6.755268664	3.842362495	75.81%	1.490585496	4.34082668	5.554109559
1995	6.591311561	3.653718911	80.40%	1.215052353	3.945161917	5.162828692
1996	6.363617203	3.500512403	81.79%	1.64663524	4.126736853	5.30145506
1997	6.317788874	3.394203439	86.13%	1.739813325	4.260856539	5.583514336
1998	6.089023776	3.298970873	84.57%	1.440350477	4.045879996	5.490530026
1999	5.857674556	3.175970585	84.44%	1.57233906	3.859703791	5.267634775
2000	5.696027995	3.20831759	77.54%	2.549716353	4.540961831	5.886709499
2001	5.894473768	3.444663071	71.12%	2.744295125	5.535316206	6.775833333
2002	5.640760253	3.255406794	73.27%	1.964459274	4.426559347	5.728978628

Oil Prices (Deflated $ per Barrel)						
Year	Crude Oil at Refining	Oil Products at Refiners' Resale	Oil Products at End Use	Refining % Markup	Retailing % Markup	Total % Markup
1990	19.99139673	29.07371679	33.53264398	45.43%	15.34%	60.77%
1991	16.71372918	25.20633802	29.93528863	50.81%	18.76%	69.57%
1992	15.65128331	23.06267125	27.4997209	47.35%	19.24%	66.59%
1993	13.5926881	21.72941532	26.13374446	59.86%	20.27%	80.13%
1994	12.56120426	20.35833613	23.14001038	62.07%	13.66%	75.74%
1995	13.5139443	20.18667979	22.34106762	49.38%	10.67%	60.05%
1996	15.76355123	22.94704186	25.31271628	45.57%	10.31%	55.88%
1997	14.26821782	21.69818243	24.40494728	52.07%	12.47%	64.55%
1998	9.228070603	16.35137456	18.61121996	77.19%	13.82%	91.01%
1999	12.56197275	18.54293531	20.76664123	47.61%	11.99%	59.60%
2000	19.54475157	27.51950817	29.26235226	40.80%	6.33%	47.14%
2001	15.693083	22.24602213	26.88707194	41.76%	20.86%	62.62%
2002	16.06224546	26.42472647	24.43727353	64.51%	-7.52%	56.99%
	Mean Domestic Cost at Refiners' Purchase	Mean Domestic Price on Gasoline, Propane and Kerosene	Mean Domestic Price on Gasoline, Propane and Kerosene	Determined as Margins on Subsequent Production and Distribution Stages		

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