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Determinants and Real Effects of Joint Hedging: An Empirical Analysis of the US Petroleum Industry

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Abstract. We study the intensity of joint hedging of oil and gas prices by US petroleum firms. We aim to explain the rationale for and find the determinants of joint hedging, as well as its impact on firm market value, performance, and riskiness. Joint hedging that takes into account the interdependence between risks should have a positive impact on firm value in the presence of multiple risks. We verify this theory in an innovative way, by testing the effects of hedging oil and gas prices simultaneously and by using an instrumental variable framework to attenuate the problem of endogeneity between firm value and risk management. We find evidence of higher market value, higher performance, and lower riskiness for firms with a high propensity to jointly hedge their oil and gas production to a greater extent. We show that joint hedging dominates single-commodity hedging.

Keywords: Joint hedging, enterprise risk management, oil price, gas price, hedging intensity, bivariate probit, causality, firm value.

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Introduction

In the presence of friction in financial markets, risk management theory suggests that hedging may have a positive impact on non-financial firms by reducing cash flow and earnings volatility. Indeed, corporate managers often opt to hedge against different market- and industry-specific factors in the hopes of limiting the cost of risk and, hopefully, obtaining higher firm valuations.

Evidence in the corporate risk management literature suggests that the marginal benefits of hedging the firms' exposures exceeds the marginal costs associated with it. Indeed, a study led by Bartram et al. (2009), spanning 48 countries and including over 7,000 non-financial firms, demonstrates that 54.3% of companies use derivatives to hedge against risks ranging from foreign currency exposure to interest rate uncertainty. This suggests that managers do indeed see the value of hedging.

Firms producing oil and natural gas are intrinsically hedgers because they are subject to the risk of commodity prices, which can experience large drawdowns. Oil and natural gas prices fluctuate significantly in response to factors such as geopolitical instability and supply-and-demand shocks. Sometimes, the most profitable outcome for a firm is to halt production. This real option may have significant economic costs when oil and gas producing firms exercise the option to leave the oil or natural gas in the ground when market conditions are unfavorable. To protect their performance, other firms opt to hedge their production through financial assets to face future price uncertainty. Financial hedging, however, comes at a cost, and thus, corporate risk management must balance the costs and rewards to achieve the greatest firm value.

As such, we observe that oil and gas producers choose different levels of hedging based on discretionary factors such as management risk appetite, economic outlook, forecasted future production, market imperfections, and geographical location. Discrepancies in hedging behaviors have raised important research questions in the literature: What are the determinants of undertaking hedging? How do hedging decisions affect firm value? Which risk necessitates the highest level of hedging to maximize firm value? Should the company hedge in the short or the long run? Which hedging instruments are most appropriate? (Smith and Stulz, 1985; Tufano, 1996; Graham and Smith, 1999; Graham and Rogers, 2002; Carter et al., 2006; Mnasri et al., 2017; Dionne et al., 2018).

We explore a new question by analyzing the joint hedging decision of oil and gas prices in the US oil and gas industry, with quarterly data from 1998 to 2010: Should producers hedge the price of both commodities at once? And if so, to what extent? First, we gauge the impact of firms' financial and operational characteristics, their managerial risk aversion, and the petroleum market's conditions on the hedging decisions of oil and gas producers. Second, we revisit the hedging premium issue, in an instrumental variable framework, to determine whether the decision to hedge commodity prices jointly has any causal effect on oil and gas producers. Third, we compare joint hedging to single-commodity hedging activities on firms' market value, performance, and risk. To our knowledge, the causal effect of a joint hedging decision on firm value has not yet been studied for any industry.[1]

Joint hedging may be related to enterprise risk management (ERM), but is different in nature. Joint hedging is a risk management strategy for different assets or commodities, while ERM is a framework for risk management in an enterprise. Joint hedging can be implemented in a company

[1] In short, we use 'firm value' for firm market value, performance, and risk; and 'performance' for accounting performance. We should mention that our approach is suitable for the hedging of two commodity prices and two input prices, or one commodity price and one input price.

without an ERM framework. Our test on the efficiency of joint hedging will be conducted without a control for ERM because we do not have this information. We suspect however that firms with an ERM framework would use joint hedging more often.[2]

The rest of the paper is organized as follows. The next section offers a literature review of the main results on hedging in non-financial industries. It also discusses the motivation for joint hedging. Section 2 presents the data. Section 3 develops the econometric methodology, and Section 4 discusses the estimation results obtained from the bivariate probit model. Section 5 investigates the causal analysis of the real effects of joint hedging on the firm, using an instrumental variable analysis, and shows the superiority of joint hedging on firm value. Section 6 concludes.

1. Literature review and motivation

The empirical literature on joint hedging is recent. Liu et al. (2017) analyze joint hedging in the oil industry and compare two joint hedging criteria: the second-order lower partial moment (LPM_2) approach of Fishburn (1977) to the mean variance (MV) approach. The LPM_2 approach is more related to portfolio downside risk than the symmetric MV approach. They find that LPM_2 is more effective than MV. They do not compare joint hedging to single-commodity hedging. Power and Vedenov (2010) analyze joint hedging in the cattlemen hedging environment and find that hedging ratios are lower under the LPM_2 approach. Fei et al. (2021) is the only contribution that compares single hedging to joint hedging. It compares the relative hedging effectiveness of joint hedging to single-commodity hedging, and shows that joint hedging always dominates single-commodity

[2] On the efficiency of ERM, see Kleffner et al. (2003), Liebenberg and Hoyt (2003), Hoyt and Liebenberg (2011), Eckles et al. (2014), Grace et al. (2014), and the survey of Gatzert and Martin (2015).

hedging with the LPM_2 measure of risk. The paper does not analyze the effect of joint hedging on firm value.

In this research we are more concerned with the corporate literature on risk management, in which, to our knowledge, the effectiveness of joint hedging has not been studied. To compare the hedging of two commodity prices separately with the simultaneous hedging of two prices, we estimate multivariate econometric models under different hedging scenarios and compare the effect of the predicted hedge ratios on firm market value, performance, and risk. To reduce potential reverse causality between hedging and the different measures of firm value, we estimate the hedging equations with instrumental variables. In this manner, we contribute to the literature on corporate hedging decisions by considering risk management with the hedging of two commodity risks simultaneously.

It is worth mentioning that the preceding theoretical and empirical research on corporate risk management has largely been built on a single-risk exposure environment. However, many non-financial firms have multi-risk exposure due to the nature of their operational activities. For example, natural resource companies producing multiple commodities are exposed to multiple risks with interconnected market conditions requiring interlinked single-risk hedging strategies with mutual effects. Ignoring the connectedness between hedging decisions in a multi-risk environment, coupled with the endogeneity problem, might have led to contradictory and inconclusive results in the prior research as regards the motivations and real effects of corporate risk management, particularly for some production industries such as the petroleum industry and the gold mining industry. This necessitates the use of a multidimensional framework to better assess the joint hedging decisions of firms' managers. Froot et al. (1993) show how taking into account the dependence between risks affects the optimal hedging decision of internal investment financing. However, they do not analyze the effect of joint hedging on firm value.

In our study, to gain a better understanding of the interactions in the joint decision-making process about hedging intensities for oil and gas, we need to look at the mechanisms that connect these commodities. Oil production ramps up with increased oil prices: since these firms have a real option on the extraction of oil and gas, it allows them to react to macroeconomic price trends by adjusting their production. As a result of increased oil production, gas production can also increase—in this case because the two resources are extracted from the same source in the ground. Thus, as oil production increases, naturally, the amount of gas extracted and produced may also increase as a by-product. To cement this relationship, we also explore the cointegration of oil and gas prices, which has been discussed at length in the literature. In a study focusing on the switching relationship between oil and gas prices, Brigida (2014) underscores the idea of price cointegration between oil and natural gas. We can synthesize both mechanisms as follows: a higher demand for oil, which results in higher oil prices, also increases the production of natural gas due to the associated gas production effect. Then, due to the cointegration of both prices, oil being higher on a long-time horizon means that gas prices also move upward, in tandem. Therefore, these mechanisms help explain why the hedging intensity for gas production decreases with an increased aggregate demand of oil. As oil prices soar, it drives oil production, which also increases gas production. Then, the increase in gas price levels due to the cointegration between oil and gas prices decreases the intensity of hedging for gas production (Independent Statistics & Analysis, 2020). All these facts motivate the analysis of the joint decision to hedge both prices simultaneously.

1.1 Rationales for hedging

1.1.1 Underinvestment and overinvestment

Reducing the cost of underinvestment is often touted as one of the main reasons for enhancing a firm's hedging value. Underinvestment originates from the principal-agent problem between stockholders and debtholders. Gay and Nam (1998) study the problem of underinvestment with a sample of 325 non-financial firms. They find results that support the theory of underinvestment costs being an important determinant for hedging. They obtain that firms with good investment opportunities tend to use derivatives more when they incidentally have low levels of liquidity. Also, their study supports the claim that a natural hedge is created for firms that experience a high correlation between internally generated funds and investment expenses.

Underinvestment costs are also highlighted in Froot et al. (1993) and Bessembinder (1991): due to financial market frictions, firms with more growth opportunities need to do more hedging to protect them from more costly external financing, explained by asymmetric information between lenders and borrowers. Through increased hedging, the firms protect their internal financing, and underinvestment decreases.

Morellec and Smith (2007) provide further insight into the principal-agent problem by incorporating manager-stockholder conflicts to study hedging rationales. Their conclusion shows that firms with a lower market-to-book ratio face higher overinvestment and tend to hedge more to control this specific cost. These findings provide a further rationale for Bartram et al. (2009), whose research demonstrates that large firms (with an international scope), which are characterized by lower growth opportunities (lower market-to-book value), tend to hedge more to reduce the cost of overinvestment.

1.1.2 Distress costs and leverage

The first study on how hedging affects distress costs is Mayers and Smith (1982), who find evidence that, in the presence of costly financial distress, lowering the volatility of cash flows and lowering the associated probability of default through risk management have positive effects on the firm.

Hedging, financing, and investing decisions are tightly intertwined. Lin and Smith (2007) investigate this relationship and determine that, in the presence of costly financial distress, a more efficient firm is less likely to hedge. On the other hand, the more it invests in riskier investments, the more it tends to hedge. [3]

Other studies have delivered evidence suggesting that firms with more debt load tend to use derivatives to a larger extent. For instance, the study by Berkman et al. (1997) focuses on corporate derivative use by New Zealand corporations, and finds that hedging increases as leverage does. Other studies corroborate this finding, such as Dolde (1995), Graham and Rogers (2002), and Haushalter (2000). In a simultaneous equations model, Dionne and Triki (2013) obtain that leverage increases the hedge ratio. But the contrary is not true. Firms in the gold mining industry do not increase their leverage with more hedging.

1.1.3 Taxes

In the presence of a convex tax function, a firm can benefit from cost-effective hedging. Smith and Stulz (1985) study this relationship and verify that a firm facing an increased convexity of the tax function will have incentive to increase hedging. This is explained by the fact that hedging reduces

[3] See also Mo et al. (2021).

the volatility of taxable income, which has the effect of reducing the expected value of tax. This theory has been further tested empirically by Graham and Smith (1999). They demonstrate that firms facing a convex tax function experience a 5.4% reduction in the volatility of expected tax liabilities following a hedge that reduces the variability of the firm's taxable income by 5%. Dionne and Triki (2013) obtain a similar result in the gold mining industry.

1.1.4 Firm size and focus

Firm size and focus are also important determinants to consider when looking at hedging. Wei et al. (2017) study this relationship by looking at the sustainability and economic viability of hedging in the real estate investment trust (REIT) industry. The authors find that firms with a higher concentration of a given property type tend to hedge more than do the firms that are diversified in terms of property type and size. They find a weaker relationship with geographical diversification, however, suggesting that geographical risk is less of a concern for REITs. This effect is more pronounced for smaller firms than larger firms, which implies a non-linearity in hedging and firm size. They also find that smaller firms tend to have higher hedge ratios than do larger firms. The opposing viewpoint is put forth by Gézcy et al. (1997), who find evidence of a positive relationship between firm size and derivative.

1.2 Real implications of hedging

Mackay and Moeller (2006) contribute to the literature by deriving a model to estimate how valuable corporate risk management is for firms that choose to hedge. As such, they take a keen interest in the oil industry, assembling a sample of 34 oil refiners and regressing firm revenues and costs with input and output prices. The motivation behind this method was to demonstrate that hedging in the presence of nonlinear revenues and costs relative to prices can create value for the firm. By accepting the tradeoff of incurring convex costs to hedge concave revenues for oil and gas firms, Mackay, and Moeller (2006) obtain an increase in firm market value of 4% using the Tobin's Q measure.

Jin and Jorion (2006) also attempt to shed light on the question by looking at 119 oil and gas producers in the US over a three-year period (1998–2001). The first step in their analysis consists of testing the stock price and commodity price sensitivities with respect to hedging intensity. Their results show a negative relationship between a firm's hedging and the market beta. Then, using the Tobin's Q measure, they find no evidence of any value effect of hedging in the oil and gas industry.

Other studies also corroborate the weak link between hedging and firm-value maximization: Hentschel and Khothari (2001), with a large sample involving 425 US firms, conclude that companies using derivatives to hedge (and even those with large derivatives positions) experience little economically significant value-enhancing effects in the form of reduced stock volatility, as compared to non-users, thus incurring hedging costs for no discernible benefits.

Allayanis and Weston (2001) obtain a positive hedging premium of 4.87% on the Tobin's Q. They also address an alternative question for a higher Tobin's Q being associated with hedging firms: firms that already have a large Tobin's Q may be more inclined to hedge because they inherently invest in higher-growth, riskier investment ventures. By controlling for this effect, they reject this alternative explanation through a time-series analysis of a changing hedging policy, and thus conclude that firms with a higher Tobin's Q do not hedge more than those with a lower one. In a study analyzing Swedish companies, Prambourg (2004) arrives at a similar conclusion on hedging currency risk. A hedging premium has also been detected in other industries. Carter, Rogers, and

Simkins (2003), in their study focusing on the airline industry, corroborate Allayanis and Weston's (2001) findings that hedging has a significantly positive impact on firm value.

Dionne and Mnasri (2018) reconsider the effect of hedging on firm value by applying the marginal treatment effect methodology (MTE) of Carneiro et al. (2009) and Heckman et al. (2006), to better identify the firms with a greater causal effect. Using a sample of US firms in the oil industry, Dionne and Mnasri (2018) find evidence of a higher marginal market value for firms with a higher hedging propensity score. They also find evidence of a higher marginal risk reduction premium and a higher marginal accounting value for the same firms. These oil producers with higher propensity scores to hedge also have significant average treatment effects for firm financial value, idiosyncratic risk, and systematic risk. Finally, Mnasri et al. (2017) verify that non-linear hedging derivatives, such as options, are more efficient to reduce risk and increase firm value, while Dionne et al. (2018) show that short-run hedging dominates long-run hedging.

2. Data and dependent variables: Construction and statistics

2.1 Data construction

The starting sample consists of quarterly data for 150 oil and gas producing firms between 1998 and 2010, amounting to a large panel of 6,326 firm-quarter observations. The 150 firms were filtered with the following criteria: they needed to have a minimum of 5 years of oil and gas reserve data, have 10-K and 10-Q filings available on the EDGAR database, and have data available on Compustat and Bloomberg to provide more information on different variables. Quarterly data about oil-and-gas hedging activities are hand-collected from 10-K and 10-Q reports. More details on the construction of this data are available in Mnasri et al. (2017) and Dionne et al. (2018).

2.2 Data description

Table 1 summarizes the descriptive statistics of our starting pooled dataset of 6,326 firm-quarter observations. Earnings per share (EPS) from operations for the 150 firms average at $8.18, with a median of $0.09. This indicates an asymmetric earnings distribution, with a notably positive skewness. Use of leverage is prevalent in our firms of interest, with an average leverage ratio of 52%. Another interesting observation is the high level of liquidity that these firms have on hand, which translates to a high ability to honor their short-term liabilities, as evidenced by a quick ratio of 1.56, compared to an average quick ratio of 0.3 in 2019 for the oil and gas industry (CSI Market, 2019). More than a quarter of the firms sampled pay a dividend to their shareholders.

Table 1 – Descriptive statistics of the 150 firms' financial and operational characteristics

Variable	Obs	Mean	Median	1st quartile	3rd quartile	STD
EPS from operations	6,127	8.18	0.09	-0.03	0.49	284.69
Investment opportunities	6,295	0.13	0.06	0.04	0.11	2.33
Leverage ratio	6,044	0.52	0.52	0.34	0.66	0.29
Liquidity	6,069	1.56	0.28	0.08	0.85	5.33
Dividend payout	6,326	0.27	0.00	0.00	1.00	0.44
Oil reserves	6,326	276.71	8.01	0.95	53.35	1,277.73
Institutional ownership	6,326	0.34	0.22	0.00	0.69	0.35
Geographical diversification of oil production	6,326	0.12	0.00	0.00	0.00	0.27
Geographical diversification of gas production	6,326	0.08	0.00	0.00	0.00	0.23
Oil production risk	6,246	0.27	0.17	.08	0.34	0.30
Gas reserves	6,326	1,504.19	99.46	13.71	571.70	5,888.22
Gas production risk	6,222	0.27	0.18	.09	0.36	0.28
CEO ownership	6,028	0.04	0.00	0.00	0.00	0.02
Number of CEO options	6,326	174,386	0.00	0.00	120,000	681,759
Number of analysts	6,326	5.11	2.00	0.00	8.00	6.914
Price_Quantity correlation (oil)	6,228	0.114	0.199	-0.43	0.683	0.599
Price_Quantity correlation (gas)	6,216	0.075	0.056	-0.37	0.555	0.525

This table displays the summary statistics for the 150 firms sampled in the study. We can find the number of observations, the mean, the median, the lower quartile, the upper quartile, and the standard deviation of all relevant variables describing the sample. See Table A1 for further details on the construction of the variables.

This data also highlights important details about oil and gas production and reserves. For instance, oil reserves (including developed and undeveloped) amount to 277 million barrels per firm, while gas reserves amount to 1,504 billion cubic feet per firm. We notice a moderately low concentration of oil and gas activities and geographical diversification (on average), with Herfindahl indices of 0.12 and 0.08 for oil and for gas, respectively. However, the standard deviations of 0.27 and 0.23 indicate a high dispersion in the data in terms of industry concentration.

Finally, it is important to control for the sampled firms' manager characteristics to understand hedging behavior and extent. On average, managers hold 4% of the firms' stocks, and their stock option holdings equate to more than 174,000 units. These variables rely on making a distinction between highly risk-averse managers who hedge their production to a large extent, as opposed to weakly risk-averse managers with low oil and gas production hedging.

2.3 Hedging activities

Table 2 breaks down the sample of 6,326 firm-quarters into observations with and without gas hedging and/or oil hedging. Oil and gas producers report hedging activities for 3,489 firm-quarters, accounting for almost 55% of the whole dataset. Of these 3,489 firm-quarters, 2,255 report hedging activities for both oil and gas simultaneously: almost 64.63% of the hedging subsample. Firm-quarters with only gas hedging account for 25.27% of the hedging subsample, with 882 observations. Finally, there are 352 firm-quarters with only oil hedging, or 10% of the hedging subsample. Remarkably, this breakdown of the hedging decisions reveals that petroleum companies tend to hedge oil and gas commodities simultaneously. In what follows, we analyze in depth the hedging behavior of petroleum companies and particularly the joint decision about the hedging intensities for both commodities.

Table 2 – Distribution of the hedging decisions by number of firm-quarters

	Hedging activity: Firm-quarters		
	Oil hedgers	Non-oil hedgers	Total
Gas hedgers	2,255	882	3,137
Non-gas hedgers	352	2,837	3,189
Total	2,607	3,719	6,326

This table breaks down the total sample of 6,326 firm-quarters into observations with and without oil hedging and with and without gas hedging.

Next, we construct production-based hedging ratios by instrument[4] and by horizon for both oil and gas separately. Following Haushalter (2000), the oil (gas) hedging ratio for each fiscal year is calculated by dividing the hedged notional quantities by the predicted oil (gas) production quantities. We collect data relative to hedged notional quantities for each fiscal year from the current year to five years ahead. Oil (gas) production quantities are predicted for each fiscal year based on the daily oil (gas) production realized in the current fiscal year. Subsequently, we calculate aggregated hedging ratios by horizon for oil and gas separately.

Table 3 and Table 4 report descriptive statistics for these hedging ratios by horizon for oil and for gas, respectively. Overall, these two tables indicate an average hedging ratio for the current fiscal year (i.e., HR0) of around 46% (51%) for oil (gas) expecting production. Hedging ratios for subsequent fiscal years are decreasing steadily across horizons in terms of extent and frequency.

[4] Table OA.1 in the Online appendix reports a breakdown of the different type of derivative instruments used by oil and gas hedgers in our sample.

Table 3 – Summary statistics for oil hedging ratios by horizon

Hedge ratio	Obs	Mean	Median	1st quartile	3rd quartile	STD
HR0	2,587	46.070	44.564	24.315	63.889	27.876
HR1	1,723	38.328	36.043	16.437	54.737	27.338
HR2	907	30.848	26.798	9.526	46.392	25.680
HR3	431	27.352	19.946	7.340	43.654	25.777
HR4	185	23.254	14.686	7.215	33.860	24.589
HR5	61	21.887	19.685	4.563	38.933	18.171

This table reports summary statistics for oil hedging ratios (HR) by horizon (from the current fiscal year, HR0, to five fiscal years ahead, HR5).

Table 4 – Summary statistics for gas hedging ratios by horizon

Hedge ratio	Obs	Mean	Median	1st quartile	3rd quartile	STD
HR0	3,108	50.874	48.955	27.557	70.809	29.963
HR1	2,295	37.617	30.912	14.441	54.947	29.416
HR2	1,225	27.467	19.402	5.983	41.129	28.059
HR3	548	22.101	11.581	4.021	31.144	27.150
HR4	266	17.975	7.590	2.611	17.804	27.099
HR5	127	18.648	5.916	3.280	21.753	26.030

This table reports summary statistics for gas hedging ratios (HR) by horizon (from the current fiscal year, HR0, to five fiscal years ahead, HR5).

2.4 Dependent variables

Based on the hedging ratio for the current fiscal year, i.e., HR0, we construct binary variables to distinguish between firms that hedge to a greater or lesser extent. So, we assign a value of 0 for firms that rank below the 25th percentile in terms of the extent of their hedging for the current fiscal year (HR0) for oil and gas, respectively (low-hedging firms). Similarly, we assign a value of 1 to firms that rank above the 75th percentile of the sample in terms of hedging for oil and gas, respectively (high-hedging firms). These percentiles are chosen because they are wide and categorical enough to allow us to quantifiably distinguish between firms that hedge their oil or gas production to either a small or large extent. This helps us emphasize their defining characteristics. Also, by focusing on these two tranches, we reduce noise by filtering out firms that do not have a definitive stance (low or high) on hedging. These binary variables are used subsequently in a bivariate probit methodology with instrumental variables.

We excluded firms that do not have any hedging activity to retain consistency when assigning the low-hedging label to firms; this implies some level of positive hedging. Firms at zero hedging are very different from those at a small level of hedging. This discontinuity with a mass point at zero is still an open research question in the literature.

2.5 Univariate results

Table 5 reports tests for differences between the means and medians of the relevant firms' financial and operational characteristics by oil hedging intensity, as constructed previously, namely, the dummy variable measuring high and low oil-hedging intensity. Table 6 reports the same tests by gas hedging intensity. The means are compared by using a *t*-test assuming unequal variances; the medians are compared by using a non-parametric Wilcoxon rank-sum Z-test.

The univariate analysis reveals considerable differences in firms' characteristics in terms of their hedging intensities. Table 5 and 6 show that oil and gas producers with high-intensity hedging appear to have higher investment opportunities and higher financial constraints, that is to say, they have lower operational performance, higher financial leverage, and lower cash reserves, and they pay less dividends. These findings corroborate the conjecture that a financially constrained firm with high investment opportunities hedges more to avoid the underinvestment problem, as postulated by Mayers and Smith (1982) and Froot et al. (1993). Univariate results also show that oil and gas producers that hedge to a greater extent are less diversified geographically, and have lower oil and gas reserves and higher production uncertainty. Moreover, price-quantity correlation appears to be positively related to high-intensity hedging. These findings suggest that petroleum companies tend to hedge more when they have lower operational flexibility, proxied by geographical diversification; higher additional unhedgeable risk, as measured by production uncertainty; and revenue volatility, because quantities and prices are moving in the same direction.

Relating to managerial stockholding, results are inconclusive. In fact, the mean and median comparison are not consistent across intensities of oil and gas hedging. Even though results show that managerial stockholding is, on average, higher for oil producers using high-intensity oil hedging, as suggested by Smith and Stulz (1985) and Tufano (1996), the opposite appears to be the case for gas hedging intensities. The median comparison indicates that managerial option holding is greater for low-intensity hedgers, for both oil and gas, suggesting that risk-averse managers with higher option holdings will prefer less hedging, to increase the volatility of the firm's revenues due to the convexity of the options' payoff. This finding is in line with the conjecture made by Smith and Stulz (1985) and Tufano (1996), depending on the moneyness of the option contracts. Univariate tests also show that institutional ownership and the number of analysts are lower for users of higher hedge intensities, for oil and gas, indicating that petroleum firms tend to hedge more to lessen problems related to weak governance and information asymmetry. Finally, results indicate that petroleum firms are induced to hedge more when oil and gas price volatility is higher.

Table 5 – Firm's financial and operational characteristics by oil hedging intensity

	(1)			(2)			(1) vs (2)
	High intensity			Low intensity			
Variable	Obs	Mean	Median	Obs	Mean	Median	*t*-Stat Z-score
EPS from operations	632	0.254	0.180	646	0.421	0.365	1.894* 5.752***
Investment opportunities	635	0.099	0.062	647	0.079	0.059	-2.264** -0.430
Leverage	633	0.654	0.621	647	0.547	0.531	-8.593*** -10.338***
Liquidity	637	0.334	0.104	647	0.485	0.213	2.296** 8.021***
Dividend payout	647	0.279	0.000	647	0.518	1.000	9.006*** 8.740***
Oil reserves (in log)	647	3.488	3.457	647	4.106	4.287	6.198*** 5.405***
Institutional ownership	647	0.475	0.517	647	0.578	0.723	5.717*** 5.195***
Geographic diversification (oil)	647	0.048	0.000	647	0.225	0.000	13.770*** 12.409***
Oil production risk	647	0.259	0.167	647	0.197	0.138	-4.691*** -3.695***
Price_quantity correlation (oil)	647	0.177	0.282	647	0.097	0.165	-2.4563** -1.970**
Oil price volatility	646	4.031	2.808	647	3.554	2.674	-2.676*** -3.467***
Oil price basis	646	-0.007	0.008	647	-0.006	0.008	0.4532 0.632
CEO % of stockholding	632	0.007	0.000	645	0.003	0.001	-2.282** 2.825***
CEO number of options (×10000)	647	29.909	0.000	647	20.524	6.000	-1.553 4.188***
Number of analysts	647	6.599	4.000	647	10.629	9.000	9.298*** 9.089***

This table reports the univariate analysis for the firm's financial and operational characteristics, and the condition of the oil market, by oil hedging intensity, i.e., high versus low intensity. See Table A1 for further details on the construction of the independent variables. The means (mean low – mean high) are compared by using a *t*-test assuming unequal variances; the medians (median low – median high) are compared by using a non-parametric Wilcoxon rank-sum Z-test.

Table 6 – Firm's financial and operational characteristics by gas hedging intensity

	(1)			(2)			(1) vs (2)
	High intensity			Low intensity			
Variables	Obs	Mean	Median	Obs	Mean	Median	*t*-Stat Z-score
EPS from operations	760	0.063	0.140	776	0.270	0.350	1.299 8.442***
Investment opportunities	775	0.106	0.062	777	0.088	0.059	-1.381 0.001
Leverage	764	0.607	0.583	773	0.596	0.554	-0.906 -2.362**
Liquidity	769	0.353	0.109	776	0.414	0.176	1.597 5.527***
Dividend payout	777	0.295	0.000	777	0.480	0.000	7.633*** 7.496***
Gas reserves (in log)	777	5.693	5.812	774	6.339	6.179	7.334*** 12.746***
Institutional ownership	777	0.420	0.369	777	0.548	0.674	7.509*** 6.969***
Geographic diversification (gas)	777	0.013	0.000	777	0.110	0.000	12.827*** 9.787***
Gas production risk	777	0.263	0.183	777	0.200	0.141	-5.395*** -4.856***
Price_quantity correlation (gas)	777	0.108	0.069	777	0.084	0.108	-0.943 2.362**
Gas price volatility	776	0.806	0.543	777	0.715	0.468	-3.216*** -11.223***
Gas price basis	776	0.154	0.125	777	0.112	0.094	-4.602*** -6.343***
CEO % of stockholding	759	0.003	0.000	774	0.005	0.000	3.825*** 4.785***
CEO number of options (×10000)	777	15.264	0.000	777	26.721	4.373	3.166*** 5.327***
Number of analysts	777	6.651	4.000	777	9.651	8.000	7.829*** 8.060***

This table reports the univariate analysis for the firm's financial and operational characteristics, and the condition of the gas market, by gas hedging intensity: high versus low intensity. See Table A1 for further details on the construction of the independent variables. The means (mean low – mean high) are compared by using a *t*-test assuming unequal variances; the medians (median low – median high) are compared by using a non-parametric Wilcoxon rank-sum Z-test.

3. Joint decision-making about hedging intensity for oil and gas production

In this section, we focus our analysis on the joint decision about hedging intensities for oil and gas commodities. We retain a final subsample of 614 firm-quarter observations with a high or low simultaneous hedging intensity for oil and gas. Table 7 gives a breakdown of these hedging intensities and shows that oil and gas producers hedge both commodities to the same extent. In fact, a joint high-hedging intensity for both commodities occurs in almost 41% of the firm-quarters and the joint low-hedging intensity is seen in 42% of the observations; different hedging intensities arise in almost 175 of cases. Table 8 reports tests of differences between the means and medians of the final subsample for the regression analysis: 251 observations for high (1,1) and 258 observations for low (0,0), with few exceptions. The results are similar to those in Table 5 and Table 6, confirming the representativeness of the studied sample.

Table 7 – Hedging intensity breakdown

	Oil hedging intensity		
Gas hedging intensity	High	Low	Total
High	251	54	305
Low	51	258	309
Total	302	312	614

This table breaks down the total subsample of 614 firm-quarters into observations with simultaneous high- or low-hedging intensity for oil and gas. High and low intensity are defined based on the extent of hedging for the current fiscal year HR0. High intensity is above the 75th percentile of HR0 and low intensity is below the 25th percentile of HR0.

Table 8 – Financial and operational characteristics of firms with joint high- and low-hedging intensity

	(1)			(2)			(1) vs (2)
	High intensity			Low intensity			
Variables	Obs	Mean	Median	Obs	Mean	Median	*t*-Stat Z-score
EPS from operations	240	0.230	0.110	258	0.598	0.615	2.153** 6.549***
Investment opportunities	251	0.100	0.059	258	0.082	0.056	-0.973 -0.036
Leverage	244	0.636	0.603	258	0.564	0.533	-4.040*** -4.874***
Liquidity	247	0.218	0.087	258	0.477	0.223	4.563*** 6.494***
Dividend payout	251	0.382	0.000	258	0.628	1.000	5.700*** 5.532***
Institutional ownership	251	0.440	0.413	258	0.610	0.756	6.144*** 5.792***

CEO % of stockholding	242	0.002	0.000	256	0.003	0.000	2.128** 2.451**
CEO number of options (×10000)	251	18.261	0.000	258	24.926	4.000	0.777 2.422**
Number of analysts	251	6.984	4.000	258	13.407	13.000	8.763*** 8.265***
Oil reserves (in log)	251	3.300	3.346	258	4.752	4.908	9.325*** 8.701***
Gas reserves (in log)	251	5.923	5.828	258	6.989	7.509	7.376*** 6.743***
Geographic diversification (oil)	251	0.059	0.000	258	0.284	0.235	10.823*** 9.466***
Geographic diversification (gas)	251	0.019	0.000	258	0.179	0.000	10.329*** 9.508***
Oil production risk	251	0.298	0.199	258	0.184	0.130	-4.979*** -4.542***
Gas production risk	251	0.308	0.209	258	0.172	0.116	-6.381*** -6.770***
Price_quantity correlation (oil)	251	0.182	0.276	258	0.256	0.407	1.522 2.176**
Price_quantity correlation (gas)	251	0.164	0.192	258	0.069	0.057	-2.089** -1.844*
Oil price volatility	250	4.885	3.471	258	3.093	2.445	-6.266*** -6.601***
Gas price volatility	250	0.884	0.810	258	0.722	0.500	-3.267** -3.868***
Oil price basis	250	0.000	0.009	258	-0.016	-0.011	-2.669*** -2.064**
Gas price basis	250	0.136	0.094	258	0.125	0.094	-0.714 -0.219

This table reports the univariate analysis for the firm's financial and operational characteristics with joint high- and low-hedging intensity. See Table A1 for further details on the construction of the independent variables. The means (mean low – mean high) are compared by using a *t*-test assuming unequal variances; the medians (median low – median high) are compared by using a non-parametric Wilcoxon rank-sum Z-test.

3.1 Bivariate probit model

Firms producing both oil and natural gas are faced with the added challenge of needing to consider their hedging strategy for two commodities simultaneously. Indeed, firms only have limited resources to hedge their production of oil and gas, and thus, must consider several factors before choosing to hedge. Some of these include the risk factors producers face.

By analyzing the hedging of both oil and gas simultaneously, we will gain a better understanding of the determinants for this hedging allocation. Thus, we will take the analysis further by studying this unique feature of oil and gas companies (as opposed to a single commodity). We will be using the bivariate probit model, which is a joint model for two binary outcomes that generalizes the index function model, from one latent variable to two latent variables, which may be correlated (Cameron and Trivedi, 2005).

Before we delve into the results of our analysis, we succinctly present this estimation method. A bivariate probit uses the same basic tenets in its construction as a univariate probit, but the difference, as the name implies, is that, in the regression model, we have two dependent variables (Y_1 and Y_2), which are simultaneously and jointly a function of the regressors.

Thus, due to the binary nature of the dependent variables, and the joint regression function, we have 4 different outcomes to analyze:

- Firms that hedge at a low intensity for both oil (Y_1) and gas (Y_2):

  ($Y_1 = 0$ and $Y_2 = 0$);

- Firms that hedge at a high intensity for both oil and gas:

  ($Y_1 = 1$ and $Y_2 = 1$);

- Firms that hedge at a high intensity for oil but a low intensity for gas:

  ($Y_1 = 1$ and $Y_2 = 0$);

- Firms that hedge at a low intensity for oil but a high intensity for gas:

  ($Y_1 = 0$ and $Y_2 = 1$).

The bivariate probit regression is the appropriate method in this instance because it will allow us to model the effects of the explanatory variables on the decision to hedge both oil and gas production, jointly and concurrently. Also, this model will help address any potential endogeneity between the decisions to hedge oil and gas, by accounting for correlations and relationships of unobserved terms and residuals.

For the unobserved latent variables Y_1^* and Y_2^* we specify the following equations:

$$Y_1^* = X_1^{'}\beta_1 + \varepsilon_1$$
$$Y_2^* = X_2^{'}\beta_2 + \varepsilon_2 \tag{1}$$

where X_1 and X_2 are vectors of explanatory variables.

The random disturbances ε_1 and ε_2 are jointly normal with mean zero, variance one, and correlation denoted as ρ:

$$\left\{\begin{matrix}\varepsilon_1\\ \varepsilon_2\end{matrix}\middle| X_1, X_2\right\} \sim N\begin{bmatrix}0\\0\end{bmatrix}\begin{pmatrix}1 & \rho\\ \rho & 1\end{pmatrix}. \tag{2}$$

Thus, our observed dichotomous variables, denoted as Y_1 and Y_2, are specified using the latent variables as follows:

$$Y_1 = \begin{cases}1 \; for \; Y_1^* > 0\\ 0 \; otherwise\end{cases}$$

$$Y_2 = \begin{cases}1 \; for \; Y_2^* > 0\\ 0 \; otherwise.\end{cases}, \tag{3}$$

Finally, the probabilities for the different possible outcomes could be summarized for i, j = 0 or 1:

$$P(y_1 = i, y_2 = j) = \Phi\left(X_1^{'}\beta_1, X_2^{'}\beta_2, \rho\right) \tag{4}$$

where Φ is the joint normal distribution.

To estimate the bivariate probit coefficients, the maximum-likelihood estimation method is applied to obtain the model parameters. Using the latent variables described earlier and our postulated equations, we can write the likelihood function as

$$L = \Pi \begin{Bmatrix} P\left(\varepsilon_1 > -X_1'\beta_1, \varepsilon_2 > -X_2'\beta_2\right) + P\left(\varepsilon_1 < -X_1'\beta_1, \varepsilon_2 > -X_2'\beta_2\right) \\ +P\left(\varepsilon_1 > -X_1'\beta_1, \varepsilon_2 < -X_2'\beta_2\right) + P\left(\varepsilon_1 < -X_1'\beta_1, \varepsilon_2 < -X_2'\beta_2\right) \end{Bmatrix}. \quad (5)$$

We then maximize the log likelihood function to find the estimators for our bivariate probit regression coefficients.[5]

$$\ln L = \sum \begin{Bmatrix} ln\ \Phi\left(X_1'\beta_1, X_2'\beta_2, \rho\right) + ln\ \Phi\left(-X_1'\beta_1, X_2'\beta_2, -\rho\right) \\ +ln\ \Phi\left(X_1'\beta_1, -X_2'\beta_2, -\rho\right) + ln\ \Phi\left(-X_1'\beta_1, -X_2'\beta_2, \rho\right) \end{Bmatrix}. \quad (6)$$

3.2 Instrumental variable

Measuring global real economic activity has a crucial role in determining the aggregate demand for commodities. Energy commodities (namely, oil and gas) are even closely tied to the aggregate economic demand, due to the increasing globalization of commerce and the need to ship goods around the world. Kilian (2009) proposes the Kilian index as a non-lagging index of real economic activity, which approximates the average shipping costs.

The freight and shipping industry is strongly dictated by the supply of and demand for commodities. Indeed, if aggregate demand experiences a surge, we can expect that shipping services will also experience a surge (and vice versa). Supply-and-demand pressures will also push shipping prices upward or downward. However, with advances in shipping technology and capacity, the supply line is driven outward, thereby decreasing prices. Since technology and

[5] We apply the biprobit function in Stata to estimate the bivariate model with seemingly unrelated regressions.

capacity have continued to advance in recent years, as outlined by Hamilton (2019), real prices have declined constantly. Now, taking the growth of the GDP, the increase in shipping capacity, and advances in technology as trending over time, we can analyze the residuals from a time-series regression of the real shipping costs as a proxy for the cyclicity of real economic output.

As stated earlier, the premise behind the Kilian index is simply that real economic activity drives shipping costs, which translates into temporarily higher shipping costs when the aggregate demand surges. The Kilian index starts with a nominal cost of bulk dry cargo shipping, denoted as x_t, and initialized to 1 for January 1968, that is, $x_{1968:1}$. Through December 2007, Kilian adds, on a monthly basis, the average of the monthly growth rate across a set of different freight rates, as follows:

$$x_t = x_{t-1} + \frac{\sum_{i=1}^{N} \Delta\, log(shipping\ cost_{i,t})}{N} \tag{7}$$

where $shipping\ cost_{i,t}$ is the freight rate for a particular bulk dry cargo i and month t.[6]

For the period from January 2008, Kilian (2009) used the Baltic Dry Index shipping costs to calculate the x_t value. The Baltic Dry Index (BDI) is a widely recognized benchmark for the price of moving dry materials across 20 maritime routes. With this monthly iteration, the relationship between the nominal cost of shipping, x_t, and the BDI can be summarized as follows:

$$x_t = x_{t-1} + \Delta\, log(BDI_t). \tag{8}$$

[6] Freight rates for different bulk dry cargos are issued monthly by Drewry's Shipping Insight: https://www.drewry.co.uk/home.

Kilian (2009) converts the nominal index x_t to a real index by subtracting the logarithm of the US consumer index (CPI_t) and regressing it on a time-linear trend to obtain a detrended[7] real freight rate index:

$$x_t - log(CPI_t) = \alpha + \beta t + \varepsilon_t \qquad (9)$$

The residuals from (9) constitute the Kilian index[8] of real economic activity.

For our purposes, we choose the level and the change (i.e., the first difference) in the Kilian index as our two instrumental variables. We use the level of the Kilian index to discover the long-run relationship between real economic activity and the hedging intensity for the expected oil and gas production. In contrast, the change in the Kilian index makes it possible to apprehend the effects of an instantaneous change in the real economic activity on hedging intensity, that is, the short-run relationship between hedging intensities and period-to-period fluctuations in real economic activity.[9]

During our sample period, and on a monthly basis, the Kilian index has a correlation of about 76% with both the West Texas Intermediate (WTI) oil spot price and the NYMEX near-month crude oil futures price, and around 68% with both the Henry Hub Natural Gas spot price and the NYMEX near-month natural gas futures price. Figures 1 and 2 show graphically the temporal evolution of the Kilian index and the oil and gas spot prices. Overall, the resulting high-correlation coefficients reflect the high predictive power of the Kilian index for the prevalent spot prices and near-term

[7] The time trend reflects technological advances in shipbuilding. It may also be related to long-run trends in the demand for sea transport (Kilian, 2009).

[8] Updated versions of this index are now published every month by the Federal Reserve Bank of Dallas at https://www.dallasfed.org/research/igrea. They are also available through Haver Analytics and through the FRED database at the Federal Reserve Bank of St. Louis.

[9] We calculate the correlation between the Kilian index and its changes to verify the existence of any possible multicollinearity problem. This correlation appears to be relatively low, at around 12.5%.

future prices for crude oil and natural gas. Thus, the evolution of the Kilian index gives a clear vision of the oil and gas market and hedging conditions.

Figure 1: Kilian index versus the WTI spot oil price

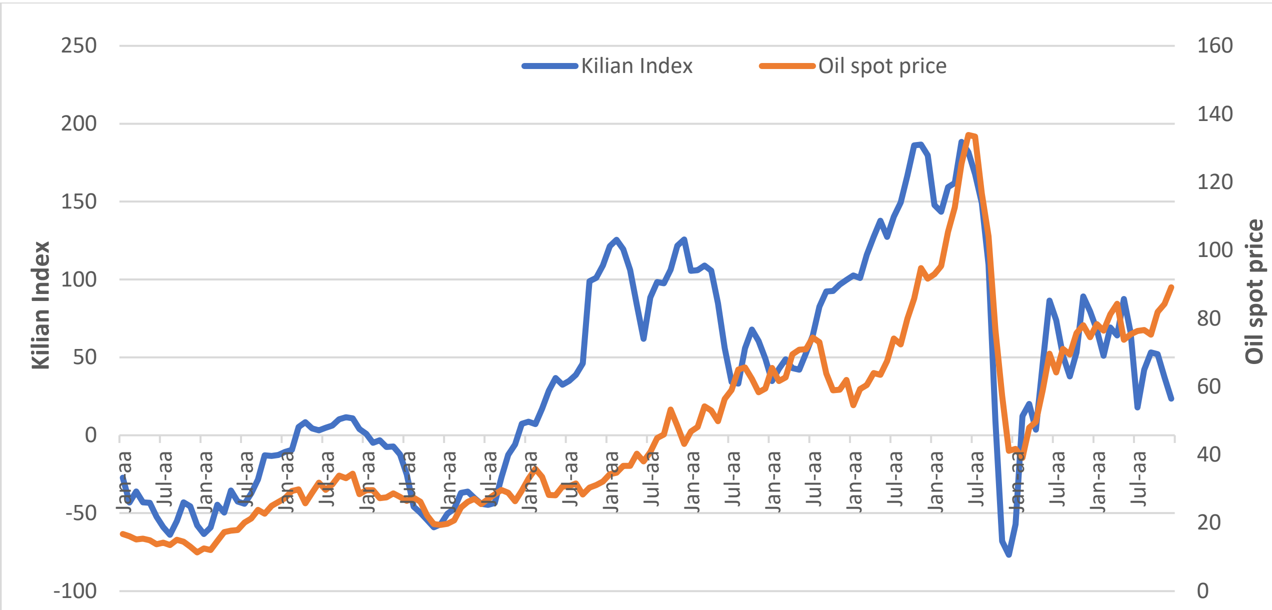
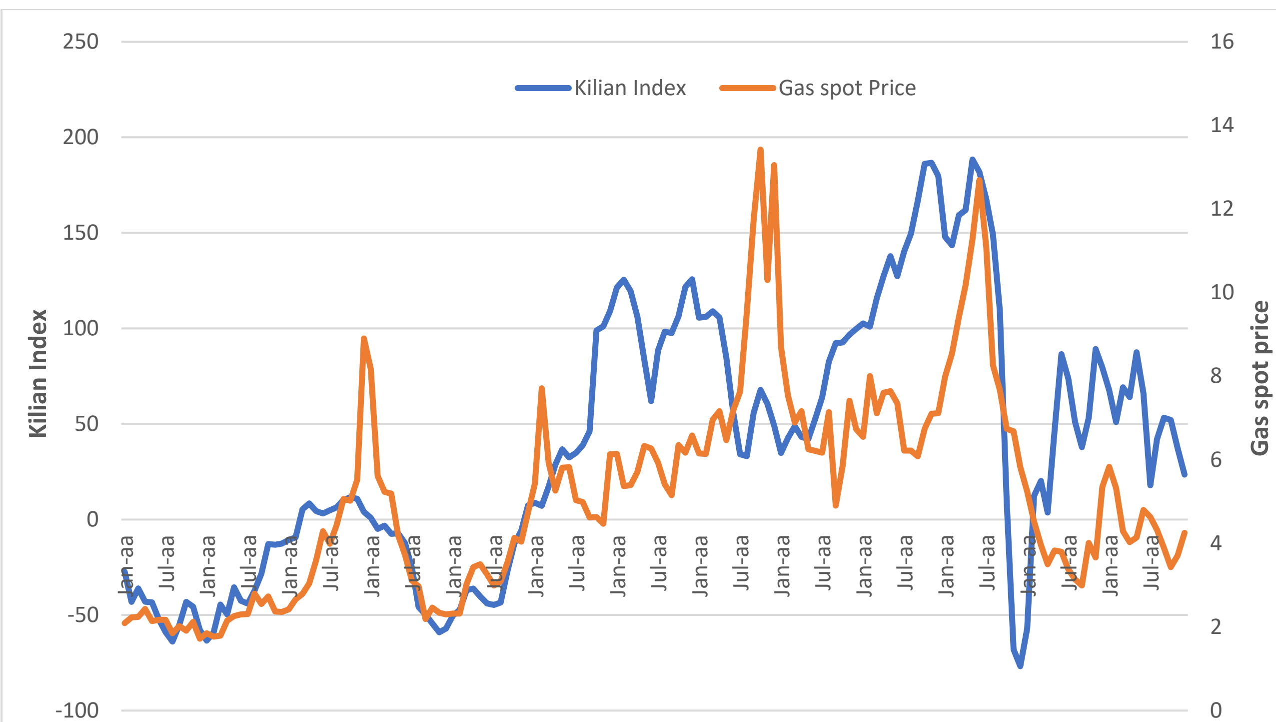


Figure 2: Kilian index versus the Henry Hub Natural Gas spot price



Our two instruments may capture the dynamic effects of market conditions on corporate hedging behavior. First, the current effect is induced by the actual (period-to-period) trend in real economic activity and reflected by the change in the Kilian index. The second effect is more related to the expected turnaround or reversal of the trend in real economic activity, knowing its current magnitude, as illustrated by the level of the Kilian index. For example, we can have an actual increase from one quarter to the next but for a currently weak real economic activity, as reflected by a lower Kilian index. On the other hand, the real economic activity can decrease from one quarter to another while currently being at its highest level. These two dynamic effects could be concomitant or opposite, depending on how the firm's manager perceives them.

How the manager perceives and reacts to the current and expected market conditions, proxied by our two instruments, is sometimes referred to as selective hedging, active risk management, or manager market views, in the corporate risk management literature (Stulz, 1996). In fact, managers alter the timing and size of their derivative positions based on their market views. Alternatively, the period-to-period fluctuations in real economic activity, as proxied by the changes in the Kilian index, influence managers' near-term market views; and the level of real economic activity, as proxied by the level of the Kilian index, will impact long-term market views.[10]

4. Bivariate probit regression results

The results of the bivariate probit in Table 9 offer significant insight into the joint decision on hedging intensity that firms make for their production of oil and gas. First, we start by analyzing

[10] Brown et al. (2006) examine the importance of managerial views by directly surveying managers about their risk management practices, and they find that managers' market views have a significant effect on hedge ratios for many firms. More importantly, the two most important factors impacting the hedge ratios are a long-term market view on gold prices and a near-term market view on gold prices.

some statistics related to the estimation of the bivariate probit model, as given in the lower part of Table 9. These statistics reveal that the correlation coefficient of the residuals, i.e, rho, from the estimation of the two equations, is about 0.79, which is indeed highly statistically significant, as indicated by the *p*-value of the Wald test, suggesting that the bivariate probit model is more appropriate than the estimation of two separate univariate probit models. Moreover, the lower panel of Table 9 gives two additional log-likelihood values: the first corresponds to running the univariate probit model for the first equation (i.e., oil hedging intensity), and the second corresponds to running the univariate probit for the second model (i.e., gas hedging intensity). The joint log-likelihood is just the sum of these two log-likelihoods of the separate probits, and is given by the comparison log likelihood in the lower panel of Table 9. The comparison between the log-likelihoods indicates that the bivariate probit model fits the data better than the separate probits.

Importantly, results concerning our two instrumental variables, namely, the level and the change in the Kilian Index, as described above, show a negative and statistically highly significant coefficient for the change in the level index for both dependent dummy variables. This result suggests that oil and gas producers tend to jointly decrease the extent of their oil and gas hedging when real economic activity is increasing from period to period. In fact, an increasing real economic activity induces a more vigorous demand for industrial commodities, and more specifically for crude oil and natural gas, and thus higher current spot prices. Consequently, oil and gas producers have less hedging needs for the nearest-term when real economic activity is increasing in the short-run from period to period.

Intriguingly, our second instrument, the level of the Kilian index, has a positive and statistically significant coefficient. This suggests that when real economic activity is at its highest levels, petroleum companies tend to hedge their expected oil and gas production to a greater extent. At first glance, this seems counterintuitive. However, with a deeper scrutiny of the temporal evolution of the long-run Kilian index and the oil and gas spot prices, we can find plausible explanations. We estimate the stochastic diffusion processes for oil and gas prices, which appear to be mean-reverting.[11] The estimation reveals a long-run mean of $43/barrel for WTI, with a daily volatility of $1.70 and an average daily mean-reversion speed of about 1.55/1000, resulting in a half-life of 445 days, i.e., the time to travel halfway from the current level to equilibrium (without accounting for daily volatility). The Henry Hub Natural Gas has a long-run mean of $4.31/MMBtu, with a daily volatility of $0.40 and an average daily mean-reversion speed of 1.53/100, giving a half-life of 45 days without accounting for daily volatility.

Consequently, the positive significant coefficient for the level of the Kilian index could be explained by firm managers' selective hedging behavior. In fact, when oil and gas spot prices are highly induced by the higher real economic activity, firm managers have a bearish long-term market view, due to the mean-reverting behavior of spot prices, and they are inclined to hedge to a greater extent. On the other hand, when oil and gas spot prices are low, due to slower real economic activity, firn managers have a bullish long-term market view and hedge to a lesser extent. Brown et al. (2006) similarly find, for the gold-mining industry, that changes in hedge ratios are positively associated with changes in gold prices, suggesting that gold producers hedge more when

[11] We estimate the following simple discrete-time model of a mean-reverting process: $X_{t+1} = X_t + \kappa(\mu - X_t) + \varepsilon_{t+1}$, where X_t is the current value of the process at time t, μ is the long-run mean of the process, κ is the adjustment coefficient, and $\varepsilon_{t+1} \backsim \mathbb{N}(0, \sigma_\varepsilon^2)$ is a random chock independent of X_t. This is just like estimating the following regression: $X_{t+1} - X_t = \kappa\mu - \kappa X_t + \varepsilon_{t+1}$. If the estimated slope coefficient $-\hat{\kappa}$ is positive, there is no mean-reversion. If $-\hat{\kappa}$ is negative, then $\hat{\kappa}$ is positive, indicating the presence of a mean-reversion process, conditional on its statistical significance. The estimation is done using daily spot prices for WTI crude oil and Henry Hub Natural Gas extracted from the US Energy Information Agency website. WTI crude oil daily prices are from January 1986 to April 2022, and Henry Hub Natural Gas daily prices are from January 1997 to April 2022. Estimations are available upon request. We repeat the same estimations during our sample period (1998–2010) and find evidence of the mean-reversion process for oil and gas spot prices. We also do the estimation using monthly observations and find similar results, however with lower statistical significance for the WTI crude oil spot price.

gold prices increase and hedge less when gold prices decrease. Brown et al. (2006) mention that such a hedging strategy (i.e., selective hedging) could earn excess returns when gold prices are mean-reverting, and they find some evidence that gold prices do mean-revert, albeit very slowly during the 1978-1998 period.

Liquidity, the next variable of interest, has a negative and significant coefficient. This result suggests that the joint hedging intensity for oil and gas production tends to increase when liquidity reserves decrease. Thus, firms with a liquidity constraint prefer to hedge more because they are more exposed to a potential risk event, elevating their expected distress costs and prompting them to intensify their hedging activities. The coefficients for the geographical diversification of oil and of gas are negative and significant at the 10% and 1% threshold, respectively. This result suggests that geographical diversification is a determining factor considered by energy firms when making the joint decision to hedge their oil and their gas production, respectively. In fact, firms' propensity to hedge decreases as their production of oil and gas is more geographically diversified. An interpretation of this tendency is that a firm's overall hedging strategy relies on how geographically diverse their production is, because this diversification reduces firms' risk, making them less sensitive to price shocks, whereas firms whose production is geographically concentrated, which is inherently riskier, tend to hedge more to reduce their risk profile. Table 9 also shows that petroleum companies with a higher gas-production risk, tend to increase the hedging intensity of their expected gas production more, probably to stabilize their generated cash flows when produced gas quantities are more volatile.

Lastly and interestingly, the number of analysts following the firm is significantly negatively related to hedging intensity. Thus, it appears that firms with lower information asymmetry, due to higher analyst coverage, have less need to pursue aggressive hedging strategies. A managerial explanation is advanced by Breeden and Viswanathan (1996) and DeMarzo and Duffie (1991), who postulate that managers are inclined to engage in risk management to better communicate their skills to the labor market.

Table 9 – Bivariate probit regression for oil and gas hedging intensity

Variable	(1) Oil hedging intensity	(2) Gas hedging intensity
Change in the Kilian index	-0.0056***	-0.0054***
	(0.001)	(0.001)
Level of the Kilian index	0.0064***	0.0053***
	(0.002)	(0.002)
EPS from operations	-0.0005	-0.0475
	(0.053)	(0.039)
Investment opportunities	0.5078	0.2293
	(0.438)	(0.275)
Leverage ratio	0.3450	-0.1447
	(0.534)	(0.535)
Liquidity ratio	-0.6744***	-0.7229***
	(0.242)	(0.220)
Dividend payout	-0.1375	-0.0642
	(0.275)	(0.287)
Oil (Gas) reserves (in log)	0.0887	0.2351*
	(0.068)	(0.127)
Institutional ownership	-0.3603	-0.4129
	(0.384)	(0.449)
Oil (Gas) geo diversification	-0.8851*	-2.4426***
	(0.466)	(0.813)
Oil (Gas) price volatility	0.0073	-0.0977
	(0.025)	(0.115)
Oil (Gas) basis	0.3650	-0.1318
	(1.128)	(0.319)
Oil (Gas) production risk	0.1313	0.8860**
	(0.456)	(0.376)
Price_quantity correlation (oil/gas)	0.0733	-0.0893
	(0.170)	(0.167)
CEO ownership	4.1476	-14.7762

Variable	(1) Oil hedging intensity	(2) Gas hedging intensity
	(15.639)	(18.018)
Number of CEO options	0.0016	0.0018
	(0.002)	(0.002)
Number of analysts	-0.0566***	-0.0675***
	(0.021)	(0.023)
Constant	0.0427	-0.4798
	(0.450)	(0.750)
Observations	576	
Log likelihood	-529.2241	
Number of firms	79	
Wald chi2	155.3263	
Significance	0.0000	
Rho	0.7914	
p-value of the Wald test of rho=0	0.0000	
Log likelihood for the first equation	-301.7115	
Log likelihood for the second equation	-291.1822	
The comparison log likelihood	-592.8937	

This table shows the results of the seemingly unrelated bivariate probit regressions, which test the firms' *joint* decision about the extent of hedging their oil and gas production. Both dependent variables, oil hedging intensity and gas hedging intensity, are dummy variables taking the value of 1 for a high extent, i.e., higher than or equal to the 75th percentile, and taking the value of 0 for a low extent, i.e., equal to or lower than the 25th percentile. These percentiles are calculated based on HR0: the hedging ratio for the current fiscal year. The level and changes in the Kilian index are our two instrumental variables. Control variables related to the firm's financial and operational characteristics are included in lagged values (first lag). See Table A1 for further details on the construction of the control variables. Heteroskedasticity-consistent standard errors clustered at the firm level are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The previous estimation of the bivariate probit helps to get predictions of conditional probabilities for hedging oil and gas at low or high intensities, as described below.

p00: determines the predicted probability that a firm in the sample has both a low hedging intensity for its oil production and a low hedging intensity for its natural gas production. We can denote this probability as follows:

$$Pr\left(y_{1j}=0, y_{2j}=0\right). \tag{10}$$

p11: determines the predicted probability that a firm in the sample has both a high hedging intensity for its oil production and a high hedging intensity for its natural gas production:

$$Pr\left(y_{1j}=1, y_{2j}=1\right). \tag{11}$$

p10: determines the predicted probability that a firm in the sample has a high hedging intensity for its oil production while having a low hedging intensity for its natural gas production:

$$Pr\left(y_{1j}=1, y_{2j}=0\right). \tag{12}$$

p01: determines the predicted probability that a firm in the sample has a low hedging intensity for its oil production while having a high hedging intensity for its natural gas production:

$$Pr\left(y_{1j}=0, y_{2j}=1\right). \tag{13}$$

These predicted probabilities will be employed to analyze the real effects of joint price hedging on firm value.

5. Real effects of joint price hedging

5.1 Estimation methodology

To estimate the real effects of the joint hedging of oil and gas, we regress various metrics related to firm market value, risk, and performance (dependent variables) on the predicted probabilities of hedging intensities (low versus high) for oil and gas, given by the bivariate probit estimation discussed in Section 4. Control variables pertaining to the firm's financial and operational characteristics and to oil and gas market conditions are included. The firm's market value is proxied by Tobin's Q (in log), measured by the ratio of the sum of the company's market value of equity, book value of debt, and book value of preferred shares to the book value of its assets. The firm's performance is measured by the return on equity (ROE). The firm's risk profile is proxied using different variables: i) The firm's total risk is measured by the standard deviation of daily stock returns during each quarter. ii) The firm's systematic risk (i.e., market beta) measures the stock returns' sensitivity to the CRSP value-weighted portfolio estimated using the four factors of Fama and French (1993) and Carhart (1997) and the daily returns on the near-month WTI crude oil futures and the near-month natural gas futures in the NYMEX. The estimation is based on daily returns during each quarter in the sample. iii) The firm's specific risk is measured by the standard deviation of the residuals coming from the estimation of the factor model discussed previously.

5.2 Real effects results

In this section, we run a variety of regressions. We regress the dependent variables based on firm metrics, namely, market valuation, performance, and risk, on the variables p11, p10, p00, and p01, detailed above. For the sake of conciseness, we focus our analysis on the two extreme situations, p11 and p00, indicating joint high-intensity hedging and joint low-intensity hedging, respectively, for both commodities. The real effects related to the two other predicted probabilities, p10 and p01, are discussed briefly below, and results are available in the Online appendix.

5.2.1 Real effect of joint high intensities of oil and gas hedging

Table 10 summarizes the results of the first regression, in which we regress the firm's Tobin's Q, return on equity (ROE), total risk, systematic risk, and idiosyncratic risk on the predicted probability p11 and control variables. The p11 denotes the predicted propensity to hedge oil and gas to a larger extent, simultaneously. It is worth noticing that the interpretation of the results of

Table 10 is from the comparison of the petroleum companies with high-intensity hedging with petroleum companies with lower-intensity hedging.

Table 10 reveals a positive and statistically highly significant effect of the predicted probability p11, coming from the bivariate probit estimation, on the firm's Tobin's Q, with a value of 0.543, suggesting that an increase of 1% in the propensity to hedge both commodities at the highest extent will achieve an economically significant increase in the firm's value by 0.543%. This finding is consistent with the valuation premium for corporate hedging advocated by a large body of literature. Allayannis and Weston (2001) give the first direct evidence of the positive relation between currency derivative usage (proxied by a dummy variable) and firm value (as defined by a natural logarithm of the firm's Tobin's Q) and show that, for a sample of 720 non-financial firms, the market value of foreign currency hedgers is 5% higher on average than of non-hedgers. Carter et al. (2006) investigate the jet fuel hedging behavior of firms in the US airline industry in 1993–2003 and find an average hedging premium of 12%–16%, where they retain dummy variables to proxy for the existence of hedging activities. Bartram et al. (2009) explore the real effects of derivative use for a large sample of 6,888 non-financial firms from 47 countries during 2000–2001. Their evidence suggests that using derivatives is associated with a higher firm value. Pérez-Gonzalez and Yun (2013) exploit the introduction of weather derivatives in 1997 as a natural experiment for a sample of energy firms. They find evidence of positive effects of weather-derivative use on a firm's value, as measured by the market-to-book ratio.

Pertaining to the firm's return on equity, Table 10 shows a positive effect of high-intensity hedging for oil and gas, but only statistically significant at the level of 10%. Table 10 also indicates a statistically significant negative effect of high-intensity hedging for oil and gas on the firm's risk profile, that is on the firm's total risk and idiosyncratic risk. Our results show that a 1% increase in the predicted probability of hedging oil and gas production to a greater extent will reduce the firm's total risk by almost 0.58% and decrease the firm's specific risk by 0.03%. These findings corroborate previous findings in one stream of the related literature. Guay (1999) looks at a sample of 254 non-financial corporations that began using derivatives in the fiscal year 1991, and reports that new derivative users experience a statistically and economically significant 5% reduction in stock return volatility, as compared to a control sample of non-users. Using a sample of S&P 500 non-financial firms for 1993, Allayannis and Ofek (2001) find strong evidence that foreign-currency hedging reduces firms' exchange-rate exposure. Bartram et al. (2011) find evidence that using derivatives reduces total risk. The impact of the firm's systematic or market risk is positive but statistically insignificant. This latter finding is in line with the results of Adam and Fernando (2006), who examine the outstanding gold derivative positions for a sample of 92 North American gold mining firms for the period 1989-1999, and obtain that using derivatives translates into value gains for shareholders since there is no offsetting increase in the firm's systematic risk.

Table 10 – Real effects of joint high hedging intensities for oil and gas

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
p11	0.5426***	0.5671*	-0.5874***	-0.0331***	0.3244
	(0.136)	(0.336)	(0.154)	(0.010)	(0.344)
EPS from operations	-0.0018	0.0126	0.0051	0.0004	0.0336***
	(0.006)	(0.025)	(0.010)	(0.001)	(0.012)
Investment opportunities	0.0089	-0.1002**	-0.0137	-0.0018*	0.1207***
	(0.032)	(0.043)	(0.017)	(0.001)	(0.041)
Leverage ratio	-0.0222	0.1915	0.2958	0.0226*	0.3106
	(0.125)	(0.331)	(0.195)	(0.012)	(0.238)
Liquidity ratio	0.1081**	0.0852**	-0.0440*	-0.0019	0.1059
	(0.041)	(0.041)	(0.023)	(0.002)	(0.089)
Dividend payout	0.0493	0.0025	0.0301	0.0024	0.0706
	(0.084)	(0.050)	(0.041)	(0.002)	(0.100)
Oil reserves (in log)	-0.0473	0.0339	-0.0375*	-0.0019	-0.0433
	(0.036)	(0.060)	(0.021)	(0.001)	(0.061)
Institutional ownership	0.0888	-0.0882	-0.1711	-0.0158*	-0.1806
	(0.101)	(0.174)	(0.137)	(0.008)	(0.290)
Oil geographical diversification	0.0781	0.2824	-0.1280	-0.0060	-0.4987

	(0.091)	(0.244)	(0.174)	(0.011)	(0.344)
Gas geographical diversification	0.5072	0.4319	-0.6968*	-0.0347**	0.1386
	(0.319)	(0.279)	(0.365)	(0.017)	(0.636)
Oil price volatility	-0.0353***	-0.0402*	0.0498***	0.0018***	0.0039
	(0.006)	(0.020)	(0.007)	(0.000)	(0.012)
Oil basis	0.9305***	0.5331	-0.6171**	-0.0290*	-0.8215
	(0.251)	(0.411)	(0.299)	(0.017)	(0.761)
Oil production risk	-0.1306	-0.1946	0.0354	0.0037	0.1344
	(0.097)	(0.191)	(0.072)	(0.005)	(0.194)
Price_quantity correlation (oil)	0.1236***	0.0594*	-0.0046	-0.0002	0.0515
	(0.046)	(0.032)	(0.039)	(0.002)	(0.093)
Gas basis	-0.0866	-0.1016	0.1467**	0.0060	0.0346
	(0.067)	(0.100)	(0.067)	(0.004)	(0.162)
Gas price volatility	0.0385*	0.0421	0.0822***	0.0024*	0.0755
	(0.022)	(0.050)	(0.027)	(0.001)	(0.054)
Gas reserves (in log)	0.0407	-0.1509**	0.0692	0.0007	0.1835**
	(0.049)	(0.074)	(0.046)	(0.002)	(0.080)
Gas production risk	0.0293	-0.1201	0.0011	0.0031	0.0645
	(0.088)	(0.132)	(0.075)	(0.005)	(0.162)
Price_quantity correlation (Gas)	0.0197	0.0099	0.0469	0.0006	0.1149*
	(0.043)	(0.045)	(0.037)	(0.002)	(0.065)
CEO ownership	-1.8424	-8.9333	-0.5770	0.1004	-4.4014
	(3.072)	(8.287)	(2.427)	(0.125)	(4.116)
Number of CEO options	0.0006*	0.0003	0.0005	0.0000	0.0002
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Number of analysts	0.0124***	0.0180*	-0.0134***	-0.0007**	0.0017
	(0.004)	(0.009)	(0.004)	(0.000)	(0.009)
Constant	-0.0814	0.4627	0.2979	0.0352**	-0.3702
	(0.236)	(0.314)	(0.260)	(0.015)	(0.492)
Observations	574	571	573	555	555
R-squared	0.2346	0.0712	0.3293	0.2530	0.0617
Number of firms	79	79	78	75	75
F statistic	4.9653	2.5858	9.0027	7.5904	4.4395
Rho	0.6287	0.3768	0.7363	0.5915	0.4221
Panel-level standard deviation	0.2801	0.3640	0.3965	0.0151	0.5460
Standard deviation of epsilon_it	0.2152	0.4681	0.2373	0.0125	0.6389

This table displays the results of the time series cross-sectional regressions with fixed effects when regressing the dependent variables (firm's Tobin's Q, ROE, total risk, systematic risk, and idiosyncratic risk) on the predicted probability p11, which corresponds to the probability of simultaneously high hedging intensities for both oil and gas production, coming from the bivariate probit estimation, and control variables related to firm's financial and operational characteristics and to oil and gas market conditions. Control variables are included in lagged values (first lag). See Table A1 for further details on the construction of control variables. Heteroskedasticity-consistent standard errors clustered at the firm level are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5.2.2 Real effect of joint low-intensity oil and gas hedging

Table 11 summarizes the results of the second regression, in which we regress the sample firms' Tobin's Q, return on equity (ROE), systematic risk, and idiosyncratic risk on the predicted probability p00 and control variables. The p00 denotes the predicted propensity to hedge oil and gas to a lower extent simultaneously. It is worth noticing that the interpretation of the results of Table 11 is for companies with low-intensity hedging relative to companies with high-intensity hedging.

Table 11 shows that hedging at lesser extents has the exact opposite real effects as hedging at higher extents, which are mentioned in Table 10. In fact, Table 11 reveals a statistically and economically significant negative effect for the predicted propensity p00 on the firm's market valuation, with a coefficient of -0.69. This means that an increase of 1% in the predicted probability of being in the lower-percentile hedging reduces the firm's value by 0.69%. Table 11 also indicates that lower-intensity hedgers should have a lower return on equity, as compared to higher-intensity hedgers. These findings show that there will be an erosion in the shareholders' wealth for lower-intensity hedgers, as compared to more aggressive hedgers.

For firm riskiness, the results in Table 11 suggest that petroleum companies that are among the lower-quintile hedgers have experienced a higher risk profile, compared to companies among the upper-quintile hedgers. A 1% increase in the predicted probability, p00, increases the firm's total risk by about 0.66% and 0.03% for the firm's specific risk. More firm risk, reflected by a more volatile share price, can erode shareholder value because it increases the probability of default and, consequently, its associated expected financial distress. The effect on the firm's systematic risk, measured by its market beta, is negative and statistically insignificant.

Table 11 – Real effects of joint low hedging intensities for oil and gas

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
P00	-0.6908***	-0.4195*	0.6625***	0.0351***	-0.3502
	(0.138)	(0.224)	(0.172)	(0.010)	(0.283)
EPS from operations	-0.0037	0.0092	0.0073	0.0005	0.0322***
	(0.005)	(0.024)	(0.010)	(0.001)	(0.012)
Investment opportunities	0.0111	-0.0832**	-0.0203	-0.0023**	0.1251***
	(0.031)	(0.033)	(0.015)	(0.001)	(0.038)
Leverage ratio	-0.0221	0.1918	0.2941	0.0226*	0.3110
	(0.121)	(0.334)	(0.191)	(0.012)	(0.240)
Liquidity ratio	0.1428***	0.0811**	-0.0701**	-0.0031*	0.1191
	(0.045)	(0.037)	(0.027)	(0.002)	(0.090)
Dividend payout	0.0579	-0.0041	0.0246	0.0020	0.0742
	(0.083)	(0.045)	(0.044)	(0.003)	(0.101)
Oil reserves (in log)	-0.0508	0.0416	-0.0369	-0.0020	-0.0429
	(0.035)	(0.056)	(0.023)	(0.001)	(0.061)
Institutional ownership	0.0742	-0.0879	-0.1591	-0.0148*	-0.1908
	(0.091)	(0.175)	(0.130)	(0.008)	(0.291)
Oil geographical diversification	0.0386	0.2366	-0.0857	-0.0035	-0.5231
	(0.105)	(0.229)	(0.165)	(0.011)	(0.332)
Gas geographical diversification	0.4428	0.3011	-0.6023*	-0.0289*	0.0838
	(0.309)	(0.209)	(0.340)	(0.015)	(0.630)
Oil price volatility	-0.0360***	-0.0390**	0.0501***	0.0018***	0.0038
	(0.005)	(0.019)	(0.007)	(0.000)	(0.012)
Oil basis	0.9400***	0.3847	-0.5790*	-0.0266	-0.8416
	(0.241)	(0.439)	(0.302)	(0.017)	(0.711)
Oil production risk	-0.1360	-0.1826	0.0370	0.0035	0.1360
	(0.094)	(0.191)	(0.074)	(0.005)	(0.193)
Price_Quantity correlation (oil)	0.1036**	0.0573*	0.0117	0.0006	0.0432
	(0.044)	(0.033)	(0.035)	(0.002)	(0.093)
Gas basis	-0.0899	-0.0947	0.1472**	0.0061	0.0342
	(0.066)	(0.103)	(0.070)	(0.004)	(0.162)
Gas price volatility	0.0373*	0.0465	0.0818***	0.0023*	0.0760
	(0.022)	(0.051)	(0.027)	(0.001)	(0.055)
Gas reserves (in log)	0.0409	-0.1376*	0.0650	0.0005	0.1853**
	(0.049)	(0.073)	(0.044)	(0.002)	(0.078)
Gas production risk	0.0456	-0.0772	-0.0227	0.0017	0.0775
	(0.088)	(0.124)	(0.078)	(0.005)	(0.163)
Price_Quantity correlation (Gas)	0.0319	0.0104	0.0372	0.0001	0.1200*
	(0.041)	(0.046)	(0.036)	(0.002)	(0.065)
CEO ownership	-2.7095	-10.4244	0.5351	0.1592	-4.9584
	(3.150)	(8.742)	(2.647)	(0.139)	(4.001)
Number of CEO options	0.0007**	0.0006	0.0003	-0.0000	0.0003
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Number of analysts	0.0147***	0.0162**	-0.0147***	-0.0007**	0.0023
	(0.005)	(0.008)	(0.005)	(0.000)	(0.008)
Constant	0.4185*	0.7618*	-0.1787	0.0092	-0.1105
	(0.247)	(0.393)	(0.319)	(0.019)	(0.530)

Observations	574	571	573	555	555
R-squared	0.2546	0.0652	0.3345	0.2534	0.0618
Number of firms	79	79	78	75	75
F statistic	6.7731	2.5833	10.2676	10.7825	4.3112
Rho	0.6203	0.3643	0.7369	0.5806	0.4244
Panel-level standard deviation	0.2715	0.3555	0.3956	0.0148	0.5485
Standard deviation of epsilon_it	0.2124	0.4696	0.2364	0.0125	0.6388

This table displays the results of the time series cross-sectional regressions with fixed effects when regressing the dependent variables (firm's Tobin's Q, ROE, total risk, systematic risk, and idiosyncratic risk) on the predicted probability p00, which corresponds to the probability of simultaneously *low* hedging intensities for both oil and gas production, coming from the bivariate probit estimation, the control variables related to firm's financial and operational characteristics, and oil and gas market conditions. Control variables are included in lagged values (first lag). See Table A1 for further details on the construction of the control variables. Heteroskedasticity-consistent standard errors clustered at the firm level are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Overall, the results conveyed by tables 10 and 11 are complementary and mutually confirmed. In fact, the summarized results converge with the conclusion that hedging to a greater extent in the oil and gas industry increases firm value and reduces firm riskiness.

We estimate the same regression using the predicted probability that a firm in the sample has a high hedging intensity for its oil production while having a low hedging intensity for its natural gas production, that is, p10. We have results showing coefficients for p10 with the same signs as in Table 10, however, with no statistical significance. Results are reported in Table OA.2 in the Online appendix. We also use the predicted probability that a firm in the sample has a low hedging intensity for its oil production while having a high hedging intensity for its natural gas production, that is, p01. We have coefficients for p01 with same signs as in Table 11 but statistically insignificant. Results are reported in Table OA.3 in the Online appendix.

5.3 The superiority of joint hedging

In this section, we investigate the relevance and the superiority of a joint hedging strategy to assess the real effects of hedging intensity on firm value over an estimation based on separate, single-risk exposures or a stand-alone framework. We do so by comparing the real effects reported in Table 10 using the predicted probability of a simultaneous high hedging intensity for both oil and gas, i.e., p11, coming from the bivariate probit regression and the real effects using a univariate probit estimation for the predicted probabilities of a high hedging intensity for oil and gas separately. Overall, Table OA.4 reports the estimations and shows that the stand-alone predicted probabilities of the univariate probits have a non-significant effect on firm value and risk. By itself, a predicted probability of high intensity for oil has a significant negative effect on firm risk.

Furthermore, we calculate the joint predicted probability of having a high hedging intensity for both oil and gas simultaneously by multiplying the two predicted probabilities coming from the univariate probit estimation, that is, we are supposing that the correlation between the residuals of the two estimations is equal to zero.

Results are reported in Table OA.5 and reveal a significant positive impact on firm value and a significant negative effect on the firm's total and specific risk. Noticeably, the positive effect on the firm's return on equity is insignificant. To go further, we gauge the economic magnitude of the real effects by comparing the coefficients reported in Table 10 for the predicted probabilities from the bivariate probit, i.e., p11, with the coefficients reported in Table AO.5 for the joint probabilities coming from the univariate probits, as described previously. We examine whether these coefficients are statistically equal or different. Table 12 summarizes the coefficients from Table 10 and Table OA.5 beside the Wald test for the equality of estimated coefficients.

Table 12 – Comparison of the real effects

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
Joint probability of high intensity from the bivariate probit	0.5426***	0.5671*	-0.5874***	-0.0331***	0.3244
	(0.136)	(0.336)	(0.154)	(0.010)	(0.344)
Joint probability of high intensity from univariate probits	0.4419***	0.5319	-0.5200***	-0.0298***	0.2269
	(0.138)	(0.323)	(0.137)	(0.009)	(0.319)
Wald test with H0: coefficients are equal	15.77***	0.57	3.67**	2.82*	2.00
p-value	0.0000	0.4488	0.0555	0.0929	0.1576

We use Stata's command *suest* allowing tests for intra-model and cross-model hypotheses by performing Wald tests of simple and composite linear hypotheses about the estimated parameters.

Interestingly, the Wald test reveals that the joint estimation considering the simultaneity between managerial hedging decisions in a multi-risk environment, that is, the bivariate probit, leads to an economically and statistically higher firm market value and lower firm total and specific risks, compared to isolated estimations based on univariate probits.

To sum up, these findings reveal two interesting facts: i) using separate predicted probabilities can be misleading, by showing insignificant real effects of hedging-related choices, and ii) assuming a zero correlation between the decision process in a multi-risk exposure environment can induce economically smaller effects compared to a full-joint framework considering the interactions of corporate hedging activities.

To further examine the appropriateness and relevance of the joint estimation of the manager's decision-making process regarding the extent of hedging for both commodities, i.e., oil and gas, we compare the predicted probabilities coming from the bivariate probit with real frequencies calculated based on data documented in Table 7. Table 13 gives these observed frequencies (Observed) alongside the predicted probabilities from the bivariate probit estimation (Joint estimation). Remarkably, the joint estimation predicts probabilities that are very close to the observed decision frequencies, indicating that the bivariate probit captures very well managers' simultaneous decisions about hedging intensities for oil and gas.

Table 13 – Observed frequencies and predicted probabilities for oil and gas hedging intensities

		Oil hedging intensity	
		High	Low
Gas hedging intensity			
High	Observed	40.88%	8.79%
	Joint estimation	39.24%	9.90%
	Independent	30.07%	19.07%
Low	Observed	8.31%	42.02%
	Joint estimation	9.27%	41.59%
	Independent	18.43%	32.43%

We further calculate the predicted probabilities for high hedging intensities for oil and gas separately, using univariate probit estimations assuming independent managerial choices.[12] We then calculate the predicted probabilities for the different combinations of hedging intensities for oil and gas, namely, high and/or low intensity for oil and gas. These independent predicted probabilities are shown in Table 13 (Independent). Interestingly, we observe that the univariate probit estimations fail to accurately predict the managerial decision process. In fact, the predicted probabilities, for either a simultaneously high or simultaneously low intensity for both commodities, are surprisingly underestimated. By contrast, the predicted probabilities for the combinations of high and low intensity for oil and gas are astonishingly overestimated—more than double the observed frequencies. Overall, these findings indicate that managerial decision-making about hedging intensities for oil and gas is a simultaneous process and that the interdependence

[12] The dependent variable for each univariate probit is a dummy variable that takes the value of 1 when the oil (gas) hedging intensity is considered high (above the 75th percentile) and 0 when it is low (below the 25th percentile).

between these decisions should be considered through a joint estimation framework to better capture managerial hedging behavior in a multi-risk environment.

6. Conclusion

We revisit the real effects associated with corporate risk management by considering the joint hedging of two market risk exposures, namely, oil and gas price risk We take a multi-dimensional approach by looking at the hedging question from different angles. We first analyze the joint decision to hedge both oil and natural gas prices simultaneously, using a bivariate probit panel regression. Then, we study the effects of the joint decision to hedge oil and gas production on the market's firm value, risk, and performance. We do our analysis in an instrumental variable framework to account for the endogeneity of the hedging decision.

We use appropriate instruments for the need to hedge and to reflect managers' market views, that is, the Kilian index, which measures real global economic activity based on a short-term view of real shipping costs. We find that, jointly, hedging intensities for oil and natural gas decrease when real global economic activity is increasing from period to period, as proxied by changes in the Kilian index. Also, hedging intensities tend to be higher when the current level of real economic activity is high, as proxied by the level of the Kilian index. This raises some interesting implications for the timing of hedging and for managers' responses to changing real economic conditions. So, we can talk about managers' near-term and long-term market views, which appear to have opposite effects on the extent of hedging.

Armed with these two instruments (the level and the change in the Kilian index), we estimate a bivariate probit model and generate predicted probabilities for the joint decision about oil and gas hedging intensities. Then, in a second step, we test for a hedging premium by analyzing whether firm value is enhanced as a result of the hedging intensity for oil and gas. We regress market value, accounting performance, and risk measures on different combinations of hedging behavior. We find a positive relationship between firms that tend to hedge oil and gas simultaneously to a greater extent and their Tobin's Q and their return on equity. This implies that firms with a tendency to hedge more aggressively than their counterparts, in the lower hedging quintiles, enjoy a higher market valuation. Finally, we find evidence to suggest that firms with a high propensity to hedge to a larger extent face significantly lower riskiness, as compared to firms with low hedging intensities. Finally, we show that joint hedging dominates single-commodity hedging.

Hedging is a costly proposition, one that is still heavily debated in the literature; however, our paper lends credence to the claim that the benefits of joint hedging outweigh its costs and serves to increase firm value.

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Appendix

Table A1 – Variables' definitions

Variable	Construction	Source
EPS from operations	Quarterly earnings per share from operations	Compustat
Investment opportunities	Quarterly capital expenditure, with a scale by net property, plant, and equipment at the beginning of the quarter	Compustat
Leverage ratio	Ratio of the book value of total debts to the total book value of assets	Compustat
Liquidity	Ratio of cash and cash equivalents to the book value of current liabilities	Constructed manually
Dividend payout	Dividends declared for the quarter (dummy variable)	Constructed manually
Oil reserves	The quantity (in millions of barrels) of the total proved developed and undeveloped oil reserves. This variable is disclosed annually. We repeat the same observation for the same fiscal year quarters. The raw value of this variable (in millions of barrels) is used in Table 1 (Descriptive Statistics). The logarithm transformation of this variable is used elsewhere.	10-Ks and Bloomberg
Institutional ownership	Percentage of shares owned by institutional investors	Thomson Reuters
Geographical diversification of oil production	Constructed using $1-\sum_{i=1}^{N}\left(\frac{q_1}{q}\right)^2$, where q_1 represents the daily oil production in the *i* region (Latin America, North America, Middle East, Africa) while q is the total daily production of oil	Constructed manually
Geographical diversification of gas production	Constructed using $1-\sum_{i=1}^{N}\left(\frac{q_1}{q}\right)^2$ where q_1 represents the daily gas production in the i region (Latin America, North America, Middle East, Africa) while q is the total daily production of gas	Constructed manually
Oil price volatility	Historical volatility measured with the standard deviation of oil daily spot prices during the quarter	Constructed manually
Oil basis	The oil basis is measured by the ratio of the average oil futures prices for exchange traded futures for the next 12 months, divided by the oil spot price at the end of the quarter minus one. Spot price is proxied by the West Texas Intermediate price. Spot and future oil prices are extracted from Bloomberg.	Constructed manually

Oil/Gas production risk	Coefficient of variation of daily oil (gas) production. This coefficient is calculated for each firm by using rolling windows of 12 quarterly observations. The daily oil (gas) production is disclosed annually. We repeat the same observation for the same fiscal year quarters.	Constructed manually, Bloomberg, 10K reports
Gas price volatility	Historical volatility measured with the standard deviation of gas daily spot prices during the quarter	Constructed manually
Gas basis	The gas basis is measured by the ratio of the average gas future prices for exchange traded futures for the next 12 months divided by the gas spot price at the end of the quarter minus one. Gas spot price is proxied by multi-region averages of gas indices in the United States (Henry Hub, Gulf Coast, and others). Gas spot and futures prices are extracted from Bloomberg.	Constructed manually
Gas reserves	The quantity of the total proved developed and undeveloped gas reserves. This variable is disclosed annually. We repeat the same observation for the same fiscal year quarters. The raw value of this variable (in billions of cubic feet) is used in Table 1 (Descriptive Statistics). The logarithm transformation of this variable is used elsewhere.	10K reports and Bloomberg
Price–quantity correlation (oil/gas)	Correlation coefficient between daily oil (gas) production and oil (gas) spot prices. These correlation coefficients are calculated for each firm by using rolling windows of 12 quarterly observations	Bloomberg and 10–K reports
CEO ownership	Percentage ownership of the firm by its CEO	Thomson Reuters
CEO option holding	Number of options on company stock held at the end of the quarter by the CEO	Thomson Reuters
Number of analysts	Number of analysts following the firm, and subsequent issues earnings forecast for the quarter	I/B/E/S

Determinants and real effects of joint hedging: An empirical analysis of the US petroleum industry

Online appendix

Table OA.1 – Derivative instruments used by oil and gas hedgers

	Gas hedging		Oil hedging	
Derivative instrument	Number of firm-quarters	Percentage of use	Number of firm-quarters	Percentage of use
Swap contracts	2,255	45.58	1,711	45.25
Put options	522	10.55	448	11.85
Costless collar	1,840	37.19	1,403	37.11
Forward or futures contract	161	3.25	105	2.78
3-ways collar	169	3.42	114	3.02
Total	4,947	100	3,781	100

The table reports the different type of financial instruments used by the sample firms that report non-zero oil and gas hedging activities in each firm-quarter observation. The values for each instrument indicate the number of firm-quarters and the fraction (in percentage) of use.

Table OA.2 – Real effects of joint high hedging intensity for oil and low hedging intensity for gas

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
p10	0.8358*	0.1082	-0.5794	-0.0140	0.0664
	(0.493)	(0.574)	(0.504)	(0.025)	(0.829)
EPS from operations	-0.0115	0.0073	0.0130	0.0007	0.0310**
	(0.008)	(0.027)	(0.012)	(0.001)	(0.014)
Investment opportunities	0.0494	-0.0617**	-0.0560***	-0.0041***	0.1426***
	(0.038)	(0.027)	(0.013)	(0.001)	(0.036)
Leverage ratio	-0.0698	0.1901	0.3236	0.0225*	0.3170
	(0.129)	(0.332)	(0.195)	(0.013)	(0.241)
Liquidity ratio	0.0609*	0.0262	0.0111	0.0015	0.0719
	(0.036)	(0.037)	(0.037)	(0.002)	(0.070)
Dividend payout	0.0403	-0.0215	0.0449	0.0033	0.0604
	(0.081)	(0.038)	(0.042)	(0.002)	(0.106)
Oil reserves (in log)	-0.0403	0.0555	-0.0510	-0.0028	-0.0328
	(0.039)	(0.058)	(0.032)	(0.002)	(0.069)
Institutional ownership	0.0637	-0.0727	-0.1601	-0.0169**	-0.1659
	(0.096)	(0.180)	(0.134)	(0.008)	(0.276)
Oil geographical diversification	0.1042	0.2449	-0.1322	-0.0051	-0.5130
	(0.100)	(0.217)	(0.118)	(0.008)	(0.362)
Gas geographical diversification	-0.1132	0.1395	-0.1636	-0.0123	-0.0507
	(0.273)	(0.319)	(0.268)	(0.016)	(0.652)
Oil price volatility	-0.0325***	-0.0366*	0.0467***	0.0016***	0.0058
	(0.006)	(0.019)	(0.008)	(0.000)	(0.012)
Oil basis	0.4957**	0.1446	-0.1665	-0.0046	-1.0560
	(0.240)	(0.448)	(0.266)	(0.015)	(0.645)
Oil production	-0.0978	-0.1609	0.0014	0.0019	0.1511

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
risk					
	(0.091)	(0.192)	(0.078)	(0.005)	(0.190)
Price_quantity correlation (oil)	0.1218***	0.0801*	-0.0126	-0.0012	0.0633
	(0.046)	(0.045)	(0.036)	(0.002)	(0.085)
Gas basis	-0.0719	-0.0812	0.1284*	0.0051	0.0441
	(0.065)	(0.106)	(0.071)	(0.004)	(0.163)
Gas price volatility	0.0389*	0.0527	0.0771***	0.0019	0.0813
	(0.022)	(0.057)	(0.026)	(0.001)	(0.061)
Gas reserves (in log)	0.1094*	-0.1138	0.0088	-0.0022	0.2089**
	(0.055)	(0.085)	(0.047)	(0.003)	(0.086)
Gas production risk	0.1864*	-0.0329	-0.1335	-0.0018	0.1048
	(0.108)	(0.115)	(0.099)	(0.006)	(0.175)
Price_quantity correlation (gas)	0.0037	-0.0070	0.0644*	0.0015	0.1059
	(0.046)	(0.045)	(0.037)	(0.002)	(0.064)
CEO ownership	-6.7873	-11.6032	3.7351	0.3014*	-6.1362
	(4.536)	(8.797)	(3.413)	(0.179)	(5.363)
Number of CEO's options	0.0010***	0.0007	0.0000	-0.0000	0.0005
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Number of analysts	0.0033	0.0100*	-0.0042	-0.0001	-0.0033
	(0.004)	(0.006)	(0.004)	(0.000)	(0.008)
Constant	-0.2630	0.4262	0.4332	0.0408**	-0.4115
	(0.286)	(0.398)	(0.311)	(0.017)	(0.533)
Observations	574	571	573	555	555
R-squared	0.2015	0.0592	0.2958	0.2066	0.0595
Number of firms	79	79	78	75	75
F statistic	4.0313	1.7521	9.2164	17.7217	4.5245
Rho	0.6537	0.3523	0.7197	0.6059	0.4200
Panel-level standard	0.3021	0.3475	0.3896	0.0160	0.5443

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
deviation					
Standard deviation of epsilon_it	0.2198	0.4711	0.2431	0.0129	0.6396

This table displays the results of the time series cross sectional regressions with fixed effects when regressing the dependent variables (firm's Tobin's Q, ROE, total risk, systematic risk, and idiosyncratic risk) on the predicted probability p10, which corresponds to the probability of a simultaneous high hedging intensity for oil and low hedging intensity for gas production coming from the bivariate probit estimation, and control variables related to firm's financial and operational characteristics, and oil and gas market conditions. Control variables are included in lagged values (first lag). See Table A.1 for more details on the construction of control variables. Heteroskedasticity-consistent standard errors clustered at the firm level are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table OA.3 – Real effects of joint low hedging intensity for oil and high hedging intensity for gas

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
p01	-0.0827	-1.2860	0.3725	0.0225	-0.1231
	(0.401)	(1.052)	(0.251)	(0.015)	(0.768)
EPS from operations	-0.0053	0.0049	0.0099	0.0007	0.0311***
	(0.007)	(0.022)	(0.011)	(0.001)	(0.012)
Investment opportunities	0.0445	-0.0783**	-0.0485***	-0.0037***	0.1407***
	(0.040)	(0.037)	(0.013)	(0.001)	(0.035)
Leverage ratio	-0.0154	0.1109	0.3106	0.0233*	0.3122
	(0.138)	(0.338)	(0.209)	(0.013)	(0.245)
Liquidity ratio	0.0493	0.0062	0.0239	0.0021	0.0689
	(0.031)	(0.035)	(0.035)	(0.002)	(0.068)
Dividend payout	0.0282	-0.0056	0.0495	0.0033	0.0604
	(0.083)	(0.049)	(0.040)	(0.002)	(0.103)
Oil reserves (in log)	-0.0269	0.0316	-0.0533*	-0.0026	-0.0343
	(0.040)	(0.062)	(0.028)	(0.002)	(0.065)
Institutional ownership	0.1023	-0.1055	-0.1758	-0.0171**	-0.1654
	(0.102)	(0.186)	(0.141)	(0.008)	(0.285)
Oil geographical diversification	0.0542	0.4283	-0.1434	-0.0074	-0.4998
	(0.109)	(0.282)	(0.138)	(0.009)	(0.400)
Gas geographical diversification	0.2236	-0.1267	-0.3254	-0.0130	-0.0511
	(0.357)	(0.260)	(0.369)	(0.017)	(0.681)
Oil price volatility	-0.0324***	-0.0375*	0.0467***	0.0016***	0.0058
	(0.006)	(0.019)	(0.007)	(0.000)	(0.012)
Oil basis	0.5536**	0.2265	-0.2305	-0.0066	-1.0461
	(0.248)	(0.424)	(0.275)	(0.015)	(0.637)
Oil production	-0.1018	-0.1674	0.0037	0.0021	0.1503

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
risk					
	(0.094)	(0.188)	(0.076)	(0.005)	(0.190)
Price_quantity correlation (oil)	0.1464***	0.0698*	-0.0262	-0.0014	0.0641
	(0.049)	(0.035)	(0.041)	(0.002)	(0.090)
Gas basis	-0.0668	-0.0908	0.1282*	0.0052	0.0434
	(0.065)	(0.103)	(0.068)	(0.004)	(0.162)
Gas price volatility	0.0493**	0.0332	0.0754***	0.0021*	0.0801
	(0.021)	(0.053)	(0.026)	(0.001)	(0.054)
Gas reserves (in log)	0.0761	-0.0817	0.0226	-0.0024	0.2102**
	(0.058)	(0.078)	(0.047)	(0.003)	(0.089)
Gas production risk	0.1001	0.0243	-0.0924	-0.0018	0.1056
	(0.103)	(0.128)	(0.091)	(0.006)	(0.170)
Price_quantity correlation (gas)	0.0021	-0.0198	0.0688*	0.0018	0.1044
	(0.046)	(0.048)	(0.037)	(0.002)	(0.063)
CEO ownership	-4.2000	-12.6390	2.2713	0.2862*	-6.0857
	(3.614)	(9.310)	(3.222)	(0.164)	(4.400)
Number of CEO's options	0.0009***	0.0004	0.0002	-0.0000	0.0004
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Number of analysts	0.0046	0.0074	-0.0044	-0.0001	-0.0035
	(0.005)	(0.005)	(0.003)	(0.000)	(0.008)
Constant	-0.0969	0.5605	0.2877	0.0365**	-0.3900
	(0.262)	(0.349)	(0.307)	(0.017)	(0.508)
Observations	574	571	573	555	555
R-squared	0.1906	0.0684	0.2942	0.2087	0.0595
Number of firms	79	79	78	75	75
F statistic	3.8986	1.3567	10.1051	17.1790	4.0126
Rho	0.6656	0.3615	0.7234	0.6106	0.4197
Panel-level standard	0.3123	0.3527	0.3937	0.0162	0.5440

Variable	(1) Tobin's Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
deviation Standard deviation of epsilon_it	0.2213	0.4688	0.2434	0.0129	0.6396

This table displays the results of the time series cross sectional regressions with fixed effects when regressing the dependent variables (firm's Tobin's Q, ROE, total risk, systematic risk, and idiosyncratic risk) on the predicted probability p01, which corresponds to the probability of a simultaneous low hedging intensity for oil and high hedging intensity for gas production coming from the bivariate probit estimation, and control variables related to firm's financial and operational characteristics, and oil and gas market conditions. Control variables are included in lagged values (first lag). See Table A.1 for more details on the construction of control variables. Heteroskedasticity-consistent standard errors clustered at the firm level are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table OA.4 – Real effects of univariate predicted probabilities of high intensity hedging for oil and gas

Variable	(1) Tobins'Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
Probability of high intensity hedging for oil	0.4929	0.9118	-0.5652**	-0.0229	0.1252
	(0.354)	(0.719)	(0.279)	(0.015)	(0.520)
Probability of high intensity hedging for gas	0.1506	-0.4527	-0.0817	-0.0133	0.2450
	(0.359)	(0.655)	(0.340)	(0.021)	(0.622)
EPS from operations	-0.0044	0.0035	0.0087	0.0005	0.0337**
	(0.007)	(0.022)	(0.012)	(0.001)	(0.014)
Investment opportunities	0.0063	-0.0945**	-0.0133	-0.0019*	0.1213***
	(0.029)	(0.045)	(0.018)	(0.001)	(0.039)
Leverage ratio	-0.0488	0.0976	0.3321*	0.0234*	0.3191
	(0.136)	(0.329)	(0.180)	(0.012)	(0.237)
Liquidity ratio	0.1272***	0.0794**	-0.0586**	-0.0027	0.1167
	(0.041)	(0.038)	(0.024)	(0.002)	(0.091)
Dividend payout	0.0594	0.0163	0.0197	0.0020	0.0721
	(0.083)	(0.055)	(0.043)	(0.003)	(0.102)
Oil reserves (in log)	-0.0571	0.0147	-0.0265	-0.0017	-0.0418
	(0.038)	(0.067)	(0.028)	(0.002)	(0.066)
Institutional ownership	0.0666	-0.1344	-0.1442	-0.0148*	-0.1837
	(0.094)	(0.200)	(0.133)	(0.008)	(0.292)
Oil geographical diversification	0.0994	0.4019	-0.1620	-0.0059	-0.5229
	(0.096)	(0.274)	(0.162)	(0.010)	(0.338)
Gas geographical diversification	0.3810	-0.0870	-0.5039	-0.0295*	0.1651
	(0.347)	(0.430)	(0.328)	(0.018)	(0.810)
Oil price volatility	-0.0358***	-0.0400**	0.0501***	0.0018***	0.0036
	(0.006)	(0.020)	(0.007)	(0.000)	(0.012)

Variable	(1) Tobins'Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
Oil basis	0.9598***	0.4342	-0.6179**	-0.0292*	-0.8083
	(0.244)	(0.432)	(0.305)	(0.017)	(0.756)
Oil production risk	-0.1338	-0.1877	0.0359	0.0037	0.1336
	(0.095)	(0.187)	(0.072)	(0.005)	(0.194)
Price_quantity correlation (oil)	0.1058**	0.0314	0.0144	0.0005	0.0482
	(0.047)	(0.043)	(0.036)	(0.002)	(0.097)
Gas basis	-0.0924	-0.1052	0.1522**	0.0062	0.0345
	(0.066)	(0.101)	(0.070)	(0.004)	(0.162)
Gas price volatility	0.0318	0.0248	0.0902***	0.0025**	0.0770
	(0.024)	(0.056)	(0.027)	(0.001)	(0.058)
Gas reserves (in log)	0.0512	-0.0956	0.0511	0.0003	0.1775*
	(0.058)	(0.098)	(0.049)	(0.003)	(0.098)
Gas production risk	0.0619	0.0180	-0.0485	0.0018	0.0575
	(0.123)	(0.148)	(0.073)	(0.005)	(0.187)
Price_quantity correlation (gas)	0.0247	0.0041	0.0437	0.0003	0.1191*
	(0.043)	(0.047)	(0.038)	(0.002)	(0.065)
CEO ownership	-2.8393	-12.7667	0.8968	0.1435	-4.2649
	(4.034)	(8.449)	(2.502)	(0.147)	(5.176)
Number of CEO's options	0.0006*	0.0004	0.0004	0.0000	0.0003
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Number of analysts	0.0133**	0.0141*	-0.0135***	-0.0007**	0.0028
	(0.005)	(0.008)	(0.005)	(0.000)	(0.010)
Constant	-0.1848	0.3279	0.4101	0.0403***	-0.4078
	(0.244)	(0.350)	(0.250)	(0.015)	(0.504)
Observations	574	571	573	555	555
R-squared	0.2491	0.0726	0.3364	0.2571	0.0619
Number of firms	79	79	78	75	75
F statistic	5.7147	2.7725	9.1221	7.4172	4.9281
Rho	0.6210	0.3762	0.7371	0.5845	0.4227

Variable	(1) Tobins'Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
Panel-level standard deviation	0.2732	0.3637	0.3957	0.0149	0.5472
Standard deviation of epsilon_it	0.2134	0.4682	0.2363	0.0125	0.6395

This table displays the results of the time series cross sectional regressions with fixed effects when regressing the dependent variables (firm's Tobin's Q, ROE, total risk, systematic risk, and idiosyncratic risk) on the predicted probabilities coming from a univariate probit estimation for a high intensity hedging for oil and gas separately, and control variables related to firm's financial and operational characteristics, and oil and gas market conditions. Control variables are included in lagged values (first lag). See Table A.1 for more details on the construction of control variables. Heteroskedasticity-consistent standard errors clustered at the firm level are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table OA.5 – Real effects of bivariate predicted probability of high intensity hedging for oil and gas simultaneously
assuming a zero correlation

Variable	(1) Tobins'Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
Joint predicted probability high intensity hedging	0.4419***	0.5319	-0.5200***	-0.0298***	0.2269
	(0.138)	(0.323)	(0.137)	(0.009)	(0.319)
EPS from operations	-0.0010	0.0139	0.0039	0.0003	0.0336***
	(0.006)	(0.026)	(0.010)	(0.001)	(0.013)
Investment opportunities	0.0118	-0.1023**	-0.0137	-0.0018*	0.1253***
	(0.033)	(0.044)	(0.017)	(0.001)	(0.041)
Leverage ratio	-0.0273	0.1847	0.3031	0.0230*	0.3105
	(0.126)	(0.330)	(0.197)	(0.013)	(0.238)
Liquidity ratio	0.0935**	0.0767**	-0.0322	-0.0012	0.0928
	(0.041)	(0.038)	(0.025)	(0.002)	(0.085)
Dividend payout	0.0434	-0.0001	0.0350	0.0026	0.0660
	(0.084)	(0.050)	(0.040)	(0.002)	(0.101)
Oil reserves (in log)	-0.0419	0.0371	-0.0417*	-0.0020	-0.0396
	(0.037)	(0.060)	(0.022)	(0.001)	(0.061)
Institutional ownership	0.0830	-0.0966	-0.1627	-0.0159*	-0.1758
	(0.101)	(0.177)	(0.139)	(0.008)	(0.289)
Oil geographical diversification	0.0667	0.2744	-0.1180	-0.0056	-0.5062
	(0.086)	(0.248)	(0.166)	(0.011)	(0.356)
Gas geographical diversification	0.4109	0.3557	-0.6083*	-0.0297*	0.0647
	(0.323)	(0.245)	(0.363)	(0.016)	(0.624)
Oil price volatility	-0.0349***	-0.0402*	0.0496***	0.0018***	0.0043
	(0.006)	(0.020)	(0.007)	(0.000)	(0.013)
Oil basis	0.8936***	0.5479	-0.6098**	-0.0284*	-0.8776
	(0.254)	(0.410)	(0.298)	(0.017)	(0.756)
Oil production risk	-0.1342	-0.2052	0.0423	0.0043	0.1332
	(0.099)	(0.193)	(0.074)	(0.005)	(0.195)
Price_quantity correlation (oil)	0.1281***	0.0609*	-0.0077	-0.0003	0.0557
	(0.046)	(0.032)	(0.038)	(0.002)	(0.092)
Gas basis	-0.0855	-0.1041	0.1473**	0.0061	0.0363
	(0.067)	(0.099)	(0.067)	(0.004)	(0.162)

Variable	(1) Tobins'Q	(2) ROE	(3) Firm risk	(4) Specific risk	(5) Market risk
Gas price volatility	0.0416*	0.0439	0.0797***	0.0022*	0.0779
	(0.022)	(0.050)	(0.027)	(0.001)	(0.054)
Gas reserves (in log)	0.0421	-0.1548**	0.0707	0.0006	0.1891**
	(0.050)	(0.076)	(0.047)	(0.002)	(0.080)
Gas production risk	0.0250	-0.1367	0.0124	0.0039	0.0660
	(0.085)	(0.136)	(0.074)	(0.005)	(0.166)
Price_quantity correlation (gas)	0.0138	0.0057	0.0522	0.0009	0.1107*
	(0.044)	(0.045)	(0.036)	(0.002)	(0.065)
CEO ownership	-2.2538	-9.0683	-0.3069	0.1276	-4.9444
	(3.119)	(8.359)	(2.598)	(0.126)	(4.148)
Number of CEO's options	0.0006*	0.0003	0.0005	0.0000	0.0003
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Number of analysts	0.0108**	0.0172*	-0.0123***	-0.0006**	0.0000
	(0.004)	(0.009)	(0.004)	(0.000)	(0.009)
Constant	0.0062	0.5713*	0.1925	0.0301*	-0.3379
	(0.239)	(0.333)	(0.281)	(0.016)	(0.489)
Observations	574	571	573	555	555
R-squared	0.2249	0.0716	0.3264	0.2506	0.0608
Number of firms	79	79	78	75	75
F statistic	4.5536	2.4361	8.7589	7.3855	4.2275
Rho	0.6309	0.3790	0.7365	0.5939	0.4207
Panel-level standard deviation	0.2832	0.3656	0.3976	0.0152	0.5447
Standard deviation of epsilon_it	0.2166	0.4680	0.2378	0.0126	0.6392

This table displays the results of the time series cross sectional regressions with fixed effects when regressing the dependent variables (firm's Tobin's Q, ROE, total risk, systematic risk, and idiosyncratic risk) on the predicted probabilities of a high hedging intensity for oil and gas simultaneously. This joint predicted probability is the product of the two probabilities coming from a univariate probit estimation for a high intensity hedging for oil and gas separately assuming a zero correlation between residuals. Control variables related to firm's financial and operational characteristics, and oil and gas market conditions. Control variables are included in lagged values (first lag). See Table A.1 for more details on the construction of control variables. Heteroskedasticity-consistent standard errors clustered at the firm level are reported in parentheses. The superscripts ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.