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Effects of oil price uncertainty on the comparability between observed premiums and real options premiums: evidence from acquisitions

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, second reader, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

In my study, I explore the effects of oil price uncertainty on the premium spread – the difference between a hypothetical real options premium and the actual premium paid in historical acquisition deals. In this premium spread, I calculate the hypothetical real options premium for 263 acquisitions between 1991-2021 using the dividend-adjusted Black-Scholes model. Using both Ordinary Least Squares and Logistic Regressions, I find that an increase in oil price uncertainty, on average, decreases the premium spread. I also find that oil price uncertainty is unable to explain the probability that an acquiring company overpays for its target company. My study implies that, as oil price uncertainty increases, the premiums estimated using real options theory become more comparable to the actual premiums paid by companies. This finding should encourage reluctant investors and top management to complement their standard valuation practices with real options analysis in the presence of oil price uncertainty.

Keywords: oil price, real option valuation, mergers and acquisitions, uncertainty

JEL codes: E23, G11, G34

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CHAPTER 1 Introduction

Amidst the recent rise in global tension, the sizeable impact that uncertainties in the commodity market can have on the global economy has become the focus of academia. More recently, the uncertainty in oil prices has risen because of the Russia-Ukraine War (Fang & Shao, 2022). Due to this uncertainty in oil prices, both individuals and businesses have been affected through multiple facets such as household spending and weaker confidence in financial markets (Liadze et al, 2022). Aside from these macroeconomic effects, an interesting and relevant notion to consider is how it could be affecting the realm of corporate finance. Within this realm, a multitude of techniques exist that practitioners can use to value investments. An increasingly popular family of such valuation techniques is Real Options Valuation (ROV). While ROV models bring forth several advantages, simpler and more straightforward models such as the Net Present Value (NPV) and Discounted Cash Flow (DCF) models are still considered standard practices across industries (Block, 2007). Academics and practitioners primarily attribute the limited use of ROV models to their complexity and encouragement of excessive risk-taking. However, academia has not sufficiently explored whether the introduction of oil price uncertainty corroborates these limitations and, consequently, lead to the sustained unpopularity of ROV models. Therefore, the question arises: how comparable are the results of ROV models to the results that companies ultimately arrive at as oil price uncertainty changes?

Conveniently, existing finance literature has partially researched this relationship. On the ROV side, the findings of Dunis & Klein (2005) suggest that a difference in the real options and actual takeover premiums (the difference between the acquisition's total deal value and the target's current market value at the time of acquisition) exists but is inconsistent. In their study, they investigate fifteen acquisition deals – a financial event in which an acquiring company (acquiror) purchases majority stakes from its target company (target) - in the European financial services sector in the 1990s. They find that seven of the fifteen targets were undervalued, given that the real options premium was above the actual takeover premium. They also find that the actual volatility of the target was higher than the volatility used by the acquirors in their valuation process, demonstrating how acquirors in their dataset may have underestimated changes in volatility. On the oil price uncertainty side, Barrows et al. (2023) relate oil price uncertainty to Mergers & Acquisitions (M&A) activity in the Oil & Gas (O&G) industry using 4,323 M&A transactions. With the use of a Distributed Lag model in which the percentage of acquisition change is regressed against one lag of oil price uncertainty, they conclude that an increase in oil price uncertainty leads to a decrease in M&A activity. They also conclude that firms operating in the 'upstream' – that is, on the side of oil extraction and refining - are more sensitive to this uncertainty, as opposed to downstream firms that focus on oil distribution.

Despite such existing studies on real options benchmarking and oil price uncertainty effects, no study has looked specifically at the direct relationship between the two. This research gap can be attributed to practitioners writing off ROV analysis due to the limitations previously mentioned. As such, my contribution to existing literature comes from my aim to address the reluctance of companies in the application of ROV models. If the results of ROV theory are comparable to results observed in historical acquisitions in the presence of oil price uncertainty, companies that overlook ROV analysis should not shy away from including it in their valuation practices. Furthermore, it may indicate that more companies are beginning to include ROV analysis in their valuation practices. My approach is also unique in its use of the spread between the real options and actual takeover premiums. This way, I can quantify the magnitude by which the results between ROV and real-life results differ.

Therefore, to investigate these potential relations, I will replicate the methodology of Dunis & Klein (2005) and expand on the investigation of Barrows et al. (2023) on oil price uncertainty. Firstly, I use the approach of Dunis & Klein (2005) in calculating the real options and actual takeover premiums. Then, I use both an Ordinary Least Squares (OLS) and Logistic (Logit) regression to explore how oil price uncertainty affects the spread between the real options premium and the actual premium paid by the acquiror. In effect, I will replicate Dunis & Klein (2005) by changing the context of the model they used, and conceptually expand the framework of Barrows et al. (2023) by replacing M&A activity with the spread in the real options premium and takeover premium in the regression. My study's research question is therefore:

"How does oil price uncertainty affect the spread between the real options premium and the actual takeover premium paid by companies in acquisition deals?"

Given this research question, I will conduct analyses on a sample of 263 acquisitions that occurred between 1991-2021. Following Dunis & Klein (2005), the methodology will first make use of the dividend-adjusted Black-Scholes formula to estimate real options premiums per acquisition. This real options premium will then be compared to that specific deal's actual takeover premium. The spread between these two premiums will be regressed, using OLS, on oil price uncertainty alongside control variables. The control variables will be market uncertainty, economic policy uncertainty, firm-specific financials, and industry classification. I will also generate a binary variable based on whether the real options premium is less than the actual takeover premium. This binary variable will be fed into a Logit Regression in which it will be regressed against oil price uncertainty and the same control variables as aforementioned.

In my study, I find that an increase in oil price uncertainty, on average, decreases the spread between the real options premium and the actual takeover premium. In other words, the real options and actual takeover premiums become more comparable to each other as more oil price uncertainty is introduced. Furthermore, oil price uncertainty does not sufficiently explain the probability of the actual takeover premium being greater than the real options premium.

I structure my study as follows. In Chapter 2, I review existing literature on ROV theory as well as oil price uncertainty. I also explain the advantages and limitations of ROV models in comparison to standard valuation models. In Chapter 3, I explain my data collection and processing to facilitate the analysis between ROV results, historical acquisition results, and oil price uncertainty. Then, I describe the setup of the OLS and Logit Regression models that I use to conduct analysis on the processed data in Chapter 4. The results are then reported and consequently discussed in Chapter 5, in which I evaluate the performance of each model and the effects of the explanatory variables. I separate the discussion of oil price uncertainty from other variables given that it is the variable of interest in my study. In Chapter 6, I summarize my findings while also mentioning implications, limitations, and potential future research for my study.

CHAPTER 2 Theoretical Framework

2.1 Real Options Valuation (ROV)

ROV is, simply put, the application of option pricing models on a firm's investment opportunities. Since its conception by Stewart Myers in 1977, ROV has expanded into several applications which can be categorized as options that a firm can make towards a project. This is analogous to the definition of a real option according to Antikarov & Copeland (2001), in that it is "the right, but not the obligation to take an action" at a "predetermined price … for a predetermined period of time" (p. 5). These options mostly take the form of the following: (1) option to expand, (2) option to abandon, (3) option to wait/defer, and (4) option to contract. For instance, a semiconductor company that can easily expand its production rate may conduct real options analysis to decide, based on the success of its product, to do so. If the sales of its products are less than expected, then ROV theory will estimate an investment value that will inform this company not to expand. As such, these different approaches allow a company to personalize the model to accommodate their goals, while still being bounded by conventional practices in valuing options. More theoretically, Myers (1977) states that ROV is akin to thinking of assets as call options such that their value partially depends on "further discretionary investment" (p. 17).

Over the past five decades since its conception, ROV has garnered a lot of attention from academics and practitioners alike. While other valuation methods are built upon static analysis (refer to section 2.1.1), ROV models allow the user to factor in the concept of time and flexibility. This idea of flexibility is only remotely possible outside of ROV using Decision Tree Analysis (refer to section 2.1.2).

This dynamism that ROV offers is most evident in that it is an antithesis to the concept of short-termism. Short-termism, as defined by Myers (2015), is the phenomenon with which investors prefer "quick financial results" over long-term value (p. 17). Amongst the three reasons stated, the author finds that short-termism occurs at the unawareness that investment payoffs are generated from the future exercise of real options. In other words, the benefits of taking on investments are only realized once a decision to, for instance, expand is made. In their paper, the author uses an aircraft as an example: while the initial build of the aircraft generates a negative payoff, the creation of a successful build grants management the option to modify or re-engine future builds. As evident, the success of the initial build does not lead to an obligation for management, but rather options that they can take to develop their project.

These benefits are best captured by two dominating models within ROV theory - the Cox-Ross-Rubenstein (CRR) and Black-Scholes (BS) models (Danylyshyn et al., 2019). The former model operates in a decision tree system, in which the option value is based on the "binomial law": its value can either increase or decrease to a respective up- or down-state (p. 2697). This system can then be expanded into multiple steps that result in an increasing number of lattices. One limitation of the CRR, according to Wang & de Neufville (2005), is its assumption that there is no path-dependency in the process. In the previous case of the semiconductor company, a consolidated increase in sales means that the production facilities must be expanded. In this context, Wang & de Neufville (2005) highlight that, for example, such expansion may lead to the unseen expansion of a facility's thermal power system because of more electricity use. Above all, this increase in capacity would result in more efficient production. Conversely, if an increase in sales is not met, then this thermal power system's capacity would not considerably increase, and an expansion in production down the line will not benefit from this capacity increase. Hence, this assumption holds in the realm of option pricing but falters in the application of ROV, given that real-life investments are almost always path-dependent.

The BS, on the other hand, operates more algebraically. For this same reason, it is bounded by more assumptions than the CRR. To foreshadow the Methodology section, the BS is a limited version of the CRR model in that it assumes an infinite number of steps in the binomial lattice. This assumption leads to the use of a continuous distribution to value options. This is different from discrete distributions which can only take on a finite number of values. For example, rolling a die follows a discrete distribution since it can only take integer values between one and six. However, measuring an individual's weight would follow a continuous distribution, since it can take on any value within an interval of outcomes. One individual's weight may be 72.60 KG, while another may be 95.22 KG. In the context of stock prices, a continuous distribution entails a "continuum of possible stock price changes" (Allen et al., 2014, p. 545). In this regard, the application of the BS model is appropriate when valuing the stock and, consequently, the value of a company.

However, the use of a continuous distribution is widely considered the BS' biggest limitation; as I explain in section 2.1.2, the BS model makes use of mathematics that is not easily understood by most managers. Ironically, Perlitz et al. (1999) also consider the BS' use of a continuous distribution to be its greatest strength since it allows for "closed-form solutions" (p. 10).

2.1.1 ROV versus NPV

As aforementioned, ROV's biggest benefit is its ability to incorporate flexibility in investment decision-making. This feature is not possible in models such as the commonly used Net Present Value (NPV) model, in which, according to Triantis (2005), it is assumed that projects only follow one path of uncertainty resolution. Furthermore, standard NPV analyses place very little value on options for possible investments. Firms are assumed to either invest all their allocated capital at the moment of analysis (if NPV is greater than zero) or not (if NPV is less than zero). These limitations are directly corrected by ROV, given that: (1) all possible scenarios are considered, and (2) it could suggest a certain amount of time to expand/defer/abandon an investment. Recent advances in the realm of ROV further reinforce its advantages over the NPV model. Davis & Cairns (2017) finds that, in the case of perfect reversibility (that lump investments made for a project can be fully reversed), NPV analysis is unnecessary since risk profile, volatility, and growth rate of future cash flows are irrelevant. Instead, investors can simply compare the marginal revenue of the investment with “Jorgenson’s cost of capital” (p. 173). On the other hand, when a degree of irreversibility is introduced to the investment path, the ROV approach is most relevant since it can measure optimal timing.

A stronger opponent of the ROV - according to Antikarov & Copeland (2001) - is Decision Tree Analysis (DTA), which also makes use of a lattice system to value investments. This model combats the NPV limitation of focusing on most-likely values. Instead of operating using only the value that is most likely to be observed, DTA recognizes and focuses on multiple ‘steps’ or ‘scenarios’ that the value of the investment can take on, allowing top management to identify and decide how to continue with the investment for each step of the tree. As such, it has become common practice to complement an NPV model with DTA analysis.

While DTA corrects the rigidness of the NPV approach, it still has disadvantages, both in general and vis-à-vis ROV. Antikarov & Copeland (2001) explains that DTA violates the “law of one price” (p. 91). In a scenario where a firm uses DTA to determine if a potential investment should be deferred, the firm must calculate a project-wide discount rate based on expected cash flows and their respective probabilities. However, this fixed discount rate, which is applied to all steps of the tree - will not match the cash flows posited by all options in the tree. Firstly, both the option and cash flow payoffs will differ at each point of the tree. The use of a fixed discount rate is already incorrect since the firm erroneously assumes that all payoffs in the tree have the same probabilities. In essence, this change in probabilities means that risk is not constant throughout the tree. Secondly, recall that options can either provide a positive payoff or a zero payoff since the option holder is not obliged to exercise the option if it leads to a loss. Cash flows cannot be modeled in the same way. If the investment cost is larger than the expected cash flow at certain points of the tree, then the lower bound of the cash flow interval at those points will be negative and not zero. There would then be an inconsistency between the option and expected cash flow payoffs, violating the law of one price.

Secondly, and in conjunction with the previous limitation, DTA is only concerned with scenarios that are distinctly separate – or, in mathematic jargon, mutually exclusive - from each other. For instance, the general practice in DTA is to create two scenarios against the most-likely scenario: the bull and bear cases. The former depicts an optimistic future path, while the latter depicts a pessimistic path. While this is more robust to future uncertainty compared to traditional NPV analyses, it is still inferior to what ROV analysis offers. As previously mentioned, ROV models operate through a continuous distribution which, as best described by Triantis (2005), considers “all possible future paths” (p. 15).

2.1.2 Usage in the real world

The increasing number of research papers written on the topic of ROV theory has not translated to a proportional increase in firms that have adopted this valuation practice. Multiple papers still point towards the fact that NPV models are still the leading model for valuation in virtually all valuation practices. The study of Graham & Harvey (2001) finds that 75% of CFOs that responded used NPV "always or almost always" in valuing potential M&A deals. Similarly, Block (2007) finds that only 14.3% of respondents from a data universe within the Fortune 1,000 index conducted ROV analysis, while 25.3% considered using the method in the future. According to their survey, the author finds that ROV is unpopular for four main reasons: (1) lack of support from top management; (2) the DCF and NPV models are already proven; (3) ROV encourages taking on more risk than appropriate; and (4) it requires too much sophistication.

Additionally, another reason for this general unpopularity is best described by Triantis (2005) in its "Real Options as an Extreme Sport" critique (p. 5). The author explains that, while conducting ROV carefully is impressive, ROV users are unlikely to feel comfortable attempting such analysis in their own business or explaining it to top management. Indeed, this critique is similar to the above-mentioned reasons that Block (2007) found. This is hardly a surprise; static models such as the NPV have been generally accepted due to their simplicity and straightforwardness. It is this simplicity that allows for the eventual creation of heuristics, allowing companies to rely on rule-of-thumb analyses that are generally accurate. This simplicity also allows investors to apply valuation techniques to factors that do not feed into ROV models. One example of such a factor is synergy. Synergy, according to Damodaran (2005), is conventionally valued by comparing the separate DCF estimates of the acquiror and target with the estimate of the combined company. This combined company estimate is conducted using "expected growth rates and cash flows" that arise due to the acquisition (p. 7). In ROV models, however, the combined company estimate - as I explain in detail in section 4.1 – is simply the separate future market values of the acquiror and target added together. In effect, their market values are not jointly estimated using the same expected growth rate and cash flows but are instead treated as separate entities throughout the valuation process.

2.2 Oil Price Uncertainty (OPU)

The topic of oil and its price is interesting since, as echoed beforehand, it is regarded as one of the most important commodities in the world. This has many implications, all of which suggest one important notion: that changes in oil prices can have serious consequences on the macro- and micro-economic setting. From a macroeconomic perspective, changes in oil prices can change the geopolitical and economic relationship between countries, as seen recently through the Russia-Ukraine War (Liadze et al. 2022). On the other hand, individuals and businesses together are impacted by factors such as energy costs. For these reasons, the subject of oil price uncertainty has become increasingly popular.

Arguably the most affected by OPU - at least in the world of corporate finance - are firms that operate in the upstream O&G business. Fonseca et al. (2017) investigate the difference in the value of African oil fields when applying NPV versus ROV. Here, the variation between ROV theory and standard practices is best observed. Naturally, the standard NPV approach does not factor in OPU. Hence, when applied against predicted oil prices, the authors arrive at a negative NPV of USD -968,000,000 for the oil field (p. 301). Conversely, when incorporating OPU and managerial flexibility using ROV theory in the form of a CRR model, the oil field's estimated value not only becomes positive but rises to a value of USD 432,000,020 (p. 302). In this case, the combination of ROV and OPU demonstrates how the value of the option premium increases with uncertainty. This is supported by Haushalter et al. (2002), in which it is also mentioned that the value of oil reserves, and consequently "the equity value of oil producers" should increase with oil price uncertainty (p. 272). In essence, the standard practice of using the most-likely scenario in NPV analysis versus the incorporation of a binomial tree in ROV analysis is applied, in which the latter is successful in identifying the merits of uncertainty. However, this proportionality may be a sign of caution, rather than a sign to invest.

This sign of caution is investigated by Barrows et al. (2023) through their investigation of OPU effects on M&A activity in the O&G sector. Using time-series analysis, the authors find that the acquisition likelihood of firms decreases during years of high "crude oil price uncertainty" (p. 73). Furthermore, they find that both vertical and horizontal M&A deals are affected similarly, with mixed evidence that vertical deals are more affected. Vertical deals occur within the supply chain which, in the context of the O&G sector, is best characterized by the integration of upstream operations such as oil drilling with downstream operations such as oil processing. In theory, vertical deals will be more affected vis-à-vis horizontal deals since the objective of the latter is to diversify. Nevertheless, the authors find that firm-specific factors such as "return on assets, dividend payers, and capital availability" have more of an impact on M&A activity (p. 75). One of the most important findings in this article, however, is that OPU has stronger explanatory power in the change of M&A frequency over economic policy uncertainty.

Outside of corporate finance, OPU also influences the stock market – in particular, investor reaction to certain movements. Dutta (2017) investigates how OPU could affect stock returns for clean energy firms. Using the returns of the CBOE Crude Oil Volatility Index (OVX) as a proxy for OPU – as opposed to "traditional oil price series" that is usually employed – the author finds that a decrease in the OVX leads to a decrease in the volatility of clean energy prices (p. 1164). Consequently, the author finds evidence that a decrease in this volatility encourages investors to finance new energy firms more. This is partially in line with the findings of Barrows et al. (2023), in which less oil price uncertainty leads to an increase in M&A activity.

Of course, the effects of OPU are not limited to the realm of corporate finance. In fact, its effects are stronger in other facets of business. One such facet is its effects on energy consumption by companies. Intuitively, an increase in OPU will induce firms to consume less energy to reduce costs. Kuper & Soest (2006) finds that the elasticity of energy demand in firms is asymmetrically impacted by OPU – asymmetric in that an increase in energy prices leads to a smaller decrease in energy use, whereas a decrease leads to a stronger increase in usage.

Perhaps one of OPU's most serious implications is its effects on unemployment rate. Kocaaslan (2019) finds that OPU amplifies the increase in unemployment rate, at least in the US. Using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, they find that the conditional variance of the change in oil price is significant at the 1% level. They also find that - in accordance with Kuper & Soest (2006) - there is sign asymmetry, in that positive oil price shocks "significantly increase unemployment" as opposed to negative shocks that only bring slight improvements (p. 580).

What is not clear in the realm of OPU however, is how to measure it. Simply put, there is no consensus in academia as to how this should be done. Where Dutta (2017) uses the returns of the OVX as a measure of OPU, Kuper & Soest (2006) and Kocaaslan (2019) make use of a GARCH model using oil prices. Barrows et al. (2023) then use an estimate of implied volatility instead of the GARCH. The easiest method is that of Phan et al. (2020), in which the authors manually calculate the standard deviation using oil prices. In essence, these different approaches to measuring OPU infers how undeveloped the study of OPU is.

2.3 Hypotheses

Based on the presentation and discussion of existing literature thus far, I am now able to formulate two relevant hypotheses that I will test in my study.

Hypothesis 1: An increase in OPU increases the spread between the hypothetical premium calculated by ROV theory (ROV Premium) and the premium observed in historical acquisitions (AT Premium).

Hypothesis 1 is rooted in the mathematics of the BS, in that an increase in uncertainty increases the value of the option (refer to section 4.1.2). This proportionality is also corroborated by the findings of articles explored in section 2.2, in which oil price uncertainty increases the ROV Premium (Fonseca et al., 2017; Haushalter et al., 2002). An increase in OPU, ceteris paribus, would then lead to an increase in the value of the ROV Premium. If companies still generally use NPV-based models in their valuation analysis as postulated by Block (2007) in section 2.1.2, the AT Premium will be smaller for acquisitions that occurred in periods of high OPU. As Koller et al. (2015) explain, higher uncertainty in the stock returns of a company will lead to a higher discounting factor in both the NPV and DCF models. An increase in uncertainty will make firms more conservative, increasing the discount rate they use and consequently decreasing the value of the acquisition. Hence, the acquisition value will be closer to the market value of the target company. The combination of an increasing hypothetical ROV Premium and decreasing AT Premium in historical acquisitions will lead to the premium spread becoming larger.

Hypothesis 2: An increase in OPU decreases the probability that an overpayment occurs.

In the context of acquisitions, overpayment is defined as the acquiror paying a premium for a target that is larger than the premium estimated by valuation analysis. Based on this definition, I hypothesize that an increase in OPU decreases the probability of overpayment. In other words, that an increase in OPU decreases the probability that the hypothetical ROV Premium is systematically lesser than the AT Premium. This hypothesis is like Hypothesis 1 in that its mechanism is explained using the proportional relationship between uncertainty and the ROV Premium. As OPU increases, the ROV Premium increases while the AT Premium decreases. Therefore, the probability that the ROV Premium is systematically lesser than the AT Premium decreases. This systematic difference will potentially be explained by the findings of Liadze et al. (2022), in which an increase in OPU because of the Russia-Ukraine War has negatively affected investor confidence in financial markets. If the same finding is observed during other periods of higher OPU, then the AT Premium will also decrease substantially and fall under the ROV Premium.

CHAPTER 3 Data

3.1 ROV variables

To facilitate the calculation of the ROV Premium, several variables that feed into option pricing are first converted into ROV variables. This conversion replicates the method used by Dunis & Klein (2005), in which they make use of a dividend-adjusted BS to calculate the ROV Premium. Most of the data necessary to calculate the ROV Premium were collected from CapitalIQ (2023) using its screening application. In this application, I make use of relevant filters to collect data that fit the criteria also set forth by Dunis & Klein (2005). Table 1 describes the filters used.

Filter	Value
Industry Classification	Energy; Industrials; Technology; Healthcare; Utilities
Date Announced	01 Jan 1991 to 31 Dec 2021
Acquisition Status	Closed
Company Type	Public Company

Table 1: Filters for Acquisition deals screening in CapitalIQ.

Amongst the filters, an important factor is that both the acquiror and target must remain public after the acquisition, at least for a period of one year before and after. This is important as it allows me to determine a hypothetical future market value – one year after the acquisition - for both the acquiror and target. It is also important to filter only for acquisitions that have been closed (in other words, the acquisition process has been completed); otherwise, incomplete acquisitions that are still ongoing or were unsuccessful may be included. I also include acquisitions from the five industry classifications in table 1 to enable inter-industry comparative studies. Based on the data collection by Maghyereh & Abdo (2020), the financial, insurance, real estate, not-for-profit organizations, and governmental enterprises industries are particularly omitted since these industries are heavily characterized by a "regulatory footprint" (p. 6). After eliminating observations that were missing data, I arrive at a data universe consisting of 263 M&A deals between January 1, 1991, and December 31, 2021.

Data regarding the interest rates are gathered from Finaeon (2023), in which data regarding bond yields per country were available as far as 1928. In conjunction with the acquisition data, I collect bond yields starting from January 1, 1991, until December 31, 2021. Here, I use the 3-month Treasury Bill Yield per country that appeared in the dataset, following the data collection applied by Dunis & Klein (2005). Moreover, I determine these yields monthly. This is because daily yields for most countries are unavailable between 1991 and 2021. Therefore, when determining the domestic rate in ROV calculations, the relevant month's bond yield will be used. Finally, I collect the uncertainty (standard deviation) of each acquiror once again using CapitalIQ (2023). This was done using CapitalIQ functions in Excel, in which uncertainty for each acquiror was measured one year after the acquisition occurred.

3.1.1 Premium variables

Firstly, I perform the calculation of the ROV Premium using the dividend-adjusted BS formula (refer to section 4.1), which is in line with the method of Dunis & Klein (2005). Then, to calculate the AT Premium, I subtract the target's market value (in other words, market capitalization) four weeks prior to announcement from the total acquisition value that the acquiror paid for the target. I measure market value four weeks prior as opposed to the day of announcement since this eliminates any effect from market reactions. Both values are also calculated in USD.

Continuing with the methodology of Dunis & Klein (2005), I transform the ROV and AT Premiums to percentage values, benchmarked against the cumulated market value of the acquiror and the target four weeks prior to announcement. Taking these two sets of observations, I calculate Premium Spread which I define in my study as the difference, in percentage terms, between the ROV and AT premiums. I also transform Premium Spread by means of cube-rooting. I explain this transformation in more detail in section 4.2.

	Observations	**Mean**	**Standard Deviation**	**Min**	**Max**
ROV Premium	263	20.86%	.117	2.28%	81.96%
AT Premium	263	13.22%	.216	-20.52%	128.67%
Premium Spread	263	7.64%	.232	-110.67%	66.47%

Table 2: Descriptive Statistics for Premium variables.

Note: Mean, Minimum, and Maximum are measured in percentage terms. ROV Premium and AT Premium are benchmarked against the cumulated market value of the acquiror and target four weeks prior to announcement.

Firstly, I observe that the ROV Premium is, on average, larger than the AT Premium. I also observe that the standard deviation of the ROV Premium is lesser than that of the AT Premium. A potential reason for these initial findings is that I calculate all ROV Premium using the same model and that it cannot be less than zero. Therefore, the variation in the ROV Premium is unaffected by negative observations that may decrease its sample mean. Conversely, the AT Premium may be calculated using any valuation technique. It can also be less than zero in the case that the acquisition value of the target is smaller than its market value four weeks prior to announcement.

3.1.2 Overpaid dummy variable

Following the probabilistic nature of Hypothesis 2, I must construct a binary variable. This means that the variable must only possess either the values 0 or 1, which are mutually exclusive from each other. Hence, I separate the differences in the ROV and AT Premiums into whether the latter is larger than the former. If so, then the acquisition is considered overpaid since the actual premium paid is larger than what is estimated using ROV analysis. This way, I successfully separate the two cases, allowing me to regress the explanatory variables on a binary variable to explore Hypothesis 2.

3.2 Uncertainty variables

3.2.1 Oil Price Uncertainty (OPU)

I first collect oil price data from US Energy Information Administration (2023a). Here, I download West Texas Intermediate (WTI) oil spot prices with a daily frequency between January 1, 1991, and December 31, 2021. The use of WTI over Brent crude oil follows the methodologies of previous studies within the oil price uncertainty realm (Phan et al, 2020; Maghyereh & Abdoh, 2020). Then, to determine the annualized uncertainty, I first calculate the daily percentage return of the underlying spot prices. Following the methodology of Maghyereh & Abdoh (2020), I make use of equation (1) to calculate the annualized uncertainty of oil prices,

$$OPU_t = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(r_t - E(r_t))^2} * \sqrt{N} \tag{1}$$

in which $E(r_t)$ is the average return measured across the time horizon, N is the number of days in a year that a spot price was measured, and r_t is the daily oil return which is calculated using equation (2),

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{2}$$

where p_t and p_{t-1} represent the current and previous daily oil spot prices, respectively.

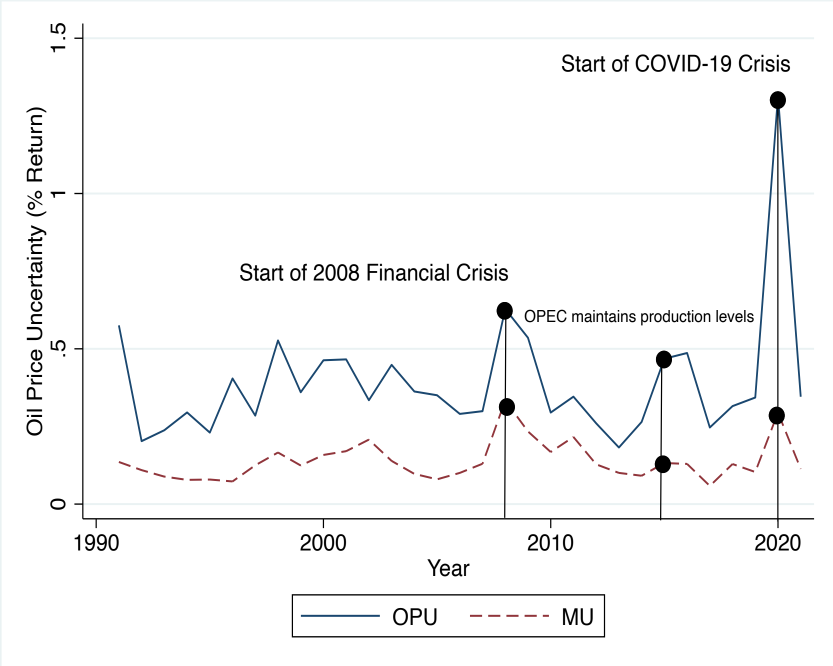

Figure 1: Oil price uncertainty (OPU) and market uncertainty (MU) between 1991-2021.

As can be seen in figure 1, this OPU variable successfully reacts to events that could raise uncertainty in oil prices. One example of this is the heightened uncertainty between 2008-2009 due to the 2008 global financial crisis. Additionally, the increase between 2015-2016 in OPU may be a result of a perceived global oversupply of oil and the Organization of the Petroleum Exporting Countries' consequent decision to maintain current production levels (Arezki & Matsumoto, 2017). Of course, the 2020 rise in uncertainty is a result of the COVID-19 pandemic and its negative implications on the global economy.

3.2.2 Market Uncertainty (MU)

According to Koller et al. (2015), a "value-weighted, well-diversified market portfolio" is most appropriate for modeling stock and market returns (p. 298). For this reason and as used by Phan et al. (2020), I opt to proxy market uncertainty using the Morgan Stanley Capital International (MSCI) World Index. By performing the same method of modeling the uncertainty of oil prices using equations (1) and (2), I arrive at an appropriate measure of MU. Figure 1 also illustrates the corresponding uncertainty curve of MU that will be used in the analysis.

When comparing OPU and MU, I observe that they seem to follow an identical pattern across the study's time horizon. The same rise in uncertainty in 2008 and 2020 is observed in both uncertainty measures. However, the increase in OPU between 2015 and 2016 is not directly observed in MU, which demonstrates that there are events that asymmetrically affect both variables. The uncertainty in the index I use to proxy MU is also less volatile, given that MU is never larger than OPU across the time horizon.

3.2.3 Economic Policy Uncertainty (EPU)

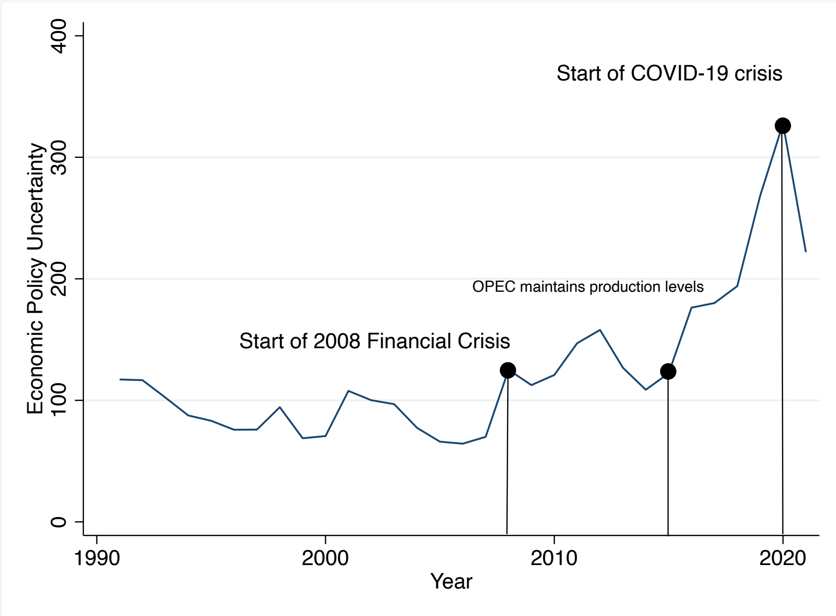

Figure 2: Economic Policy Uncertainty (EPU) between 1991-2021.

As is done by Barrows et al. (2023), I opt to also control for EPU. This data is taken from Baker et al. (2023), in which data take on the form of an index that measures EPU using "newspaper coverage frequency" (Baker et al., 2016, p. 1598). Both economic and non-economic events across the short-term and long-term feed into this EPU value. Baker et al. (2016) describe the process of creating this uncertainty index as follows. First, they obtain a monthly count of keywords that are related to economic uncertainty from the "leading newspapers" of a country (p. 1599). Then, they perform a time-series regression that models the average unit standard deviation for each interval. These unit standard deviations are finally normalized, allowing the EPU series to act as an index. For this reason, EPU is different from OPU and MU since the underlying source of uncertainty of the former is not the return of an underlying instrument. Despite this difference, figure 2 demonstrates that OPU/MU and EPU follow a similar trend across the time horizon. After the 2008 financial crisis, however, EPU seems to consolidate while OPU and MU fall back to previous yearly trends.

CHAPTER 4 Method

My methodology consists of three stages: (1) the calculation of the ROV Premium to construct the Premium Spread variable, (2) an OLS Regression, and (3) a Logit Regression.

4.1 Calculation of the ROV Premium

To calculate the hypothetical ROV Premium, I start by defining the underlying ROV theory. Understanding the Cox-Ross-Rubenstein Model (CRR) is necessary to understand the dividend-adjusted BS model implemented by Dunis & Klein (2005). As mentioned in section 2.1, the CRR is best characterized by its use of a binomial distribution to value options. In other words, it is assumed that, at a certain point in time, the price of the underlying stock (S) either increases or decreases to a respective up (S_u) and down (S_d) value. This is best illustrated through a binomial tree, which includes S, S_u, and S_d. Then, to calculate a call option premium through CRR, an option valuation lattice must also be constructed in which C_u and C_d are calculated. These two systems are illustrated in figure 3.

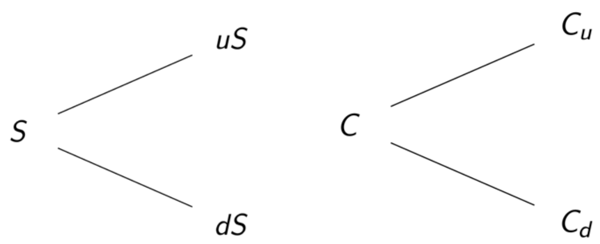

Figure 3. One Period Binomial Tree (left diagram) and Options Valuation Lattice (right diagram).

Then, to solve for the option value, Antikarov & Copeland (2001) explain the mechanisms of the "replicating portfolio approach" (p. 93). This approach involves replicating an option through a combination of two financial instruments: stocks and bonds. Namely, we need to find the number of shares (Δ) and how much we should borrow or lend (B) to replicate an option. An important assumption made is that the underlying stock has a continuous (re-invested) dividend yield of δ, hence why academics describe the model as dividend-adjusted. As such, the number of shares bought/sold at a future point in time $t + h$ – where h represents an increase in time - is equal to $e^{\delta h}$. This gives us a hypothetical portfolio value of $\Delta S_h e^{\delta h}$ with S_h being the price of the stock at time h. Similarly, the bond will also increase in value according to an interest factor of e^{rh}, where r represents the risk-free interest rate. Therefore, to replicate the option payoff, the following combination of the stock and bond,

$$\Delta S_h e^{\delta h} + e^{rh} B \tag{3}$$

will be bought and borrowed. This relationship allows for the calculation of C_u and C_d, depending on which way the stock price moves,

$$\left(\Delta * uS * e^{\delta h}\right) + \left(B * \ e^{rh}\right) = C_u \tag{4}$$
$$\left(\Delta * dS * e^{\delta h}\right) + \left(B * \ e^{rh}\right) = C_d \tag{5}$$

where u and d represent the up and down movement in the price of the underlying stock, respectively. Hence, to calculate the value of an option using the replicating portfolio approach, equation (6) must be solved,

$$\Delta S + B = \ e^{-rh}(C_u \frac{e^{(r-\delta)h} - d}{u-d} + C_d \frac{u - e^{(r-\delta)h}}{u-d}) \tag{6}$$

in which the equation's left side represents the number of stocks and buy/short as well as the amount to borrow/lend to replicate the value of the option premium.

An applied case of the CRR is the BS model. This model is best described, according to Mcdonald (1982) as a "limiting case of the binomial formula", given that it assumes an infinite number of steps in the binomial tree (p. 349). This infinite number of steps translates to the model's use of a cumulative normal distribution to describe stock returns. Hence, to calculate a call option, Antikarov & Copeland (2001) draws on the put-call parity condition to determine the following equation,

$$C = Se^{-\delta T} N(d_1) - Ke^{-rT} N(d_2) \tag{6}$$

where K represents the strike price – the price threshold at which the option is exercised. In this equation, Antikarov & Copeland (2001) explain that $N(d_2)$ represents the probability that the call option will be exercised, while $N(d_1)$ represents the amount of "units of the underlying" needed to replicate the option (p. 110). I then calculate d_1 and d_2 using equations (7) and (8),

$$d_1 = \frac{ln\left(\frac{S}{K}\right) + \left(r - \delta + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}} \tag{7}$$
$$d_2 = d_1 - \sigma\sqrt{T} \tag{8}$$

Next, a conversion of the variables from the traditional option pricing theory and ROV must be made. Table 3 represents the required conversions, based on the methodology of Dunis & Klein (2005).

BS variable	ROV variable
Share Price	Cumulated market value of target and acquiror, four weeks prior to announcement
Strike Price	Cumulated market values of target and acquiror one year after*
Volatility	Standard deviation of returns one year after acquisition
Dividend Yield	Dividend yield one year after acquisition
Risk-free Rate	Domestic three-month bill rate of acquiror
Time to Maturity	One year

Table 3: Conversion of financial option BS variables to ROV variables.
Note: *Market values were first estimated separately using Capital Asset Pricing Model theory and then added together to create the Strike Price.

When referring to a financial option, the share price is simply the current market value of the underlying stock. Dunis & Klein (2005) proxies this variable using the cumulated market value of the target and acquiror firms, four weeks prior to the acquisition announcement. As mentioned earlier, collecting values four weeks prior to announcement allows for a measurement of the market value that is close to the event while, at the same time, is not affected by the market through factors such as investor sentiment.

The strike price is proxied by a cumulated future market value of the target and acquiror firms. Based on the instructions of Koller et al. (2015), I calculate this value using the Capital Asset Pricing Model (CAPM), which makes use of an equity beta, risk-free rate, and market premium. By transforming the original equation, I arrive at an equation for the hypothetical market value,

$$V_h = V_0(r_f + \beta(R_m - r_f)) \tag{9}$$

where V_h is the hypothetical future market value, V_0 is the current market value, r_f is the risk-free rate, β is the equity beta, and R_m is the market return. I calculate the equity beta by taking the historical percentage return of each firm's equity monthly and regressing them against the gross, unhedged percentage return of the MSCI World Index. In essence, equation (8) multiplies the cumulated market value of both firms by the return on equity to arrive at a separate hypothetical market value for both firms, after one year. Once this value is calculated for both the target and the acquiror, they are then added together to proxy the strike price variable.

I measure uncertainty and dividend yield using CapitalIQ (2023), in which the acquiror's stock information is directly taken from CapitalIQ's financial database. I collect both the uncertainty and dividend yield of each acquiror's stock return starting from the announcement date and ending 365 days after. Lastly, the risk-free rate for each acquiror was determined using data retrieved from Finaeon (2023). I opt to use the 3-month rate for two reasons: (1) since the time to maturity of the real option is one year, using a short-term interval is generally preferred for consistency; (2) the 3-month rate is more robust to long-term fluctuations and hence to interest rate risk. I then match a risk-free rate to each acquiror using its main country of operations as well as the month and year that the acquisition occurred.

4.2 Ordinary Least Squares (OLS) Regression

The first technique I use in my study is an OLS regression which I conduct to answer Hypothesis 1. For the variable selection process, I include variables that are both relevant and used in previous literature. The dependent variable in this OLS Regression is Premium Spread (PS), which I define as the spread between the ROV Premium and the AT Premium, both expressed in percentage terms. The equation I am testing is as follows,

$$\sqrt[3]{\mathrm{PS_i}} = \beta_0 + \beta_1\mathrm{OPU_i} + \beta_2\mathrm{MU_i} + \beta_3\mathrm{EPU_i} + \beta_4\mathrm{Ln(Target\ Size)_i} + \beta_5\mathrm{Target\ ROA_i} + \beta_6\mathrm{Domestic_i} + \beta_7\mathrm{Energy_i} + \beta_8\mathrm{Healthcare_i} + \beta_9\mathrm{Industrials_i} + \beta_{10}\mathrm{Technology_i} + \varepsilon \tag{10}$$

where OPU, MU, and EPU are the separate uncertainty variables (collectively referred to as the Uncertainty variables). The firm-specific control variables are as follows: Domestic is a dummy variable that holds the value 1 if the acquiror and target are incorporated in the same country; Ln(Target Size) is the target's log-transformed market capitalization; Target ROA is the target's return on assets (collectively referred to as firm-specific variables). These firm-specific variables are included so that I can compare my findings with those of Dunis & Klein (2005) and Barrows et al. (2023). The Industry control variables are separated into: (1) Energy; (2) Healthcare; (3) Industrials; (4) Technology; and (5) Utilities (collectively referred to as industry variables). Since the last five variables are indicators of which industry the acquisition is occurring in, one of these variables – in this case, the Utilities variable - must be omitted from analysis to avoid multicollinearity.

My implementation of a cube-root transformed dependent variable is justified by its adherence to OLS assumptions. In this model, I look specifically at the assumptions of homoskedasticity and normally-distributed residuals. The violation of these assumptions can either lead to biased results, inconsistency, or the implication that the estimated model is not the most efficient specification. Hence, I conduct multiple tests, all of which I present and explain in Appendix B. Through these tests, I find that the initial model, absent from any transformations, fails to follow the assumption of normally-distributed residuals. When looking at possible transformations, I find that both a log- and square-root transformation of Premium Spread still does not solve this violation. Ultimately, I find that a cube-root transformation follows both the assumptions of homoskedasticity and normally-distributed residuals. Therefore, I conduct my analysis using the cube-root transformation of Premium Spread.

4.3 Logistic (Logit) Regression

To answer Hypothesis 2, I opt to use a Logit Regression. As aforementioned, a Logit Regression is performed when the dependent variable is binary since it estimates the change in log-odds of the dependent variable. Thus, using the transformation described in section 3.1.2, I regress the Overpaid dummy variable against the three uncertainty variables as well as the control variables also present in the OLS regression, as depicted in equation (11).

$$\text{Overpaid}_i = \beta_0 + \beta_1 \text{OPU}_i + \beta_2 \text{MU}_i + \beta_3 \text{EPU}_i + \beta_4 \text{Ln(Target Size)}_i + \beta_5 \text{Target ROA}_i + \beta_6 \text{Domestic}_i + \beta_7 \text{Energy}_i + \beta_8 \text{Healthcare}_i + \beta_9 \text{Industrials}_i + \beta_{10} \text{Technology}_i + \varepsilon \qquad (11)$$

According to Brooks (2019), a Logit Regression works by bounding the dependent variable's outcome within a (0,1) interval. The dependent variable outcomes then follow a cumulative logistic distribution, which appears in the shape of an S instead of a straight line (as it is with OLS Regression). This is important since probabilities do not exist below 0 and above 1. Moreover, I make use of a Logit model over a Probit model since the difference between both is negligible, while the former is considered standard practice in academia (Brooks, 2019).

4.4 Robustness tests

As robustness tests for the OLS and Logit Regressions, I will produce five different models, all of which have distinct variable selections of the Uncertainty, firm-specific, and industry control variables. I will also run the OLS and Logit Regression models using a different definition of the oil spot prices, such that the underlying contracts are not WTI oil spot prices, but Brent Crude oil spot prices. Data on Brent Crude oil spot prices will be collected from US Energy Information Administration (2023b).

To close this section, I include a detailed description of how I use Stata to perform these statistical analyses in Appendix A.

CHAPTER 5 Results & Discussion

In this section, I report the results of the OLS and Logit Regressions. The variable of interest for the OLS Regression is Premium Spread. For the Logit Regression, it is the Overpaid dummy variable. Each model regresses its variable of interest against the Uncertainty, firm-specific, and industry variables. Tables 4 and 5 exhibit the results of the OLS and Logit Regressions respectively.

The interpretation of the OLS results in table 4 is only possible by first 'untransforming' the coefficient. As such, the coefficients of each variable must be cubed to arrive at their original values. This cubed coefficient is then interpreted as follows: a one unit increase in the variable in question, ceteris paribus, leads to an increase/decrease in Premium Spread by the variable's coefficient. Since Premium Spread is formatted in percentage terms, the coefficient must also be interpreted in percentage terms. In the case of Ln(Target Size), its coefficient represents an elasticity – therefore, its coefficient must be untransformed and then interpreted as a one percent increase rather than a one unit increase.

For the Logit Regression, interpretation of each variable must be done as follows: a one unit (in the case of Ln(Target Size), a one percent) increase in the variable in question, ceteris paribus, leads to an increase/decrease in the log-odds of the Overpaid variable by the variable's coefficient.

5.1 Hypothesis 1

	Dependent variable: Cube-root of Premium Spread *Ordinary Least Squares Regression*				
	(1)	(2)	(3)	(4)	(5)
OPU	-.004	-.317*** (.097)	-.323***	-.328***	-.332***
	(.080)		(.094)	(.092)	(.090)
MU		1.39***	1.24***	1.29***	1.20***
		(.250)	(.247)	(.237)	(.237)
EPU		-.016	-.015	-.006	-.009
		(.020)	(.020)	(.019)	(.019)
Ln(Target Size)			-.010**		-.006
			(.004)		(.004)
Target ROA			-.001**		-.001**
			(.001)		(.001)
Domestic			-.016		-.015
			(.048)		(.019)
Energy				.049	.031
				(.052)	(.053)
Health Care				.088*	.045
				(.052)	(.054)
Industrials				.104**	.084
				(.051)	(.052)
Technology				.153***	.118**
				(.051)	(.053)
Constant	.530	.476	.559	.379	.463
	(.033)	(.035)	(.048)	(.058)	(.074)
Observations	263	263	263	263	263
R^2	.000	.137	.199	.249	.280
Adjusted R^2	-.005	.124	.174	.221	.242
AIC	-270.29	-295.82	-304.79	-315.76	-318.40

Table 4: OLS Regression of cube-root transformed Premium Spread against Uncertainty, firm-specific, and industry variables using WTI oil prices.

Note: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are reported in parenthesis.

5.1.1 Discussion on model performance

From models (1) to (5), I observe a steady increase in model performance. The changes in the R^2, Adjusted R^2, and AIC measures between models (1) to (2) demonstrate the additional explanatory power of MU and EPU. Across models (2) to (5), the improvements in the three measures are incremental, with the AIC slightly improving between models (4) and (5). The three performance measures indicate that out of the five models, model (5) has the strongest explanatory power on Premium Spread. Namely, its Adjusted R^2 indicates that the explanatory variables in model (5) are able to explain 24.20% of the variation in Premium Spread. Model (5) also holds the lowest AIC value, which, as mentioned above, is a slight improvement from model (4).

5.1.2 Discussion on OPU

Model (1) regresses Premium Spread against OPU alone. Interestingly, this is the only model in which OPU is insignificant. Although insignificant and small, the coefficient of OPU is negative, which follows suit with the other models. Across models (2) to (5), the coefficient of OPU is consistently negative and significant at the 1% level. This indicates that, based on my sample and alongside control variables, OPU influences the spread between the ROV Premium and the AT Premium. In model (5), the coefficient of OPU is -.332. By cubing this coefficient, I interpret it as follows: a one unit increase in OPU leads to, on average, a decrease of 3.66% in the Premium Spread. Since this coefficient's sign is negative, I observe that OPU's effect on Premium Spread is opposite to what I predict in Hypothesis 1.

An alternative explanation to this finding is that companies actively incorporate more ROV theory into their valuation process in the presence of higher OPU. This is possible in the case that top management places higher importance on flexibility, and as such will adopt ROV analysis to benefit from its dynamism. Thanks to this dynamism, these companies are then more robust to sudden changes in oil prices in their acquisition valuation. Another possible explanation for the sign of OPU's coefficient is that companies are including value-adding acquisition factors that do not feed into the BS model. This is in line with the inclusion of synergy effects in the acquisition value as postulated by Damodaran (2005). Such changes to the value estimation do not feed into the calculation of the ROV Premium, at least when calculated using the dividend-adjusted BS model used by Dunis & Klein (2005). When combining these two explanations, an increase in OPU will increase both the ROV and AT Premiums while increasing the latter by a higher magnitude. Consequently, this leads to a decrease in the Premium Spread.

5.1.3 Answer to Hypothesis 1

Based on the result of table 1, the coefficients estimated for OPU suggest an effect that contradicts Hypothesis 1. Namely, Hypothesis 1 predicts that an increase in OPU increases Premium Spread. Instead, the opposite is observed – an increase in OPU, on average, decreases Premium Spread. This may be a result of companies implementing ROV analysis in their valuations during periods of high OPU as well as including factors that asymmetrically affect the ROV and AT Premiums such as synergy.

Therefore, I conclude my analysis of OPU in Hypothesis 1 by rejecting it, given that there is evidence that an increase in OPU decreases Premium Spread.

5.1.4 Discussion on control variables

Across models (2) to (5) in table 1, the coefficients of all control variables except for EPU hold their expected sign and magnitude. To discuss each variable, I explore model (5) given that it is the best-performing model and that it includes all variables. Contrary to OPU, MU exhibits a positive sign and is significant at the 1% level. The coefficients of Ln(Target Size), Target ROA, and Domestic are negative, and only Target ROA is significant at the 5% level. The industry control variables all exhibit a positive coefficient, which is interpreted as their effects when benchmarked against Utilities, the industry variable dropped due to multicollinearity. Out of the industry controls, only Technology is significant.

Based on its coefficient's negative sign, Ln(Target Size) meets my expectations. The ROV Premium decreases because larger firms, as studied by Reinganum (1982), experience lower equity betas. Lower equity betas, compared to higher equity betas, lead to a cumulated hypothetical market value that is smaller and closer to the current market value in the BS model. Furthermore, Duffee (1995) finds that bigger firms, in general, experience less uncertainty in their stock return. Hence, a lower equity beta and a decrease in uncertainty will also decrease the ROV Premium. On the other hand, The AT Premium will also decrease based on the findings of Gondhalekar et al. (2006) that acquirors pay higher premiums for smaller firms since they can be "more easily integrated into the acquiror's operations" (p. 739).

EPU, while insignificant, exhibits a negative coefficient. The same explanation for OPU most likely applies in the case of EPU; companies make use of ROV analysis in the presence of more uncertainty to become more flexible with their investment decisions. This unexpected coefficient sign can also be a result of OPU picking up some of the effects of EPU, given that OPU also exhibits a negative sign.

5.1.5 Robustness tests

Based on the consistent significance of OPU and MU as well as the small deviations of all coefficients across the five models, the OLS Regression is robust to changes in variable selection. Moreover, the results of the OLS Regression in table 4 are robust to the use of a different oil series. In Appendix C, I use Brent Crude oil spot prices instead of WTI spot prices to model oil price uncertainty. As evident in Appendix C, the coefficient of OPU is still significant in all but the first model, which is also observed in table 4. Both models also exhibit similar coefficients across all the variables, where the effects of OPU are slightly stronger when Brent Crude oil spot prices are used instead of WTI oil spot prices.

5.2 Hypothesis 2

	Dependent variable: Overpaid				
	Logistic Regression				
	(1)	(2)	(3)	(4)	(5)
OPU	1.39	-.435	-.202	-.227	-.334
	(.922)	(1.36)	(1.53)	(1.44)	(1.57)
MU		2.99	4.16	3.08	4.71
		(4.01)	(4.34)	(4.23)	(4.49)
EPU		.737**	.695**	.690**	.699*
		(.307)	(.344)	(.339)	(.375)
Ln(Target Size)			.323***		.263***
			(.077)		(.083)
Target ROA			.026*		.023
			(.016)		(.017)
Domestic			1.25***		1.16**
			(.477)		(.491)
Energy				-.710	-.036
				(.649)	(.707)
Health Care				-1.55**	-.373
				(.695)	(.707)
Industrials				-2.02***	-1.23*
				(.687)	(.741)
Technology				-2.77***	-1.65**
				(.734)	(.796)
Constant	-1.76	-2.20	-5.38	-0.696	-4.26
	(.416)	(.507)	(.896)	(.765)	(1.23)
Observations	263	263	263	263	263
Pseudo R^2	.008	.028	.149	.133	.202
AIC	289.04	287.16	258.61	264.94	251.11

Table 5: Logit Regression of the Overpaid dummy variable against Uncertainty, firm-specific, and industry variables using WTI oil prices.

Note: *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors are reported in parenthesis.

5.2.1 Discussion on model performance

For the Logit Regression models, I use Pseudo R^2 and AIC as measures for model performance. The performance of model (2) is a marginal increase from model (1), given that both the Pseudo R^2 and AIC measures only slightly improve. Moving to model (3) in which firm-specific control variables are included, the Pseudo R^2 does increase to .149 while the AIC decreases from 287.16 to 258.61. When industry controls are included in place of firm-specific controls, model performance slightly decreases. I observe improvements to model performance after including all control variables in model (5), in which the Pseudo R^2 increases by .069 and the AIC decreases by 13.83. Of all the models, I observe that model (5) indicates the highest pseudo R^2 and the lowest AIC. In this model, the Pseudo R^2 is .202, which is interpreted as follows: the explanatory variables can explain 20.20% of the variation in the dependent variable. As such, I conclude that for the Logit Regression, model (5) has the best explanatory power.

5.2.2 Discussion on OPU

In this Logit Regression, I observe that the coefficient of OPU is insignificant across all models. Starting with model (1), the coefficient of OPU, although insignificant, is positive. The coefficient of OPU in models (2) to (5) becomes negative but maintains insignificance. Disregarding insignificance, this can be interpreted such that an increase in OPU decreases the probability that the ROV Premium is lesser than the AT Premium. Moreover, I observe that its coefficient, when compared to other variables, varies largely across all models.

These findings suggest that, while OPU is able to explain the change in Premium Spread, it cannot sufficiently explain whether the ROV or AT Premium is systematically larger than the other. A simple explanation for this finding is that other factors (which will be discussed in section 5.2.4) as well as those that are absent from my study play a larger role in determining which is larger. For instance, Brown & Cliff (2005) find that investor sentiment is significant in explaining deviations in stock price valuations. However, the creation of an investor sentiment variable is beyond the time and scope of my study.

5.2.3 Answer to Hypothesis 2

Based on the results of this Logit Regression, I conclude that the effects I observe from OPU do not fall in line with Hypothesis 2. The Logit Regression suggests that OPU does not influence whether an acquisition is overpaid or not. Disregarding this insignificance, however, the coefficient of OPU meets my predictions of Hypothesis 2 - an increase in OPU is linked to a decrease in the probability of overpayment. Nevertheless, I conclude my analysis of OPU in Hypothesis 2 by rejecting it, given that there is no evidence that an increase in OPU decreases the Overpaid dummy variable.

5.2.4 Discussion on control variables

The sign and magnitude of all the control variables' coefficients except for MU and EPU meet expectations. Through the explanation in section 5.1.4, Ln(Target Size) correctly indicates a positive and significant coefficient. Target ROA exhibits a small but positive effect on the log-odds of Overpaid. Similarly, Domestic also exhibits a positive but larger effect on Overpaid. Compared to the dropped industry variable, Utilities, all industry variables have more of a negative effect on Overpaid.

The positive effect of Domestic variable on Overpaid is partially supported by Dunis & Klein (2005). In their findings, acquisitions that occur within borders, as opposed to cross-border acquisitions, demonstrate larger acquisition premiums. According to Reuer et al. (2012), this is because domestic acquisitions are characterized by less information asymmetry between the acquiror and target. The convenience of domestic acquisitions, in terms of information and agency costs, also adds to this increase in the AT Premium. Hence, the sign, significance, and coefficient of the Domestic variable follow expectations.

Both MU and EPU also exhibit positive coefficients, which opposes my expectation of a negative effect on Overpaid from the Uncertainty variables. A possible explanation for this is that companies are more observant of these two uncertainties and that they see an increase in uncertainty as value-adding rather than value-destroying. Naturally, this is possible if companies adopt ROV analysis during periods of high uncertainty. This explanation echoes the same notion as in section 5.1.1: companies could be incorporating more ROV analysis when there is higher uncertainty since it allows them to be more flexible and robust to sudden changes in oil prices. If factors such as synergy are also included in the AT Premium but not in the ROV Premium, then the former will increase more than the latter. This line of thinking then makes it possible for the AT Premium to become systematically larger than the ROV Premium as more uncertainty is added, provided the asymmetric effect of factors such as synergy is large enough.

5.2.5 Robustness tests

Based on the slight changes in all variables' coefficients across models, I observe that the Logit Regression is robust to changes in variable selection. I also change the source of oil prices for the OPU variable by using Brent Crude oil price instead of WTI price. Appendix D exhibits the small changes in the coefficients and identical significance levels for all variables when compared to the results in table 5. As such, the Logit Regression is robust to structural changes in the independent variable.

CHAPTER 6 Conclusion

In my study, I explore the effects of oil price uncertainty on the spread between the real options premium and the actual takeover premium. Previous literature indicates that oil price uncertainty affects several facets of business and economics such as M&A activity, stock returns, and unemployment. However, no literature has specifically looked at the effects of this uncertainty on the results of real options models – particularly the Black-Scholes model - in the context of acquisitions. In this context, there is also no existing literature that compares the results of real options models with standard models when other types of uncertainty, apart from that of the underlying stock, are introduced. Hence, the purpose of my study is then to determine if oil price uncertainty affects the hypothetical valuation of real options models as compared to the observed valuations that companies arrive at in the context of acquisitions. The research question of my study is:

"How does oil price uncertainty affect the spread between the real options premium and the actual takeover premium paid by companies in acquisition deals?"

To answer this research question, I produce a variable for the spread in the real options premium and the actual takeover premium observed in acquisitions. I calculate the real options premium using the dividend-adjusted Black-Scholes model. Then, to determine the effects of oil price uncertainty on this spread, an Ordinary Least Squares and Logistic Regression are conducted. Through this, I find that oil price uncertainty does affect the premium spread, but in the direction opposite to what I hypothesize. Instead of increasing the premium spread, an increase in oil price uncertainty decreases it. Oil price uncertainty also fails to explain, with significance, the probability that an acquisition's actual takeover premium is larger than the real options premium – in essence if an acquiror has overpaid for their target.

My study ultimately concludes that the spread between the real options premium and actual takeover premium is negatively affected by an increase in oil price uncertainty. In other words, the real options premium and the actual takeover premium approach each other as oil price uncertainty increases. A potential explanation for this observation is that companies are implementing more real options theory in their valuation techniques in the presence of higher oil price uncertainty. Furthermore, other acquisition factors such as synergies – which do not feed into the Black-Scholes model – may be increasing the actual takeover premium. Inputs of the real options model such as hypothetical future market value and return on assets may also play a role by counteracting the effects of uncertainty on the real options premium.

6.1 Implications to investors and top management

Implications of my study apply mostly to investors and top management that display a sustained reluctance towards the use of real options theory in their valuations. This reluctance is a result of how real options theory may encourage excessive risk-taking. To reiterate my results, my findings imply that real options theory becomes more comparable to the actual valuation practices that companies employ as more oil price uncertainty is introduced. It could also demonstrate how companies – in the process of valuing an acquisition - switch to real options analysis when they are aware that oil price uncertainty has increased. Although my findings seem counter-intuitive, they should encourage both investors and top management to explore the use of more real options theory in acquisition valuation and to actively challenge the notion that real options encourage excessive risk-taking in the presence of uncertainty. My study should also encourage both parties to pay special attention to the comparability of the results from real options models with results from the standard Net Present Value model by performing them parallel to each other. Seeing this increase in comparability even when more uncertainty is introduced should make both parties more comfortable in, at the very least, complementing their Net Present Value model with real options analysis.

6.2 Limitations and future research

The limitations of my study mostly lie in the absence of control variables that are difficult to measure. Given the limited number of observations for acquisitions in which both the target and acquiror stay public after the acquisition event, the inclusion of more variables – especially more obscure and complex ones - will further decrease the number of observations. Another limitation of my study is that the use of the dividend-adjusted Black-Scholes model requires several inputs, all of which do not have a standardized proxy in academia or practice. The proxies I use in my study replicate those used by Dunis & Klein (2005) which deviates from more complicated models used in corporate finance textbooks. Therefore, readers should be aware of this when interpreting my results. If readers were to attempt to replicate my results, they should do so using the dividend-adjusted Black-Scholes model and the accompanying proxies used by Dunis & Klein (2005).

For future research, I suggest the use of different proxies and/or real options models to explain the relationship between real options and oil price uncertainty. As previously mentioned, the proxies used by Dunis & Klein (2005) are only one of several proxy sets that can be used to estimate a real options premium. For example, changing the proxy of the share price to the acquiror and target's cumulated market value at the date of announcement – as opposed to four weeks prior - might change how the premium spread reacts to oil price uncertainty. Moreover, it may also be interesting to see if oil price uncertainty has the same effect on other real options models such as the Cox-Ross Rubenstein model. Since the Black-Scholes model is a special version of the Cox-Ross-Rubenstein that requires several assumptions, there may be a difference in the effects of oil price uncertainty on the more general model.

Finally, it may also be interesting to explore the Black-Scholes model I use in a more granular case: intracompany projects. For instance, one can explore the relationship between oil price uncertainty and the premium spread in the context of oil exploration, where the decision to expand or contract by a company is feasible. While this will require more data that is less public, it examines the use of real options theory in the best setting: in projects in which flexibility is clearly defined and feasible.

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APPENDIX A STATA Do-file and explanation

OLS Regression

I start with transforming the dependent variable of the OLS Regression by raising Premium Spread to the power of 1/3, which effectively cube-root transforms the variable. I also log transform the Target Size variable, which is performed by Barrows et al. (2023) to address the skew in company size observations.

```
gen cbrtpremiumspreadpercent = (premiumspreadpercent)^(1/3)
gen lnsize = ln(targetsize)
```

After transforming the dependent variable, I then regress Premium Spread in five models, all of which have differing variable specifications. I also use the commands “whitetst” and “estat ic” to produce a White’s Test and Akaike Information Criterion estimate. Both the R^2 and Pseudo R^2 are already included in the estimation of the regression models.

```
\\ Model 1
reg cbrtpremiumspreadpercent opu
whitetst
estat ic

\\ Model 2
reg cbrtpremiumspreadpercent opu mu epu
whitetst
estat ic

\\ Model 3
reg cbrtpremiumspreadpercent opu mu epu lnsize targetroa i.domestic
whitetst
estat ic

\\ Model 4
reg cbrtpremiumspreadpercent opu mu epu i.energy i.healthcare
i.industrials i.technology i.utilities
whitetst
estat ic

\\ Model 5
reg cbrtpremiumspreadpercent opu mu epu lnsize targetroa i.domestic
i.energy i.healthcare i.industrials i.technology i.utilities
whitetst
estat ic
```

Logistic Regression

I first start with generating the dependent variable by creating a condition for each observation – that the ROV Premium is lesser than the AT Premium. Before setting up this condition, I generate the

Overpaid variable that holds the value 0 for all observations. The value 0 is then replaced with 1 for each observation if the above-mentioned condition is met.

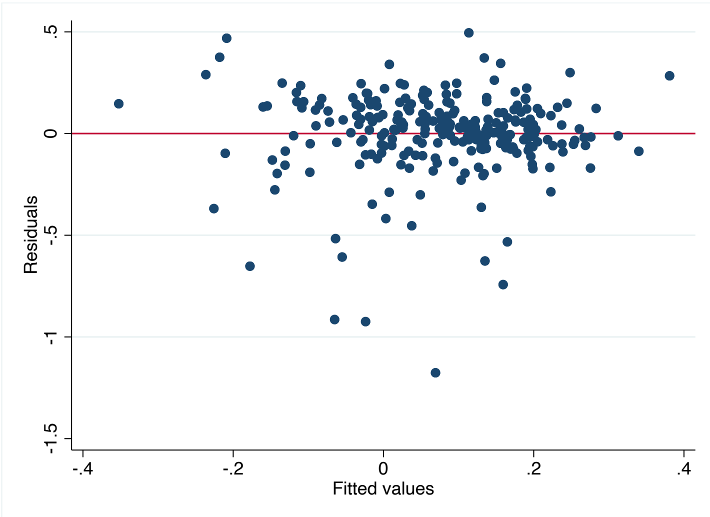
```
gen overpaid = 0
replace overpaid = 1 if rovpremium < actualtakeoverpremium
```

Like the OLS Regression, I conduct the Logit Regression through five models, all with different variable selections. A White's Test ("whitetst") is not included for two reasons: (1) Stata simply does not allow for its use, and (2) the Logit Regression, in theory, is robust to heteroskedasticity.

```
\\ Model 1
logit overpaid opu
estat ic

\\ Model 2
logit overpaid opu mu epu
estat ic

\\ Model 3
logit overpaid opu mu epu lnsize targetroa i.domestic
estat ic

\\ Model 4
logit overpaid opu mu epu i.energy i.healthcare i.industrials
i.technology i.utilities
estat ic

\\ Model 5
logit overpaid opu mu epu lnsize targetroa i.domestic i.energy
i.healthcare i.industrials i.technology i.utilities
estat ic
```

APPENDIX B OLS Regression assumption testing

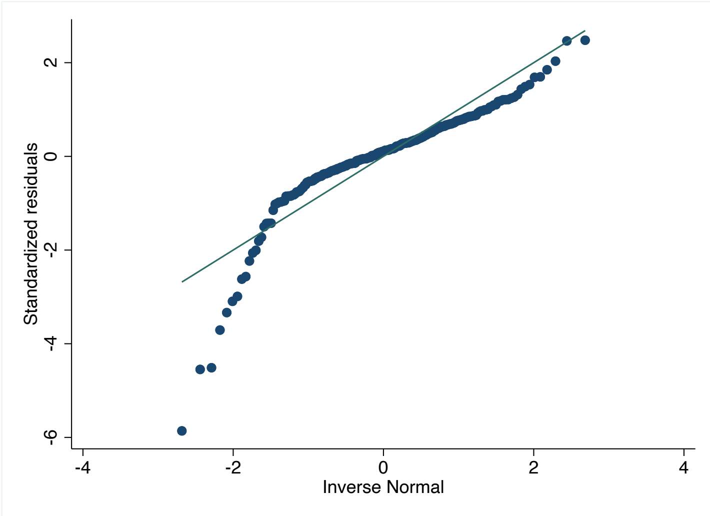
In the process of selecting a model specification, I make use of several statistical tests to test OLS assumptions. I start my assumptions testing by regressing the base dependent variable - which looks at the difference between the ROV Premium and the AT Premium - against the initial regression model. The first assumption I test is that of homoskedasticity, which Brooks (2019) formally defines as the observation that "the variance of the errors is constant" (p. 257). For this assumption, I create a Residuals-versus-fitted plot of the initial regression model, which is illustrated in figure 1.



Appendix B, figure 1: Residuals-versus-fitted plot of initial regression model.

At first glance, there seems to be no pattern in the distribution of the residuals across fitted values. For clarification, I also perform a White test, which tests the null hypothesis that the variance of the residuals is constant. I arrive at a P-value of 0.553, which means the assumption of constant variance holds.

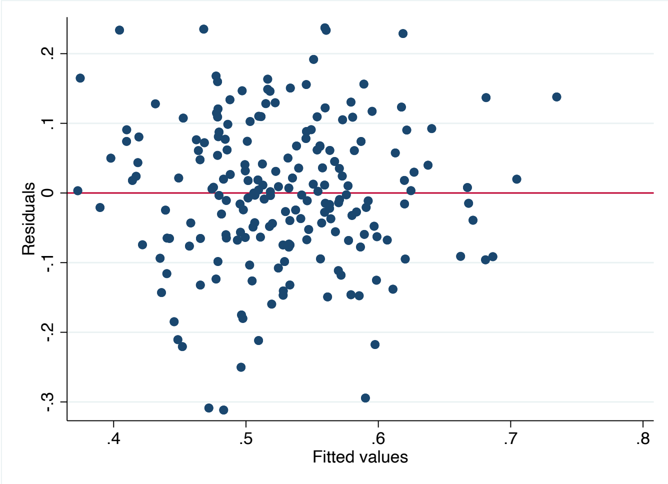
Next, I test the assumption that the residuals are normally distributed. For this assumption, I produce a QQ plot in which the standardized residuals are plotted on an inverse normal curve. If these residuals follow a normal distribution, then their curve will fit onto a 45-degree line. As evident in figure 2, there is a deviation by residuals from this line. I also conduct a Bera-Jarque test, which tests for the presence of non-normality in a variable. By running this test on the non-standardized residuals of the initial regression model, I arrive at a P-value that is very close to zero – this is then evidence to reject the null hypothesis that the residuals are normally distributed.



Appendix B, figure 2: QQ plot of standardized residuals from initial regression model.

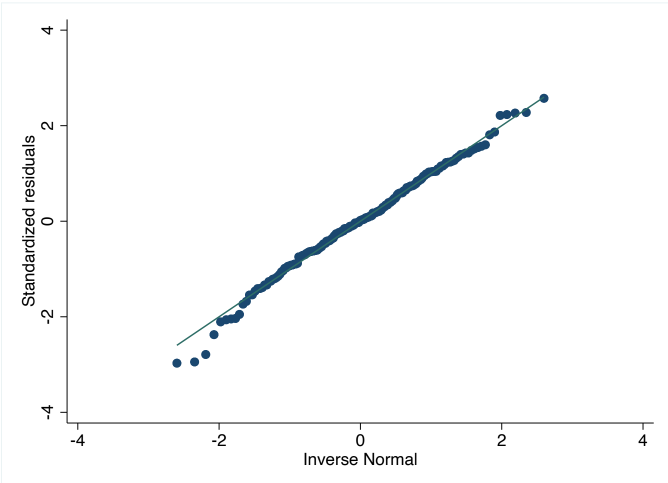
Despite the presence of non-normality in the residuals, Brooks (2019) and Kwak & Kim (2017) both mention that this sample can be violated if the sample size is large enough. Kwak & Kim (2017) specifically mentions a sample size of 30, at which the test statistics starts to "asymptotically follow the appropriate distributions"; in this case, the appropriate distribution is the normal distribution (p. 288). Nevertheless, when possible, improvements to the model specification must be made.

The standard log transformation of the dependent variable, however, did not lead to a normal distribution in the residuals. I find the same when performing a square-root transformation of the dependent variable. Another transformation described by Cox (2011) is the cube-root transformation. When testing the model using this specification, I find first that the homoskedasticity assumption holds. Running the same Residuals-versus-fitted plots of the Uncertainty and control variables against the cube-root Premium Spread, I arrive at figure 3, which presents a plot that looks relatively more 'random' than what is presented in figure 2.



Appendix B, figure 3: Residuals-versus-fitted plot of a regression model with cube-root transformed Premium Spread.

Furthermore, the White's Test also indicates a P-value of .673. As such, the homoskedasticity assumption is met. Next, I run the normality tests used for the initial regression model. The QQ plot now falls within the 45-degree line, as can be seen in figure 4.



Appendix B, figure 4: QQ plot of standardized residuals from regression model with cube-root transformed Premium Spread.

Running the Bera-Jarque test on non-standardized residuals also gives me a P-value of .230, which indicates that there is no evidence to reject the assumption of normally-distributed residuals. Therefore, since the cube-root transformed Premium Spread behaves better than the base dependent variable, its log- and square-root transformations, I continue my analysis using the cube-root transformation of Premium Spread.

APPENDIX C Hypothesis 1 robustness test: changing oil price source

	Dependent variable: Cube-root Premium Spread				
	Ordinary Least Squares Regression				
	(1)	(2)	(3)	(4)	(5)
OPU	-.035	-.306***	-.316***	-.330***	-.339***
	(.088)	(.108)	(.105)	(.102)	(.101)
MU		1.35***	1.21***	1.26***	1.18***
		(.256)	(.253)	(.243)	(.242)
EPU		-.022	-.020	-.012	-.014
		(.020)	(.020)	(.019)	(.019)
LN(Target Size)			-.010**		-.006
			(.004)		(.004)
Target ROA			-.001*		-.001**
			(.001)		(.001)
Domestic			-.017		-.015*
			(.020)		(.020)
Energy				.053	.034
				(.052)	(.053)
Health Care				.088*	.045
				(.052)	(.055)
Industrials				.105**	.084
				(.051)	(.053)
Technology				.157***	.121**
				(.051)	(.0053)
Constant	.515	.478	.565	.382	.470
	(.035)	(.037)	(.050)	(.059)	(.075)
Observations	263	263	263	263	263
R^2	.001	.125	.189	.240	.272
Adjusted R^2	-.004	.112	.163	.213	.234
AIC	-270.45	-293.23	-302.26	-313.49	-316.88

Appendix C: OLS Regression of cube-root Premium Spread against Uncertainty, firm-specific, and industry variables using Brent Crude oil spot prices.
Note: *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors are reported in parenthesis.

APPENDIX D Hypothesis 2 robustness test: changing oil price source

	Dependent variable: Overpaid				
	Logistic Regression				
	(1)	(2)	(3)	(4)	(5)
OPU	1.39	-.435	-.202	-.227	-.334
	(.922)	(1.36)	(1.53)	(1.44)	(1.57)
MU		2.99	4.16	3.08	4.71
		(4.01)	(4.34)	(4.23)	(4.49)
EPU		.737**	.695**	.690**	.699*
		(.307)	(.344)	(.339)	(.375)
LN(Target Size)			.323***		.263***
			(.077)		(.083)
Target ROA			.026*		.023
			(.016)		(.017)
Domestic			1.25***		1.16**
			(.477)		(.491)
Energy				-.710	-.036
				(.649)	(.707)
Health Care				-1.55**	-.373
				(.695)	(.707)
Industrials				-2.02***	-1.23*
				(.687)	(.741)
Technology				-2.77***	-1.65**
				(.734)	(.796)
Constant	-1.76	-2.20	-5.38	-0.696	-4.26
	(.416)	(.507)	(.896)	(.765)	(1.23)
Observations	263	263	263	263	263
Pseudo R^2	.008	.028	.149	.133	.202
AIC	289.04	287.16	258.61	264.94	251.11

Appendix D: Logit Regression of the Overpaid dummy variable against Uncertainty, firm-specific, and industry variables using Brent Crude oil spot prices.

Note: *p < 0.1, **p < 0.05, ***p < 0.01. Standard errors are reported in parenthesis.