# Global Oil and Gas stocks: anomalies, systematic risks, and mispricing

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**Abstract**

Our work delves into evaluation of anomaly and factor risk premia in the global Oil and Gas (OG) stocks – a sector that makes up approximately 10 percent of global GDP and is fundamental to global, regional, and country growth cycles. We aim to uncover if the valuations are rewards for bearing systematic risks or being exposed to mispricing – present at macro and micro levels. We find, one, not all anomaly returns result in factor return premia. Two, OG sector-specific factor variation is more important, however, global factor variation also brings meaningful information to explain time series variability of anomaly portfolios. Three, the latest asset pricing models capture time-series and cross-sectional return variation better than the prior benchmarks. Finally, price changes in the global OG market are relatively efficient. That is, portfolio diversification absorbs mispricing attributable to firm characteristics. In contrast, high beta, relative strength, and investment variations induce mispricing, although only marginally and at firm-level analysis. We conclude that risk-based pricing mechanisms in the global OG sector are unique: not all systematic risk factors are important. To highlight this, we report that value and momentum effects are found missing for the global OG stocks. The vital factors that link to portfolio and stock return variations are size, investment – measured by total assets, and firm profitability. These findings are critical for portfolio managers to develop investing and risk management strategies by knowing what factor risks are important and the macro and micro determinants of mispricing in the global OG stocks.

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## 1. Introduction

Cochrane (2011) document that with the abundance of anomalies in the cross-section of expected returns and potential systematic factors in the plethora of factor models descends asset pricing literature into chaos. The buck has not stopped here; since then, several of the anomalies that have challenged famous Fama and French three factor (1992, 1993, 1996, FF3) model have brought new asset pricing models to explain the cross-section of expected returns.[5] These new models providing risk-adjustments include Fama and French five factor (2015, FF5), and Hou, Xue and Zhang q-factor (2015, HXZ) model, among several others.[6] In addition to the availability of tens of other anomalies and models, the determination of differences in average returns also brings a non-risk explanation that challenges market efficiency. That is, expected differences in average returns represent mispricing in the previous periods (DeBondt & Thaler 1985; Haugen, 1995; Stambaugh & Yuan, 2017; Daniel, Hirshleifer & Sun, 2020, among others).

As the number of anomalies are on the rise (e.g., Harvey, Liu & Zhu 2016; Hou et al., 2021), we note that this evidence from anomalies to risk models have not accosted to Oil and Gas (OG) sector companies to the recent advances in asset pricing (AP) literature, as far as we know. For the OG firms, most of the studies are limited to country level analysis to know the common macro and market determinants of OG equity returns (Boyer and Filion, 2007; Kavussanos & Marcoulis 1997; Sadorsky, 2001, among others). Only recently, however at country level, a few of studies have examined micro-economic and mispricing based explanations for the OG companies in the UK (Sansui &Ahmed, 2016), the US (Zhu et al., 2020), and China (Cheema & Scrimgeour 2019). Sansui and Ahmed (2016) document market and size are important systematic factors for the UK OG firms and find absence of BM and momentum effects. Zhu et al. (2020) examine several anomalies and document evidence for pervasive mispricing. They link the cross-sectional spreads to changes in investor sentiment in the spirit of Stambaugh, Yu and Yuan (2012). Cheema and Scrimgeour (2019) report that long-short differentials of mispriced anomalies are more predictable

[5] Prior to this situation, FF3 model simplified the laborious work by explaining hard to price effects in data such as size and value premia etc. and notably using few sources of common movement in average returns.

[6] Cochrane (2006) noted that Fama and French (1996) for the furtherance of empirical work in AP literature initiated the shift to better focus on the differences in average returns, the spread in betas for the candidate risk factors in the model, and the economic size of the pricing errors rather than a test with which almost all the models are incomplete description of average returns i.e. Gibbbon, Ross and Shanken (1989, GRS) F-test. Hou et al. (2019) and Fama and French (2016) show that even most of the latest models using different construction schemes fail on a powerful test of type GRS F-test.

when conditioned on oil price rises than oil price declines displaying mispricing linked to aggregate shifts in oil prices. That is, they confirm anomaly zero-cost strategies (ZCS) depart from their fundamental values following oil price rises and that correction follows in subsequent periods as oil prices fall.

A separate and important research strand links oil price shifts and volatility to firm level return variations and features. Notable works include Maghyereh and Abdoh (2020) and Ilyas et al. (2021). The former study documents that there is an adverse asymmetric impact of oil volatility, when classified into positive and negative price changes, on US corporate investments. Whereas the Ilyas et al. (2021) using firm-level data in the global OG sector show that corporate investments are negatively linked to oil price uncertainty and economic policy uncertainty – an effect that is pronounced in oil producing countries than oil consuming countries.

As we could see in both the research strands, more often stock return variations or corporate strategic actions such as investments are linked to oil price fluctuations and mispricing related variations approximated by investor sentiment, oil and economic uncertainty. These developments are important to understand how macro changes in oil production – divided into demand and supply related shocks – and other macro factors influence equity returns. Nonetheless, there has been little attention to the presence of anomaly-based return variation in the global OG firms. That is, there is no empirical evidence that evaluates the presence of anomalies in the OG sector, links the return variations on OG specific anomalies to prominent AP models, and compares AP models relative to specifications that accounts for mispricing.

Undoubtedly, examination of macro changes from oil prices, volatility, uncertainty, and economic policy uncertainty are fundamental to link with firm level, portfolio and aggregate equity return and characteristic variations. We note that there is a clear gap in existing research that falls short on isolating if the return variation in OG sector stocks is a consequence of systematic return variation or is a response firm level characteristic. In this vein our research, answers the highlighted questions and provide new evidence by developing microeconomic based return-factorization while accounting for stock-specific characteristics.

Our research design optimizes the use of firm level data to create characteristics portfolios to decipher if equity returns in OG sector are explanation of risk-based investing rules or market reactions that priorly have been explained by macro-finance variability in most of the instances

(Degiannakis, Filis & Arora 2018; Smyth & Narayan, 2018; Demirer, Ferrer & Shahzad, 2020; Salisu, Ebuh & Usman, 2020). Our work provides depth to the existing evidence that predominantly links equity return variation to aggregate macro-finance and oil price variations (Maghyereh & Abdoh, 2020; Cheema & Scrimgeour, 2019; Alomran & Alsubaiei, 2022; Song & Yang, 2022; Ren, Jin & Lin, 2023). Whereas our research discovers AP anomalies and their reasonable explanations in global OG firms, it adds a new dimension to the empirical AP pricing literature by focusing primarily on OG stocks, patterns within them, their likely drivers, and whether they are explained by mispricing relative to systematic factor changes.This enables our work to furnish new evidence on the identified gaps in the OG stock pricing patterns and is the main contribution of our work.

The first contribution of this work is the constructing of systematic factors in the cross-section of OG sector stocks. To the best of our knowledge, OG sector specific risk factors have not attracted due consideration in energy finance literature. Two, results in our work contribute to the puzzle whether return differentials on anomalies are a result of risk-based investing or are outcome of prior mispricing linked to firm characteristics (DeBondt & Thaler, 1985; Haugen, 1995). Three, our work deciphers between the factor return variation at the global OG sector and global equity levels proxy by the US and developed countries. Thus, in addition to comparing model performance of several AP models, our work contrasts on the relative importance of sector specific and global factor variation in explaining valuations of the OG firms. Four, our work contributes to the discussion of whether OG stock returns are influenced by mispricing. In here we bring and test both narratives simultaneously when previous findings have fallen short of this. Prior evidence has either used a benchmark that is not sector specific or is no longer regarded appropriate in the mainstream AP literature. Finally, our work also contributes to the evidence base that assesses if firm decisions such as corporate investments translate into systematic factors or merely depicts the transitory sock-specific return variation that feeds into sentiment and/or uncertainty variations.

To examine if the expected returns in the global OG stocks are explained by factors that mimic risk-related return variation or are consequence stock characteristics depicting non-risk explanation, we retrieve equity and firm characteristic data across 86 countries for approximately 4,500 firms. Using data on global OG sector companies, we perform a multi-level analysis in relation to the identified research questions and gaps in this work. We begin by constructing characteristic portfolios for a range of anomalies followed by computing the long-short ZCS to assess if these firm characteristics yield anomalous return differentials. In addition, we also construct systematic factors belonging to a range of prominent models in AP literature. We test if the anomaly factors are sensitive to previous period investor sentiment, economic and oil policy uncertainty changes. Using anomaly and factor data, we run a horserace among prominent AP models to evaluate if undertaken ZCS yield risk-adjusted return. Finally, we perform our simultaneous analysis by testing the relevance of systematic factors versus firm characteristics – both at portfolio and firm level.

Our results show that out of 14 anomaly ZCS 13 have significant return differentials, however when we limit universe to stocks to a more restrictive filtration – removing firms that have prices less than 5 USD – 11 anomalies maintain their persistence. The size, momentum, and investment related ZCS are not robust in the cross-section of global OG firms. It is surprising to note that relative strength investing is insignificant regardless of the filtration.[7] Testing if systematic risk factors are exposes to mispricing related pricing explanations, we note that our OG factors are not predictable by investor sentiment, economic and oil policy uncertainty related variations. The time-series analysis shows that OG specific factors explain larger return variation among the 14 anomaly portfolios. However, the best model in suppressing mispricing among long-short differentials is when we combine OG specific factors of FF5 model and HXZ model with developed countries factors. This evidence shows that extreme portfolio return differentials are explained by a combined model including sector specific and global factor variations.

Our cross-sectional results show that the HXZ model explains most of the variation in cross-sectional returns whether we test this on portfolio level or firm level. Finally, our results show that OG sector anomaly and stock returns are more responsive to systematic factor variability than being an explanation of their characteristics. This result largely shows that risk-compensation in the global OG companies is a better explanation than mispricing that is driven by firm characteristics.

The reported findings are important in knowing robust systematic risk variations that investors should account for in developing risk-based investing strategies. The size, profitability and

[7] It is widely established in the AP literature that high return premium on small stocks comes with high price volatility, lack of coverage by equity analysts and is also exposed to investor sentiment related variations as well as have low liquidity together with large bid-ask spreads. To avoid, noise related to these price variations, all subsequent analysis is reported for EG stocks after applying the 5 USD filter.

investment related factor variations are persistent at portfolio and firm levels – contributing to time series and cross-sectional variations – in the global OG sector. Largely, there is little evidence for mispricing in the cross-sectional analysis, thus our work shows that OG specific are the main drivers to explain return differentials on AP anomalies in the OG sector. Global factor return brings additional gains in explaining return premium and variation in the time series and in the cross-section. However mispricing related explanation at macro and firm level is marginal and mostly is statistically insignificant. This shows that pricing in the OG sector is largely efficient. This adds a new dimension to existing literature that uncertainties emanating from global OG sector may create board-based mispricing in the global equities (Stambaugh & Yuan, 2017; Daniel, Hirshleifer & Sun, 2020) and influence firm-level corporate investment decisions (Phan, Tran & Nguyen, 2019; Maghyereh & Abdoh 2020; Ilyas et al., 2021) but the return differential on anomalies in a highly capital-intensive sector i.e., OG is best explained by risk-based models and not by their characteristics. This is consistently established across battery of testing techniques.

Following the introduction section, a detailed literature review is presented in section 2. Section 3 presents data, construction of anomalies and AP factors. Empirical design and estimations are presented in section 4. The last section provides conclusion to our work with implications for future research.

## 2. Literature review

### *2.1.Asset pricing anomalies mispricing and factor models.*

The persistence of small firm effect and value effect in the cross-section led the consensus that CAPM is a poor explanation of average returns (Fama & French, 1992). Fama and French (1993) provide a new benchmark for risk adjustment by augment the market model specification by size and value factor-mimicking portfolios. There have been several candidate asset pricing models, but the agreement stayed that size, value and momentum related cross-sectional variations are robust candidates for risk premium in the US and across the world (Fama & French, 1996; Jegadeesh & Titman ,1993; Carhart, 1997; Asness, Moskowitz & Pedersen, 2013). However, recent evidence has brought additional anomalous variations to the fore that challenge the credibility of Fama and French three factor (FF3) model (Stambaugh et al., 2012). It is important to note that Stambaugh et al. (2012) explained how the anomaly returns that challenge FF3 model are exposed to sentiment related valuations instead of them explaining risk variations in stocks returns.

However, there has been an onslaught of anomalous patterns in stocks returns such that the number of anomalies in last one decade have grown from tens to hundreds (Cochrane, 2011). Cochrane (2011) indicates that this influx of anomalies has descended AP into chaos, as the one observed in the post-CAPM world.[8] Hou et al. (2015) using tens of anomalies show that FF3 model is unable to explain stock returns on many anomalous patterns.[9] AP literature has required updating of the risk models that capture risk variations across range of anomalies and across periods (Hou et al., 2021). In this vein, firm profitability (Novy-Marx, 2013) and investment (Aharoni, Grundy & Zeng, 2013) have been elevated as candidate risk-factors to capture variations in a wide set of anomalies. Prominent risk-based models that include profitability and investment related factors are Fama and French (2015) five factor (FF5) model, and Hou et al.'s (2015) HXZ model. These models explain significant and large number of anomalies present in the cross-section (Fama & French, 2016; Hou et al., 2021).

In a parallel line of research, Stambuagh et al. (2012) show that usual anomalies that are used as controls for systematic risks can also be polluted by sentiment based common variation: anomalies on market betas, market equity and value effects behave similar to ones describing mispricing of course with the role of long and short legs reversed. Following Haugen and Baker (1996); Acharya and Pedersen (2005) and others, it is crucial to understand if the variation in equity returns compensation is for bearing a systematic risk or is explained by mispricing related to firm characteristics. That is, after controlling for anomaly related firm or portfolio characteristic if corresponding systematic risk does not influence average returns in the cross-section, it would be an indication that the proposed factor captures mispricing related price variation and vice a versa.

### *2.2. Stock return variations and Oil and Gas sector determinants*

The oil crisis in 1970's led to global recession. Since then, there are voluminous number of studies focusing on the role of oil prices in the overall performance of the aggregate economy. In fact,

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[9] Among the many anomalous patterns leaving FF3 model adrift, most worthy of mention are accruals (Sloan 1996, ACR), net share issues, (Ikenberry, Lakonishok, & Vermaelen 1995; Loughran & Ritter, 1995, NSI), previous month stock volatility (Ang et al., 2006), operating profitability (Novy-Marx, 2013, OP), investment (Aharoni et al., 2013; Haugen & Baker, 1996; Titman, Wei, & Xie, 2004, and others, INV) and betting against CAPM beta (Frazzini & Pedersen, 2014, BETA).

eight out of nine recessions occurred in the post-World War II period are caused by the rising oil prices (Brown & Yücel, 2002). While earlier empirical studies such as Pierce et al. (1974) and Darby (1982), among others, document an inverse relationship between oil prices and aggregate economy. Later studies such as Basher and Sadorsky (2006) provide evidence on the impact of oil prices and the stock markets across various countries. Brown and Yücel (2002) conduct a survey in which they explain six transmission channels through which the oil price affects the performance of the overall economy. Among these channels, the supply side shocks are the direct channel. This channel states that an increase in oil price leads to increase the production cost which as a result translates in low aggregate output. Other channels include the wealth transfer effect, inflation effect, real balance effect, sector adjustment effect and unexpected effect. Degiannakis et al. (2018) demonstrate the effect of these transmission channels on the stock prices via the cash flow discount model.

These transmission channels are very well outlined in the survey by Degiannakis et al. (2018), with popular research theme such as, the impact of oil prices on stocks and the asymmetry of this relationship, belonging to net oil-importing and net-oil exporting countries. The impact of shocks in oil prices on the stock market returns and the relationship between oil price volatility and stock price volatility.

The consensus is that positive change in oil prices impacts stock returns negatively. Asteriou & Bashmakova (2013); Filis & Chatziantoniou (2014); Ghosh & Kanjilal (2016), among others, show that the variation in this negative relationship has sectoral dependence (see, among others, Arouri et al., 2012; Scholtens & Yurtsever, 2012; Broadstock & Filis, 2014). Lastly, the negative relationship holds for oil-importing countries and reverse effect is more plausible for oil-exporting countries (Park & Ratti, 2008; Mohanty et al., 2011; Arouri & Rault, 2012).

Another area that is explored investigates the relationship between the oil prices on the stock returns by distinguishing between the positive/negative change in oil prices on the stock returns. The studies find that the same increase and decrease in prices of oil impacts asymmetrically the stock returns. That the increase in oil prices depresses the returns more than the decrease in oil prices increases the stock returns (Jiménez-Rodríguez, 2015; Phan, Sharma & Narayan, 2015; Broadstock et al., 2016 and others). In the same vein the impact of oil price shocks on the stock returns is also analysed, these shocks are described in Kilian (2008, 2009) as, supply-side, aggregate demand and precautionary demand shocks. When the oil producing countries increases prices, as a strategy, then that does not necessarily impact the stock returns. Whereas positive shock to aggregate demand side impacts positively to stock returns, that is due to economic growth. Lastly, the positive shock to the precautionary demand impacts negatively as it is linked with uncertainty. Nevertheless, studies also find that impact of these of shocks are not unanimous across all countries and depends on the classification such as net-importing country or net-exporting country.

Apparently, the emphasis of studies linking oil prices with the stock returns, is to use oil sector as the explanatory variables for the stock returns. The lesser focus is reserved for the returns related characteristics of stocks belonging to oil and gas sector. Despite this being an important area of research in asset pricing. Among few exceptions is the study by Zhu et al. (2020) that tested the mispriced anomalies for oil and gas sector. With the rationale of existence of higher arbitrage risk in oil and gas sector may give rise to significant mispricing. Using similar pricing filter, they document that out of 15 mispriced strategies 12 are significant. The study by Stambaugh et al., (2012) identified 11 of such mispriced strategies for the US stocks that can be partially explained by the investor sentiments of Baker and Wurgler (2006). Another study on the 12 mispriced anomalies is carried out by Cheema and Scrimgeour (2019) for Chinese markets, a net oil importing country, with the different perspective. Authors find that there is more predictability in returns of the anomalies following increase in oil prices than for the decrease in the oil. Here again, the OG sector is used as the explanatory variables for the stock returns.

It is important to understand the impact of changes in oil prices, the shocks in oil prices and supply-side and demand-side related shocks on the overall returns for the global markets. Unsurprisingly, as Degiannakis et al., (2018) document that prior evidence has placed a larger focus there. Alternate themes of research include the equally important firm level view of the pricing of the OG sector firms. This type of analysis is vital for the investors and asset managers to understand the pricing dynamics of stocks traded in the OG sector. This work argues that it needs a detailed study on the various anomalies for the stocks traded in the global OG sector, to understand the linkage between the firm-based characteristics, systematic risk factors and measures of macro uncertainty such as investor sentiment, economic policy uncertainty and oil price uncertainty. This relationship is studied extensively evaluated in the asset pricing literature for the US and global stock returns in the literature (Harvey et al., 2016; Linnainmaa & Roberts, 2018; Hou, Xue, & Zhang, 2020; Chordia, Goyal, & Saretto, 2020; Chen & Zimmermann, 2021, and others).

## 3. Data

Our sample comprises mainly energy sector stocks from 86 countries over the period from January 1992 to December 2020. This data is retrieved from Refinitiv DataStream. We retain the dead firms in our sample to eliminate survivorship bias and all price data is retrieved in USD denomination. The risk factors for the US and the developed countries, together with one month US T-Bills rate, are taken from Ken French data library. The HXZ model factors for the US are retrieved from authors' data pages. We are thankful to Kenneth French and the team of Hue et al. (2015) paper for making their datasets available in open access.

In curating data, we apply several filters to create a representative, consistent and comparable dataset. The application of filters follows for noted issues in DataStream and emerging market data. Please refer to Ince and Porter (2006); Griffin, Kelly and Nardari (2010) among others for details on the variety of multilevel filters are applied in our work to remove data inconsistencies, gaps, and exclusion of non-equity firm listing in the final dataset.

### *3.1.Data filtering*

We apply several static screens at the firm level. These screens are applied in two steps. First, we restrict our sample to firms (i) listed in the domestic market, (ii) listed on major stock exchange of the country, (iii) in case a firm has more than one classes of stock listed on exchange, we pick the major class only i.e., the one with biggest market capitalization and liquidity and (iv) quoted in local currency. 4,492 firms survived the static filters energy sector firms (1,527 firms from the US, 1,511 from Canada and 1,454 from other countries). We then retrieve accounting data from World Scope and financial data from Thomson Reuters DataStream for the remaining firms. The final sample was further reduced to 3,782 firms due to lack of data availability on different firm characteristics across sample years. This inaccessibility of data usually occurs for the initial years in our sample period. Table 1 presents firm characteristics for which data is downloaded across all firms in the sample.

The second step applies dynamic filters on the firm level data. We drop a firm observation if (i) return is greater than 900% in any month, (ii) return in current month or return in the previous month is bigger than 300%, and [(1 + current month return) * (1 + previous month return) −1] is smaller than 50%, (iii) market capitalization is below 5% breakpoint of sample firms, (iv) the price is less than 5 USD, (v) illiquid stock i.e., stock is traded less than 3 days in a month, (vi) daily data entries are removed if more than 90% of the stocks have zero returns.

In summary, the initial sample includes 12,331 firms. For comprehensive details on data retrieval and curation please refer to Table AI in Appendix A that displays the data reduction after application of both static and dynamic filters for energy firms. Finally, data for 14 firm characteristics are consistently available across the sample period and across countries in our work and thus impose the limit on number of anomaly portfolios constructed in this work.

### *3.2.Anomalies Appendix A*

We initiate our work by constructing single sort portfolios for the noted 14 firm characteristics. These anomalies enable tracking of return premium related to a firm characteristic (Daniel et al., 2020). More often, these anomaly features are examined through risk-adjustment using a benchmark model to see if these anomalous returns are analogous to changes in systematic risks (Stambaugh et al., 2012).

1. SIZE Banz (1981)

2. BTPV Rosenberg, Reid, and Lanstein (1985)

3. MOM Jegadeesh and Titman (1993)

4. INV Titman, Wie and Xie (2006), Cooper, Gulen, and Schill (2008)

5. OPM Fama and French (2015)

6. ROE Haugen and Baker (1996)

7. TOTA Hou et al. (2021)

8. OFCF Lakonishok, Shleifer, and Vishny. (1994).

9. EBIT Altman (1968), Soliman (2008)

10. GPM Novy-Marx (2013)

11. VOL3 Ang et al. (2006)

12. LIQ Amihud (2002)

13. PER Basu (1977)

14. REV Barbee, Mukherji, and Raines (1996)

The portfolio construction criteria are as follows. First, at the end of every month, stocks are sorted in ascending order based on some firm characteristic and decile breakpoints are calculated. Second, stocks are assigned to one of the decile groups based on a firm characteristic and their next month capitalization weighted returns are tracked for a respective decile/portfolio. Third, in every month, a cross-sectional average is computed to get the monthly portfolio returns. Fourth, to create zero investment portfolio, we take long and short positions in extreme portfolios. Fifth, this rebalancing is repeated monthly to compute the cross-sectional average of all months in the sample period of our work. In total, we have data for 14 different characteristics resulting in 140 deciles portfolios in total and 14 long-short investment strategies using the extreme portfolios depending on the identified anomalous return variation linked to a particular firm-characteristic.[10] Table AII of Appendix AI presents the 14 characteristics and their detailed definitions used in this study.

### *3.3.Factor construction*

We restrict our analysis to prominent risk models in the asset pricing literature to determine if the cross-sectional return patterns are driven by systematic risk factors or if these return differentials are the consequence of mispricing in energy stocks. These models are Sharpe (1964); Lintner (1965); Mossin (1966) CAPM, Fama and French three-factor (FF3, 1996) and Carhart (1997) four-factor model adding momentum factor to FF3 model. In relation to, chaos in asset pricing literature there have been updating of prior AP benchmarks: Fama and French (FF5, 2015) have augment their FF3 model with two additional factors of profitability and investment. In an independent work, Hou et al. (2015) proposed q-investment theory-based model that includes market, size, profitability, and investment related systematic factors. Fama and French (2016) and Hou et al., (2019) show that their model can explain returns on a larger set of anomalies than the prior risk-

[10] More often, the long-short portfolios are $10^{th}$ decile of a characteristic portfolio minus $1^{st}$ characteristic portfolio e.g., high BM ratio ($10^{th}$) portfolio/decile minus low BM ratio portfolio/decile. However, when it comes to SIZE anomaly the differential is reversed for the long-short portfolio: it is $1^{st}$ decile-$10^{th}$ decile i.e., the small capitalization portfolio minus large capitalization portfolio.

adjusting AP models. To keep up with the new set of AP models, we also compute systematic factors of these former two models. We note that all factors except the market factor are two-way sorts following Fama and French (1996) that controls for size using the median breakpoint of firm capitalization resulting two portfolios followed by creating three additional portfolios with the 2nd characteristic by dividing stocks using 30% and 70% breakpoints in the cross-section of global OG sector stocks.[11]

### *3.4. Preliminary Analysis – anomalies and systematic factors*

We begin our preliminary analysis by first assessing the cross-sectional dispersion in long and short portfolios of the constructed 14 anomaly portfolios. Table 2 Panel A reports average returns of long, short, and long minus short portfolios when we exclude the small capitalization firms whose prices fall below 5% breakpoint of the entire sample in any month. Out of 14 anomalies (long – short), 13 are significant at 1% level. Only momentum long-short portfolio average return is insignificantly estimated and the sample average for momentum anomaly is also the lowest across all anomaly long-short differentials. The largest return differential (5.3% per month) is linked with size anomaly in the sample period. Liquidity and price to earnings ratio are the two anomalies that provide 1.2% average returns per month. For all other anomalies, the average monthly returns range between 1.2% (Liquidity and price-to-earnings ratio) to 3.9% (profitability using EBIT).

Given the dominance of size anomaly per small firms in the sample, we employ a more restrictive filter of 5 USD to mitigate the pricing fluctuations linked to microcaps – a filter usually used for the US microcaps (Amihud, 2002; Fama & French, 2015). The average returns on anomaly portfolios using 5 USD filter are presented in Panel B of Table 2. Unsurprisingly, the size anomaly returns are now insignificant and reduced to only half a percent from the large average value of 5.3% per month. We also note that the removal of microcaps, the number of significant anomalies i.e., long-short return differentials, reduce to nine and a general decrease in average returns is observed in the characteristic portfolio return differentials. Regardless of the types of filtrations on the price/capitalization levels of energy firms in our sample period, there is significant cross-

[11] We construct 14 systematic risk factors following the procedure described in (Bali, Engle & Murray, 2016). Table AIII of Appendix AI, however, only describes the procedure used to construct the systematic risk factors mapped by the AP models tested in our work. We note that the excluded factors either do not bring important time-series and cross-sectional information or are outperformed by the models contained in this work.

sectional dispersion across several anomalies. We regard the significant average differentials in Panel B to provide stronger evidence that there is presence of anomaly-based pricing in global energy stocks. Thus, it is worth investigating if these anomalous patterns follow risk-based explanation or are driven by mispricing linked to firm-characteristics.

As the average returns and their significance in Table 2 across panels A and B show that microcaps may influence anomalous returns, we limit our empirical analysis to the universe of stocks after the exclusion of firms having prices below 5 USD.

The summary statistics of the risk mimicking factors of FF3 model, WML of Carhart (1997) model, and investment and profitability factors of FF5 and HXZ models in the cross-section global oil and gas stocks are reported in Table 3 panel A.  Using the criteria of t-stats of 3.0 or above, only market, value, RMW and ROE (both linked to firm profitability) and I/A are significant factors for the global oil and gas stocks. The insignificance of SMB, WML and CMA factors follows from the insignificant average return for size, momentum, and investment ZCS in Table 2 panel B. However, the significance of average returns on I/A factor linked to investment ranking criterion shows the divergence in ranking criterion employed: total assets (TOTA) bring return that is significant in the cross-section, whereas changes in it (INV) is not linked to significant return differential.

Panel B of Table 3 presents the correlation matrix of the OG sector systematic factors present across employed AP benchmarks. The return on ROE factor has high negative correlations with size and value factor returns, whereas a strong association between RMW factor and ROE factor returns is unsurprising as both proxy firm profitability. The I/A factor returns show a strong correlation structure with value factor returns and a high dependence is seen with market (positive) and ROE (negative) factor returns as well. Another important correlation pattern is observed between market and value factors. For the rest, the reported correlation patterns display weak dependence structure.

## 4. *Empirical methods and testing*

To explain the return differential on 14 ZCS and $14 \times 10$ Oil and Gas portfolios – the latter are employed in time series and cross-sectional regressions only - empirical analyses are sectioned into performance, time-series, and cross-sectional estimations.[12]

### *4.1. Performance evaluation of ZCS*

We begin our empirical analysis by using performance evaluation measures applied in the investment management including Jensen-alpha, Sharpe-ratio, and Treynor's ratio (TR). Table 5 presents statistics on performance evaluation metrices. The results for Jensen-alpha show that there is not a remarkable difference whether we use a global proxy for market portfolio or benchmark the performance of an anomaly ZCS in reference to a portfolio of global Oil and Gas firm only. The key takeaway is that except momentum anomaly all ZCS have large unexplained average returns.

To examine the relative risk profiles of the 14 ZCS, we limit our performance evaluation exercise to Oil and Gas industry index only.[13] The Sharpe-ratio of the anomaly portfolio shows that the risk-to-reward ratio which is linear in this sector should be approximately one and the only anomaly that comes near to this criterion is liquidity anomaly. SIZE and MOM anomaly offers marginal returns to the underlying risk of these two anomalies. The rest of the anomalies bring substantial reward relative to the underlying sectoral risk premium: this could be as large as 7 times – ROE (profitability) ZCS – of the risk-premium of the broad-based industry benchmark.

When it comes to TR, also known as reward-to-volatility ratio, it is obvious that the global industry benchmark estimates the risk profiles of most of the anomalies incorrectly. Out of 14 industry betas, eight of them are incorrectly estimated. However, if the industry benchmark is employed to compute investment performance of these portfolios, then revenue-based anomaly (TR=0.269) is the most suitable investing candidate relative to industry risk profiling. The REV ZCS is followed by PE (0.126), SIZE (0.083) and BM (0.04) zero-cost strategies.

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[12] This work limits factor models to FF3, Carhart, FF5 and HXZ models for brevity. Unreported results for the excluded factors are available upon request and we confirm results using them in factor models do not bring any qualitative and quantitative difference to the findings reported in this work.

[13] We note that we also use a global market index to compute Jensen alpha and other risk profiling ratios provided in Table 5 and we find little to no difference in the choice of global EG index vs. global proxy for stocks such as excess returns on CRSP US index or MSCI global index.

### *4.2. Systematic factor and macro-level mispricing measures*

Literature has shown that China, the US and global equity returns, and corporate investment decisions are influenced by investor sentiment, economic and oil policy uncertainty measures (Ratti, Seol and Yoon, 2011; Chen, Lee & Zeng, 2019; Phan, Tran & Nguyen, 2019; Ilyas et al., 2021; among others). To examine if the constructed global OG factors in our work are also exposed to the noted wide-spread measures of mispricing. We run univariate regressions for all systematic factors present in the competing AP models: systematic factors are dependent variables, and we use lagged changes in the investor sentiment, economic policy uncertainty and oil price uncertainty indices as independent variables. For details refer to Table 4.[14]

The results show that the effect of mispricing linked to these macro-variables is economically and statistically insignificant. These results show that our systematic factors measure what they are designed for i.e., risk related return variation in the cross-section of global OG stock returns.

### *4.3.Model comparisons – time series regressions*

To initiate the model comparisons, we estimate CAPM, FF3, Carhart model, FF5 model and HXZ models for each of the 14 ZCS. The model equations for each of the noted AP model are presented, in the same order, in equations 1 to 5.

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \varepsilon_{i,t} \quad (1),$$

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \varepsilon_{i,t} \quad (2),$$

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,WML}WML_t + \varepsilon_{i,t} \quad (3),$$

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,CMA}RMW_t + \beta_{i,CMA}CMA_t + \varepsilon_{i,t}$$

(4),

and

$$R_{i,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) + \beta_{i,ME}ME_t + \beta_{i,I/A}I/A_t + \beta_{i,ROE}ROE_t + \varepsilon_{i,t} \quad (5).$$

[14] We use global measures of investor sentiment and economic policy uncertainty indices available from Jeffery Wurgler and economic policy uncertainty webpages. For oil price uncertainty index we follow the procedure noted in Ilyas et al. (2021), please refer to their work for details.

On the LHS of the model equations are the monthly returns ($R_{i,t}$) for anomaly i's decile portfolios. For ease of discussion, we annotate market model specification-CAPM as Model (M) 1. M2 is FF3 model that augments CAPM by SMB and HML factors. M3 is the Carhart model that adds WML factor to FF3 model. M4 is the FF5 specification that adds profitability (RMW) and investment (CMA) factors to FF3 model. Finally, M5 is HXZ q-factor model that accounts for factors linked to market, size (ME), investment (I/A) and profitability (ROE).

Following Fama and French (2015), we limit the appraisal metrics to model alphas i.e., intercepts, model factor betas, and adjusted r-squared values. These values for each of the models are assimilated to compute average performance of the candidate AP model. Below, we provide a brief explanation on these performance metrics.

#### *4.3.1. Average alphas*

Fama and French (2015, 2016) use the average alpha $A(\alpha_i)$ of all the LHS portfolios to compare contesting models. This work also documents this metric for a meaningful comparison when GRS F-test rejects even the best of the cross-sectional AP model. This enables us to assess which model reduces mispricing in relative terms in the cross-section of anomalies.

#### *4.3.2. Average Absolute alphas*

It is possible that average alpha measure may return low relative mispricing for have large positive and negative alphas values for a model, especially for the extreme portfolios (Stambaugh, Yu and Yuan, 2012). Therefore, to adjust for the large alpha variation Fama and French (2016) employ average of absolute alphas ($A|\alpha_i|$) across all LHS portfolio for model comparison.

#### *4.3.3. Average adjusted r-squared*

All competing models are also evaluated with respect to their average adjusted r-squared values. That is, this metric will display to what extent of return variation in the expected returns of oil and gas anomalies is captured by a candidate AP model.

To distinguish OG anomaly deciles corresponding to US, global or sector factor variations, we repeat all estimations using OG, the US, and developed countries' factors and meaningful combinations of them. These results are summarized in Table 6. In panel A, we use OG specific factors to proxy systematic return variations global oil and gas firms, whereas panels B and C provide results when we employ factors capturing US specific and developed countries' factor variations, respectively. In panel D, all test-statistics are computed using different factor combinations to assess if sector and aggregate factor variations – US and developed countries – do a better job in describing time series differences in 140 anomaly-deciles.

We start our time series analysis by analysing the GRS test of Gibbons, Ross and Shanken (1989). With the null hypothesis of if a model jointly suppresses intercepts of all 140 portfolios, the test statistics are provided in Table 6. Consistent with Fama and French (2015, 2016), we report that all models fail to explain cross-sectional variation in model intercepts of the OG anomaly portfolios jointly. That is, GRS-test rejects all model specifications. Implying that the null hypothesis of model alphas is jointly zero is rejected for all models. The summary results show this result is robust whether we use global OG sector specific factors (Panel A), US-specific (Panel B) or developed countries (Panel C) – the US and developed country factors are used to account for global shifts in risk mimicking structures, or their combinations (Panel D) in the candidate AP models.

This is followed by informative tests when all models are inadequate explanations of anomalous returns in OG sector makes matters rather absolute to the extent of being inconclusive. To get ahead of this, we resort to relative model comparison tests of average alphas ($A\alpha_i$), average absolute alphas ( $A|\alpha_i|$) and average adjusted r-squared values. When it comes to former two ratios, a large differential between the two implies that lower value of $A\alpha_i$is an artifact of having negative intercepts – poor model fit. The reported results show that OG specific factors-based ratios are lower than the counterpart AP model using the US and developed countries factors in competing AP models. The best models are the FF5 model and a six-factor specification that adds WML to FF5 model. For these two specifications, the difference between the average alpha and average absolute alphas is 0.001 showing that both models are relatively good fit and intercepts largely describe mispricing in the OG anomaly deciles. However, for the rest of the models either the differences are large, or the level of mispricing is substantially higher than the winning models. These two models also explain the largest return variation in the 140 anomaly portfolios: average adjusted r-squared of 22.6% is the largest among all competing models.

Using OG sector specific factors, we also notice that FF3 factor brings the largest differential between average alphas and average absolute alphas i.e., FF3 model in panel C is a poor fit in more instances than the rest of the models and by a large amount. The same is implied for FF3+WML model.

Overall, our results show that there are marginal differences between average alphas and average absolute alphas across all models and the type of factor used in panels B and C. Even though the mispricing levels exceed the average alphas and average absolute alphas, the intercepts using the US and the developed countries factor more often estimate mispricing more precisely. This is displayed by the closeness of average alphas and average absolute alphas in panels A and B.

Motivated by this precision, we consider the possibility that the US and developed countries factors – for their ability to proxy global shifts in risk premia – may bring independent information to that of better performing OG specific factors. We attempt several combinations and provide results with the best models that suppress mispricing even better than what we have witnessed in panel C for FF5 and FF5+WML model specifications. First, we find that the combination of OG specific and the developed countries factor structures bring complementing information. We observe an increased average adjusted r-squared value for this model (panel D of Table 6) than the best performing model of FF5 and FF5+WML (panel C of Table 6). So is the case that mispricing whether we use average values or average absolute values of model intercepts. Two, we further improve on explaining time series return variability in 140 anomaly deciles when we add HXZ factors that are OG-specific inclusive of market factor. We report an average alpha value of 0.0067, average absolute alpha value of 0.007 and average adjusted r-squared value of 28.7%.

### *4.4. Cross-sectional tests – risk versus characteristics*

The time series regressions show that there is a large cross-sectional mispricing that is not explained by the asset pricing models or combinations of them. This leads to two questions. One, does the better performing models' factors carry a risk premium. Two, is return variation a response to changes in systematic factors or are they linked to changes in firm characteristics – the significance of this will represent the greater presence of mispricing that is left unexplained by systematic factors. To test both questions, we move to our next analysis and run panel regressions.

#### *4.4.1. Portfolio-level analysis*

To estimate if the cross-sectional return variation across stocks is linked to systematic factors or their idiosyncratic firm characteristic, we estimate fixed-effect panel regression[15]:

$$R_{p,t} = \mu + \Lambda F_{i,t} + \Gamma PC_{i,t-1} + \xi_{i,t} \quad (6),$$

$R_{p,t}$ is the vector of monthly returns on the 140 anomaly portfolios. $\Lambda$ is the vector of coefficients on *'$i$'* systematic factors contained in matrix $F_{i,t}$. Likewise, $\Gamma$ is the vector of coefficients on *'$i$'* portfolio characteristics – average of firm characteristics in the portfolio – contained in $PC_{i,t-1}$ corresponding to factors in the $F_{i,t}$.

For ease of analysis to evaluate which factors and characteristics are significant patterns in the global oil and gas anomaly portfolio returns, we follow the guidelines provided by Harvey et al. (2016) and use a t-stat threshold of 3.0. With the abundance of anomalies and factors and issues of data mining, they document that a conventional criterion of t-stats greater than equal to 2.0 is too low. They propose that to gauge the significance of a factor in the cross-section of expected a higher bar of t-stats equal to 3.0 or more should be employed as robust evidence on the significance of the pattern. This restriction provides a simplified and statistically consistent rule on the admissibility and presence of a cross-sectional pattern in stock returns.

The output of cross-sectional tests using fixed-effect panel regression is presented in Table 7. For CAPM, FF3 and Carhart models, we find that factor exposures on market, SMB and HML meet the higher bar of t-stat >= 3.0. With the same token there is no evidence of the characteristic related mispricing in the cross-section for the characteristics incorporated in these three models.

The insignificance of WML factor exposures prevails even in FF5+WML model, however in the estimation of FF5 model augmented or not augmented with WML i.e., M4 and M5, we find that CMA factor exposures fall below the threshold of t-stat of 3.0 or more. The coefficient on investment related portfolio characteristic meets this criterion. However, the estimated coefficient is not economically and financially meaningful: as investment undertaking of a company increase their returns reduce. This expectation is different to the manner CMA is invoked in Fama and French (2015). It is safe to infer that investment factor does not influence cross-sectional variations

[15] The regression estimations account robust standard errors: effects of small sample bias and larger variance of standard errors are entertained.

in the anomaly portfolios undertaken in our work, but investment related characteristic also does not provide any evidence for mispricing.

The results for the HXZ model and related characteristics show that all factor exposures are positively and significantly linked to cross-sectional variations in the test portfolio returns. The log of market capitalization is significantly linked to cross-section return variation. However, the exposure is negative showing that possibly there is large firm related mispricing size premium is different from portfolio's size characteristics.

The final model M7 in Table 7 brings together all factors in the competing AP models and their corresponding portfolio characteristics. This specification shows that value effect is absent when we account for HXZ related ROE and I/A factors in the model. However, in consideration to the constraint of t-stat of 3.0 or above market, SMB, RMW, ROE and I/A are cross-sectionally robust to explain the return differentials in the anomaly portfolios in our work. This specification provides comprehensive evidence against characteristics related mispricing in the OG stocks: the coefficients do explain differentials in a meaningful way and not significant using the t-stat threshold of 3.0 or more. In sum, not all factor structures are relevant in the cross-section of OG anomaly portfolios, but the return differentials are explained by significant factors linked to market, size, profitability (both revenues and ROE) an investment (using total assets as proxy for investment not by changes in it).

### *4.4.2. Stock-level analysis*

To estimate if the cross-sectional return variation across stocks is linked to systematic factors or their idiosyncratic firm characteristic, we estimate fixed-effect panel regression:

$$R_{s,t} = \mu + \Lambda F_{i,t} + \Gamma FC_{i,t-1} + \xi_{i,t} \qquad (7),$$

$R_{s,t}$ is the vector of monthly excess return on OG company s in our sample. $\Lambda$ is the vector of coefficients on *'$i$'* systematic factors contained in matrix $F_{i,t}$. Likewise, $\Gamma$ is the vector of coefficients on *'$i$'* firm characteristics contained in $FC_{i,t-1}$ corresponding to factors in the $F_{i,t}$.

The output of these regressions is reported in Table 8. Sticking with the criterion of t-stats of 3.0, we find that cross-sectional sensitivities for CAPM and FF3 models' factors are plausible and are highly significant. However, market beta is adversely linked in the cross-section as use firm-level return variation in the panel. We find evidence for size characteristic as the coefficient on log of firm capitalization is positively linked to excess returns on stocks, however coefficient on lnBM ratios is negative showing as firm's BM ratio increases the excess stock return decrease. That is, we find systematic risk factors of market, SMB and HML are linked to expected stock returns when all firms are taken together, however if there is mispricing then that is only present for firm capitalization in the OG firms.

The momentum factor sensitivity is unable to meet the t-stat threshold of 3.0 and problematically is also negative. Providing robust evidence on the consistency of our prior results that momentum factor is not important for OG sector returns. However, firm-level time series momentum when added as characteristic we find that OG stocks are exposed to momentum related mispricing, while keeping everything else constant.

The coefficients on investment and profitability factors in FF5 and FF5+WML models have t-stats of less than 3.0, however firm level characteristics are positive and significant. This displays that proxy used to capture investment and profitability in the FF5 model is significantly related to mispricing than capturing risk-mimicking factor variations in the global OG sector. However, when we test for the same factors using HXZ model, using different definitions, we find M6 in Table 8 has positive and highly significant estimates on ROE and I/A factors. Furthermore, we also note that systematic risk variation in the HXZ model factors derives mispricing related characteristic explanation redundant. That is, for lnROE the coefficient is negative and insignificant, and it is also negative for lnTA however is significantly estimated. In either case both the coefficients depict that there is no mispricing related to these firm characteristics in the cross-section of OG stocks.

However, the combined specification shows that market, size, value and firm profitability contain systematic return variation when we account for firm-level return variability. There are differences in characteristic-related mispricing: high beta, winner, and increased investment allocating (with changes in Total assets) firms in the cross-section are exposed to departure from fundamental values explained by noted firm attributes than the corresponding factor risks.

## *5. Discussion and concluding remarks*

The assessment of AP anomalies in the OG stocks is limited to the US and China equity markets (Cheema & Scrimgeour, 2019; Zhu et al., 2020). This analysis predominantly examines if return and risk-adjusted returns on anomalies are exposed to mispricing approximated by investor sentiment. The risk adjustments have limited to models such as FF3 model that have been shown to lack cross-sectional depth to explain returns on several anomalies (Stambaugh et al., 2012; Hou et al., 2015 and Fama & French, 2015, among others). Another strand of research examines how firm outcomes e.g., corporate investments are exposed to economic and oil policy uncertainty. Our work provides a new dimension in the evaluation of stock return variations by developing anomalies in the global OG stocks using firm attributes, consistently available across countries, that have been known to be difficult to explain by risk-models. In addition, we construct systematic factors that are part of recent additions/extensions of prior AP benchmarks. We follow this, by evaluating if the factor returns are exposed to investor sentiment, economic and oil price uncertainties. Finally, our work contributes to the AP literature to evaluate if the global OG stock return variations are explained by risk-based explanations (by adding recent AP models) or firm characteristics depicting mispricing.

Our evidence suggests that there are several persistent anomalies in the cross-section of global OG sector stocks. However, not all translate into factor return variation. Furthermore, the analysis if robust systematic factors are exposed to widespread mispricing linked to investor sentiment and economic and oil price uncertainty measure shows that largely factors describe risk-related return variation. That is, none of the factors are exposed to investor sentiment related variation. Whereas only market and size factors are exposed to oil uncertainty variations at 1% significant t-values and with respect to economic policy uncertainty only I/A factor show significant response at 1% critical t-values. Factor variation is meant to capture variations in investor opportunity set and their exposure to different dimensions of mispricing – investor sentiment, economic policy uncertainty and oil price uncertainty – show that these factors mostly have economically marginal impact and mostly are statistically insignificant.

The time-series analysis shows that OG specific factor variation relative to global factor returns – whether proxy by the US or developed country factors – is more important to explain 140 anomaly decile portfolio return variations. However, a model that combines OG specific and global factor portfolios suppresses the unexplained decile portfolio returns the most. This suppression of unexplained returns shows that both types of systematic factor bring independent information to explain the anomaly decile portfolio return variations.

Finally, the cross-sectional analysis evaluates if competing AP model – recent and prior benchmarks – explain return differentials on 140 anomaly portfolios/deciles. Or the performance of AP models disappears when we control for corresponding firm characteristics, i.e., simultaneous analysis as a micro measure of mispricing at the firm-level. Breaking down these results at portfolio and stock levels brings forward important patterns in the cross-sectional variations in the anomaly portfolios.

First, our results display that the size effect is robust in the cross-section whether we examine at portfolio or firm level. However, we find that there is a reverse mispricing effect present at portfolio level only: large capitalization firms at portfolio level are exposed to characteristics mispricing. Second, one of the most daunting and persistent value and momentum effects (Asness et al., 2013) are found missing in the portfolio level analysis, however, value effect emerges at the stock-level cross-sectional analysis. Our work finds distortions in pricing in the global OG factor, characteristic related mispricing with respect to BM ratios is absent both at portfolio and stock level analyses but winners' effect is present at firm level analysis.

Three, the profitability and investment factors are vital for risk adjustments as per the HXZ model factor characterization – the investment factor uses TA as the ranking criterion that is different from lagged changes in total assets in the HXZ and FF5 models.[16] The same factors are not economically and statistically meaningful as defined by Fama and French (2015) – FF5 model. However, a conventional type of investment measurement as in the FF5 model (and in HXZ model as well) as a portfolio (firm) attribute is cross-sectionally linked to over (under) valuation. That is, the effect of investment characteristic – in a capital-intensive industry – brings mispricing in the valuation of portfolios (stocks) resulting in lower (higher) future returns. Our work contributes to portfolio analysis of global OG stocks – in a capital-intensive industry – by showing that (i) the

[16] Our work creates investment factor using market capitalization scaled total assets to distinguish from the investment factors of HXZ and FF5 models. We find that anomaly and factor returns are significant only when former rule is employed. We argue that in a highly capital-intensive global EG sector the level of investments as measured by total assets capture systematic return variations. As our analysis show, this is not the case when we use INV as the ranking criterion noted in Fama and French (2015) and Hou et al. (2015) for their CMA and I/A anomaly differentials and systematic factors. We decode this pattern as industry specific: when it comes to corporate investment decisions, the history of corporate investments matters more than transitory shifts in investments to asset ratio. Our results show that changes in investment-to-asset ratios are rather linked to mispricing for he global EG portfolio and stock returns – although in opposite directions.

persistence of investments as measured by the level of total assets captures systematic factor return variation, and (ii) changes to investment are linked to cross-sectional mispricing.

The estimation of a full model that brings all systematic factor belonging to competing AP models and their respective characteristics show that mostly systematic return variations prevail and make characteristic related mispricing redundant in the cross-section of global OG stock returns. This finding is robust regardless of whether we conduct our analysis at portfolio or firm level data. Important observations are that large capitalization and investment firms return lower future returns in the cross-section, whereas corresponding factors and value factor cross-sectionally describe size and investment effect at the portfolio level analysis. Profitability is another robust descriptor of factor return variation, present both at portfolio and firm levels. The absence of momentum effect – at all stages of our empirical analyses – is best summarized by the firm level mispricing effect: relative strength firms predict large future returns. That is, market overreaction persists but does not result in systematic factor variation. This observation only prevails in the firm level analysis. However, the high beta stocks that usually are known as loser portfolios Daniel and Moskowitz (2016) present the alternate mispricing effect that also is limited to our stock level analysis.

Overall, we conclude that where risk-related pricing effects are persistent across the multi-level empirical analysis. It shows limited mispricing related valuation effect for the global OG stocks. The mispricing related effect is absorbed by constructing diversified portfolios and therefore, relatively is present more at the stock level price changes. Our evidence provides credence to macro-finance studies that show how valuations and risk are influenced by corporate investment decisions in the global OG sector companies. The implications of our work will help portfolio managers in understanding factor and return structures in the global OG sector companies to develop/support new investing strategies, rebalancing needs, risk planning as well as identifying sources of mispricing at the portfolio and firm level. In essence, our results are important for developing robust decision-making processes and investment evaluation of the investment portfolios while knowing what adequate benchmarks are and what are the opportunities after incorporating relevant risk-adjustments.

Nonetheless, the sum of all analysis is that there is unexplained return variation that is not even explained by systematic risk factors – found at both timeseries and cross-sectional analyses. We identify future research opportunities lay in developing novel pricing measures – risk or mispricing related – to know what explains the large risk-adjusted portfolio returns. These possibilities may explore linking global OG stock return variations to macro-variations such as shifts in business cycles, ESG pricing effects, deciphering between the supply and demand related oil shocks, geo-political risks and other corporate finance variables such as tax-breaks and subsidies, capital structure of firms, equity and debt capital choices across market states, among others.

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## Table 1 Details of variables used in analysis

This table presents variables used in the study. The column labelled as 'Variable Name' contains the variable names, variable condes are reported in column labelled as 'Mnemonic', the currency of variables are reported in column labelled as 'Currency' and the last column provides data sources for each variable.

| S No. | Variable Name | Mnemonic | Currency | Data Source |
|---|---|---|---|---|
| 1 | Total Return Index | RI | USD | DataStream |
| 2 | Closing Price | P | USD | DataStream |
| 3 | Market Value | MV | USD | DataStream |
| 4 | Price to Book Value | PTBV | N/A | DataStream |
| 5 | Operating Profit Margin | WC08316 | N/A | World Scope |
| 6 | Return on Equity | WC08301 | N/A | World Scope |
| 7 | Total Assets | WC02999 | USD | World Scope |
| 8 | Free Cash Flows from Operations | WC05507 | USD | World Scope |
| 9 | Earnings Before Interest and Taxes | WC18191 | USD | World Scope |
| 10 | Gross Profit Margin | WC08306 | N/A | World Scope |
| 11 | Trading Volume | VO | N/A | DataStream |
| 12 | Price to Earnings Ratio | PE | N/A | DataStream |
| 13 | Revenue/Sales | WC01001 | USD | World Scope |

## Table 2 Average returns of zero-cost strategies

This table shows the average returns across all anomaly variables. The returns on long and short portfolios are shown under columns 'Short' and 'Long' respectively. The Long-Short column shows the return of zero cost strategies which takes long/short positions in extreme decile portfolios. Panel A reports average returns of long, short, and long minus short portfolios whose price is equal to or greater than 5% of the entire sample in any month. Whereas Panel B shows the average returns on same strategies when stock price is equal to or greater than 5 USD and their respective market capitalization is greater than or equal to the 10 percent of the entire sample in any month. The sample runs from January 1992 until December 2020. All returns are reported monthly, and t-statistics are reported in parenthesis.

| **Portfolios** | **Panel A: 5% Price Filter** | | | **Panel B: 5 USD Price** | | |
|---|---|---|---|---|---|---|
| | **Short** | **Long** | **Long - Short** | **Short** | **Long** | **Long - Short** |
| **SIZE** | 0.007 | 0.060 | 0.053 | 0.008 | 0.012 | 0.005 |
| (1992:01) | (2.41) | (11.51) | (11.56) | (2.62) | (2.31) | (1.06) |
| **BTPV** | -0.002 | 0.024 | 0.026 | 0.002 | 0.015 | 0.013 |
| (1992:01) | (-0.49) | (4.21) | (5.21) | (0.44) | (3.18) | (3.34) |
| **MOM** | 0.004 | 0.010 | 0.006 | 0.012 | 0.009 | -0.003 |
| (1992:01) | (0.48) | (2.00) | (0.86) | (1.73) | (2.03) | (-0.43) |
| **INV** | 0.011 | 0.033 | 0.022 | 0.004 | 0.012 | 0.007 |
| (1992:01) | (2.14) | (6.13) | (3.92) | (0.86) | (2.61) | (1.53) |
| **OPM** | 0.000 | 0.024 | 0.024 | -0.008 | 0.015 | 0.023 |
| (1992:01) | (-0.04) | (6.02) | (5.39) | (-1.48) | (4.20) | (5.37) |
| **ROE** | -0.010 | 0.023 | 0.033 | -0.015 | 0.019 | 0.034 |
| (1992:01) | (-1.54) | (7.02) | (6.38) | (-2.41) | (5.77) | (7.56) |
| **TOTA** | -0.004 | 0.016 | 0.020 | 0.002 | 0.011 | 0.010 |
| (1992:01) | (-1.14) | (2.85) | (4.00) | (0.43) | (2.29) | (2.20) |
| **OFCF** | -0.003 | 0.015 | 0.018 | -0.003 | 0.013 | 0.016 |
| (1992:01) | (-0.45) | (3.16) | (5.41) | (-0.52) | (2.63) | (4.00) |
| **EBIT** | -0.020 | 0.019 | 0.039 | -0.009 | 0.016 | 0.026 |
| (1992:01) | (-2.80) | (4.64) | (7.23) | (-1.46) | (4.43) | (5.91) |
| **GPM** | -0.003 | 0.026 | 0.029 | 0.006 | 0.016 | 0.010 |
| (1992:01) | (-0.49) | (5.88) | (7.64) | (1.50) | (3.96) | (2.58) |
| **VOL3** | -0.021 | 0.009 | 0.030 | -0.016 | 0.007 | 0.023 |
| (1992:01) | (-2.61) | (3.44) | (3.84) | (-1.94) | (2.67) | (2.95) |
| **LIQ** | 0.007 | 0.019 | 0.012 | 0.007 | 0.013 | 0.006 |
| (1992:01) | (2.37) | (3.57) | (2.49) | (2.42) | (2.61) | (1.21) |
| **PER** | 0.016 | 0.003 | 0.012 | 0.015 | 0.005 | 0.010 |
| (1992:01) | (2.81) | (0.84) | (2.76) | (3.33) | (1.17) | (3.23) |
| **REV** | -0.010 | 0.013 | 0.023 | -0.005 | 0.010 | 0.015 |
| (1992:01) | (-1.95) | (3.44) | (5.32) | (-1.12) | (2.95) | (3.85) |

## Table 3 Descriptive statistics and correlation matrix

This table shows (in Panel A) the average returns (μ), standard deviation (σ), t-statistics (t-Stat) and number of observations (N) for systematic risk factors which are employed in various asset pricing models. These factors are constructed by following the procedure described in (Sharpe, 1964; Fama & French,1993; Carhart,1997; Fama & French, 2015; Hou et al.,2015). These factors are market factor (MKT-RF), small minus big factor (size, SMB), high minus low factor (value, HML), winners minus losers' factor (momentum, WML), conservative minus aggressive factor (investment, CMA), robust minus weak factor (profitability, RMW), high minus low return factor (return on equity, ROE) and low minus high factor (investment, I/A). Panel B shows the correlation matrix of factors contained in the noted models. For consistency, all factors are reported for the sample that excludes stocks with price less than 5 USD and market capitalization below 10% of the entire sample in any month. All returns are reported monthly, and the sample period is from January 1992 to December 2020.

**Panel A: Summary stats**

| | MKT-RF | SMB | HML | WML | CMA | RMW | ROE | I/A |
|---|---|---|---|---|---|---|---|---|
| **μ** | 0.008 | 0.002 | 0.011 | 0.000 | 0.004 | 0.015 | 0.019 | 0.008 |
| **σ** | 0.056 | 0.034 | 0.033 | 0.058 | 0.063 | 0.039 | 0.047 | 0.033 |
| **T-Stat** | 2.50 | 1.14 | 6.18 | -0.02 | 1.04 | 7.06 | 7.63 | 4.30 |
| **N** | 348 | 348 | 348 | 348 | 348 | 348 | 348 | 348 |

**Panel B: Correlation Matrix**

| | MKT-RF | SMB | HML | WML | CMA | RMW | ROE | I/A |
|---|---|---|---|---|---|---|---|---|
| MKT-RF | 1 | | | | | | | |
| SMB | 0.245 | 1 | | | | | | |
| HML | 0.345 | 0.174 | 1 | | | | | |
| WML | -0.048 | -0.049 | 0.050 | 1 | | | | |
| CMA | -0.130 | -0.159 | -0.097 | -0.019 | 1 | | | |
| RMW | -0.168 | 0.075 | -0.117 | -0.057 | 0.084 | 1 | | |
| ROE | -0.370 | -0.197 | -0.325 | -0.017 | 0.153 | 0.656 | 1 | |
| I/A | 0.318 | 0.244 | 0.768 | -0.005 | -0.138 | -0.088 | -0.348 | 1 |

## Table 4 Systematic risk factors and global measures of mispricing

This table shows the results of the following regression models:

$y_{i,t} = \theta_i + \vartheta_i Sent_{t-1} + \varepsilon_{i,t}$ (a),

$y_{i,t} = \theta_i + \rho_i \Delta Oil_{t-1} + \varepsilon_{i,t}$ (b), and

$y_{i,t} = \theta_i + \pi_i \Delta EPU_{t-1} + \varepsilon_{i,t}$ (c).

Where, $y_{i,t}$ represent the systematic risk factors of the models employed in our work. $Sent_{t-1}$, $\Delta Oil_{t-1}$ and $\Delta EPU_{t-1}$ are changes to the investor sentiment, oil price uncertainty and economic policy uncertainty indices. These are global indices, and the only exception is the investor sentiment index, where we assume the US index proxy global shifts in sentiment. The sample period for equations (a and b) starts from January 1992 and for equation (c) it begins in January 1997. Whereas the end period is December 2020 for all regressions. T-statistics are reported in parenthesis.

| Variables | MKT-RF | SMB | HML | MOM | CMA | RMW | ROE | I/A |
|---|---|---|---|---|---|---|---|---|
| $Sent_{t-1}$ | -0.002 | 0.001 | 0.001 | 0.002 | -0.002 | 0.006 | 0.005 | 0.001 |
| | (-0.55) | (0.37) | (0.20) | (0.29) | (-0.31) | (1.84) | (1.14) | (0.40) |
| $\Delta Oil_{t-1}$ | 0.001 | 0.001 | 0.000 | -0.001 | -0.001 | 0.000 | -0.00 | -0.000 |
| | (2.40) | (3.13) | (0.60) | (-1.27) | (-1.09) | (0.05) | (-0.60) | (-0.43) |
| $\Delta EPU_{t-1}$ | -0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 |
| | (-0.29) | (1.44) | (2.00) | (1.76) | (0.02) | (-0.58) | (-1.43) | (4.26) |

## Table 5 Performance evaluation of zero-cost strategies

This table shows the risk adjusted return of zero cost (long minus short) strategies. In the second column risk adjusted returns are shown using global Oil and Gas sector value weighted excess returns, whereas third column repeats the same using CRSP value weighted excess average returns for the US stocks. In subsequent columns Sharpe ratio ($SR_p = \frac{Rp - Rf}{\sigma_p}$, where Rp is long minus short portfolio returns, Rf is the risk-free rate and $\sigma_p$ is the standard deviation of long minus short portfolio returns), and Treynor's ratio ($TR_p = \frac{Rp - Rf}{\beta_p}$, where Rp and Rf are same as defined above and $\beta_p$ is the long minus short portfolio beta) are shown for each strategy. These ratios are calculated using energy sector value weighted market returns. For consistency, all statistics are reported for the sample that excludes stocks with price less than 5 USD and market capitalization below 10% of the entire sample in any month. The sample period runs from January 1992 to December 2020. T-statistics are shown in parenthesis.

| ***ZC Strategies*** | ***Alpha*** | | ***SR*** | ***TR*** |
|---|---|---|---|---|
| | ***MR_ENERGY*** | ***MR_CRSP*** | | |
| ***SIZE*** | 0.005<br>(1.01) | 0.003<br>(0.61) | 0.636 | 0.083 |
| ***BTPV*** | 0.012<br>(3.00) | 0.010<br>(2.56) | 2.857 | 0.040 |
| ***MOM*** | 0.000<br>(-0.01) | -0.002<br>(-0.41) | 0.113 | 0.001 |
| ***INV*** | 0.008<br>(1.55) | 0.008<br>(1.71) | 1.127 | -0.227 |
| ***OPM*** | 0.026<br>(6.19) | 0.027<br>(6.52) | 4.921 | -0.048 |
| ***ROE*** | 0.038<br>(9.23) | 0.040<br>(9.93) | 7.138 | -0.049 |
| ***TOTA*** | 0.008<br>(1.86) | 0.007<br>(1.52) | 1.749 | 0.027 |
| ***OFCF*** | 0.017<br>(4.31) | 0.016<br>(3.95) | 3.502 | -0.068 |
| ***EBIT*** | 0.028<br>(6.85) | 0.030<br>(7.19) | 5.471 | -0.050 |
| ***GPM*** | 0.010<br>(2.69) | 0.009<br>(2.42) | 2.062 | -0.094 |
| ***VOL3*** | 0.026<br>(3.45) | 0.029<br>(3.91) | 2.699 | -0.035 |
| ***LIQ*** | 0.007<br>(1.52) | 0.006<br>(1.36) | 0.787 | -0.015 |
| ***PER*** | 0.010<br>(3.10) | 0.011<br>(3.29) | 2.626 | 0.126 |
| ***REV*** | 0.015<br>(3.76) | 0.015<br>(3.77) | 3.350 | 0.269 |

## Table 6: GRS Test Using Standard Asset Pricing Models

This table tests different versions of asset pricing models using GRS, F-test. The null hypothesis of GRS test is that all portfolio (strategies) alphas are jointly equal to zero. Six versions of asset pricing models that include Capital Asset Pricing Model (CAPM) of Sharpe (1964), three factor model of Fama and French (1993), four factor model of Carhart (1997), five factor model of Fama and French (2015), six factor model and investment factor model of Hou et. al., (2015) are tested. The GRS test statistics are shown under column labelled as 'GRS-test', probabilities are reported under column 'P-Values', $A\alpha_i$ is the average of model intercepts for all 14 zero-cost strategies undertaken in our work. The absolute alphas are reported in column labelled as $A|\alpha_i|$ and adjusted r-squared are reported in the last column. Panel A displays the statistics using global Oil and Gas (OG) factors, Panel B reports the statistics using the US factors, Panel C shows the statistics using developed market factors and Panel D reports the statistics using all factors that include OG, US and developed market factors in the noted models. The sample period is at monthly frequency and runs from January 1992 to December 2020.

| **Tested Model** | **GRS-test** | **P-Values** | $A\alpha_i$ | $A\|\alpha_i\|$ | $AR^2_{dj}$ |
|---|---|---|---|---|---|
| **Panel A: GRS Using Energy Factors** | | | | | |
| CAPM | 10.77 | 0.000 | 0.015 | 0.015 | 0.043 |
| FF3 | 10.31 | 0.000 | 0.011 | 0.014 | 0.175 |
| FF3 + WML | 10.28 | 0.000 | 0.011 | 0.014 | 0.174 |
| FF5 | 5.54 | 0.000 | 0.008 | 0.009 | 0.226 |
| FF5 + WML | 5.53 | 0.000 | 0.008 | 0.009 | 0.226 |
| HXZ Model | 3.923 | 0.000 | 0.009 | 0.009 | 0.205 |
| **Panel B: GRS Using US Factors** | | | | | |
| CAPM | 11.071 | 0.000 | 0.015 | 0.015 | 0.047 |
| FF3 | 12.601 | 0.000 | 0.015 | 0.015 | 0.098 |
| FF3 + WML | 11.797 | 0.000 | 0.016 | 0.016 | 0.128 |
| FF5 | 10.765 | 0.000 | 0.014 | 0.0143 | 0.111 |
| FF5 + WML | 10.293 | 0.000 | 0.015 | 0.015 | 0.141 |
| HXZ Model | 10.342 | 0.000 | 0.015 | 0.015 | 0.118 |
| **Panel C: GRS Using Fama French Developed Factors** | | | | | |
| CAPM | 10.863 | 0.000 | 0.015 | 0.015 | 0.054 |
| FF3 | 11.569 | 0.000 | 0.014 | 0.015 | 0.113 |
| FF3 + WML | 10.755 | 0.000 | 0.015 | 0.015 | 0.136 |
| FF5 | 9.15 | 0.000 | 0.014 | 0.013 | 0.121 |
| FF5 + WML | 8.93 | 0.000 | 0.014 | 0.014 | 0.143 |
| HXZ Model | N/A | N/A | N/A | N/A | N/A |
| **Panel D: GRS Using All Factors** | | | | | |
| All Factors (OG + FF5 – US) | 5.25 | 0.000 | 0.008 | 0.009 | 0.262 |
| All Factors (OG + FF5 – Developed) | 4.52 | 0.000 | 0.007 | 0.008 | 0.266 |
| All Factors (OG + FF5 – Developed + HXZ Model – US) | 2.859 | 0.000 | 0.007 | 0.007 | 0.287 |

## Table 7 Panel regressions: portfolio-level estimations

This table shows the portfolio level results of panel regressions using fixed effects. In each model (M1 through M7), systematic risk factors are included along with portfolio level characteristics. M1 is the market factor model, M2 is the Fama and French three factor model, M3 is the Carhart four factor model, M4 is the Fama and French five factor model, M5 is the Fama and French five factor model augmented with momentum factor, M6 is the Investment facto model and M7 included all factors. For consistency, all estimations are reported for the sample that excludes stocks with price less than 5 USD and market capitalization below 10% of the entire sample in any month. The sample period is from January 1992 until December 2020. However, the estimation period starts from January 1997 as five years are utilized to calculate betas that are used as characteristics in all the regression models. T-statistics are reported in parenthesis.

| **Variables** | **M1 Ret** | **M2 Ret** | **M3 Ret** | **M4 Ret** | **M5 Ret** | **M6 Ret** | **M7 Ret** |
|---|---|---|---|---|---|---|---|
| MR-RF | 1.138 | 1.042 | 1.042 | 1.037 | 1.037 | 1.042 | 1.036 |
| | (87.99) | (106.59) | (106.30) | (112.23) | (112.41) | (107.96) | (109.19) |
| SMB | | 0.450 | 0.452 | 0.337 | 0.334 | 0.373 | 0.319 |
| | | (15.36) | (15.28) | (11.48) | (11.40) | (13.05) | (10.32) |
| HML | | 0.142 | 0.139 | 0.096 | 0.099 | | 0.011 |
| | | (6.77) | (6.74) | (5.63) | (5.73) | | (0.51) |
| WML | | | 0.002 | | -0.010 | | -0.006 |
| | | | (0.76) | | (-2.16) | | (-1.07) |
| CMA | | | | 0.019 | 0.019 | | 0.016 |
| | | | | (2.88) | (2.95) | | (2.48) |
| RMW | | | | 0.119 | 0.118 | | 0.090 |
| | | | | (8.63) | (8.45) | | (6.30) |
| ROE | | | | | | 0.065 | 0.057 |
| | | | | | | (4.78) | (3.72) |
| I/A | | | | | | 0.083 | 0.077 |
| | | | | | | (4.71) | (4.24) |
| Beta | 0.001 | 0.002 | 0.002 | -0.003 | -0.003 | -0.000 | -0.003 |
| | (0.51) | (1.86) | (1.84) | (-2.31) | (-2.37) | (-0.02) | (-2.02) |
| Ln_MV | | -0.000 | -0.000 | -0.001 | -0.001 | -0.001 | -0.002 |
| | | (-0.96) | (-1.21) | (-2.94) | (-2.94) | (-4.17) | (-4.08) |
| Ln_BTPV | | 0.000 | 0.000 | -0.001 | -0.001 | | -0.000 |
| | | (1.46) | (0.88) | (-2.01) | (-1.90) | | (-0.72) |
| PRET (2-12) | | | -0.025 | | 0.017 | | 0.008 |
| | | | (-2.07) | | (1.15) | | (0.51) |
| Ln_INV | | | | -0.001 | -0.001 | | -0.001 |
| | | | | (-3.61) | (-3.83) | | (-3.88) |
| Ln_PRF | | | | 0.001 | 0.001 | | 0.001 |
| | | | | (2.76) | (2.78) | | (1.39) |
| Ln_ROE | | | | | | -0.000 | -0.000 |
| | | | | | | (-1.22) | (-2.19) |
| Ln_TA | | | | | | 0.001 | -0.000 |
| | | | | | | (1.33) | (-0.34) |
| Constant | 0.000 | -0.001 | -0.000 | 0.010 | 0.009 | -0.001 | 0.012 |
| | (0.29) | (-0.36) | (-0.06) | (3.51) | (3.24) | (-0.08) | (1.27) |
| Observations | 48,720 | 48,625 | 48,625 | 14,882 | 14,882 | 28,956 | 12,267 |
| R-squared | 0.666 | 0.710 | 0.710 | 0.754 | 0.754 | 0.756 | 0.766 |
| Number of ID | 140 | 140 | 140 | 138 | 138 | 138 | 135 |

## Table 8 Panel regressions: firm-level estimations

This table shows the stock level results of panel regressions using fixed effects. In each model (M1 through M7), systematic risk factors are included along with stock level characteristics. M1 is the Market factor model, M2 is the Fama and French three factor model, M3 is the Carhart four factor model, M4 is the Fama and French five factor model, M5 is the Fama and French five factor model augmented with momentum factor, M6 is the Investment facto model and M7 included all factors. For consistency, all estimations are reported for the sample that excludes stocks with price less than 5 USD and market capitalization below 10% of the entire sample in any month. The sample period is from January 1992 until December 2020. However, the estimation period starts from January 1997 as five years are utilized to calculate betas that are used as characteristics in all the regression models. T-statistics are reported in parenthesis.

| Variables | M1<br>Ret | M2<br>Ret | M3<br>Ret | M4<br>Ret | M5<br>Ret | M6<br>Ret | M7<br>Ret |
|---|---|---|---|---|---|---|---|
| MR-RF | 1.125 | 0.998 | 0.949 | 0.899 | 0.889 | 0.994 | 0.891 |
| | (57.48) | (56.26) | (52.31) | (34.57) | (34.91) | (50.69) | (34.41) |
| SMB | | 0.699 | 0.574 | 0.397 | 0.321 | 0.558 | 0.307 |
| | | (28.82) | (25.21) | (9.45) | (8.17) | (22.88) | (7.51) |
| HML | | 0.224 | 0.282 | 0.147 | 0.198 | | 0.213 |
| | | (11.32) | (14.41) | (4.88) | (6.73) | | (5.55) |
| WML | | | -0.035 | | -0.062 | | -0.052 |
| | | | (-4.29) | | (-3.99) | | (-3.30) |
| CMA | | | | 0.011 | 0.031 | | 0.030 |
| | | | | (0.79) | (2.23) | | (2.10) |
| RMW | | | | 0.068 | 0.083 | | 0.051 |
| | | | | (2.10) | (2.58) | | (1.22) |
| ROE | | | | | | 0.170 | 0.098 |
| | | | | | | (9.85) | (2.73) |
| I/A | | | | | | 0.123 | -0.063 |
| | | | | | | (5.91) | (-1.55) |
| Beta | 0.002 | -0.001 | 0.002 | 0.006 | 0.010 | -0.002 | 0.009 |
| | (1.15) | (-0.59) | (1.28) | (1.76) | (3.70) | (-0.98) | (2.99) |
| Ln_MV | | 0.008 | 0.003 | 0.008 | 0.004 | 0.001 | 0.004 |
| | | (9.05) | (4.62) | (3.97) | (2.16) | (0.77) | (1.93) |
| Ln_BTPV | | -0.022 | -0.007 | -0.016 | -0.004 | | -0.002 |
| | | (-7.96) | (-6.35) | (-4.63) | (-2.04) | | (-0.58) |
| PRET (2-12) | | | 0.736 | | 0.585 | | 0.557 |
| | | | (41.89) | | (18.68) | | (16.45) |
| Ln_INV | | | | 0.004 | 0.004 | | 0.003 |
| | | | | (6.55) | (7.23) | | (6.33) |
| Ln_PRF | | | | 0.004 | 0.001 | | 0.000 |
| | | | | (2.96) | (0.86) | | (0.03) |
| Ln_ROE | | | | | | -0.001 | 0.001 |
| | | | | | | (-1.50) | (0.84) |
| Ln_TA | | | | | | -0.023 | -0.002 |
| | | | | | | (-6.84) | (-0.53) |
| Constant | 0.000 | -0.072 | -0.036 | -0.001 | 0.012 | 0.156 | 0.023 |
| | (0.20) | (-11.57) | (-7.69) | (-0.07) | (1.43) | (5.42) | (0.66) |
| Observations | 111,953 | 91,555 | 88,171 | 18,370 | 17,748 | 63,183 | 15,757 |
| R-squared | 0.129 | 0.240 | 0.290 | 0.229 | 0.265 | 0.300 | 0.276 |
| Number of ID | 1,345 | 1,114 | 1,077 | 771 | 751 | 865 | 699 |

# Appendix A

## Table AI: Energy Sector Information

This table summarizes information related to the sample size and length of energy sector related firms.

| **Description** | **# Firms** | **Percentage** |
|---|---|---|
| Total listed firms in the Oil and Gas sector (OG) | 12331 | 100% |
| Total listed Firms in the OG sector after filtration | 4492 | 100% |
| Total OG sector countries coverage in DataStream | 86 | N/A |
| United States | 1527 | 33.99% |
| Canada | 1511 | 33.64% |
| Others | 1454 | 32.37% |
| Firm level data available in DataStream | 3782 | 84.19% |
| Firm level data not available in DataStream | 711 | 15.83% |
| Average No. of Firms in the sample | 1134 | N/A |
| Average No. of Firms with 5% price filter | 1114 | N/A |
| Average No. of Firms with Price >= 5 USD Filter | 420 | N/A |
| Start Period | 1992:01 | N/A |
| End Period | 2020:12 | N/A |

## Table AII: Description on construction of anomaly portfolios

This table outlines the construction of anomaly deciles/portfolios. The sorting variables are monthly firm characteristics and in case when they are available at lower frequency such as quarterly or yearly e.g., investment and BM ratio, we scale them by their monthly to have monthly sorting breakpoints.

| Symbol | Description | Operationalization |
|---|---|---|
| **Panel A: Anomaly Variables** | | |
| SIZE | Total Market Capitalization | Size is the product of month end closing price and number of shares outstanding. |
| BTPV | Inverse of Price to Book Value | BTPV is the inverse of PTBV and is calculated by dividing the t-1 year-end book value by previous month closing price. |
| MOM | Momentum | Momentum is calculated by taking the average of past 11 months monthly returns. |
| INV | Change is Total Assets | INV is calculated by dividing the change in total assets (year t-2 - year t-1) by total assets of year t-1. INV is scaled by Market Capitalization to get monthly numbers. |
| OPM | Operating Profit Margin | OPM is the ratio of operating income to net sales. OPM is scaled by market capitalization to get monthly values. |
| ROE | Return on Equity | ROE is calculated by dividing net income over total common equity. ROE is scaled by Market Capitalization to get monthly numbers. . |
| TOTA | Total Assets | TOTA is calculated by summing the current assets and fixed assets. TOTA is scaled by market capitalization to get monthly numbers. |
| OFCF | Free Cash Flows from Operations | OFCF is calculated by adding Cash Flows from Financing Activities, Cash Flows from Investing Activities and Change is Net Working Capital. OFCF is scaled by market capitalization to get the monthly numbers. |
| EBIT | Earnings Before Interest and Taxes | EBIT is calculated by adding back interest (which is paid on debt) in pre-tax income. EBIT is scaled by market capitalization to get monthly numbers. |
| GPM | Gross Profit Margin | GPM is calculated by subtracting the cost of goods sold from total revenue and dividing by total revenue. GPM is scaled by market capitalization to get monthly numbers. |
| VOL3 | Last three months Volatility | VOL3 is the last three months standard deviation calculated by using the daily returns. |
| LIQ | Liquidity | LIQ is the ratio of the sum of total zero return days in a month divided by total trading days in a month. |
| PTER | Price to Earnings Ratio | PTER is the ratio of price to earnings. |
| REV | Total Revenue | REV is the total revenue. REV is scaled by Market Capitalization to get monthly numbers. |

## Table AIII: Description on systematic factors

This table shows the construction procedure for each systematic factor across the factor models evaluated in this work. Panel B: Systematic factors – Except market portfolio all systematic factors from SMB onwards are follow double sorting. That is, across all factors, the first sort is based on firm capitalization using the median breakpoint. The second sort is based on 30% and 70% breakpoint of the 2nd characteristic i.e., Book to market, momentum returns, investment, profitability, return on equity and total assets.

| Symbol | Description | Operationalization |
|---|---|---|
| MKT-RF | Market Excess Returns | MKT-RF is calculated by subtracting the risk-free rate from monthly value weighted average returns of all stocks in the sample. |
| SMB | Small minus big market cap | All stocks are sorted based on size and book value. Six portfolios are constructed using the intersection of median size and 30%-70% book value breakpoints. SMB is the average returns of the 50% small-capitalized stocks minus average returns of 50% big-capitalized stocks controlling for book value of each stock. |
| HML | High minus low book to market | All stocks are sorted based on size and book value. Six portfolios are constructed using the intersection of median size and 30%-70% book value breakpoints. HML is the average returns of 30% high book value stocks minus average returns of 30% low value stocks controlling for the size effect. |
| WML | winners minus losers | All stocks are sorted based on size and past 11 months average returns. Six portfolios are constructed using the intersection of median size and 30%-70% past 11-months average returns breakpoints. WML is the average returns of 30% high past 11-month average return stocks minus 30% of the low past 11-month average return stocks controlling for the size effect. |
| CMA | Low minus high investment | All stocks are sorted based on size and investment. Six portfolios are constructed using the intersection of median size and 30%-70% investment breakpoints. CMA is the average returns of 30% low investment stocks minus average returns of 30% high investment stocks controlling for the size effect. |
| RMW | High minus low operating profit | All stocks are sorted based on size and operating profitability. Six portfolios are constructed using the intersection of median size and 30%-70% operating profitability breakpoints. RMW is the average returns of 30% high profitability stocks minus average returns of 30% low profitability stocks controlling for the size effect. |
| ROE | Low minus High return on equity | All stocks are sorted based on size and return on equity. Six portfolios are constructed using the intersection of median size and 30%-70% return on equity breakpoints. ROE is the average returns of 30% low return on equity stocks minus average returns of 30% high return on equity stocks controlling for the size effect. |
| I/A | Low minus High return on investment | All stocks are sorted based on size and total assets. Six portfolios are constructed using the intersection of median size and 30%-70% total assets breakpoints. I/A is the average returns of 30% low total assets stocks minus average returns of 30% high total assets stocks controlling for the size effect. |

### Table AIV: Descriptive statistics for US factor returns and Correlation matrix

This table shows (in Panel A) the average returns (μ), standard deviation (σ), t-statistics (t-Stat) and number of observations (N) for systematic risk factors which are employed in various asset pricing models. These factors are downloaded from French data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) and Hou-Xue-Zhang data library https://global-q.org/index.html). These factors are market factor (MKT-RF), small minus big factor (size, SMB), high minus low factor (value, HML), winners minus losers' factor (momentum, WML), conservative minus aggressive factor (investment, CMA), robust minus weak factor (profitability, RMW), high minus low return factor (return on equity, ROE) and low minus high factor (investment, I/A). Panel B shows the correlation matrix of factors contained in the noted models. All returns are reported monthly, and the sample period is from January 1992 to December 2020.

**Panel A: Summary stats**

| | **MKT-RF** | **SMB** | **HML** | **WML** | **CMA** | **RMW** | **ROE** | **I/A** |
|---|---|---|---|---|---|---|---|---|
| **μ** | 0.007 | 0.001 | 0.001 | 0.004 | 0.002 | 0.003 | 0.003 | 0.002 |
| **σ** | 0.043 | 0.032 | 0.031 | 0.048 | 0.02 | 0.026 | 0.028 | 0.02 |
| **T-Stat** | 3.04 | 0.58 | 0.60 | 1.55 | 1.87 | 2.15 | 2.00 | 1.87 |
| **N** | 348 | 348 | 348 | 348 | 348 | 348 | 348 | 348 |

**Panel B: Correlation Matrix**

| | **MKT-RF** | **SMB** | **HML** | **WML** | **CMA** | **RMW** | **ROE** | **I/A** |
|---|---|---|---|---|---|---|---|---|
| MKT-RF | 1 | | | | | | | |
| SMB | 0.246 | 1 | | | | | | |
| HML | -0.091 | -0.226 | 1 | | | | | |
| WML | -0.295 | 0.024 | -0.218 | 1 | | | | |
| CMA | -0.325 | -0.142 | 0.637 | 0.013 | 1 | | | |
| RMW | -0.399 | -0.546 | 0.375 | 0.064 | 0.266 | 1 | | |
| ROE | -0.485 | -0.470 | 0.101 | 0.504 | 0.150 | 0.689 | 1 | |
| I/A | -0.292 | -0.231 | 0.651 | -0.032 | 0.911 | 0.324 | 0.177 | 1.000 |