FOLLOWING THE STREAM

THE EFFECTS OF SOCIAL NORMS ON OIL, GAS, AND COAL STOCKS

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Abstract:

In this paper, we provide new evidence on social norms' implications for financial markets by studying U.S. oil, gas, and coal stocks in the period of 2000-2018. Following the methodology of Hong and Kacperczyk (2009), we show that these stocks, similar to the conventional "sin stocks" of alcohol, gaming, and tobacco firms, are less held by institutional investors subject to norm pressure. Furthermore, we find that the attribute of being an oil, gas, or coal stock is associated with superior stock return and lower market valuation, consistent with investors being subject to limited risk sharing. Although the relationship does not appear as consequential in shorter timespans, our findings support the viewpoint that financial markets may not only be susceptible to norms associated with social practice, but also environmental practice.

Keywords:

Social norms, Institutional ownership, Neglected stocks, Firm value

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1. Introduction

Despite costly for an individual to follow, social norms persist because of the social sanction imposed by loss of reputation from breaking the norm[1] (Akerlof, 1980). For this reason, social norms are of importance in determining economic outcomes in many contexts, including financial markets. Hong and Kacperczyk (2009) show that investors subject to norms pay a financial cost in abstaining from alcohol, gaming, and tobacco stocks, by them referred to as "sin stocks". We document whether a similar pattern applies to oil, gas, and coal stocks, considering the public view on emitting fossil fuels. The consumption of oil, gas, and coal today accounts for more than 76% of the U.S. carbon dioxide emissions (U.S. Environmental Protection Agency, 2019). At the same time, the concern for carbon emissions is visible in the investment sphere with carbon-related restrictions being one of the top environmental, social, governance (ESG) criteria taken into consideration by U.S. institutional investors (The Forum for Sustainable and Responsible Investments, SIF, 2018). If a sufficiently strong social custom exists that make the community view fossil fuels as harmful products, then oil, gas, and coal stocks may behave in a similar fashion to sin stocks. This would imply that financial markets are susceptible for norms associated with environmental concerns.

In our paper, we adopt the approach developed by Hong and Kacperczyk (2009), and focus on social norms' implications for oil, gas, and coal stocks by examining their institutional ownership, analyst coverage, and stock price. Because of the carbon debate's particular prevalence in the 21st century, we focus on the recent timeframe of 2000-2018. To isolate the period of the global financial crisis with its particular market conditions (e.g. Bekaert, Ehrmann, Fratzscher, and Mehl, 2014; Lins, Servaes, and Tamayo, 2017), we further execute the test procedure for the three subperiods of (1) 2000-2006, (2) 2007-2009, and (3) 2010-2018. This approach also allows us to address the fact that social norms might change over time.

For our empirical analysis, we compile an extensive dataset on stocks listed in the U.S. We show that, similar to sin stocks, oil, gas, and coal stocks are associated with less institutional holding, higher stock returns, and lower valuations, although they surprisingly exhibit a higher level of analyst coverage. However, the results are less apparent during the financial crisis, and are not as consistent when focusing on the shorter timespans. Throughout out study we include a comprehensive set of control variables on firm characteristics as well as industry fixed effects to distinguish the impact attributed to being an oil, gas, or coal stock.

We begin our analysis by examining institutional ownership. In contrast to retail investors, institutional investors are subject to external scrutiny and disclosure requirements, which make them susceptible to social norm pressure (e.g. Dennis and Strickland, 2002; Hong and Kacperczyk, 2009). For this reason, we hypothesize that oil, gas, and coal stocks have less institutional ownership than stocks of otherwise comparable characteristics. We further take into account that different types of institutional investors are restricted by varying degrees of norm pressure, with bank trusts, insurance companies, and pension funds ("grey institutions") being more sensitive to social norm pressure than investment companies, investment advisors, and hedge funds ("independent institutions"). The latter investor group tends to act as natural arbitrageurs in the market as well as to exert more pressure on corporate managements to drive change (e.g. Ferreira and Matos, 2008). Hence, we hypothesize that grey institutions are associated with a greater magnitude of ownership shortfall in oil, gas, and coal stocks than independent institutions. Furthermore, since sell-side analysts provide their services primarily to institutional investors (Hong and Kacperczyk, 2009), we hypothesize that oil, gas, and coal stocks are less followed by analysts than comparable stocks.

[1] We define a social norm "as an act whose utility to the agent performing it depends in some way on the beliefs or actions of other members of the community" (Akerlof, 1980).

Considering the timeframe of 2000-2017, we find the attribute of being an oil, gas, or coal stock to be associated with 1.7% less institutional ownership relative to stocks of otherwise comparable characteristics, at statistical significance. Moreover, when distinguishing the respective subperiods, we find that the oil, gas, and coal effect on institutional ownership has changed direction over time. The first two periods covering the years 2000-2009 report a negative effect at statistical significance, whereas the final period of 2010-2017 reports a positive effect at statistical significance. We find that the positive effect in the final period has been driven by an increase in the oil, gas, and coal stock ownership held by independent institutions, and in particular hedge funds and investment companies. We find that the norm-pressured grey institutions have been associated with a more extensive shortfall in oil, gas and coal stock holding than independent institutions, consistently over our timeframe. Despite the lower institutional ownership, our analysis further reveals that oil, gas and coal stocks have consistently been associated with a higher level of analyst coverage relative to comparables, by approximately 2 analysts a year.

Next, we hypothesize that oil, gas, and coal stocks exhibit higher stock returns and lower market valuations than stocks of otherwise comparable characteristics. This hypothesis is based on the work of Merton (1987) on neglected stocks, considering the impact of limited risk sharing on the cost of capital and that of limited arbitrage (e.g. Shleifer and Vishny, 1997). This phenomenon is referred to by Hong and Kacperczyk (2009) as the "neglect-effect hypothesis". We test the implications on return using two separate estimates. The first estimate considers time-series returns adjusted for well-known predictors of stock return (Fama and French 1993; Carhart 1997). The second estimate uses cross-sectional regressions controlling for firm characteristics. We find no statistical significance for the time-series return, whereas the cross-sectional estimate supports our hypothesis. From the latter test, we find that oil, gas, and coal stocks have had a 50 basis points (bps) monthly, or 6% annualized, higher stock return over the timeframe of 2000-2018, at statistical significance. Furthermore, to test the occurrence of depressed stock valuations, we look at three types of valuation ratios: market-to-book, price-to-earnings, and price-to-EBITDA. We find evidence for oil, gas, and coal stocks having a lower market-to-book and price-to-EBITDA ratio over the timeframe, corresponding to a valuation discount of 17% and 21%, respectively.

Moreover, it can be argued that oil, gas, and coal firms are facing not only a pressure from societal norms, but also a future of declining demand due to the ongoing energy transition away from fossil fuels (International Energy Agency, IEA, 2019). This additional effect might have negative implications for the valuation of oil, gas, and coal firms. To examine the consistency between the estimates on superior stock return and valuation discount for the timeframe of 2000-2018, we apply the Gordon growth model. Taking the 6% annual higher stock return and the average valuation discount of 19%, we find that the magnitude of the superior stock return exceeds the magnitude of the valuation discount. In line with Hong and Kacperczyk's (2009) reasoning, we pose the question of whether the estimated superior returns may be influenced by unexpectedly good cash flow news, or perhaps unexpectedly positive outcomes from litigation events. We cannot find evidence of that the valuation discount derives from lower growth prospects.

Although our estimated stock returns may be influenced by additional factors, our findings support the viewpoint that social norms can have consequences for stocks associated with pollution and environmentally harmful products. While Hong and Kacperczyk (2009) examined alcohol, tobacco and gaming stocks, no study has from the best of our knowledge documented the implications of social norms for stocks associated with environmental issues. We furthermore bring new insights into the increasingly important investor group of institutions by using a more comprehensive dataset on institutional investor segments, based on Ferreira and Matos (2008).

2. Literature review

2.1. Institutional investors and their behavior

At the core of this study is the role of institutional investors. We define an institutional investor as a company or organization that professionally invests money on behalf of other people, in contrast to retail investors who primarily invest on behalf of themselves (Nofsinger and Sias, 1999). As institutional investors often buy and sell substantial blocks of stocks, they constitute an important investor group and often take part in firms' boards of directors (McCahery, Sautner, and Starks, 2016). There are several types of institutional investors with different investment strategies and purposes. Ferreira and Matos (2008) define six types of institutional investors, which are categorized into grey institutions versus independent institutions. Grey institutional investors comprise bank trusts, insurance companies, and pension funds including endowments. Independent institutional investors cover investment companies (which are usually mutual fund companies), investment advisors, and hedge funds including venture capital. Institutional investors have been found to share a preference for the stock of large and widely held firms (Ferreira and Matos, 2008). Moreover, it has been found that grey institutional investors are more loyal to corporate management than independent institutional investors, with the latter investor group exerting more pressure on corporate management to bring about change (Brickley, Lease, and Smith, 1988; Chen, Harford, and Li, 2007; Ferreira and Matos, 2008).

2.2. Institutional investors' impact on analyst coverage, stock return and market valuation

Provided that institutional investors constitute an investor group of substantial size and importance, it can be argued that there will be implications for a stock should institutional investors choose to systematically abstain from investing in it. As articulated by Merton (1987), the size of a firm's investor base is connected to the firm's cost of capital and expected return. Namely, a decrease in the relative size of a firm's investor base will tend to increase the firm's cost of capital and by extension decrease the value of the firm. Hong and Kacperczyk (2009) furthermore show that alcohol, gaming, and tobacco stocks are subject to higher stock returns and lower valuations as a result of sin stocks being subject to an institutional investor negligence. The link between stock negligence and a higher expected stock return is attributed to a lack of risk sharing among investors and idiosyncratic risk. First, a smaller investor base implies that the risk associated with investing in a stock is more concentrated among investors. The investors that choose to invest will therefore require a higher expected return. Thus, the cost of capital of the stock is higher and the market value is lower. Second, the limited risk sharing implies that the firm-specific risk, i.e. idiosyncratic risk, and not just the stock beta, comes into play in determining stock price. Therefore, the Capital Asset Pricing Model (CAPM) no longer holds and abnormal returns may occur.

An implicit assumption of the neglect-effect relationship is the idea of limited arbitrage. As explained by Sharpe and Alexander (1990), financial arbitrage plays a critical role in keeping markets efficient because of its effect to bring security prices to fundamental values. Translated into the context of neglected stocks, this means that the depressed stock prices in light of limited risk sharing, should be taken advantage of by other parts of the investor universe, ultimately bringing stock prices back to intrinsic values. However, Shleifer and Vishny (1997) show that financial arbitrages are more complex in nature than the traditional definition suggests, as arbitrageurs face both risk and constraints in carrying out arbitrage opportunities. In line with this argument, Hong and Kacperczyk (2009) articulate that not enough arbitrage capital is brought to bear on neglected sin stocks, which is why their stock prices tend to stay depressed.

2.3. Further empirical findings

A set of studies have been carried out focusing on the relationship between the environmental and social responsibility of firms and their cost of capital. Heinkel, Kraus, and Zechner (2001) illustrate that exclusionary ethical investing can lead to polluting firms being held by fewer investors, resulting in a higher cost of capital and lower market valuations for these firms. In line with Merton (1987), they point to the decreased risk sharing among investors as the main driver behind the effect. Furthermore, Ferrell, Liang, and Renneboog (2016) find evidence that a positive correlation exists between corporate social responsibility (CSR) and firm value approximated by Tobin's q. They also articulate that a higher CSR score is associated with lower idiosyncratic risk, lower cost of capital, and higher abnormal returns. Although oil, gas, and coal firms may differ in their overall score of CSR, one can argue that they shall score naturally low in the environmental dimension since they sell and market products that heavily contribute to climate change (SIF, 2018).

3. Data and methodology

We base our analysis on four interconnected tests on U.S. stocks over the timeframe of 2000-2018. With specifications replicating the procedure presented in Hong and Kacperczyk (2009), the four tests consider (1) institutional stock ownership, both on a total level and by different institutions, (2) stock analyst coverage, (3a) time-series stock return, (3b) cross-sectional stock return, and (4) stock valuation.

Besides carrying out the test procedure for the entire timeframe of 2000-2018, we divide the time-window into the three consecutive subperiods of 2000-2006, 2007-2009, and 2010-2018, for which we run the regressions. This approach is adopted for two main reasons. First, it addresses the possibility that the social norm pressure against oil, gas, and coal stocks may have changed over time. Second, it allows us to isolate and distinguish the period of the global financial crisis, something we deem appropriate considering the stock market's particular conditions during periods of financial turmoil. Such particular conditions include high market volatility (Bekaert et al., 2014), institutional investors' deviating trading patterns (Dennis and Strickland, 2002; Ben-David, Franzoni, and Moussawi, 2012), and the decline in investor confidence favoring firms with high levels of social capital (Lins, Servaes, and Tamayo, 2017). In line with Bekaert et al. (2014), we define the global financial crisis as taking place from August 2007 until March 2009, the time-window which constitutes our second subperiod. In August 2007 equity markets initially fell and central banks started intervening for the first time to provide liquidity to financial markets. The tests that consider institutional ownership, analyst coverage and market valuation are carried out on an annual basis. For these tests, we define the time-windows without considering specific months, which means that the time of the financial crisis is approximated as covering the years of 2007, 2008, and 2009.

3.1. Data collection

We collect daily and monthly stock data for U.S. stocks traded on the NYSE, AMEX and NASDAQ in the timeframe of 1997-2018 from The Center for Research in Security Prices (CRSP). Specifically, we retrieve data on closing price[2], exchange code, share code, share volume, number of shares outstanding, and SIC-code. The exchange code corresponds to the stock exchange where the stock trades. The CRSP share code is a two-digit code describing the type of share traded. The SIC-code stands for Standard Industrial Classification, which corresponds to a four-digit numerical representation of the industry to which the stock belongs (U.S. Securities and Exchange Commission, SEC, 2020). From CRSP we also export a

[2] When closing price is not available it is substituted for the time's average bid-ask spread by CRSP.

comprehensive dataset on stock inclusion in the Standard & Poor's 500 index (S&P 500) over the same period.

Furthermore, we gather annual and quarterly data on financial fundamentals over the period of 1997-2018 from Compustat, including data on total assets, total intangible assets, common equity, total liabilities, current and long-term debt, research and development expenditures (R&D), and earnings. The earnings measure is calculated by adding the income before extraordinary items available to common stockholders, deferred taxes from the income statement, and investment tax credit.

We download data on monthly returns for 49 industry portfolios over the period 1997-2018 from Kenneth R. French's online data library at Dartmouth University. The portfolio classification is based on Fama and French's (1997) 48 industry groups, besides the industry "computers" being divided into "software" and "hardware". From the same source, we collect monthly data on various predictors of stock return, such as the market premium, small-minus-big, and high-minus-low defined by Fama and French (1993), the momentum factor defined by Carhart (1997), as well as the risk-free rate corresponding to the 1-month T-bill return. The market premium is defined as the value-weighted return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX or NASDAQ with share codes of 10 or 11, net the aforementioned T-bill rate.

In line with Ferreira and Matos (2008), we gather data on stock holdings from the FactSet database. For equities traded in the U.S., FactSet retrieves institutional holdings from the mandatory and quarterly 13F filings and N-30D filings of the Securities and Exchange Commission. We download data for the following institutional investor types: bank trusts, insurance companies, pension funds including endowments, investment advisors, investment companies, and hedge funds including venture capital. The stock holding of an institutional investor type, as well as the stock holding of all institutional investors as a consolidated group, are reported as a ratio of market capitalization for each stock and quarter. Since FactSet at the time of the analysis reports data up until 2017, the test on institutional ownership excludes the year of 2018. Using FactSet as our source for institutional ownership separates our paper from Hong and Kacperczyk (2009), which used CDA Spectrum. Our choice is motivated by the more detailed data on investor types' stock ownership available in FactSet.

The data on analyst coverage is drawn from the Institutional Brokers Estimates System (IBES) database, which reports the number of earnings estimates issued on a stock by sell-side analysts on a typically quarterly basis. IBES created their Academic Research Program over 30 years ago to provide both summary and individual analyst forecasts of company earnings, cash flows, and other important financial items, as well as buy-sell-hold recommendations. We download data on stock recommendations for the period of 2000-2018.

We carry out a similar screening procedure to that described in Hong and Kacperczyk (2009) to receive our final data sample. To begin with, we exclude stocks that have a CRSP share code other than 10 or 11, as well as stocks with a first digit SIC-code of 6. By removing firms with share codes other than 10 or 11, we ensure to only test for ordinary common shares. By eliminating firms with a first digit SIC-code of 6, we remove firms that belong to the financial services industry. To compile the different datasets from CRSP, Compustat, FactSet and IBES, we merge observations based on stock ticker and date. This means that observations that do not have a matching ticker and date across the datasets are eliminated from the sample. However, a stock does not need to have a complete time-series data to be included in the sample. The final sample consists of a universe of stocks for which data is available in both CRSP and Compustat, alongside FactSet and IBES for the respective tests. Our screening procedure results in that the amount of observations is maximized for each test. The remaining stocks' SIC-codes are matched with the corresponding industry code as defined in the Fama-French 49 industry portfolio classification.

3.2. Identifying oil, gas, and coal stocks

We use the Fama-French 49 industry portfolios to identify oil, gas, and coal stocks in our stock universe. We define a stock as an oil, gas, or coal stock if it belongs to industry group 29 (Coal) or industry group 30 (Oil and gas). These industry groups cover stocks that have a SIC-code within the ranges of 1200-1299, 1300, 1310-1339, 1370-1382, 1389, 2900-2912, and 2990-2999. Table 1 presents a set of summary characteristics for the final sample, where Panel A exhibits the total number of oil, gas, and coal stocks included for each test and year. For our monthly tests, the figure represents the number of observations at the end of the year. The number of oil, gas, and coal stocks amounts to between 70-120 per test and year. We note that the number of oil, gas, and coal stocks included in the sample is increasing over the years.

We further construct a comparable group to account for the potentially misleading explanatory power that resides in the broader sectors of similar businesses rather than in oil, gas, and coal. It could be the case that investors avoid sectors possessing similar characteristics to the oil, gas, and coal sector rather than that they avoid the oil, gas, and coal industries specifically. With the inclusion of the comparable group as a control variable, the effect connected to oil, gas, and coal stocks cannot be interpreted in terms of favoritism of some broader sectors over others in the stock market. With the aim to construct a comparable group based on business risk and practice, we make use of the one digit SIC-code, which intends to capture the general common characteristics shared in the products, services, production, and delivery system of a business (SEC, 2020). Specifically, we define the comparable group as comprising stocks with the one digit SIC-code of 1, that is, the same as oil, gas, and coal stocks. This procedure results in a comparable group that includes stocks belonging to industry group number 18 (Construction), 27 (Gold), and 28 (Mining), besides the original industry groups of 29 and 30. Part of industry group 30 are firms with SIC-codes in the range of 2900-2912 (Petroleum refining) and 2990-2999 (Miscellaneous products of petroleum & coal). Since these firms are a part of the established oil, gas, and coal group, they as well have been added to the comparable group. The remainder of the stocks with a one-digit SIC-code of 2 are not included since their operations are not deemed as suitable matches.

Table 1: **Summary characteristics of final sample**

This table reports summary characteristics for our final sample. In Panel A, we report the year-by-year number of oil, gas, and coal stocks included in the Tests 1-4. In Panel B, we report the industry rolling market beta calculated over the last 36 months for the years 2000-2017, the data for which is retrieved from Kenneth R. French's online library.

Panel A: Number of individual oil, gas, and coal stocks included in the samples

	Test 1	Test 2	Test 3a	Test 3b	Test 4
2000	84	78	99	101	97
2001	86	78	92	97	97
2002	78	76	88	91	86
2003	81	72	88	89	89
2004	82	76	91	90	90
2005	82	76	92	95	91
2006	92	90	99	102	103
2007	93	90	105	109	105
2008	95	90	106	109	107
2009	95	92	107	107	106
2010	88	86	100	107	99
2011	89	84	99	106	99
2012	100	96	108	111	109
2013	101	94	108	112	108
2014	105	96	109	113	110
2015	106	97	111	112	110
2016	107	96	109	111	112
2017	114	105	118	124	116
2018	n.a.	108	118	125	119

Table 1: Summary characteristics of final sample (continued)

Panel B: Industry portfolio betas 2000-2017

Industry	Beta	Industry	Beta
Agriculture	0.78	Aero	0.98
Food	0.45	Ships	1.15
Soda	0.65	Guns	0.43
Beer	0.40	Gold	0.46
Smoke	0.57	Mines	1.43
Toys	1.01	**Coal**	**1.56**
Fun	1.44	**Oil**	**0.91**
Books	1.02	Utilities	0.41
Household	0.57	Telecommunication	0.96
Clothes	0.98	Personal services	0.92
Healthcare	0.61	Business services	1.09
Medical Equipment	0.74	Hardware	1.53
Drugs	0.64	Software	1.40
Chemicals	1.16	Chips	1.58
Rubber	1.02	Laboratory equipment	1.41
Textiles	1.28	Paper	0.91
Building materials	1.16	Boxes	1.10
Construction	1.36	Transportation	0.95
Steel	1.74	Wholesale	0.92
Fabricated products	1.29	Retail	0.86
Machinery	1.40	Meals	0.77
Electrical equipment	1.28	Other	0.92
Autos	1.44	Total	1.06

Panel B shows the industry rolling market beta calculated over the last 36 months for all of the industry portfolios over the timeframe of 2000-2017. The beta for the oil and gas industry is 0.91 whilst that of coal is 1.56. The industry groups of construction, gold, and mining, which are part of the comparable universe, have betas of 1.36, 0.46, and 1.43, respectively.

3.3. Tests and variables

3.3.1. Institutional ownership regressions

In the first test, we investigate whether oil, gas, and coal stocks are less held by institutional investors compared to stocks of otherwise comparable characteristics. We also divide the institutional investors into the two groups of grey institutions and independent institutions, and examine their respective stock holdings. We add a set of control variables based on Hong and Kacperczyk (2009) to adjust for other firm characteristics that may be of importance in determining institutional ownership. We construct the following regression to estimate the effect of being an oil, gas, or coal stock on the level of institutional ownership:

$$(1)\ IO_{it} = \beta_0 + \beta_1 OGCDUM_{it} + \boldsymbol{\beta}_2 \mathbf{X}_{it} + \varepsilon_{it},$$

where $OGCDUM_{it}$ is a dummy variable that equals one if a stock is an oil, gas, or coal stock, and zero otherwise, X_{it} is a vector of control variables, and ε_{it} is the measurement error. The dependent variable IO_{it} is the total stake institutions hold in stock *i* at time *t*, divided by the stock's market capitalization. A graph that illustrates the evolution of total institutional ownership for the timeframe 2000-2017 is shown in Figure 1. The average institutional ownership for oil, gas, and coal stocks has consistently been above that of the stock universe as a whole, with some intersections. We further note that the institutional ownership has been increasing for the entire period, with the institutional ownership for the stock universe increasing at a faster pace than for oil, gas, and coal stocks. However, the figure fails to capture other underlying reasons determining institutional ownership.

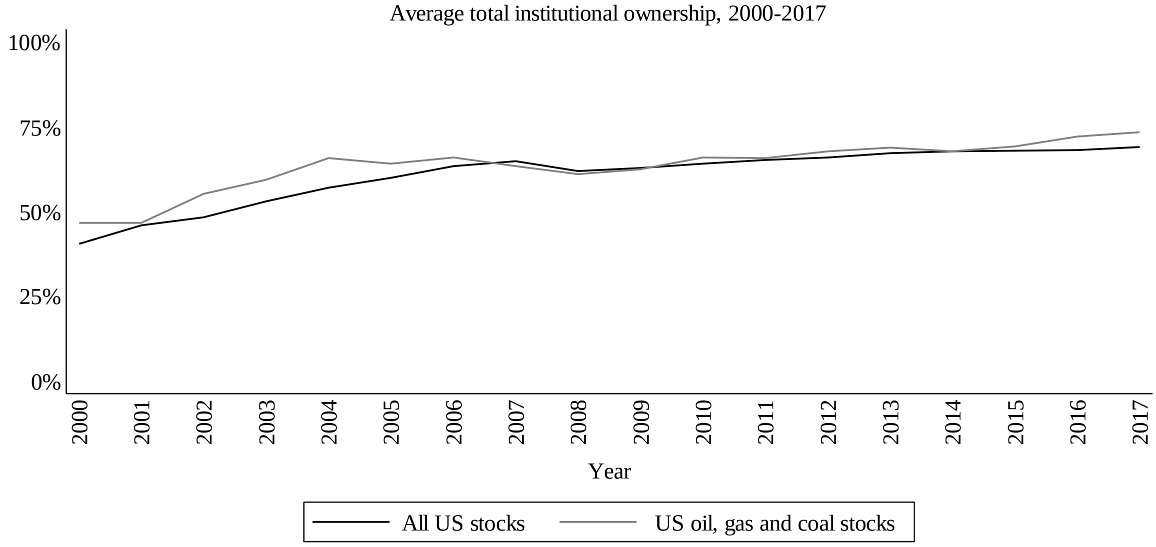

Figure 1: Average institutional ownership. This figure plots the annual institutional ownership for each year 2000-2017 for our sample. Institutional ownership spans from 0 to 100% and reflects the stock held by institutional investors as a percentage of stock market capitalization. The ownership ratio is aggregated for all stocks (dark line) as well only for oil, gas, and coal stocks (grey line). The ratios are winsorized at the 1st and 99th percentile.

Based on Ferreira and Matos (2008), we also create the two dependent variables IO_GREY_{it} and IO_INDEP_{it}. The variable of IO_GREY_{it} corresponds to the sum of stock ownership held by bank trusts, insurance companies, and pension funds in stock *i* at time *t*. IO_INDEP_{it} is the sum of stock ownership held by investment advisors, investment companies, and hedge funds in stock *i* at time *t*. To examine the stock ownership of grey and independent institutions separately, we replace the variable of IO by IO_GREY and IO_INDEP. An overview of the sample means of the two variables over time is presented in Figure 2. We see that most of the consolidated institutional stock ownership is attributed to the independent institutions. Additionally, independent institutional ownership has been increasing over time in contrast to grey institutional ownership, which has remained relatively flat. When it comes to IO_GREY, institutional ownership for oil, gas, and coal stocks has been above that of the stock universe except for in the timeline's beginning and end. For IO_INDEP, we observe that the ownership in oil, gas, and coal stocks exceeds that of the stock universe during the period of 2000-2006, after which the ratios converge. However, the same case as in the graph on total institutional ownership applies, where the result has not accounted for other influencing factors.

The vector X_{it} of the regression includes the control variables $LOGSIZE_{it}$, $BETA_{it}$, $LOGMB_{it}$, $PRINV_{it}$, STD_{it}, and RET_{it}[3]. $LOGSIZE_{it}$ is the natural logarithm of stock *i*'s market capitalization at the end of year *t*. $LOGMB_{it}$ is the natural logarithm of stock *i*'s market-to-book ratio at the end of year *t*. $PRINV_{it}$ is the inverse of stock *i*'s share price at the end of year *t*. RET_{it} is the average monthly raw return of stock *i* in year *t* and STD_{it} is the standard deviation of daily raw returns for stock *i* in year *t*. $BETA_{it}$ is the 36-months rolling industry beta of firm *i* based on the Fama-French 49 industry portfolio classification in year *t*.

[3] In order to remove potential outliers from extraordinary occasions, the variables STD and RET have been winsorized at the 1st and 99th percentile.

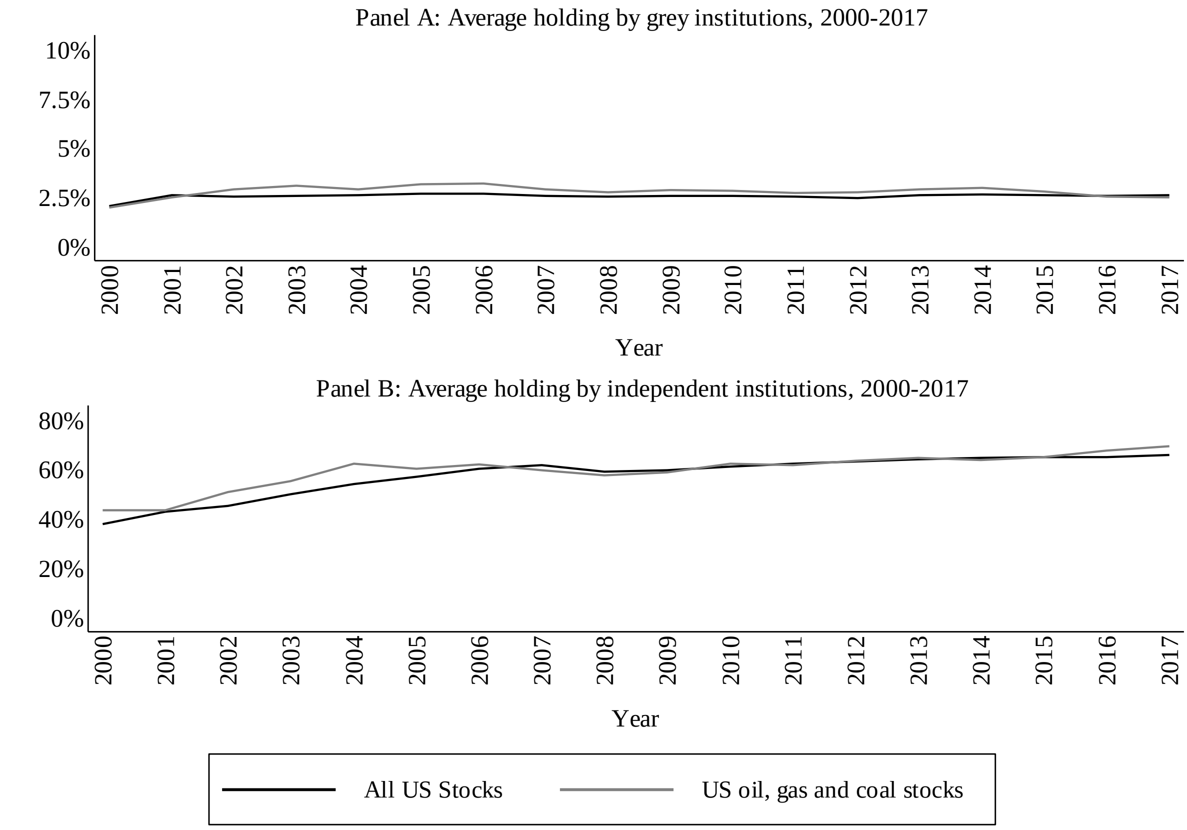

Figure 2: Average institutional ownership by investor segment. This figure plots the annual average institutional ownership for all stocks (dark line) and for oil, gas, and coal stocks (grey line) from 2000-2017, divided by two investor groups. Institutional ownership spans from 0 to 100% and reflects the stock held by institutional investors as a percentage of stock market capitalization. In Panel A, the ownership ratio for grey institutions (banks trusts, insurance companies, and pension funds) is presented. In Panel B, the ownership ratio for independent institutions (investment advisors, investment companies, and hedge funds) is presented. The ratios are winsorized at the 1st and 99th percentile.

We furthermore include the dummy variables $NASD_{it}$, $SP500_{it}$, and $GDUM_{it}$ in the regression. $NASD_{it}$ equals one if stock *i* is listed on the NASDAQ stock exchange in year *t*, and zero otherwise. Similarly, $SP500_{it}$ equals one if firm *i* is included in the S&P 500 during year *t*, and zero otherwise. $GDUM_{it}$ equals one if stock *i* belongs to the comparable group defined in section 3.2., and zero otherwise. We apply industry fixed effects based on the industry SIC-code to address the concern that institutional investors may favor specific industries to invest in. The coefficient of interest is β_1, which estimates the effect attributed to being an oil, gas, or coal stock on the level of institutional ownership. The null hypothesis is that β_1 equals zero, whereas we predict that it will be significantly lower than 0.

We report summary statistics of the variables in Table 2, Panel A. The means are similar to those presented by Hong and Kacperczyk (2009), confirming the accuracy of our variables. The exception is the difference in institutional ownership (IO) level, with our figure being substantially higher. We believe this can be due to our different data sources, as well as the fact that institutional ownership in the U.S. has increased over time (Ferreira and Matos, 2008). The same tendency is confirmed in Figure 1. For the period 2000-2017, the sample means of IO, IO_GREY, and IO_INDEP correspond to approximately 59%, 3%, and 56%, respectively.

3.3.2. Analyst coverage regression

For our next test, we consider the level of stock analyst coverage. Since sell-side analysts primarily cater to institutional investors, a stock with low institutional ownership is expected to exhibit a low level of analyst coverage, and vice versa. We construct the following regression to estimate the effect of being an oil, gas, or coal stock on the level of analyst coverage:

$$\text{(2) } LOGCOV_{it} = \beta_0 + \beta_1 OGCDUM_{it} + \boldsymbol{\beta_2 X}_{it} + \varepsilon_{it},$$

where $OGCDUM_{it}$ is a dummy variable that equals one if a stock is an oil, gas, or coal stock, and zero otherwise, X_{it} is a vector of control variables, and ε_{it} is the measurement error. The dependent variable $LOGCOV_{it}$ is calculated as the natural logarithm of one plus the number of analysts covering stock *i* at the end of year *t*. The control variables of the regression are the same as those described in the specifications for Test 1, and we apply the same conservative industry fixed effect measure. The coefficient of interest is β_1, which estimates the effect of being an oil, gas, or coal stock on the level of analyst coverage. The null hypothesis is that β_1 equals zero, whereas we predict that it will be significantly lower than 0. We report the summary statistics of the variables in Table 2, Panel B. The variable LOGCOV has a sample mean of 1.9192, which corresponds to an absolute number of 5.8 analysts covering the average stock per year. The statistics of the control variables differ slightly from those reported for Test 1, which can be explained by that the two tests differ slightly in sample.

3.3.3. Stock return regressions

We further carry out an examination of stock return. If oil, gas, and coal stocks are subject to a higher risk in light of limited risk sharing and idiosyncratic risk stemming from limited arbitrage, as we hypothesize, then those stocks should outperform comparable stocks. To study this effect, we make use of two separate methods. First, we run a time-series regression to analyze the time-series return of an oil, gas, and coal stock portfolio net a comparable stock portfolio. This regression includes adjustment for a set of well-known predictors of stock returns (Fama and French, 1993; Carhart, 1997), and is specified as follows:

$$\text{(3a) } EXCOMP_t = \alpha + \beta_1 MKTPREM_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 MOM_t + \varepsilon_t,$$

where $EXCOMP_t$ is the monthly return of an equal-weighted portfolio of oil, gas, and coal stocks ($OGCP_t$), net the monthly return of an equal-weighted portfolio of comparable stocks ($COMP_t$) in month *t*. The portfolios (OGCP and COMP) are calculated net of the risk-free rate. $MKTPREM_t$ (market premium) is the monthly return of the CRSP value-weighted portfolio in month *t*, net the risk-free rate. SMB_t (small-minus-big) is the monthly return of a portfolio that is long small stocks and short large stocks. HML_t (high-minus-low) is the monthly return of a portfolio that is long high book-to-market stocks and short low book-to-market stocks. MOM_t (momentum) is the monthly return of a portfolio that is long past one-year return winners and short past one-year return losers. ε_t is the measurement error. The regression is run using a 36-months rolling window with standard errors estimated using the Newey and West (1987) correction to adjust for serial correlation. The coefficient of interest is α, which captures the excess return of the oil, gas, and coal stock portfolio net the comparable portfolio, adjusted for the other factors. The null hypothesis is that α equals zero, whereas we predict that it will be significantly higher than 0. We report summary statistics of the variables in Table 2, Panel C. We note that EXCOMP has a positive value which means that the OCGP portfolio has a higher return than the COMP portfolio, before adjusting for other aspects.

Second, we employ an alternative approach where a regression is estimated for each stock individually using a cross-sectional variation. We construct the following regression to estimate the effect of being an oil, gas, or coal stock on return:

$$\text{(3b) } EXMRET_{it} = \beta_0 + \beta_1 OGCDUM_{it} + \boldsymbol{\beta_2 X}_{it} + \varepsilon_{it},$$

where $OGCDUM_{it}$ is a dummy variable that equals one if a stock is an oil, gas, or coal stock, and zero otherwise, X_{it} is a vector of control variables, and ε_{it} is the measurement error. The dependent variable $EXMRET_{it}$ is the excess return of stock *i* in month *t*. The regression includes the control variables of $LOGSIZE_{it}$, RET_{it}, $BETA_{it}$, $LOGMB_{it}$ and $GDUM_{it}$, defined in Test 1. As opposed to previously, $LOGSIZE_{it}$ and $LOGMB_{it}$ are now calculated on a monthly basis instead of on an annual basis, whilst RET_{it} for stock *i* is calculated as the average monthly stock return over the past 12 months, including month *t*. Additionally, the EXMRET regression includes the control variables of $TURN_{it}$, $LOGAGE_{it}$, and $BLEV_{it}$. $TURN_{it}$ corresponds to stock *i*'s average daily share turnover over month *t*. $LOGAGE_{it}$ is the natural logarithm of the age of firm *i*, measured by the number of years available in the Compustat database. $BLEV_{it}$ is stock *i*'s book leverage ratio in month *t*, calculated as the total debt divided by the sum of total debt and common equity. For this test, the control variables are used as forecasting measurements such that the stock characteristics in time *t-1* determine the return in time *t*. Therefore, we take the *t-1* observation of our numeric control variables and denote them with a "1" at the end: LOGSIZE1, LOGMB1, RET1, BETA1, TURN1, LOGAGE1, and BLEV1. We follow the procedure developed by Fama and MacBeth (1973) in taking the time-series means and standard deviations of the estimated cross-sectional regressions for each month. We furthermore employ Newey and West (1987) standard errors to adjust for serial correlation. The coefficient of interest is β_1, which estimates the effect of being an oil, gas, or coal stock on monthly stock return. The null hypothesis is that β_1 equals zero, whereas we predict that it will be significantly higher than 0. Summary statistics of the variables are presented in Table 2, Panel D. We note that the average monthly excess return is around 0.6%, and that the control variables report similar statistics as in the previous tests they appeared in.

3.3.4. Market valuation regressions

To investigate the market valuation of oil, gas, and coal stocks, we carry out an adaption of the procedure presented in Hong, Kubik, and Stein (2008) and focus on the three valuation ratios of market-to-book, price-to-earnings, and price-to-EBITDA (price divided by earnings before interest, tax, depreciation and amortization) as proxies for stock valuation. We construct the following regression to estimate the effect of being an oil, gas, or coal stock on valuation:

$$\text{(4) } Valuation_{it} = \beta_0 + \beta_1 OGCDUM_{it} + \boldsymbol{\beta_2 X}_{it} + \varepsilon_{it},$$

where $OGCDUM_{it}$ is a dummy variable that equals one if a stock is an oil, gas, or coal stock, and zero otherwise, X_{it} is a vector of control variables, and ε_{it} is the measurement error. The dependent variable "Valuation" corresponds to the natural logarithm of the aforementioned valuation ratios. First, $LOGMB_{it}$ is the natural logarithm of stock *i*'s market-to-book ratio at the end of year *t*. Second, $LOGPE_{it}$ is the natural logarithm of stock *i*'s price-to-earnings ratio at the end of year *t*. Third, $LOGPEBITDA_{it}$ is the natural logarithm of stock *i*'s price-to-EBITDA ratio at the end of year *t*. We include the previously mentioned control variables SP500 and GDUM. In addition, we include the variables ROE_{it}, $FROE_{it}$, $F2ROE_{it}$, and

$F3ROE_{it}$[4], which correspond to stock *i*'s return on equity for year *t* and for each of the coming three years. When the forward measures are added to the regression, the timeframe is reduced with up to three years. This will primarily impact the results for our final subperiod of 2010-2018, which we have to take into account. We also add $RDSALES_{it}$ and $RDMISS_{it}$ as explanatory variables to the regression. $RDSALES_{it}$ is the ratio of firm *i*'s R&D expenditures to firm sales in year *t*. If the data point of firm *i*'s R&D expenditures is missing in year *t*, the dummy variable $RDMISS_{it}$ equals one, and zero otherwise. The regression is estimated using the Fama and Macbeth (1973) procedure, outlined in section 3.3.3. The coefficient of interest is β_1, which estimates the effect of being an oil, gas, or coal stock on valuation. The null hypothesis is that β_1 equals zero, whereas we predict that it will be significantly lower than 0. The summary statistics of the variables are presented in Table 2, Panel E.

Table 2: **Summary statistics of dependent and independent variables**

This table reports summary statistics (mean and standard deviation) for the variables used in our four tests. In Panel A, summary statistics for the institutional ownership regression is presented. IO corresponds to a stock's level of total institutional ownership, reported as a fraction of market capitalization at the end of each year. IO_GREY indicates the fraction of shares held by grey institutions while IO_INDEP indicates the fraction held by independent institutions. LOGSIZE is the natural logarithm of a stock's market capitalization. BETA is the industry rolling market beta calculated over the last 36 months. LOGMB is the natural logarithm of a stock's market-to-book ratio. PRINV is the inverse of a stock's price at the end of a year. STD is a stock's daily return standard deviation during the past year. RET is stock's average monthly return for a year. In Panel B, LOGCOV is the natural logarithm of one plus the number of recommendations issued on a stock, measured at the end of a year. The remaining variables for Panel B are constructed in the same way as in Panel A. Panel C reports the variables for the time-series return regression. EXCOMP is the excess return of an equally weighted oil, gas, and coal stock portfolio net a comparable portfolio. OGCP is the excess return of the oil, gas, and coal stock portfolio. COMP is the excess return of the comparable portfolio. MKTPREM is the excess monthly return of the value-weighted CRSP index. SMB is the return of a portfolio long small stocks and short large stocks. HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks. MOM is the return of a portfolio long past 12-month return winners and short past 12-month return losers. Panel D reports the variables for the cross-sectional return regression. The EXMRET is the monthly excess return of a stock. LOGSIZE and LOGMB are calculated using the same method as in Panel A and B, but now on a monthly basis. BETA is the same as Panel A and B. LOGAGE is the natural logarithm of a firm's age measured by years available in the Compustat database. TURN is a stock's average daily share turnover for a month. RET is a stock's average monthly return over the past 12 months up to the current time. BLEV is a stock's book leverage ratio. Panel E reports the variables for the valuation regressions. LOGMB is the natural logarithm of a stock's market-to-book ratio, LOGPE is the natural logarithm of a stock's price-to-earnings ratio, and LOGPEBITDA is the natural logarithm of a stock's price-to-EBITDA ratio. LOGMB, LOGPE, and LOGPEBITDA are measured at the end of the year. ROE is a stock's return on equity at the end of the year. RDSALES is a stock's R&D expenditures divided by sales at the end of the year.

Panel A: Test 1. Institutional ownership, 2000-2017

	Mean	Standard deviation
IO[5]	0.5896	0.3135
IO_GREY[6]	0.0251	0.0218
IO_INDEP[7]	0.5610	0.2981
LOGSIZE	13.0528	2.1230
BETA	1.0670	0.4663
LOGMB	1.1606	1.0787
PRINV	0.2055	1.2074
STD (%)	3.1389	1.4518
RET (%)	1.0620	5.5296

[4] In order to remove potential outliers from extraordinary occasions, the variables ROE, FROE, F2ROE, and F3ROE have been winsorized by the 1st and 99th percentile.

[5] For the respective time periods of 2000-2006, 2007-2009, and 2010-2017, IO has a sample mean of 0.5195, 0.6232, and 0.6523, and a standard deviation of 0.3148, 0.3005, and 0.3018, respectively.

[6] For the respective time periods of 2000-2006, 2007-2009, and 2010-2017, IO_GREY has a sample mean of 0.0252, 0.0253, and 0.0248, and a standard deviation of 0.0242, 0.0203, and 0.0195, respectively.

[7] For the respective time periods of 2000-2006, 2007-2009, and 2010-2017, IO_INDEP has a sample mean of 0.4907, 0.5943, and 0.6242, and a standard deviation of 0.2973, 0.2860, and 0.2873, respectively.

Table 2: Summary statistics of dependent and independent variables (continued)

Panel B: Test 2. Analyst coverage, 2000-2018

	Mean	Standard deviation
LOGCOV	1.9192	0.8033
LOGSIZE	13.4919	1.9335
BETA	1.0685	0.4566
LOGMB	1.2533	1.0793
PRINV	0.1657	0.4668
STD (%)	3.0248	1.3875
RET (%)	0.8992	5.2394

Panel C: Test 3a. Time-series return, 2000-2018

	Mean	Standard deviation
EXCOMP (%)	0.3443	6.0570
OGCP (%)	0.5746	8.4987
COMP (%)	0.2303	6.9310
MKTRF (%)	0.5679	4.4636
SMB (%)	0.1661	3.3818
HML (%)	0.1426	3.1479
MOM (%)	0.4029	5.2152

Panel D: Test 3b. Cross-sectional return, 2000-2018

	Mean	Standard deviation
EXMRET (%)	0.6241	15.4904
LOGSIZE	13.0309	2.0922
LOGAGE	2.5693	0.9138
LOGMB	1.0989	1.1337
BETA	1.0609	0.4600
TURN (%)	0.8939	1.7841
RET (%)	1.0295	5.1397
BLEV (%)	23.6303	23.9099

Panel E: Test 4. Valuation, 2000-2018

	Mean	Standard deviation
LOGMB	1.2185	0.9997
LOGPE	3.0271	0.8934
LOGPEBITDA	2.1285	0.7484
ROE (%)	17.2594	39.0419
RDSALES (%)	7.3610	100.8438

4. Results

4.1 Institutional ownership

4.1.1. Total institutional ownership

The results from the regressions on total institutional ownership are presented in Table 3, where Panel A exhibits the results for the entire timeframe of 2000-2017. In column 1, we report the results from an initial permutation in which OGCDUM, GDUM, LOGSIZE, BETA, NASD, and SP500 are included as explanatory variables. The regression yields a statistically insignificant OGCDUM coefficient of -0.0131. It can be noted that the GDUM variable has a negative coefficient (-0.0867), significant at the 1% level. This means that stocks in the broader sector group exhibit lower institutional ownership, although no conclusion can be drawn for oil, gas, and coal stocks specifically. The regression reports a positive and significant coefficient for the variable LOGSIZE, indicating that institutional investors favor larger firms over smaller firms. Moreover, the coefficients of BETA and NASD are statistically insignificant. Finally, the regression yields a negative coefficient for the SP500 variable, significant at the 1% level. This indicates that stocks included in the S&P 500 have a lower level of institutional ownership than stocks that are not included, which goes in line with the results found in Hong and Kacperczyk (2009). In columns 2-5, the remaining control variables are added progressively to the regression. In column 2, the variable LOGMB is added and reports a negative and significant coefficient (-0.0225). Notably, the coefficient of OGCDUM now increases in magnitude with a coefficient of -0.0236, significant at the 10% level. In column 3, the LOGMB variable is substituted for PRINV and reports a negative but statistically insignificant coefficient. The substitution is carried out since the variables are correlated, as they both are scaled by stock price. Since using PRINV rather than LOGMB weakens the statistical significance of the test, we follow the conventional literature and continue to use LOGMB. In column 4, the variable STD is added to the regression and shows a negative and significant coefficient (-0.0264). This indicates that institutional investors favor stocks with lower volatility. In column 5, the final explanatory variable RET is added, reporting a negative and significant coefficient (-0.0028). The coefficient in front of OGCDUM remains negative and is significant at the 10% level in three out of five permutations, including the two most conservative estimates. In the final regression reported in column 5, OGCDUM has a coefficient of -0.0171.

Table 3: **Total institutional ownership regression**

In Panel A, we report the results from the regressions on institutional ownership. The dependent variable IO corresponds to a stock's level of total institutional ownership, reported as a fraction of market capitalization at the end of each year. OGCDUM equals one if a stock is an oil, gas, or coal stock, and zero otherwise. GDUM equals one if a stock belongs to the comparable group based on SIC-code, and zero otherwise. LOGSIZE is the natural logarithm of a stock's market capitalization. BETA is a stock's industry rolling market beta calculated over the last 36 months. LOGMB is the natural logarithm of a stock's book-to-market ratio. NASD equals one if a stock is traded on the NASDAQ stock exchange, and zero otherwise. SP500 equals one if a stock is included in the S&P 500 index, and zero otherwise. PRINV is the inverse of a stock's price at the end of a year. STD is a stock's daily return standard deviation during the past year. RET is a stock's average monthly return for a year. Panel B reports the results from the regressions which are now run over three subperiods, where the final permutation from Panel A is applied. All regressions are run using industry-fixed effects to the one digit SIC-code. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Total institutional ownership, 2000-2017

VARIABLES	(1)	(2)	(3)	(4)	(5)
OGCDUM	-0.0131	-0.0236*	-0.0131	-0.0177*	-0.0171*
	(0.0103)	(0.0105)	(0.0103)	(0.0092)	(0.0090)
GDUM	-0.0867***	-0.1007***	-0.0865***	-0.1045***	-0.1055***
	(0.0099)	(0.0121)	(0.0100)	(0.0102)	(0.0102)
LOGSIZE	0.1188***	0.1277***	0.1183***	0.1176***	0.1186***
	(0.0051)	(0.0055)	(0.0054)	(0.0057)	(0.0057)
BETA	0.0354	0.0358	0.0355	0.0470*	0.0462*
	(0.0279)	(0.0268)	(0.0279)	(0.0224)	(0.0221)
LOGMB		-0.0225***		-0.0223***	-0.0188***
		(0.0054)		(0.0053)	(0.0051)
NASD	0.0073	0.0210*	0.0071	0.0313**	0.0320**
	(0.0088)	(0.0103)	(0.0088)	(0.0105)	(0.0105)
SP500	-0.1992***	-0.2119***	-0.1981***	-0.1982***	-0.2049***
	(0.0206)	(0.0198)	(0.0211)	(0.0200)	(0.0207)
PRINV			-0.0026		
			(0.0043)		
STD				-0.0264***	-0.0260***
				(0.0043)	(0.0045)
RET					-0.0028***
					(0.0004)
Constant	-0.9678***	-1.0667***	-0.9612***	-0.8719***	-0.8844***
	(0.0471)	(0.0458)	(0.0541)	(0.0577)	(0.0591)
Observations	40,820	34,421	40,820	34,414	34,320
R-squared	0.4790	0.4865	0.4791	0.4963	0.4997

Table 3: Total institutional ownership regression (continued)			
Panel B: Total institutional ownership by subperiods			
	(1)	(2)	(3)
VARIABLES	2000-2006	2007-2009	2010-2017
OGCDUM	-0.0180**	-0.0492*	0.0288***
	(0.0057)	(0.0221)	(0.0056)
GDUM	-0.0299**	-0.1683***	-0.1337***
	(0.0094)	(0.0248)	(0.0058)
LOGSIZE	0.1103***	0.1113***	0.1070***
	(0.0055)	(0.0068)	(0.0065)
BETA	0.0309**	0.0599	0.0879***
	(0.0110)	(0.0373)	(0.0242)
PRINV	0.0095	-0.0099	-0.0020
	(0.0074)	(0.0098)	(0.0043)
STD	-0.0329***	-0.0041	-0.0320***
	(0.0033)	(0.0082)	(0.0068)
RET	-0.0022***	-0.0040***	-0.0029**
	(0.0004)	(0.0009)	(0.0010)
NASD	0.0244	0.0230**	0.0272**
	(0.0137)	(0.0087)	(0.0087)
SP500	-0.1541***	-0.1822***	-0.2202***
	(0.0175)	(0.0304)	(0.0291)
Constant	-0.7953***	-0.8337***	-0.7674***
	(0.0534)	(0.0996)	(0.0767)
Observations	16,626	7,048	17,024
R-squared	0.5179	0.4258	0.4718

The -0.0171 coefficient indicates that oil, gas, and coal stocks have approximately 1.7% less institutional ownership than comparable stocks. Taking this deviation and dividing it by the sample mean of 59.0% implies a shortfall of 2.9%, attributed to the effect of being an oil, gas, or coal stock. It can further be noted that the initially insignificant coefficients of BETA and NASD both report positive and significant values in the two final permutations. This indicates that institutional investors favor stocks with higher rather than lower industry betas, as well as stocks trading on NASDAQ rather than on other stock exchanges. Although Hong and Kacperczyk (2009) received a negative and statistically significant coefficient for NASD throughout the majority of regressions, our finding is comparable with the results for their final period 2000-2006.

Furthermore, we run the regression for each of the three defined subperiods of 2000-2006, 2007-2009, and 2010-2017, to see whether the effect of OGCDUM has remained consistent over time. The results are presented in Panel B. Since we want to maintain as many observations as possible in the sample, LOGMB is exchanged for PRINV[8]. Overall, the coefficients of the control variables stay consistent over the subperiods. However, the sign of the coefficient in front of OGCDUM has interestingly changed direction in the last subperiod. In the first subperiod, the regression yields an OGCDUM coefficient of -0.0180, or -1.8%, significant at the 5% level. In the second subperiod, the OGCDUM variable points in the same direction. However, in the last subperiod, the OGCDUM variable has a positive coefficient of 0.0288, or 2.9%, significant at the 1% level.

In sum, the results indicate that the attribute of being an oil, gas, or coal stock has gone from being associated with a lower level of institutional ownership in the first two periods covering 2000-2009, to being associated with a higher level of institutional ownership in the third period of 2010-2017. As reported in Table 2, Panel A, the sample mean of the stock

[8] The test on institutional ownership for the subperiods has also been carried out using the variable of LOGMB instead of PRINV, for which similar results are obtained.

universe's institutional holding was on average 52.0%, 62.3%, and 65.2% for the first, second, and third subperiod, respectively. The OGCDUM coefficient of -0.0180 for the first period of 2000-2006 thus corresponds to a 3.5% shortfall compared to the sample mean. For the period of 2007-2009, the equivalent figure corresponds to 7.9%. In the last period of 2010-2017, oil, gas, and coal stocks are associated with a 4.4% higher institutional ownership compared to the sample mean.

The hypothesis that oil, gas, and coal stocks are less held by institutional owners than stocks of otherwise comparable characteristics is confirmed for the subperiods of 2000-2006 and 2007-2009, whilst rejected for the third subperiod of 2010-2017. For the entire timeframe of 2000-2017, the results reveal that oil, gas and coal stocks have been associated with a 1.7% lower institutional ownership than comparable stocks, at statistical significance. Thus, our hypothesis is confirmed for the timeframe of 2000-2017, even though the effect appears to have changed direction over time.

4.1.2. Institutional ownership by investor segment

In this section, we report the results retrieved from the regressions that consider the stock ownership level of the two institutional investor segments of grey institutions (IO_GREY) and independent institutions (IO_INDEP). We apply the most conservative regression established in the earlier test on total institutional ownership. The results are found in Table 4.

Grey institutions: In column 1-4 in Table 4, we report the results of the regression that considers the stock ownership level of grey institutions as its dependent variable. When considering the entire timeframe of 2000-2017, it can be noted that the coefficient in front of OGCDUM is -0.0026, or -0.3%, statistically significant at the 1% level. Focusing on the respective subperiods, we note that the OGCDUM coefficient is -0.0040 in the first period at a 1% level of significance, -0.0023 in the second period at a 5% level of significance, and -0.0011 in the final period at a 5% level of significance. As reported in Table 2, Panel A, grey institutions hold on average 2.5% of the total stock ownership in the sample, a figure that stays consistent over the respective time-windows. Hence, in the overall timeframe of 2000-2017, the 0.3% lower stock ownership for oil, gas, and coal stocks represents a 10.4% shortfall relative to the sample mean. In the first time-window of 2000-2006, this shortfall corresponds to a magnitude of 15.9%, while it is somewhat lower, 9.1% and 4.4%, in the subsequent time-windows of 2007-2009 and 2010-2017, respectively. In sum, we note that the investor segment of grey institutions have a lower ownership in oil, gas, and coal stocks than stocks of otherwise comparable characteristics, although the magnitude of this effect appears to have diminished.

Independent institutions: In column 5-8 in Table 4, the regressions focusing on the stock ownership level of independent institutions are reported. Over the entire timeframe of 2000-2017, the coefficient on OGCDUM is statistically insignificant. In the first subperiod of 2000-2006, the OGCDUM variable has a coefficient of -0.0184, significant at the 5% level. In the second subperiod of 2007-2009, the coefficient of OGCDUM remains negative with a value of -0.0508, significant at the 10% level. In the third subperiod of 2010-2017 the coefficient in front of OGCDUM is positive at 0.0256, significant at the 1% level. Hence, the statistically insignificant coefficient for the entire timeframe can be attributed to a shift in the coefficient's direction over time. As reported in Table 2, Panel A, the sample mean of independent institutions' stock ownership corresponds to 49.0%, 59.4%, and 62.4% for the first, second, and third subperiods, respectively. For the time-window of 2000-2006, we conclude that the OGCDUM coefficient of -0.0184 corresponds to a 3.7% shortfall for oil, gas, and coal stocks relative to the sample mean. For the second time-window of 2007-2009, this shortfall reaches 8.5%. In the third time-window, the 0.0256 coefficient corresponds to a 4.1% higher ownership in oil, gas, and coal stocks relative to comparables. The results indicate that the oil, gas, and coal stock effect has been subject to a shift with regards to independent institutional ownership.

Table 4: Regressions on institutional ownership by investor type

In this table, we report the regressions for the dependent variables IO_GREY and IO_INDEP. The variable IO_GREY corresponds to the stock ownership of grey institutions (bank trusts, insurance companies, and pension funds), reported as a fraction of market capitalization at the end of each year. The variable IO_INDEP corresponds to the stock ownership of independent institutions (investment advisors, investment companies, and hedge funds), reported as a fraction of market capitalization at the end of each year. The regressions are run on the timeframe 2000-2017, alongside three subperiods. OGCDUM equals one if a stock is an oil, gas, or coal stock, and zero otherwise. GDUM equals one if a stock belongs to the comparable group based on SIC-code, and zero otherwise. LOGSIZE is the natural logarithm of a stock's market capitalization. BETA is a stock's industry rolling market beta calculated over the last 36 months. LOGMB is the natural logarithm of a stock's book-to-market ratio. NASD equals one if a stock is traded on the NASDAQ stock exchange, and zero otherwise. SP500 equals one if a stock is included in the S&P 500 index, and zero otherwise. PRINV is the inverse of a stock's price at the end of a year. STD is a stock's daily return standard deviation during the past year. RET is a stock's average monthly return for a year. All regressions are run using industry-fixed effects to the one digit SIC-code. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Grey institutional ownership				Independent institutional ownership			
VARIABLES	2000-2017	2000-2006	2007-2009	2010-2017	2000-2017	2000-2006	2007-2009	2010-2017
OGCDUM	-0.0026***	-0.0040***	-0.0023**	-0.0011**	-0.0080	-0.0184**	-0.0508**	0.0256***
	(0.0003)	(0.0003)	(0.0009)	(0.0004)	(0.0087)	(0.0058)	(0.0210)	(0.0053)
GDUM	0.0025***	0.0080***	-0.0023	-0.0004	-0.0974***	-0.0317***	-0.1580***	-0.1408***
	(0.0004)	(0.0004)	(0.0015)	(0.0006)	(0.0071)	(0.0087)	(0.0229)	(0.0054)
LOGSIZE	0.0057***	0.0065***	0.0053***	0.0052***	0.1038***	0.1032***	0.1051***	0.1008***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0052)	(0.0051)	(0.0064)	(0.0060)
BETA	0.0008	0.0003	0.0024	0.0026*	0.0441	0.0305**	0.0566	0.0840***
	(0.0009)	(0.0007)	(0.0015)	(0.0011)	(0.0236)	(0.0115)	(0.0355)	(0.0233)
PRINV	0.0002***	0.0014***	0.0006**	0.0001***	-0.0011	0.0081	-0.0100	-0.0021
	(0.0000)	(0.0003)	(0.0002)	(0.0000)	(0.0030)	(0.0073)	(0.0093)	(0.0042)
STD	-0.0002	-0.0005**	0.0000	-0.0017**	-0.0264***	-0.0326***	-0.0049	-0.0318***
	(0.0003)	(0.0002)	(0.0003)	(0.0006)	(0.0046)	(0.0032)	(0.0079)	(0.0063)
RET	-0.0003***	-0.0003***	-0.0002***	-0.0003***	-0.0029***	-0.0019***	-0.0037***	-0.0025**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0005)	(0.0003)	(0.0008)	(0.0009)
NASD	-0.0021**	-0.0042***	-0.0006	-0.0007	0.0223**	0.0300*	0.0241**	0.0301***
	(0.0008)	(0.0007)	(0.0010)	(0.0008)	(0.0092)	(0.0130)	(0.0093)	(0.0085)
SP500	0.0040***	0.0013	0.0051***	0.0044***	-0.1947***	-0.1520***	-0.1817***	-0.2199***
	(0.0009)	(0.0011)	(0.0009)	(0.0011)	(0.0216)	(0.0168)	(0.0293)	(0.0275)
Constant	-0.0484***	-0.0545***	-0.0464***	-0.0430***	-0.7327***	-0.7385***	-0.7782***	-0.7106***
	(0.0055)	(0.0051)	(0.0059)	(0.0083)	(0.0582)	(0.0477)	(0.0917)	(0.0695)
Observations	40,698	16,626	7,048	17,024	40,698	16,626	7,048	17,024
R-squared	0.3830	0.3820	0.3427	0.4552	0.4833	0.5082	0.4177	0.4591

Overall, the hypothesis that grey institutional investors are associated with a greater magnitude of ownership shortfall in oil, gas, and coal stocks compared to independent institutional investors, is confirmed for all subperiods. In the first period of 2000-2006, the shortfall for grey institutions was 15.9% compared to 3.7% for independent institutions. In the second period of 2007-2009, covering the financial crisis, the shortfall for grey institutions was 9.1% compared to 8.5% for independent institutions. In the third period of 2010-2017, the shortfall for grey institutions was 4.4%, which can be contrasted to the 4.1% positive figure for independent institutions. Building upon the test on total institutional ownership, we conclude that the independent institutions have been the driving force behind oil, gas, and coal stocks' higher institutional ownership in the final period of 2010-2017. In Appendix A we report the results of the regressions that consider the institutional ownership level for each separate investor type. These results bring further insights and point to the central role of investment companies and hedge funds in causing oil, gas and, coal stocks to become associated with a higher level of total institutional ownership in the final subperiod. For grey institutions, the shortfall is primarily driven by pension funds.

4.2. Analyst coverage

The results on analyst coverage are presented in Table 5, where Panel A exhibits the results for the entire timeframe of 2000-2018. In column 1, we report the results of the first permutation, in which LOGCOV is regressed on OGCDUM, GDUM, LOGSIZE, BETA, NASD, and SP500. The coefficient of OGCDUM is 0.2725, statistically significant at the 1% level. This indicates that sell-side analysts follow oil, gas, and coal stocks to a greater extent than stocks of otherwise comparable characteristics. The variable of GDUM reports a negative coefficient (-0.2875), significant at the 1% level. This means that stocks in the comparable universe are associated with less analyst coverage. Both LOGSIZE and BETA attract positive and statistically significant coefficients, suggesting that analysts tend to follow large firms as well as firms with a high industry beta. Finally, the coefficients in front of NASD and SP500 are positive and significant, which indicates that the attributes of being traded on the NASDAQ stock exchange and included in the S&P 500 are associated with a higher level of stock analyst coverage. In column 2, we present the results of the second permutation in which LOGMB is added. The coefficient in front of LOGMB is negative, significant at the 10% level. In column 3, the LOGMB variable is substituted for the variable PRINV.

Table 5: Analyst coverage regression

In Panel A, we report the results from the regression on analyst coverage for the timeframe 2000-2018. The dependent variable LOGCOV is the natural logarithm of one plus the number of recommendations for a stock, measured at the end of a year. OGCDUM equals one if a stock is an oil, gas, or coal stock, and zero otherwise. GDUM equals one if a stock belongs to the comparable group based on SIC-code, and zero otherwise. LOGSIZE is the natural logarithm of a stock's market capitalization. BETA is a stock's industry rolling market beta calculated over the last 36 months. LOGMB is the natural logarithm of a stock's book-to-market ratio. NASD equals one if a stock is traded on the NASDAQ stock exchange, and zero otherwise. SP500 equals one if a stock belongs to the S&P 500, and zero otherwise. PRINV is the inverse of a stock's price at the end of a year. STD is a stock's daily return standard deviation during the past year. RET is a stock's average monthly return for a year. Panel B reports the results from the regressions which are now run over three subperiods, where the final permutation from Panel A is applied. The regressions are run using industry-fixed effect to the one digit SIC-code. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Analyst coverage, 2000-2018

VARIABLES	(1)	(2)	(3)	(4)	(5)
OGCDUM	0.2725***	0.2696***	0.2754***	0.2562***	0.2557***
	(0.0102)	(0.0113)	(0.0093)	(0.0084)	(0.0082)
GDUM	-0.2875***	-0.3173***	-0.2941***	-0.2803***	-0.2859***
	(0.0291)	(0.0382)	(0.0289)	(0.0238)	(0.0235)
LOGSIZE	0.3136***	0.3287***	0.3313***	0.3494***	0.3591***
	(0.0092)	(0.0107)	(0.0102)	(0.0115)	(0.0108)
BETA	0.0731*	0.0632*	0.0704*	0.0464	0.0385
	(0.0313)	(0.0310)	(0.0301)	(0.0256)	(0.0243)
LOGMB		-0.0255*			
		(0.0120)			
NASD	0.1210***	0.1419***	0.1273***	0.1086***	0.1159***
	(0.0293)	(0.0333)	(0.0288)	(0.0267)	(0.0271)
SP500	0.1284***	0.1313***	0.0902***	0.0730***	0.0368**
	(0.0127)	(0.0161)	(0.0142)	(0.0179)	(0.0149)
PRINV			0.1089***	0.0891***	0.0539***
			(0.0140)	(0.0124)	(0.0084)
STD				0.0507***	0.0537***
				(0.0058)	(0.0049)
RET					-0.0173***
					(0.0015)
Constant	-2.4668***	-2.6411***	-2.7197***	-3.0751***	-3.1834***
	(0.1280)	(0.1340)	(0.1409)	(0.1611)	(0.1459)
Observations	38,277	31,518	38,277	38,276	38,244
R-squared	0.6162	0.6157	0.6206	0.6255	0.6377

Table 5: Analyst coverage regression (continued)

Panel B: Analyst coverage by subperiods

VARIABLES	(1) 2000-2006	(2) 2007-2009	(3) 2010-2018
OGCDUM	0.3325***	0.0368	0.2652***
	(0.0051)	(0.0314)	(0.0159)
GDUM	-0.1842***	-0.1964***	-0.3405***
	(0.0148)	(0.0481)	(0.0330)
LOGSIZE	0.3448***	0.3598***	0.3770***
	(0.0055)	(0.0142)	(0.0154)
BETA	0.0681***	-0.0262	0.0035
	(0.0120)	(0.0551)	(0.0823)
PRINV	0.0770***	0.0383***	0.0034
	(0.0132)	(0.0056)	(0.0158)
STD	0.0341***	0.0529***	0.1366***
	(0.0033)	(0.0121)	(0.0112)
RET	-0.0170***	-0.0161***	-0.0189***
	(0.0005)	(0.0015)	(0.0027)
NASD	0.1285***	0.1948***	0.0765**
	(0.0319)	(0.0212)	(0.0261)
SP500	0.0964**	-0.0264	0.0476*
	(0.0330)	(0.0239)	(0.0247)
Constant	-3.0496***	-3.1285***	-3.5370***
	(0.0758)	(0.2131)	(0.2474)
Observations	12,137	6,428	17,559
R-squared	0.6149	0.5933	0.6686

We note that PRINV has a positive coefficient, significant at the 1% level. We maintain the PRINV variable throughout the remainder of our permutations since it has higher explanatory power. In column 4, the variable STD is added and yields a positive coefficient at the 1% level of significance. In the final and most conservative permutation in column 5, the variable RET is added. The regression yields a negative coefficient for RET, significant at the 1% level. Throughout the progression of adding control variables, we note that the magnitudes of some control variables are reduced, although they all remain statistically significant except from BETA. Our control variables' coefficients are all in line with those found by Hong and Kacperczyk (2009) with the exception of NASD, the same case as in the test on institutional ownership. OGCDUM has a coefficient of 0.2557 in the most conservative permutation, significant at the 1% level. This result indicates that the preliminary conclusion drawn from column 1 still holds, namely that the attribute of being an oil, gas, or coal stock is associated with a higher level of analyst coverage. The average sample LOGCOV of 1.9192 corresponds to an absolute number of 5.8 analysts covering a stock. Thus, if oil, gas, and coal firms are subject to 0.2557 more analyst coverage, this means they are followed by 7.8 analysts in total, which corresponds to approximately 2 more analysts a year relative to the sample mean.

We further estimate the regression for each of our three subperiods, the results of which are presented in Panel B. We note that the coefficients of the control have stayed consistent in magnitude across the time-windows. As regards the period of 2000-2006, the coefficient in front of OGCDUM is 0.3325, significant at the 1% level. For the second period 2007-2009, however, the OGCDUM coefficient is statistically insignificant. For the final period of 2010-2018, the coefficient on OGCDUM is 0.2652, with a 1% level of significance.

In sum, our hypothesis formulated with regards to analyst coverage is rejected. The results instead indicate that oil, gas, and coal stocks receive more analyst coverage than stocks of otherwise comparable characteristics.

4.3. Stock return and market valuation

4.3.1. Time-series return

The results of the regressions on time-series returns are presented in Table 6, in which the four factors are added progressively as control variables. The results for the entire timeframe of 2000-2018 are presented in Panel A. We note that the alpha has a positive but statistically insignificant value of 0.0051, or 51 bps, when only controlling for MKTPREM, which itself is insignificant. The alpha coefficient remains insignificant as the additional factors of SMB, HML, and MOM are added as control variables.

In line with previous tests, we further conduct the analysis on time-series returns by considering the three respective subperiods. The results for the first period of January 2000 to July 2007 are reported in Panel B. The most conservative one yields an alpha coefficient of 72 bps, however at statistical insignificance. In Panel C, we report the regression for the second period of August 2007 to March 2009. The alpha coefficient is consistently positive and statistically significant at the 5% level when including the control variables MKTPREM, SMB, and HML. However, when adding the control variable MOM, the alpha becomes statistically insignificant. The results for the final period of April 2009 to December 2018 are reported in Panel D. The alpha is once again consistently positive but insignificant, reaching 21 bps in the most conservative regression reported in the fourth row. Overall, it can be concluded that alpha is positive for all the periods, although not at statistical significance.

From the test on time-series return, we cannot draw any conclusion as for the abnormal returns of oil, gas, and coal stocks.

Table 6: Time-series return regression

Panel A reports the results from the time-series return regression for the timeframe 2000-2018. EXCOMP is the excess return of an equally weighted portfolio of oil, gas, and coal stocks net the excess return of an equally weighted comparable portfolio. MKTPREM is the excess monthly return of the value-weighted CRSP index. SMB is the return of a portfolio long small stocks and short large stocks. HML is the return of a portfolio long high book-to-market stocks and short low book-to-market stocks. MOM is the return of a portfolio long past 12-month return winners and short past 12-month return losers. Panel B, C, and D report the results for the regressions which are now run for three subperiods, with Panel B from January 2000 to July 2007, Panel C from August 2007 to March 2009, and Panel D from April 2009 to December 2018. All regressions are estimated using a 36-month rolling window with Newey and West (1987) standard errors to adjust for autocorrelation. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Time-series return, 2000-2018

	ALPHA	MKTPREM	SMB	HML	MOM
EXCOMP	0.0051	-0.1173			
	(0.0067)	(0.1001)			
EXCOMP	0.0055	-0.1138	-0.1094		
	(0.0067)	(0.1263)	(0.2321)		
EXCOMP	0.0046	-0.0436	-0.1063	0.1362	
	(0.0069)	(0.1418)	(0.2304)	(0.3143)	
EXCOMP	0.0043	-0.0032	-0.1788	0.1282	0.2237
	(0.0071)	(0.1647)	(0.2114)	(0.2816)	(0.1780)

Panel B: Time-series return, Jan 2000 - Jul 2007

	ALPHA	MKTPREM	SMB	HML	MOM
EXCOMP	0.0068	-0.2719**			
	(0.0077)	(0.1059)			
EXCOMP	0.0075	-0.3088*	0.0094		
	(0.0083)	(0.1476)	(0.2194)		
EXCOMP	0.0064	-0.2617	0.0437	0.1925	
	(0.0088)	(0.1717)	(0.2174)	(0.3068)	
EXCOMP	0.0072	-0.2215	-0.0679	0.0518	0.1570
	(0.0086)	(0.1880)	(0.1916)	(0.2890)	(0.1811)

Table 6: Time-series return regression (continued)

Panel C: Time-series return, Aug 2007 - Mar 2009

	ALPHA	MKTPREM	SMB	HML	MOM
EXCOMP	0.0134**	-0.2945*			
	(0.0052)	(0.1540)			
EXCOMP	0.0137**	-0.3288	-0.0333		
	(0.0053)	(0.2166)	(0.2667)		
EXCOMP	0.0130**	-0.3145*	-0.0151	-0.3153	
	(0.0053)	(0.1567)	(0.2633)	(0.6584)	
EXCOMP	0.0044	-0.1501	-0.2843	0.3827	1.3212***
	(0.0040)	(0.1504)	(0.2070)	(0.3910)	(0.1634)

Panel D: Time-series return, Apr 2009 - Dec 2018

	ALPHA	MKTPREM	SMB	HML	MOM
EXCOMP	0.0025	0.0297			
	(0.0061)	(0.0856)			
EXCOMP	0.0025	0.0684	-0.2137		
	(0.0058)	(0.0944)	(0.2376)		
EXCOMP	0.0018	0.1674	-0.2380	0.1734	
	(0.0058)	(0.1160)	(0.2362)	(0.2597)	
EXCOMP	0.0021	0.1902	-0.2484	0.1453	0.0974
	(0.0064)	(0.1485)	(0.2278)	(0.2554)	(0.1773)

4.3.2. Cross-sectional return

The results of the regressions on cross-sectional returns are presented in Table 7. In Panel A, we report the results for the entire timeframe of 2000-2018. We present various permutations of the regression, with the specification presented in column 6 being the most conservative estimate including all control variables. In this specification, OGCDUM has a coefficient of 0.0050, statistically significant at the 1% level. This indicates that oil, gas, and coal stocks outperform other comparable stocks by 50 bps a month, corresponding to an annualized figure of 6%. The variables of LOGSIZE1 and LOGMB1 have both negative and significant coefficients, indicating that firms with higher market-to-book ratios and market capitalizations are associated with lower stock returns. This result is consistent with Fama and French (1993). We further note that the coefficient of RET1 is surprisingly negative and significant at the 1% level, which indicates that stocks with lower past returns outperform stocks with higher past returns, which goes against Carhart (1997). The coefficients in front of GDUM and BLEV1 are statistically insignificant, whereas the coefficients on BETA1 and TURN1 are both negative and significant at the 1% level. The latter findings reveal that stocks with a lower industry beta and a lower stock turnover are associated with higher stock returns. The coefficient in front of LOGAGE1 is positive at the 1% level of significance, indicating that older firms outperform younger firms in the sample. As we relax the control variables, the magnitude of the OGCDUM coefficient remains statistically significant in column 5 and 4. We draw the conclusion that one needs to adequately control for other characteristics to capture the oil, gas, and coal effect. In particular, controlling for the dummy of GDUM is important in order to separate the oil, gas, and coal effect from a more general industry effect. The majority of the control variables report similar magnitudes to those found in Hong and Kacperczyk (2009), although the level of statistical significance varies. The exception is the estimates on BETA1 and LOGAGE1, which differ in both sign and level of significance. The reason behind this anomaly could be the fact that our observations occur in a different timespan.

In Panel B, the results of the regression on cross-sectional returns are reported for each of the three subperiods. We note that the coefficient on OGCDUM is statistically significant at the 1% level in the first period of 2000-2007, at 79 bps. This corresponds to an annualized superior stock return of 9.5% for oil, gas, and coal stocks. In the two subsequent periods, the coefficient in front of OGCDUM remains positive but is statistically insignificant.

Concluding our findings on stock return, we note that the coefficient of alpha from the time-series regression and the coefficient on OGCDUM from the cross-sectional variation report similar magnitudes, although the results from the former test are essentially insignificant. We deem the most conservative estimate of OGDCUM captured in the cross-sectional variation to be most adequate in capturing the oil, gas, and coal effect, considering its conservative nature and high statistical significance. Our estimate indicates that the attribute of being an oil, gas, or coal stock has been associated with a 6% annual higher return over the timeframe of 2000-2018. The first time-window of 2000-2006 stands out as a period in which the positive oil, gas, and coal effect on stock returns has been particularly prevalent.

Table 7: Cross-sectional return regression

Panel A reports the results from the Fama and MacBeth (1973) cross-sectional regressions for the timeframe 2000-2018 on stock return. The dependent variable EXMRET is the monthly return of a stock net of the risk-free rate. OGCDUM equals one if a stock is an oil, gas, or coal stock, and zero otherwise. GDUM equals one if a stock belongs to the comparable group based on SIC-code, and zero otherwise. The lagged (i.e. previous month) values of a set of well-known predictors of stock returns are included as control variables. LOGSIZE is the natural logarithm of a stock's market capitalization, calculated on a monthly basis. LOGMB is the natural logarithm of a stock's market-to-book ratio, where book value is calculated on a quarterly basis whilst market value is calculated on a monthly basis. RET is a stock's average monthly return over the past 12 months up to the current time. BETA is a stock's industry rolling market beta calculated over the last 36 months. TURN is a stock's average daily share turnover for a month. LOGAGE is the natural logarithm of the firm's age. BLEV is a stock's book leverage ratio. The lagged variables are denoted as LOGSIZE1, LOGMB1, RET1, BETA1, TURN1, LOGAGE1, and BLEV1. Panel B reports the results from the regressions which are now run over three subperiods, where the final permutation from Panel A is applied, with column 1 from January 2000 to July 2007, column 2 from August 2007 to March 2009, and column 3 from April 2009 to December 2018. Standard errors are adjusted for serial correlation using the Newey and West (1987) correction. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Cross-sectional return, 2000-2018

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
OGCDUM	0.0035	0.0023	0.0025	0.0063**	0.0052***	0.0050***
	(0.0051)	(0.0047)	(0.0048)	(0.0026)	(0.0019)	(0.0019)
LOGSIZE1	-0.0017**	-0.0008*	-0.0008*	-0.0008*	-0.0010*	-0.0010*
	(0.0008)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
LOGMB1		-0.0043***	-0.0039***	-0.0039***	-0.0032***	-0.0032***
		(0.0014)	(0.0014)	(0.0013)	(0.0010)	(0.0010)
RET1			-0.0327***	-0.0329***	-0.0304***	-0.0316***
			(0.0095)	(0.0095)	(0.0080)	(0.0083)
GDUM				-0.0040	-0.0031	-0.0028
				(0.0027)	(0.0026)	(0.0027)
BETA1					-0.0025**	-0.0027***
					(0.0010)	(0.0010)
TURN1					-0.1440***	-0.1447***
					(0.0266)	(0.0265)
LOGAGE1					0.0015***	0.0015***
					(0.0006)	(0.0006)
BLEV1						-0.0001
						(0.0008)
Constant	0.0270***	0.0200***	0.0193***	0.0194***	0.0211***	0.0213***
	(0.0099)	(0.0066)	(0.0068)	(0.0067)	(0.0069)	(0.0071)
Observations	539,010	458,630	456,871	456,871	456,871	456,871
R-squared	0.010	0.016	0.022	0.023	0.033	0.035

Table 7: Cross-sectional return regression (continued)			
Panel B: Cross-sectional return by subperiods			
	(1)	(2)	(3)
VARIABLES	Jan 2000 - Jul 2007	Aug 2007 - Mar 2009	Apr 2009 - Dec 2018
OGCDUM	0.0079***	0.0004	0.0036
	(0.0028)	(0.0197)	(0.0033)
LOGSIZE1	-0.0024***	0.0027***	-0.0005
	(0.0005)	(0.0007)	(0.0005)
LOGMB1	-0.0055***	-0.0020**	-0.0016***
	(0.0010)	(0.0008)	(0.0005)
RET1	-0.0086	-0.0605	-0.0445***
	(0.0104)	(0.0651)	(0.0167)
GDUM	0.0029	0.0062	-0.0089***
	(0.0032)	(0.0039)	(0.0016)
BETA1	-0.0028	-0.0153*	-0.0006
	(0.0036)	(0.0076)	(0.0014)
TURN1	-0.2356***	-0.0453	-0.0909***
	(0.0398)	(0.0754)	(0.0241)
LOGAGE1	0.0023	0.0019	0.0008
	(0.0017)	(0.0013)	(0.0005)
BLEV1	0.0007	-0.0232**	0.0032
	(0.0027)	(0.0084)	(0.0029)
Constant	0.0409***	-0.0511***	0.0185*
	(0.0073)	(0.0156)	(0.0102)
Observations	200,827	41,253	203,365
R-squared	0.0708	0.0491	0.0482

4.3.3. Market valuation

The results of the regressions on market valuation are reported in Table 8. The results for the entire timeframe are presented in Panel A, where column 3 reports the most conservative specification for the regression on LOGMB. The coefficient in front of OGCDUM is -0.17 and statistically significant at the 5% level. We thus find that oil, gas, and coal stocks have a 17% valuation discount relative to comparable stocks, considering market-to-book ratio. The coefficient in front of GDUM is also negative and significant, indicating that the industry comparable stocks are as well associated with a valuation discount. The coefficients on SP500, ROE, RDSALES, FROE, F2ROE, and F3ROE are all positive and significant, while the coefficient on RDMISS is negative and significant. This means that the attributes of being included in the S&P 500, having high R&D expenditures, and having a high return on equity yield positive effects on a stock's market-to-book ratio. Overall, the control variables' coefficients go in line with those reported by Hong, Kubik, and Stein (2008) and Hong and Kacperczyk (2009). When relaxing the specification in column 1 and 2, the total amount of observations increases due the exclusion of the forward variables. The coefficient in front of OGCDUM now reaches a higher magnitude, reporting a valuation discount of 25%, at the 1% level of significance. In column 6, we estimate the same model, however this time using LOGPE as the dependent variable. The coefficient in front of OGCDUM is negative but statistically insignificant. The coefficients on the control variables remain qualitatively similar, except from the ROE variables, which now report statistically negative values in line with Hong and Kacperczyk's (2009) findings. Relaxing the control variables increases the amount of observations as shown in column 4 and 5, and the magnitude of the coefficient on OGCDUM remains consistent. Finally, in column 9, we report the regression on the valuation metric of LOGPEBITDA. In this specification, the coefficient in front of OGCDUM is once again negative and significant at the 1% level with a magnitude of -0.21. We note that our SP500 coefficient is negative and significant at the 10% level on LOGPEBITDA, whereas Hong and Kacperczyk (2009) found it to be positive and significant. Our findings indicate that oil, gas, and coal stocks' price-to-EBITDA ratios are smaller relative to comparables by 21%. The magnitude of the valuation discount remains consistent throughout the permutations when excluding the forward variables as shown in column 7 and 8.

Overall, the results indicate that oil, gas, and coal stocks are associated with a lower valuation than stocks of otherwise comparable characteristics, although no conclusion can be drawn for the valuation metric of price-to-earnings ratio, specifically. The effect attributed to oil, gas, and coal stocks yield an average valuation discount of 19% for LOGMB and LOGPEBITDA for the period 2000-2015 and 23% for the period of 2000-2018 when excluding the forward variables. With the coefficients remaining consistent throughout the permutations, we deem the 19% valuation discount as the most appropriate estimate for the entire period 2000-2018, considering its conservative nature and high statistical significance.

Furthermore, in Panel B, we report the results from the regressions for each of the three consecutive subperiods. In column 1-3, we present the results for the valuation metric LOGMB. In the first time-window of 2000-2006, the coefficient in front of OGCDUM is statistically insignificant. For the second time-window of 2007-2009, it is negative and significant at the 5% level. In the final time-window of 2010-2015, the coefficient on OGCDUM is -0.26, significant at the 1% level.

Table 8: Valuation regressions

Panel A reports the results from the Fama and MacBeth (1973) regressions on stock valuation for the period of 2000-2018, with the dependent variables LOGMB, LOGPE, and LOGPEBITDA, measured at the end of the year. LOGMB is the natural logarithm of a stock's market-to-book ratio, LOGPE is the natural logarithm of a stock's price-to-earnings ratio, and LOGPEBITDA is the natural logarithm of a stock's price-to-EBITDA ratio. OGCDUM equals one if a stock is an oil, gas, or coal stock, and zero otherwise. GDUM equals one if a stock belongs to the comparable group based on SIC-code, and zero otherwise. SP500 equals one if a stock is part of the S&P 500 index, and zero otherwise. ROE is a stock's return on equity, calculated at the end of the year. RDSALES is a firm's annual R&D expenditures divided by sales, calculated at the end of the year. RDMISS equals one if a firm is not reporting any R&D expenditures, and zero otherwise. FROE, F2ROE and F3ROE correspond to a stock's forward return on equity for one, two, and three years ahead, respectively. Panel B reports the results from the regressions which are now run over three subperiods, where the final permutation from Panel A is applied. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Valuation, 2000-2018

	LOGMB			LOGPE			LOGPEBITDA		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OGCDUM	-0.25**	-0.25**	-0.17**	-0.07	-0.07	-0.08	-0.21***	-0.21***	-0.21***
	(0.12)	(0.12)	(0.08)	(0.05)	(0.05)	(0.08)	(0.04)	(0.03)	(0.06)
GDUM	-0.40***	-0.23***	-0.23***	-0.27***	-0.14**	-0.10	-0.20***	0.01	0.02
	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.04)	(0.03)	(0.05)
SP500	0.49***	0.47***	0.39***	0.01	-0.01	-0.01	0.01	-0.03	-0.05*
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.03)	(0.02)	(0.03)
ROE	2.02***	2.04***	1.75***	-1.08***	-1.05***	-1.16***	-0.27***	-0.17***	-0.22***
	(0.16)	(0.14)	(0.18)	(0.24)	(0.22)	(0.20)	(0.06)	(0.03)	(0.03)
RDSALES		0.71***	1.08***		1.70***	2.01***		4.74***	4.95***
		(0.09)	(0.17)		(0.15)	(0.14)		(0.48)	(0.47)
RDMISS		-0.28***	-0.24***		-0.16***	-0.14***		-0.10***	-0.09***
		(0.04)	(0.02)		(0.01)	(0.01)		(0.01)	(0.01)
FROE			0.61***			0.04			0.12***
			(0.04)			(0.06)			(0.03)
F2ROE			0.20***			0.01			0.06***
			(0.06)			(0.03)			(0.02)
F3ROE			0.12***			-0.06**			-0.02
			(0.04)			(0.02)			(0.02)
Constant	0.88***	0.96***	0.86***	3.26***	3.26***	3.22***	2.21***	2.06***	2.04***
	(0.03)	(0.05)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Observations	26,234	26,234	20,005	30,474	30,474	22,759	30,049	30,049	22,498
R-squared	0.15	0.18	0.21	0.09	0.14	0.16	0.03	0.24	0.25

Table 8: Valuation regressions (continued)

Panel B: Valuation regression by subperiods

	LOGMB			LOGPE			LOGPEBITDA		
VARIABLES	2000-2006	2007-2009	2010-2015	2000-2006	2007-2009	2010-2015	2000-2006	2007-2009	2010-2015
OGCDUM	0.02	-0.46**	-0.26***	0.08	-0.24	-0.20**	-0.09	-0.28	-0.31***
	(0.05)	(0.09)	(0.05)	(0.13)	(0.25)	(0.05)	(0.07)	(0.17)	(0.06)
GDUM	-0.40***	0.14	-0.22***	-0.26**	0.12	-0.02	-0.11**	0.20	0.08
	(0.02)	(0.07)	(0.02)	(0.08)	(0.13)	(0.05)	(0.04)	(0.11)	(0.05)
SP500	0.46***	0.36**	0.33***	0.09	-0.06*	-0.10***	-0.03	-0.10**	-0.06***
	(0.09)	(0.05)	(0.02)	(0.09)	(0.02)	(0.02)	(0.08)	(0.02)	(0.01)
ROE	1.44***	1.56**	2.22***	-1.62***	-1.08**	-0.66***	-0.21***	-0.39*	-0.14**
	(0.17)	(0.31)	(0.11)	(0.14)	(0.18)	(0.10)	(0.05)	(0.11)	(0.04)
RDSALES	0.85***	0.79	1.49***	2.10***	1.64**	2.10***	5.95***	4.27***	4.14***
	(0.13)	(0.28)	(0.28)	(0.26)	(0.24)	(0.50)	(0.58)	(0.32)	(0.34)
RDMISS	-0.20***	-0.26***	-0.27***	-0.15***	-0.13***	-0.13***	-0.09***	-0.10*	-0.09***
	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
FROE	0.69***	0.35	0.64***	0.17*	-0.09	-0.03	0.16***	0.10	0.07**
	(0.05)	(0.17)	(0.07)	(0.08)	(0.16)	(0.05)	(0.04)	(0.04)	(0.02)
F2ROE	0.22**	0.48**	0.03	0.05	0.06***	-0.07***	0.05	0.11	0.05
	(0.09)	(0.10)	(0.09)	(0.04)	(0.00)	(0.01)	(0.04)	(0.04)	(0.05)
F3ROE	0.05	0.15*	0.20**	-0.09*	-0.03	-0.03	-0.07*	0.01	0.02
	(0.03)	(0.04)	(0.06)	(0.05)	(0.04)	(0.02)	(0.03)	(0.01)	(0.02)
Constant	0.89***	0.81**	0.86***	3.30***	3.10***	3.19***	2.03***	1.98***	2.08***
	(0.09)	(0.12)	(0.05)	(0.09)	(0.06)	(0.05)	(0.13)	(0.09)	(0.04)
Observations	9,336	3,579	7,090	10,204	4,099	8,456	10,068	4,043	8,387
R-squared	0.20	0.19	0.23	0.21	0.14	0.12	0.29	0.23	0.22

For LOGPE, the coefficient on OGCDUM is insignificant in the first and second subperiods, but significant at the 5% level in the final subperiod with a magnitude of -0.20. In the estimations on LOGPEBITDA, the coefficient on OGCDUM is insignificant in the first two subperiods. In the last subperiod, however, it has a magnitude of -0.31 at the 1% level of significance. The results tell a cohesive story: the negative effect on market valuation attributed to being an oil, gas, and coal stock has been particularly prevalent in the final subperiod, in which the three valuation metrics yield an average OGCDUM coefficient of approximately 0.26. This finding indicates that oil, gas, and coal firms have been associated with a 26% valuation discount in the final time-window. For the first and second time-windows covering 2000-2009, we cannot draw a similar conclusion about the magnitude of the effect.

4.3.4. Reconciling findings from stock returns and market valuations

In this section, we bridge together the results from our tests on institutional ownership, stock returns, and valuation to form an understanding of the extent to which the neglect-effect hypothesis holds for oil, gas, and coal stocks. First, we conclude that the relationship is consistent when considering the timeframe of 2000-2018. We find that oil, gas, and coal stocks have been associated with a 1.7% lower total institutional ownership than stocks of otherwise comparable characteristics. Over the same period, oil, gas, and coal stocks have exhibited a 6% higher annualized stock return, as well as an annual valuation discount of 19% relative to comparable stocks. When considering the results for the consecutive subperiods, the neglect-effect relationship is not as noticeable. In the time-window of 2000-2006, before the financial crisis, the oil, gas, and coal stocks were associated with a 1.8% lower institutional ownership and an excess stock return of as much as 9%, but we did not find evidence of a statistically significant valuation discount. In the time-window of 2010-2018, after the financial crisis, oil, gas, and coal stocks exhibited a 2.9% higher level of institutional ownership than comparable stocks. For the same period, we did not find evidence of superior stock returns, but evidence of lower stock valuations.

Moreover, returns and valuation measurements are interconnected, as the expected return is one of the key factors determining present value of a stock in financial theory. We pose the question of to what extent our implied return figure in the timeframe of 2000-2018 goes in line with our implied valuation discount over the same period. We examine this consistency by using a Gordon growth model calibration (Gordon, 1959). According to the formula, the intrinsic value of a stock equals 1 / (r - g), where *r* corresponds to the discount rate or the investors' rate of return, and *g* is the constant growth rate in perpetuity. As a benchmark, *r* is assumed to be 12% and *g* to be 4% (Hong and Kacperczyk, 2009). We find that our estimated valuation discount of 19% implies an excess return of approximately 2%, everything else equal. This excess return is lower than our 6% cross-sectional estimate. Thus, for the overall timeframe of 2000-2018, the magnitude of our implied excess return exceeds the magnitude of the implied valuation discount. It may be the case that the stock returns have been influenced by at least two additional factors over the sample period, not accounted for in the estimate. First, the returns may be impacted by unexpectedly good cash flow news. Second, uncommon litigation events, and perhaps unexpectedly positive results from such litigation, may increase returns (Hong and Kacperczyk, 2009). Interestingly, our findings do not provide evidence of that the lower valuation discount derives from the outlook of lower growth prospects. This relation would only be consistent within the Gordon growth framework should the increased cost of capital not be sufficient to offset the valuation discount.

5. Implications and Conclusion

Our paper provides evidence of social norms affecting the investing environment of stocks associated with environmentally harmful products. We find the attribute of being an oil, gas, or coal stock to be associated with a 1.7% lower institutional holding in the timeframe of 2000-2017. However, we find that from the period of 2000-2009 to 2010-2017, the aforementioned effect on total institutional ownership has shifted from negative to positive. Our analysis on different institutional investor segments reveals that this shift is attributed to independent institutions, and in particular hedge funds and investment companies. Indeed, these types of institutional investors tend to operate relatively more independently of the public view and act as natural arbitrageurs in the market (e.g. Hong and Kacperczyk, 2009). Overall, we find bank trusts, insurance companies, and pension funds – institutions that are subject to relatively more pressure from social norms – to exhibit a greater magnitude of ownership shortfall in oil, gas, and coal stocks compared to independent institutions. The tendency that independent institutional investors take a more active stance to bring about change in firms (Ferreira and Matos, 2008) can provide additional explanation to their higher inclination towards investing in oil, gas, and coal stocks.

Contradicting the idea that analysts cater to institutional investors, we find that oil, gas, and coal stocks have had a consistently higher level of analyst coverage. Nevertheless, over the timeframe of 2000-2018, the neglect-effect hypothesis of Merton (1987) is supported since the oil, gas, and coal stocks' lower degree of institutional ownership has been accompanied by superior stock returns and lower market valuations. That being said, when considering shorter timespans, the relationship is not as apparent. Using the Gordon growth model, we furthermore find the magnitude of the estimated excess returns over the period of 2000-2018 to exceed the magnitude of the estimated valuation discount. This finding points to the influence of additional factors not accounted for in the estimates. Although the short-term findings are subject to variation, the results considering the longer term support our hypothesis of oil, gas, and coal stocks' exhibiting lower institutional ownership and in addition, higher stock returns and lower valuations than stocks of otherwise comparable characteristics.

From our findings, we provide evidence that oil, gas, and coal stocks possess similar characteristics to alcohol, tobacco, and gaming stocks. Although not equivalent in magnitude, the results indicate that social norms' effects on financial markets extend beyond the "social" aspect to incorporate environmental concerns. To further verify our findings, future research needs to examine the neglect-effect relationship for oil, gas, and coal stocks in other markets and cultures, where institutional investment strategies and public opinion might differ. Additionally, it would be interesting to investigate if the relationship as well applies to stocks associated with other environmental concerns. Lastly, in light of our findings on independent institutions' high level of ownership in oil, gas, and coal stocks in recent times, it would be interesting to look at the impact institutional investors have on changes in corporate governance practices, both generally as well as in the specific context of oil, gas, and coal.

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Appendices

Appendix A. Institutional ownership by investor type

In this table, we regress institutional ownership ratio on six investor types: bank trusts, insurance companies, pension funds including endowments, investment advisors, investment companies and hedge funds including venture capital. The regressions are run on the total period 2000-2017 alongside three subperiods. OGCDUM equals one if a stock is an oil, gas, or coal stock, and zero otherwise. GDUM equals one if a stock belongs to the comparable group based on SIC-code, and zero otherwise. LOGSIZE is the natural logarithm of a stock's market capitalization. BETA is a stock's industry rolling market beta calculated over the last 36 months. LOGMB is the natural logarithm of a stock's book-to-market ratio. NASD equals one if a stock is traded on the NASDAQ stock exchange, and zero otherwise. SP500 equals one if a stock is included in the S&P 500 index, and zero otherwise. PRINV is the inverse of a stock's price at the end of a year. STD is a stock's daily return standard deviation during the past year. RET is a stock's average monthly return for a year. All regressions are run using one-digit SIC industry-fixed effects. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Bank trusts				Insurance companies				Pension funds			
VARIABLES	2000-2017	2000-2006	2007-2009	2010-2017	2000-2017	2000-2006	2007-2009	2010-2017	2000-2017	2000-2006	2007-2009	2010-2017
OGCDUM	-0.0002***	0.0001***	-0.0012***	-0.0001***	0.0003***	0.0001**	0.0003***	0.0005***	-0.0027***	-0.0042***	-0.0014	-0.0016***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0003)	(0.0003)	(0.0009)	(0.0003)
GDUM	-0.0001***	-0.0003***	0.0006***	-0.0001	-0.0003***	0.0004***	-0.0006***	-0.0007***	0.0028***	0.0079***	-0.0023	0.0004
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0014)	(0.0006)
LOGSIZE	0.0002***	0.0001***	0.0003***	0.0002***	0.0003***	0.0003***	0.0003***	0.0004***	0.0052***	0.0062***	0.0047***	0.0046***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0004)	(0.0004)	(0.0005)
BETA	0.0001**	0.0001***	0.0000	-0.0002	-0.0001	-0.0002**	-0.0000	0.0000	0.0008	0.0003	0.0024	0.0027**
	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0009)	(0.0007)	(0.0015)	(0.0010)
PRINV	0.0000	0.0000**	0.0000	0.0000	0.0000**	0.0000	0.0000	0.0000**	0.0001***	0.0014***	0.0006**	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0002)	(0.0000)
STD	0.0001***	0.0000***	0.0002***	-0.0001***	0.0000	0.0001***	-0.0000	-0.0001	-0.0002	-0.0006***	-0.0001	-0.0015**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0006)
RET	-0.0000***	-0.0000***	-0.0000***	-0.0000**	-0.0000***	-0.0000**	-0.0000**	-0.0000***	-0.0003***	-0.0003***	-0.0002***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
NASD	0.0000	0.0000	-0.0000	0.0000	-0.0002***	-0.0003***	-0.0002**	-0.0002**	-0.0019**	-0.0039***	-0.0005	-0.0006
	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0008)	(0.0007)	(0.0010)	(0.0008)
SP500	-0.0000	-0.0002**	-0.0003*	0.0002**	0.0004***	0.0009***	0.0005***	-0.0000	0.0036***	0.0007	0.0049***	0.0042***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0011)	(0.0009)	(0.0011)
Constant	-0.0021***	-0.0014***	-0.0033***	-0.0014***	-0.0028***	-0.0022***	-0.0028***	-0.0033***	-0.0435***	-0.0508***	-0.0402***	-0.0383***
	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0005)	(0.0006)	(0.0052)	(0.0049)	(0.0053)	(0.0078)
Observations	40,698	16,626	7,048	17,024	40,698	16,626	7,048	17,024	40,698	16,626	7,048	17,024
R-squared	0.0805	0.0311	0.0647	0.2662	0.1439	0.1373	0.1603	0.1409	0.3539	0.3633	0.3121	0.4219

Appendix A. (continued)

	Investment advisors				Investment companies				Hedge funds			
VARIABLES	2000-2017	2000-2006	2007-2009	2010-2017	2000-2017	2000-2006	2007-2009	2010-2017	2000-2017	2000-2006	2007-2009	2010-2017
OGCDUM	-0.0199***	-0.0097**	-0.0364*	-0.0098**	-0.0021	-0.0051***	-0.0190**	0.0093***	0.0140***	-0.0036	0.0046	0.0261***
	(0.0044)	(0.0036)	(0.0163)	(0.0038)	(0.0020)	(0.0010)	(0.0062)	(0.0017)	(0.0033)	(0.0025)	(0.0063)	(0.0017)
GDUM	-0.0358***	0.0205***	-0.1014***	-0.0685***	-0.0283***	-0.0131***	-0.0361***	-0.0420***	-0.0334***	-0.0392***	-0.0205*	-0.0303***
	(0.0039)	(0.0044)	(0.0167)	(0.0048)	(0.0018)	(0.0026)	(0.0068)	(0.0022)	(0.0051)	(0.0034)	(0.0090)	(0.0048)
LOGSIZE	0.0640***	0.0648***	0.0712***	0.0579***	0.0315***	0.0303***	0.0330***	0.0311***	0.0083***	0.0081***	0.0009	0.0118***
	(0.0034)	(0.0033)	(0.0051)	(0.0040)	(0.0017)	(0.0017)	(0.0017)	(0.0023)	(0.0009)	(0.0009)	(0.0014)	(0.0013)
BETA	0.0279**	0.0161*	0.0379	0.0647***	0.0049	0.0032	0.0064	0.0127*	0.0113	0.0112*	0.0123	0.0066
	(0.0108)	(0.0070)	(0.0285)	(0.0135)	(0.0049)	(0.0020)	(0.0105)	(0.0061)	(0.0108)	(0.0058)	(0.0107)	(0.0125)
PRINV	-0.0017	0.0021	-0.0063	-0.0008	0.0009**	0.0048**	0.0000	0.0005	-0.0003	0.0013	-0.0037**	-0.0018
	(0.0030)	(0.0048)	(0.0075)	(0.0026)	(0.0003)	(0.0020)	(0.0010)	(0.0004)	(0.0004)	(0.0008)	(0.0015)	(0.0013)
STD	-0.0191***	-0.0213***	-0.0050	-0.0381***	-0.0038***	-0.0041***	0.0031**	-0.0079***	-0.0035	-0.0072***	-0.0030	0.0142**
	(0.0025)	(0.0020)	(0.0063)	(0.0036)	(0.0008)	(0.0007)	(0.0011)	(0.0017)	(0.0023)	(0.0016)	(0.0021)	(0.0052)
RET	-0.0017***	-0.0011***	-0.0022**	-0.0016**	-0.0011***	-0.0010***	-0.0011***	-0.0011**	0.0000	0.0002	-0.0004***	0.0002
	(0.0003)	(0.0003)	(0.0007)	(0.0005)	(0.0002)	(0.0001)	(0.0002)	(0.0004)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
NASD	0.0059	0.0008	-0.0038	0.0215***	0.0062**	0.0069*	0.0076**	0.0071*	0.0102	0.0224***	0.0203**	0.0015
	(0.0065)	(0.0063)	(0.0054)	(0.0054)	(0.0023)	(0.0035)	(0.0024)	(0.0035)	(0.0058)	(0.0052)	(0.0080)	(0.0059)
SP500	-0.1171***	-0.0906***	-0.1259***	-0.1345***	-0.0196**	-0.0154**	-0.0177**	-0.0223**	-0.0580***	-0.0460***	-0.0381***	-0.0632***
	(0.0159)	(0.0120)	(0.0246)	(0.0193)	(0.0058)	(0.0062)	(0.0065)	(0.0064)	(0.0039)	(0.0044)	(0.0059)	(0.0044)
Constant	-0.4457***	-0.4442***	-0.5514***	-0.3685***	-0.2800***	-0.2718***	-0.3198***	-0.2672***	-0.0070	-0.0225	0.0930***	-0.0749
	(0.0363)	(0.0313)	(0.0729)	(0.0493)	(0.0192)	(0.0173)	(0.0193)	(0.0349)	(0.0280)	(0.0159)	(0.0261)	(0.0398)
Observations	40,698	16,626	7,048	17,024	40,698	16,626	7,048	17,024	40,698	16,626	7,048	17,024
R-squared	0.4279	0.4649	0.3999	0.4133	0.4376	0.4188	0.3840	0.4444	0.0397	0.0671	0.0298	0.0428