Journal of
Risk and Financial Management

Article

Environmental, Social, and Governance Considerations in WTI Financialization through Energy Funds

Alper Gormus [1,*], Saban Nazlioglu [2,3] and Steven L. Beach [1]

1 College of Business, University of Texas Permian Basin, Odessa, TX 79762, USA
2 Department of International Trade and Finance, Pamukkale University, Denizli 20160, Türkiye
3 Department of Economics and Finance, Nisantası University, Istanbul 34398, Türkiye
* Correspondence: gormus_a@utpb.edu

Abstract: This study investigates interactions between energy funds and the oil market and examines the influence of environmental, social, and governance (ESG) criteria in dynamic responses by fund managers and investors. We test for price and volatility transmission (also referred to as "spillover") between energy funds and the oil market using recently developed econometric techniques. After identifying specific information flows, we investigate whether certain fund characteristics, including several ESG dimensions, are associated with the existence of information transmissions. Then, in logit regressions, we seek to identify if energy fund managers and their investors make decisions using information regarding ESG metrics, including fossil fuel involvement. The results confirm bidirectional price and volatility transmission between energy funds and the oil market, consistent with evidence of the financialization of energy markets that has been identified in recent studies. Several ESG dimensions are shown to influence investor sentiment and affect price and volatility interactions. Dynamic investor decisions in funds in reaction to oil prices do not appear to be strongly influenced by the fossil fuel involvement of the funds. Fund flows do appear to influence the oil market, with fund fossil fuel involvement being an important factor. This paper evaluates the impact of granular ESG characteristics on energy mutual fund flows, price, and volatility interactions with the oil market. While our results support the findings from previous studies, they also provide several new insights into the impacts of ESG criteria and investor behavior, particularly the dynamic response by fund managers and energy market investors related to the fossil fuel involvement of the funds.

Keywords: mutual funds; energy markets; ESG

JEL Classification: G11; G15; Q43

Citation: Gormus, Alper, Saban Nazlioglu, and Steven L. Beach. 2023. Environmental, Social, and Governance Considerations in WTI Financialization through Energy Funds. *Journal of Risk and Financial Management* 16: 231. https://doi.org/10.3390/jrfm16040231

Academic Editors: Svetlozar (Zari) Rachev and W. Brent Lindquist

Received: 16 February 2023
Revised: 20 March 2023
Accepted: 29 March 2023
Published: 6 April 2023

1. Introduction

A fund's performance is influenced by its concentration in a specific style or sector (see Kacperczyk et al. 2005; Pollet and Wilson 2008; Ferreira et al. 2013, and others). Specialization in a sector allows fund managers to utilize their sector-specific expertise and take advantage of information advantages (Nanda et al. 2004). Fund characteristics can significantly impact a fund's performance (Pucker and King 2022) and how the fund interacts with external shocks.

Of particular interest recently is the impact of environmental, social, and governance (ESG) factors on company and fund performance. With the emphasis on risks associated with climate change, the focus of ESG investment decision making has turned to the metrics associated with environmental concerns, including the role of carbon-based energy sources (ESG 2022). If a linkage between oil and gas price shocks and equity markets and energy equity fund returns is confirmed, then the characteristics of energy funds help reveal how fund managers and investors incorporate ESG information into their investment decision making.

According to Epstein (2002), "'Financialization' refers to the increasing importance of financial markets, financial motives, financial institutions, and financial elites in the operations of the economy and its governing institutions, both at the national and international levels."

Palley (2007) categorized the operations of financialization in three pathways: "changes in the structure and operation of financial markets, changes in the behavior of nonfinancial corporations, and changes in economic policy." Early investigations of the phenomenon in capital markets focused on the impact of financial markets upon other markets, oftentimes commodity markets. Thus, the concept of the financialization of commodity markets, and specifically oil (WTI) pricing, concerns evidence of the interactions and impacts of financial market instruments upon the price of commodities (WTI, for example).

Tang and Xiong (2012) investigated the correlation of non-energy commodity futures and oil prices. As increasing correlations supported the hypothesis of the financialization of the commodity markets, researchers turned to additional tools to identify the interconnectedness of financial and commodity markets. Researchers have used a variety of GARCH models (VAR-GARCH, BEKK-GARCH, GARCH-MIDAS, and more) and VAR models (TVP-VAR, etc.) to examine the financialization of commodity markets (see Yang et al. 2020), Ma et al. 2019), Feng et al. (2022), etc.).

The impact of oil price shocks on stock returns is regularly a focus of research studies. While one would expect the equity prices of energy companies to be impacted by the oil market (Ordu and Soytas 2016), these shocks also strongly interact with the entire equity market (Miller and Ratti 2009; Mensi et al. 2013). Multiple studies provide evidence of price-level as well as volatility impacts. For example, Liu et al. (2015) showed the strong influence of oil prices on excess stock returns. Similarly, Anand and Paul (2021) found that oil shocks significantly impact stock returns. Looking at reverse interactions, Zhang, and Wang (2019) provide evidence of stock markets moving oil prices. From the volatility perspective, Bouri and Demirer (2016) identified the predictability of select international equity markets' volatility using the oil market. Du and He (2015) showed bi-directional volatility transmission between oil prices and the stock market (also see Gormus et al. 2014).

Furthermore, Le and Chang (2015) and Mensi et al. (2017) found bi-directional volatility interactions to be strong, especially in the long run. Phan et al. (2016) and Degiannakis and Filis (2017) showed volatility transmission from equity markets to oil markets. The bi-directional and reverse interactions observed in these studies are components of the emerging evidence of the financialization of energy markets. Commenting on this increased linkage between oil and financial markets, Degiannakis et al. (2018) asserted that equity markets will continue to impact oil prices.

A significant portion of investors evaluate environmental, social, and governance (ESG) and return characteristics while picking mutual funds (Riedl and Smeets 2017). Fooladi and Hebb (2022) found that ESG scores impact fund performance independently from asset-selection ability. El Ghoul and Karoui (2017) found corporate social responsibility (CSR) to be a significant factor in fund performance and fund flows. They argue that investors obtain some utility from non-performance attributes. Becker et al. (2022) provided evidence of higher ESG-related fund characteristics resulting in higher fund flows. Concentrating fossil-fuel attributes, Bolton and Kacperczyk (2021) suggested investors demand a higher premium for high-carbon-intensity stocks.

Moreover, Humphrey and Li (2021) showed an increase in flows to funds that reduce exposure to carbon emissions in their portfolios. On a similar note, Rohleder et al. (2022) found that stocks (and funds) reactively change their fossil fuel policies/holdings due to investors' preferences. Investors strongly react to readily available and reliable information that is easy to process (Del Guercio and Tkac 2002). Along those lines, Morningstar provides ESG-related data to investors regarding mutual fund holdings. Ammann et al.

(2019) found that the sustainability rating provided by Morningstar impacts mutual fund flows independent of other fund factors (also see Bollen 2007)

Given energy companies' increased scrutiny over their fossil fuel involvement, among other ESG criteria, we test how fund characteristics (ESG and others) impact their interaction with the oil market. Our study uses a multi-tiered approach with recently developed econometric techniques.

We first test the price and volatility relationships between energy fund prices, fund flows, and oil prices. Then, we pay particular attention to how fund flows interact with oil prices and whether fund characteristics impact the probability of those interactions. Our results indicate a robust price transmission from energy funds to oil prices. The volatility transmission tests show a bi-directional interaction with most of the funds we tested, which supports the Du and He (2015) findings, where the volatility transmission from equities to the oil market was shown to have increased after the 2008 financial crisis. When we look at fund flows, we find a variety of funds interacting with oil prices in both directions, prompting an opportunity to investigate the causes of these differential responses. Evaluating the impact of fund characteristics on fund flow and oil price interactions (from oil prices to fund flows), our results show that the Morningstar rating, manager tenure, corporate ESG risk exposure, Morningstar managed risk score, and portfolio sustainability risk score are the most important fund characteristics. Looking at the dynamics of transmission from fund flows to oil prices, we find fossil fuel involvement, corporate ESG risk exposure, the Morningstar managed risk score, and the portfolio sustainability risk score to be highly significant in impacting those interactions. It is important to note that our study does not conduct a flows-to-flows analysis. Our goal is to specifically investigate investor reactions (via flows) to shocks in oil prices.

By applying a robust econometric technique, our results support extant research finding that oil markets are highly financialized. Uniquely, our investigation shows that ESG measures are considered in investor trading across energy mutual funds and the West Texas Intermediate oil market; furthermore, it identifies potentially different attention to fossil fuel involvement by fund managers and investors.

The remainder of the paper is structured as follows. In the next section, we explain our econometric methodology. Section 3 provides information on the data used. Section 4 presents and discusses the results. Section 5 offers a summary and concluding remarks.

2. Econometric Methodology

This paper uses recently developed price and volatility transmission models that provide robust inferences about level- and variance-based time-series interactions and account for both abrupt and gradual (also referred to as "smooth") structural breaks.

2.1. Testing for Price Transmission with Structural Changes

Simply put, price transmission refers to the ability of the historical prices of one variable helping to predict the future prices of another variable. Price transmission tests evaluate "level" interactions as opposed to the volatility of the observations. The price transmission model we utilize in this study follows Nazlioglu et al. (2016) and Gormus et al. (2018), wherein the VAR model incorporates a Fourier approximation. Structural breaks are econometric encumbrances which researchers encounter when using financial time-series data (Li and Enders 2018). In the literature, structural breaks are usually controlled by using dummy variables, which implies that they are abrupt processes (for example, Perron 1989). However, a significant portion of the structural changes that exist are gradual (or "smooth"). Nazlioglu et al. (2016) extend the VAR$(p+d)$ model originally proposed by Toda and Yamamoto (1995) (TY hereafter) with Fourier approximation, presented by:

$$y_t = \gamma_0 + \sum_{k=1}^{n} \gamma_{1k} sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} cos\left(\frac{2\pi kt}{T}\right) + \Pi_1 y_{t-1} + \cdots + \Pi_{p+d} y_{t-(p+d)} + u_t \quad (1)$$

where γ_{1k} and γ_{2k} measure the amplitude and displacement of the frequency, respectively.

In the TY framework, the null hypothesis of no price transmission is based on zero restrictions on the first p parameters ($H_0: \Pi_1 = \cdots = \Pi_p = 0$) on the variable that is being tested. The Wald statistic has chi-square distribution with p degrees of freedom. Recent evidence indicates that bootstrap distribution increases test statistics' power in small samples and is robust to the stationarity and co-integration properties of the series (see Balcilar et al. 2010). Nazlioglu et al. (2016) obtained bootstrap distribution of the Wald statistic using the residual sampling bootstrap approach.[1]

In order to determine the optimal lags in the TY test and the optimal Fourier frequency and lags in the Fourier TY approach, we set the maximum number of frequencies to 3 and lags to 5. The optimal frequency and lags are determined by minimizing the Akaike information criterion.

2.2. Testing for Volatility Transmission with Structural Breaks

In addition to price transmissions, we also test for volatility interactions between energy funds and the oil market using an updated version of the Lagrange multiplier (LM) volatility transmission test developed by Hafner and Herwartz (2006) (HH hereafter). HH first estimates a GARCH (1,1) model for series i and j and is then defined as:

$$\varepsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2(1 + z_{jt}'\pi)}, \qquad z_{jt} = \left(\varepsilon_{jt-1}^2, \sigma_{jt-1}^2\right)' \quad (2)$$

where ξ_{it} is the standardized residuals of series i. ε_{jt}^2 and σ_{jt}^2 are the squared disturbance terms and the volatility for series j, respectively. The null hypothesis of no-volatility transmission ($H_0: \pi = 0$) is tested against the alternative hypothesis of volatility transmission ($H_0: \pi \neq 0$). The LM statistic is defined as:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)\, z_{jt}'\right) V(\theta_i)^{-1} \left(\sum_{t=1}^{T}(\xi_{it}^2 - 1) z_{jt}\right) \sim \chi_2^2 \quad (3)$$

The structural break problem previously identified for price transmission models also persists in volatility models. The conditional variance in a GARCH model does not have any structural changes in the volatility process. This is a significant issue because series impacted by structural breaks (abrupt or gradual) could yield incorrect inferences in the conventional GARCH framework.

Li and Enders (2018) show Fourier approximation to be useful in controlling for structural breaks in volatility transmission tests as well. To capture any shifts in the volatility process, they consider the variance equation of a GARCH (1,1) model with a Fourier approximation, defined as:

$$\sigma_{it}^2 = \omega_{0i} + \sum_{k=1}^{n} \omega_{1i,k} sin\left(\frac{2\pi k_i t}{T}\right) + \sum_{k=1}^{n} \omega_{2i,k} cos\left(\frac{2\pi k_i t}{T}\right) + \alpha_i \varepsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2. \quad (4)$$

The test statistic based on Equation (4) is labeled as Fourier λ_{LM} ($F\lambda_{LM}$). Since using Fourier approximation does not change the number of misspecification indicators in z_{jt}, $F\lambda_{LM}$ follows an asymptotic chi-square distribution with two degrees of freedom.

2.3. Significance of Fund Characteristics

In order to evaluate the impact of fund characteristics on the interactions between energy funds and the oil market, we utilize a logit regression framework. This model investigates the probability of the fund characteristics impacting the previously identified price and volatility transmissions. For example, this framework calculates whether a specific fund characteristic directly influences the likelihood of a transmission from oil prices to fund flows.

$$\boldsymbol{pr}(\boldsymbol{y_i} = \mathbf{1}|\boldsymbol{x_i}, \boldsymbol{\theta}) = \boldsymbol{e}^{\boldsymbol{x_i'\theta}} / \left(\mathbf{1} + \boldsymbol{e}^{-\boldsymbol{x_i'\theta}}\right) \tag{5}$$

where $\boldsymbol{y_i}$ is a binary dependent variable. Depending on the direction of the transmission, this variable receives a value of 1 if there is any information transmission from/to the mutual fund flows from/to oil prices and zero otherwise. The fund characteristics are represented by the vector $\boldsymbol{x_i}$, $\boldsymbol{e}$ is the base of the natural logarithm, and $\boldsymbol{\theta}$ is the coefficient matrix. The model in (5) is repetitively estimated using maximum likelihood.

3. Data

We used the funds listed under the "Energy Sector" in the Morningstar "Global Category". After eliminating funds with insufficient data, we utilized 66 funds. Because Morningstar started consistently reporting on multiple ESG characteristics in 2016, our dataset consists of daily observations over six years from 01/04/2016 to 12/31/2021. For preliminary tests, we look at returns on two energy indexes: the Morningstar US Energy index (MEST) and the Morningstar MLP Composite index (MSMLPCT). Neither of these energy indexes incorporates ESG criteria in their construction, providing an opportunity to identify transmission dynamics between energy stocks and oil prices. Index returns, fund returns, fund flows, oil prices, and the fund characteristics are all obtained from the Morningstar database.

There was a wide range of performance attributes among the funds. While the mean geometric return was 0.2%, the range was from negative 26% to positive 8.5%. As for the holding period return, the mean return was 7%, while the range was from negative 83% to positive 63% over the six-year period. As we identify bi-directional transmission between oil markets and energy indexes, these disparate results across the funds should provide an opportunity to identify fund characteristics that contribute to their differing performances. Oil prices had a geometric return of 13%, a holding period return of 105%, a mean of 17%, and a range from negative 26% to positive 56% annual return for the same period.

Since oil prices are previously shown to suffer from structural breaks, we conduct unit root tests of stationarity. A Fourier Augmented Dickey–Fuller test, developed by Enders and Lee (2012b), robust to structural shifts, is employed. The results in Table 1 shows that the null hypothesis (the existence of unit root) cannot be rejected. In other words, the results suggest the possibility of permanent shocks (abrupt and/or gradual) existing in the data. This result further justifies using a methodology for price and volatility transmissions, which accounts for structural breaks.

Table 1. Results from unit root tests for oil prices.

No Shift	Level	Difference
ADF	−2.789 *	−14.675 ***
DF-GLS	−1.104	−7.340 ***
KPSS	1.825 ***	0.046
Structural shift		
LM	−2.684	−16.924 ***
Fourier ADF	−3.759 **	−14.759 ***

Notes: ADF: Augmented Dickey and Fuller (1979) unit root test. DF-GLS: Dickey and Fuller GLS unit root test of Elliott et al. (1996). KPSS: Kwiatkowski et al. (1992) stationarity test. LM: Lee and Strazicich (2013) LM unit root test with a break. Fourier ADF: Enders and Lee (2012b) ADF unit root test with Fourier approximation. Unit root tests with no shift include a constant term. Unit root test with shift includes a structural shift in the constant term. The optimal lag(s) were determined by Schwarz information criterion for augmented Dickey–Fuller (ADF), Dickey–Fuller GLS de-trended (DF-GLS), and Lagrange Multiplier (LM) tests by setting maximum number of lags to 5. The optimal frequency and lags were determined by Schwarz information criterion for Fourier ADF by setting maximum number of lags to 5 and Fourier frequency to 1. Bartlett kernel method for spectral estimation and Newey–West method for bandwidth were used for the KPSS test. ADF critical values are −3.433 (1%), −2.862 (5%), and −2.567 (10%), DF-GLS critical values are −2.566 (1%), −1.941 (5%), and −1.616 (10%), KPSS critical values are 0.739 (1%), 0.463 (5%), and 0.347 (10%), LM critical values are -4.239 (1%), −3.566 (5%), and −3.211 (10%), and critical values for Fourier ADF test with one frequency are −4.31 (1%), −3.75 (5%), and −3.45 (10%). *** indicates statistical significance at 1 percent. ** indicates statistical significance at 5 percent. * indicates statistical significance at 10 percent.

4. Results and Discussion

The analyses of this study are presented in three separate sections:

(a) Analyze the interactions between oil price (and volatility) and energy equity market (index) performance;
(b) Analyze the interactions between oil price (and volatility) and energy equity fund performance (and fund flows);
(c) Analyze the impact of fund characteristics on the interactions between oil prices and volatility and fund prices, volatility, and fund flows (i.e., evaluate fund characteristics that influence investor preferences).

4.1. Interactions between Oil Prices and Energy Equity Indexes

In Table 2, we present tests on price and volatility transmission between oil prices and energy indexes. Before moving to analyses of individual energy funds, it is important to confirm the results from extant literature for the financialization of the oil market. Price transmission is not shown to exist from oil prices (WTI) to the energy equity indexes, but evidence of price transmission from energy equity indexes to oil prices is identified (see Table 2a). These findings align with the existing studies we previously referenced which identify the financialization of WTI prices in recent history. In Table 2b, volatility transmission is shown to be bidirectional for the Morningstar US Energy Index, but with volatility transmission from oil prices to the Morningstar Master Limited Partnership (MSMLPCT) index. The lack of volatility transmission from the MSMLPCT to oil prices indicates that dynamic trading in publicly traded MLPs (or funds of MLPs) may differ from that of publicly traded common stock (or funds of common equity), a distinction we will leave for a further analysis (we include the MLP funds in our analysis of "equity" funds). Overall, these results support the recently identified financialization of the WTI benchmark and, at a minimum, price transmission from energy equity funds to WTI.

Descriptive statistics across all funds' price returns.

G-Return		*HPR*	
Mean	0.0020	Mean	0.0703
Median	0.0203	Median	0.1280
Standard deviation	0.0674	Standard deviation	0.3213
Range	0.3447	Range	1.4698
Minimum	−0.2593	Minimum	−0.8349
Maximum	0.0854	Maximum	0.6349

Notes: TY: traditional TY approach which does not account for structural breaks, Fourier TY: Fourier TY approach with one Fourier frequency which is based on Equation (4). Maximum p is set to 5, and optimal p is determined by Akaike information criterion. p-val. is the p-value based on the bootstrap distribution with 1000 replications. VAR(p+d) models are estimated with d equal to 1. Bivariate VAR models include oil prices and equity index return variable.

Table 2. Results for price and volatility transmission between oil prices and energy equity index returns.

Results for price transmission between oil prices and energy index returns.

	Oil prices to energy index returns				Energy index returns to oil prices					
	TY		Fourier TY		TY			Fourier TY		
	Wald	p-val.	Wald	p-val.	Wald		p-val.	Wald		p-val.
MEST	1.820	0.769	1.869	0.760	23.000	***	0.000	27.379	***	0.000
MSMLPCT	3.733	0.589	3.456	0.630	21.343	***	0.001	23.559	***	0.000

Notes: TY: traditional TY approach which does not account for structural breaks, Fourier TY: Fourier TY approach with one Fourier frequency which is based on Equation (4). Maximum p is set to 5, and optimal p is determined by Akaike information criterion. p-val. is the p-value based on the bootstrap distribution with 1000 replications. VAR(p+d) models are estimated with d equal to 1. Bivariate VAR models include oil prices and equity index return variable. *** indicates statistical significance at 1 percent. ** indicates statistical significance at 5 percent. * indicates statistical significance at 10 percent.

Results for volatility transmission between oil prices and energy equity index returns.

	Oil prices to energy index returns					Energy index returns to oil prices					
	λ_{LM}		p-val.	$F\lambda_{LM}$		p-val.	λ_{LM}		p-val.	$F\lambda_{LM}$		p-val.
MEST	10.925	***	0.004	7.810	**	0.020	21.889	***	0.000	19.683	***	0.000
MSMLPCT	13.157	***	0.001	13.417	***	0.001	2.028		0.363	2.085		0.353

Notes: λ_{LM}: Volatility spillover LM test which does not account for structural breaks is based on the variance Equation (3). $F\lambda_{LM}$: volatility spillover Fourier LM test is based on the variance Equation (4) with one Fourier frequency. The mean equation is based on AR(1) model for the equity (index or fund) return and oil prices. *** indicates statistical significance at 1 percent. ** indicates statistical significance at 5 percent. * indicates statistical significance at 10 percent.

4.2. Interactions between Oil Prices and Energy MUTUAL Funds

Table 3 shows the results of bi-directional price transmission tests between oil price returns and fund returns. About 35% of the funds we tested were impacted by oil prices at 5%, and about 32% of the funds were impacted at 10% significance levels. Another way of looking at these results would be that a strong minority of energy fund returns are impacted by price shocks in the oil market. While it may be expected that all energy fund returns will be impacted by oil prices, there can be several reasons for a specific fund to not experience price transmission. Some fund portfolios may be diversified in such a way that oil price shocks do not directly transmit to those fund returns, which could be accounted by oil market exposure hedging (financial or operational) within firms held in the fund. Another related reason could be that there is a significant (longer) lag between oil price shocks and these funds' returns, but the optimized lag structures our methodologies identified were not able to capture them.

Investigating the price transmission from energy funds to the oil market produces results that may be unexpected. We find that about 80% of the fund returns directly impact oil prices. In other words, our results indicate that the fund returns directly help drive oil prices. These results are related to the findings of Zhang and Wang (2019), where they show that high-frequency stock market data are superior to lower frequency data in predicting oil prices. Beyond equity market and systematic impacts, energy funds are some of the largest institutional investors that directly or indirectly trade assets that impact the oil market. While many of these funds hold actual positions in the oil market, all of them have positions in assets that indirectly impact the oil market.

Table 3. Results for price transmission between oil prices and mutual fund returns.

	Oil prices to mutual fund returns						Mutual fund returns to oil price					
	TY			Fourier TY			TY			Fourier TY		
	Wald		*p*-val.	Wald		*p*-val.	Wald		*p*-val.	Wald		*p*-val.
BACIX	16.855	**	0.022	16.026	**	0.034	14.112	**	0.038	15.361	**	0.029
MLXAX	6.731		0.182	7.028		0.179	14.146	**	0.046	14.463	**	0.038
AAWEX	16.010	***	0.007	16.897	**	0.013	10.238	*	0.063	15.203	**	0.028
CCCAX	8.966		0.115	8.729		0.121	20.754	**	0.014	20.850	**	0.020
MLOAX	10.223	*	0.074	10.094	*	0.085	20.205	**	0.023	21.189	**	0.021
NXGAX	10.183	*	0.089	10.584	*	0.077	12.666	**	0.046	13.171	**	0.029
IEYAX	8.440		0.138	8.277		0.123	12.844	**	0.042	12.548	**	0.039
EGLAX	20.143	**	0.028	22.201	**	0.028	8.292		0.135	8.704		0.118
EIPIX	20.128	**	0.019	20.867	**	0.017	36.994	***	0.006	37.242	***	0.006
FANAX	10.657	*	0.071	10.696	*	0.076	9.906	*	0.089	11.039	*	0.063
FNARX	10.469	*	0.070	10.159	*	0.089	9.166		0.103	12.990	**	0.030
FSENX	10.439	*	0.081	10.492	*	0.059	9.861	*	0.098	11.071	*	0.065
GLPAX	9.642	*	0.092	9.132		0.113	23.855	**	0.014	24.209	**	0.013
GAGEX	12.130	*	0.059	11.491	*	0.054	13.643	**	0.044	14.475	**	0.037
HNRIX	7.751		0.166	7.184		0.189	12.900	**	0.040	17.029	**	0.017
HMSIX	8.913		0.115	8.301		0.142	24.255	**	0.010	24.581	**	0.011
ICPAX	8.362		0.133	8.652		0.129	13.234	**	0.032	14.192	**	0.029
IENAX	11.148	*	0.057	10.724	*	0.084	8.398		0.119	8.740		0.128
MLPAX	7.254		0.190	6.623		0.206	24.633	**	0.010	25.288	***	0.009
MLPLX	6.413		0.236	5.921		0.219	27.186	***	0.009	27.372	**	0.011
SPMGX	6.739		0.197	6.111		0.263	24.962	***	0.009	25.580	**	0.012
MLPDX	11.348	*	0.051	10.998	*	0.083	26.850	***	0.008	27.701	***	0.009
MLPFX	8.203		0.136	7.805		0.158	31.870	**	0.011	32.721	***	0.004
JNLM	14.101	**	0.031	14.452	**	0.032	10.378	*	0.082	11.187	*	0.057
AMLPX	7.335		0.174	6.883		0.226	18.893	**	0.011	19.601	**	0.025
CSHAX	8.852		0.116	8.613	*	0.099	19.002	**	0.022	19.435	**	0.032
OEPIX	16.607	**	0.016	15.914	**	0.024	7.257		0.110	6.303		0.241
PRPAX	10.276	*	0.081	10.458	*	0.071	17.981	**	0.023	18.327	**	0.015
RYENX	11.037	*	0.063	11.191	*	0.064	8.855		0.110	9.583	*	0.088
RYESX	17.403	**	0.010	17.084	**	0.013	5.314		0.250	4.586		0.423
SMAPX	10.355	*	0.092	10.715	*	0.079	14.224	**	0.029	14.523	**	0.029
SOAEX	7.290		0.181	6.999		0.187	21.665	**	0.018	21.760	**	0.018
INFRX	10.040	*	0.091	10.276	*	0.081	21.823	**	0.020	22.512	**	0.015
TORTX	8.737		0.112	8.851		0.113	16.554	**	0.031	16.866	**	0.026
TMLAX	13.845	**	0.041	14.195	**	0.042	26.502	**	0.012	26.861	***	0.008
VGELX	14.688	**	0.032	14.159	**	0.040	15.767	**	0.031	16.697	**	0.027

VENAX	14.079	**	0.036	14.450	**	0.032	9.990	*	0.078	10.971	*	0.075
VGENX	14.725	**	0.048	14.190	**	0.036	15.793	**	0.024	16.689	**	0.027
VLPAX	6.515		0.224	6.901		0.208	18.207	**	0.020	20.430	**	0.019
ENFR	11.508	*	0.080	11.683	*	0.066	18.917	**	0.020	19.195	**	0.025
AMLP	11.846	*	0.062	11.300	*	0.068	29.656	***	0.006	29.958	***	0.008
XLE	15.614	**	0.027	16.103	**	0.031	11.216	*	0.070	12.210	*	0.055
FENY	14.165	**	0.026	14.517	**	0.028	10.346	*	0.082	11.253	*	0.070
FXN	11.590	*	0.061	11.836	*	0.050	10.132	*	0.077	12.576	*	0.050
FCG	5.096		0.372	5.408		0.330	10.190	*	0.069	11.047	*	0.086
EMLP	21.479	**	0.012	22.089	**	0.021	34.945	***	0.007	35.110	***	0.007
MLPX	9.164		0.106	9.249		0.104	16.860	**	0.026	17.139	**	0.031
MLPA	10.708	*	0.078	10.093	*	0.083	28.932	**	0.011	29.185	***	0.009
AMZA	9.933	*	0.087	9.482	*	0.083	29.074	**	0.015	29.212	***	0.007
PXI	7.828		0.156	8.110		0.152	10.403	*	0.076	11.490	*	0.059
PXE	9.151		0.105	9.665		0.100	7.862		0.160	9.255		0.113
PXJ	15.737	**	0.019	15.682	**	0.017	8.471		0.151	8.052		0.155
RYE	13.337	**	0.041	13.868	**	0.024	7.398		0.185	8.655		0.109
PSCE	6.197		0.261	6.425		0.241	5.232		0.379	5.282		0.311
IXC	20.942	**	0.016	20.684	**	0.015	10.540	*	0.070	11.825	*	0.063
FILL	21.033	**	0.013	20.561	**	0.012	10.336	*	0.078	12.474	*	0.050
IYE	14.581	**	0.033	14.995	**	0.023	10.986	*	0.076	11.788	*	0.069
IEO	11.515	**	0.041	11.644	*	0.051	12.880	*	0.064	15.191	**	0.021
IEZ	16.761	**	0.012	16.201	**	0.019	6.053		0.173	5.418		0.335
XES	12.562	**	0.027	12.087	**	0.036	6.703		0.144	6.561		0.209
XOP	7.246		0.180	7.533		0.163	6.406		0.274	7.173		0.175
TPYP	14.650	**	0.023	14.508	**	0.048	22.796	**	0.015	22.691	***	0.006
EINC	11.161	*	0.093	11.921	*	0.065	18.078	**	0.019	19.239	**	0.020
CRAK	12.429	*	0.052	11.547	*	0.054	28.393	***	0.003	28.166	***	0.001
OIH	16.178	**	0.012	15.753	**	0.014	7.469		0.127	6.889		0.219
VDE	14.152	**	0.047	14.521	**	0.039	10.021	*	0.092	10.999	*	0.084

Notes: See Table 2a. Bivariate VAR models include oil prices and fund return variable.

Investor sentiment is shown to impact both return and volatility transmission in equity markets (Bouri et al. 2022). Recognizing the significance of fund flows in reflecting investor sentiment (see Ben-Rephael et al. 2012; Da et al. 2015 and others), we investigated the price transmission relationship between energy fund flows and oil prices. We used 44 funds that had flow data available in Morningstar. Table 4 presents our results. We found oil prices transmitting to about 47% of the fund flows we tested. On the other hand, about 43% of the fund flows were found to transmit to oil prices (with no discernable differential pattern for equity versus MLP funds). Interestingly, about 60% of the transmissions we identified are bi-directional. In other words, there is a feedback relationship between oil and mutual fund flows for more than half of the already identified price transmissions. These results can be interpreted in multiple ways. As investors increase or decrease their investments in these funds, the funds trade accordingly in the corresponding markets. The funds with unidirectional transmission from oil prices to fund flows could involve the majority of investors that are predominantly reactive to oil price shocks. If funds primarily exhibited unidirectional transmission from oil prices to fund flows, we could hypothesize that the majority of the investors were reacting to oil price shocks in their equity allocations. The findings do not support the independent interpretation of the results. The interesting finding of bi-directional transmissions which portray a feedback relationship may indicate both the reactiveness of investors as well as the managers' ability to proactively trade in markets that impact oil prices. One scenario could be that as fund flows become impacted by oil price shocks, the manager could simultaneously (or reactively) be making large enough bets that further move the oil market. An interpretation focusing on information differentials might conclude that energy equity fund managers have some form of information advantage over those traders participating only in the oil market. Potentially, equity market participants draw upon a fuller information set that facilitates trading that leads the oil markets.

Table 4. Results for price transmission between oil prices and mutual fund flows.

	Oil prices to mutual fund flows						Mutual fund flows to oil prices					
	TY			Fourier TY			TY			Fourier TY		
	Wald		p-val.	Wald		p-val.	Wald		p-val.	Wald		p-val.
BACIX	1.658		0.406	1.484		0.554	0.719		0.684	1.051		0.642
CCCAX	12.784	*	0.073	12.256	*	0.091	13.429	*	0.065	13.371	*	0.065
EGLAX	1.416		0.523	2.274		0.461	0.884		0.741	0.921		0.834
EIPIX	0.996		0.606	0.899		0.785	0.356		0.930	0.178		0.994
GLPAX	1.196		0.569	1.721		0.552	1.106		0.575	0.974		0.783
GAGEX	0.248		0.976	1.345		0.783	2.371		0.504	2.153		0.672
ICPAX	11.714	*	0.054	11.800	*	0.060	7.838		0.151	6.429		0.223
IENAX	4.082		0.360	3.625		0.386	11.063	*	0.080	10.473	*	0.081
MLPAX	34.751	***	0.000	36.275	***	0.000	3.702		0.557	3.558		0.577
MLPLX	2.491		0.332	6.297		0.144	2.540		0.333	2.521		0.466
SPMGX	34.751	***	0.001	36.275	***	0.002	3.702		0.552	3.558		0.569
MLPDX	0.748		0.683	0.946		0.728	0.527		0.798	0.819		0.801
MLPFX	17.858	**	0.017	20.628	***	0.004	11.745	*	0.062	11.900	*	0.062
JNLM	17.805	**	0.037	16.115	*	0.054	36.737	***	0.008	36.927	***	0.006
AMLPX	7.374		0.129	7.019		0.205	10.984	**	0.040	11.862	*	0.060
CSHAX	14.781	**	0.033	14.980	**	0.041	12.886	**	0.043	13.181	**	0.040
RYENX	16.886	**	0.028	18.037	**	0.029	16.272	**	0.030	15.280	**	0.026
RYESX	1.933		0.737	2.078		0.741	0.394		0.988	0.370		0.987
SMAPX	14.667	**	0.022	14.651	**	0.031	4.302		0.348	10.658	*	0.075
INFRX	23.723	***	0.005	23.255	***	0.005	1.506		0.874	1.045		0.949
TORTX	4.429		0.345	4.406		0.393	47.627	***	0.001	49.772	***	0.000
TMLAX	1.570		0.675	1.548		0.808	3.079		0.401	3.417		0.503
VENAX	37.741	***	0.007	36.317	**	0.014	19.069	**	0.019	19.614	**	0.025
AMLP	20.209	***	0.006	18.209	**	0.016	31.716	***	0.000	40.317	***	0.001
XLE	5.879		0.313	6.188		0.251	16.332	**	0.016	15.350	**	0.015
FXN	7.514		0.116	8.348		0.119	3.614		0.264	4.864		0.262
FCG	38.135	**	0.011	36.534	**	0.027	16.674	*	0.050	16.205	**	0.047
EMLP	8.431		0.160	8.410		0.137	2.619		0.696	2.911		0.652
MLPA	1.503		0.712	2.840		0.537	7.647		0.121	8.024		0.147
PXI	30.966	***	0.008	30.891	**	0.016	3.971		0.307	5.050		0.282
PXE	7.109		0.167	7.145		0.163	4.363		0.347	4.387		0.343

PXJ	3.595		0.263	3.251		0.380	4.603		0.227	5.179		0.275
RYE	43.844	**	0.010	43.820	**	0.012	29.941	**	0.017	30.950	**	0.012
PSCE	1.208		0.773	2.027		0.717	3.920		0.342	8.537		0.119
IXC	8.967		0.108	10.678		0.108	2.336		0.541	2.788		0.603
FILL	6.826		0.197	6.726		0.216	17.705	**	0.032	18.015	**	0.031
IYE	9.057		0.126	9.026		0.113	11.516	*	0.069	11.572	*	0.069
IEO	0.541		0.939	0.431		0.970	8.581		0.131	8.334		0.136
IEZ	6.777	*	0.098	8.565	*	0.090	1.684		0.530	2.900		0.429
XES	20.975	**	0.015	20.805	**	0.012	18.911	***	0.008	18.914	***	0.009
XOP	26.730	***	0.006	26.677	**	0.010	1.382		0.906	1.412		0.913
EINC	18.799	**	0.040	18.745	**	0.042	5.461		0.183	5.452		0.158
OIH	17.642	***	0.009	17.533	***	0.004	10.793	*	0.073	10.755	*	0.067
VDE	37.741	**	0.012	36.317	**	0.012	19.069	**	0.025	19.614	**	0.030

Notes: See Table 2a. Bivariate VAR models include oil prices and fund return variable. *** indicates statistical significance at 1 percent. ** indicates statistical significance at 5 percent. * indicates statistical significance at 10 percent.

While price transmissions are very important and motivate us to further investigate them in the later part of our paper (Section 4b), we also look at the volatility interactions between these funds and the oil market. These results show whether the future volatility of one variable can be predicted using the historical volatility of another variable. All but one (two by Fourier method) of the funds exhibit direct transmission from oil price volatility to fund volatility. The results for volatility transmission between oil prices and fund returns (and vis-versa) is available from the authors. These results are very robust where one of the transmissions we identified is significant at 10% level and all others are significant at either the 1% or 5% levels. The same is true in observing transmission from the fund volatility to oil price volatility. The result in Table 2b for no volatility transmission from MSMLPCT is not exhibited for all the limited partnership funds. Although it was previously suggested that an unobservable/long lag between direct price transmission to fund returns may exist, the volatility analysis seems to be capable of identifying a direct relationship for all funds. Furthermore, the persistence and blanket bi-directional volatility transmission we observe shows the extent of the interconnected nature of these funds with the oil market.

Following the same methodology used in our price transmission analysis, we test for volatility transmission relationships between the oil market and fund flows. As seen in Table 5, oil volatility transmits to fund flow volatility for about 27% (12 of 44) of the funds. When evaluating for transmission in the opposite direction, we find all fund flow volatilities transmitting to oil volatility. In other words, similar to our return volatility transmission findings, our results indicate the frequency (and magnitude) of investor trading in the energy equity funds carries into the oil market volatility.

Table 5. Results for volatility transmission between oil prices and mutual fund flows.

	Oil prices to mutual fund flows				Mutual fund flows to oil prices					
	λ_{LM}	p-val.	$F\lambda_{LM}$	p-val.	λ_{LM}		p-val.	$F\lambda_{LM}$		p-val.
BACIX	0.157	0.925	1.397	0.497	7.558	**	0.023	8.658	**	0.013
CCCAX	3.466	0.177	1.394	0.498	7.671	**	0.022	7.841	**	0.020
EGLAX	0.133	0.935	1.743	0.418	7.384	**	0.025	7.500	**	0.024
EIPIX	0.142	0.931	0.156	0.925	7.566	**	0.023	7.745	**	0.021
GLPAX	0.255	0.880	0.109	0.947	7.320	**	0.026	7.565	**	0.023
GAGEX	0.262	0.877	0.081	0.960	8.334	**	0.016	8.588	**	0.014

ICPAX	0.320		0.852	0.315		0.854	7.859	**	0.020	7.743	**	0.021
IENAX	0.873		0.646	0.737		0.692	7.984	**	0.018	8.263	**	0.016
MLPAX	3.654		0.161	1.021		0.600	8.701	**	0.013	8.113	**	0.017
MLPLX	0.006		0.997	0.013		0.994	7.326	**	0.026	7.505	**	0.023
SPMGX	3.654		0.161	1.021		0.600	8.701	**	0.013	8.113	**	0.017
MLPDX	0.082		0.960	0.579		0.749	7.687	**	0.021	7.563	**	0.023
MLPFX	7.908	**	0.019	5.996	**	0.050	18.241	***	0.000	17.600	***	0.000
JNLM	0.753		0.686	0.310		0.856	7.345	**	0.025	7.530	**	0.023
AMLPX	3.127		0.209	2.292		0.318	12.415	***	0.002	12.119	***	0.002
CSHAX	12.096	***	0.002	8.616	**	0.013	7.478	**	0.024	7.756	**	0.021
RYENX	5.408	*	0.067	10.523	***	0.005	7.696	**	0.021	7.887	**	0.019
RYESX	5.757	*	0.056	11.273	***	0.004	7.307	**	0.026	7.485	**	0.024
SMAPX	5.546	*	0.062	4.222		0.121	7.578	**	0.023	7.763	**	0.021
INFRX	55.032	***	0.000	35.771	***	0.000	8.336	**	0.015	8.138	**	0.017
TORTX	2.308		0.315	2.899		0.235	11.260	***	0.004	11.936	***	0.003
TMLAX	0.353		0.838	0.570		0.752	7.537	**	0.023	7.622	**	0.022
VENAX	3.210		0.201	1.448		0.485	7.270	**	0.026	8.026	**	0.018
AMLP	5.065	*	0.079	6.144	**	0.046	8.092	**	0.017	8.559	**	0.014
XLE	15.126	***	0.001	5.357	*	0.069	13.913	***	0.001	11.472	***	0.003
FXN	0.765		0.682	1.059		0.589	7.700	**	0.021	7.505	**	0.023
FCG	1.581		0.454	11.540	***	0.003	7.776	**	0.020	8.113	**	0.017
EMLP	0.594		0.743	1.725		0.422	8.719	**	0.013	8.999	**	0.011
MLPA	0.985		0.611	1.316		0.518	113.136	***	0.000	125.267	***	0.000
PXI	0.648		0.723	16.647	***	0.000	7.942	**	0.019	7.960	**	0.019
PXE	0.799		0.671	0.698		0.705	8.363	**	0.015	8.298	**	0.016
PXJ	0.142		0.932	4.401		0.111	7.525	**	0.023	7.577	**	0.023
RYE	33.913	***	0.000	63.395	***	0.000	7.310	**	0.026	7.378	**	0.025
PSCE	0.669		0.716	0.953		0.621	9.137	**	0.010	8.050	**	0.018
IXC	0.235		0.889	0.367		0.832	8.305	**	0.016	8.202	**	0.017
FILL	3.531		0.171	3.273		0.195	12.412	***	0.002	8.594	**	0.014
IYE	6.804	**	0.033	46.324	***	0.000	7.364	**	0.025	7.353	**	0.025
IEO	0.982		0.612	0.304		0.859	9.831	***	0.007	8.078	**	0.018
IEZ	5.603	*	0.061	3.514		0.173	8.235	**	0.016	8.359	**	0.015
XES	4.434		0.109	3.792		0.150	19.135	***	0.000	16.241	***	0.000
XOP	1.902		0.386	1.877		0.391	7.957	**	0.019	8.241	**	0.016
EINC	2.034		0.362	1.315		0.518	7.805	**	0.020	7.914	**	0.019
OIH	8.018	**	0.018	6.277	**	0.043	9.365	***	0.009	9.329	***	0.009
VDE	3.210		0.201	1.448		0.485	7.270	**	0.026	8.026	**	0.018

Notes: See Table 2b. The mean equation is based AR(1) model for the equity fund return and oil prices. *** indicates statistical significance at 1 percent. ** indicates statistical significance at 5 percent. * indicates statistical significance at 10 percent.

4.3. Impact of Fund Characteristics on the Interactions between Fund Flows and the Oil Market

As previously indicated, several prominent studies identify fund flows as a reflection of investor sentiment. In the second part of our analysis, we evaluate the unique characteristics of these energy funds and their impact on the interactions with the oil market we previously identified. We selected 14 characteristics, of which 7 are ESG-related, to investigate. For our analysis, we examine whether certain fund characteristics impact the probability of the interactions among equity prices, oil prices, and fund flows that we previously found to exist.

Using a Logit framework, we code the previously identified transmissions as the *y* variable in a binary context, where 1 denotes transmission and 0 denotes that there is none. The independent variables used are the Morningstar rating (MSR), age of the fund (AGE), manager tenure (TEN), fund size (SIZE), net expense ratio (NEXP), the difference between net and gross expense ratios (NGEXP), turnover (TURN), Morningstar sustainability rating (SUSR), corporate ESG risk exposure (ESGEXP), social risk score (SCRISK), governance risk score (GOVRISK), Morningstar managed risk score (MRS), portfolio sustainability score (PORTSUS), and fossil fuel involvement (FOSINV).

All of the Logit regressions we conducted are stable. Our Hosmer–Lemeshow (Hosmer et al. 2013) tests show a strong goodness of fit. In addition, all of the regressions have high identification percentages and high pseudo R squares. While we also considered other ESG characteristics reported by Morningstar, such as environmental risk score and historical sustainability score, our coefficient redundancy tests suggested them to be unnecessary and negatively impact our regressions' stability. All of the variables we used pass the coefficient redundancy tests and are statistically relevant in the models.

Our tests start with evaluating the fund characteristics impacting the volatility transmission from oil to fund flows. In our previous tests (see Table 5), we observed about 27% of the fund flows being susceptible to volatility information from the oil market. Table 6 shows the impact of fund characteristics on those interactions. We find three characteristics critical in these volatility transmissions: the difference between the net and gross expense ratio, turnover, and fossil fuel involvement. According to Morningstar, the difference between net and gross expense ratios signifies waived/recovered fees and expense reimbursement or recoupment. In other words, our results indicate the ability of the manager to save on fees and expenses, impacting whether there will be a direct volatility transmission to fund flows. Another characteristic we find to be significant is the turnover ratio. Since the turnover ratio relates to how frequently the fund manager trades the assets in their portfolio, it is reasonable to suspect the volatility transmission to be susceptible to this *volatility* in trading activity. Last, fossil fuel involvement is a significant factor in oil volatility driving fund flows. This finding is significant and expected. It shows that investors pay close attention to the portfolio holdings within the energy funds in which they invest. When there is a volatility shock to oil prices, investors in certain funds react. While we do not evaluate the entire portfolio structure of the funds in this study (other than the fossil fuel intensity criteria), we might suspect that funds with direct ties to the oil market are more susceptible to *reactive* investor trading. When all of the remaining characteristics are evaluated, however, we do not find any of them—including most ESG factors—to be significant in driving any of the volatility interactions.

Table 6. Impact of fund characteristics on the volatility transmission from oil price to mutual fund flows.

Variable	Coefficient	z−Statistic	Prob.
MSR	0.029577	0.048577	0.9613
AGE	0.000138	0.286444	0.7745
TEN	0.019709	0.112073	0.9108
SIZE	0.073063	1.033124	0.3015

NEXP	−0.446083		−0.384746	0.7004
NGEXP	−8.888977	**	−2.185391	0.0289
TURN	0.0053	**	2.329488	0.0198
SUSR	−0.09989		−0.06628	0.9472
ESGEXP	−32.57685		−0.372992	0.7092
SCRISK	−0.087785		−0.135489	0.8922
MRS	10.80459		0.370877	0.7107
GOVRISK	0.131208		0.143014	0.8863
PORTSUS	8.168386		0.374038	0.7084
FOSINV	0.159265	**	2.095999	0.0361
C	−16.19554		−1.108685	0.2676

McFadden R-Square 0.240109 H-L Prob. Chi-sq 0.1032. Notes: Table 6 presents Logit regression results for binary dependent variable which denote whether there is any volatility transmission from oil prices to mutual funds. The explanatory variables are Morningstar rating (MSR), age of the fund (AGE), manager tenure (TEN), fund size (SIZE), net expense ratio (NEXP), the difference between net and gross expense ratios (NGEXP), turnover (TURN), Morningstar sustainability rating (SUSR), corporate ESG risk exposure (ESGEXP), social risk score (SCRISK), governance risk score (GOVRISK), Morningstar managed risk score (MRS), portfolio sustainability score (PORTSUS), and fossil fuel involvement (FOSINV). The superscripts *, **, *** represent significance at 10%, 5%, and 1% levels, respectively. McFadden R-Square is the pseudo R square of the logit regressions. H-L Prob. is the Hosmer–Lemeshow goodness-of-fit test with a null hypothesis of the observed and expected probabilities being the same. A p-value below alpha = 0.05 rejects the null hypothesis.

While the impact of fund characteristics regarding volatility interactions is relevant, our main goal is to evaluate the impact of characteristics on the direct (level) interactions between oil prices and fund flows. Since, as previously discussed, fund flows are found to reflect investor sentiment, it is critical to see whether certain characteristics impact the action or reaction of investors.

Table 7 presents the results for fund characteristics impacting price (level) transmissions from oil to fund flows (see Table 4 for transmission tests for fund flows and oil prices). We find several fund characteristics, including ESG-related characteristics, to be impactful, with varying significance levels. The Morningstar rating, manager tenure, corporate ESG risk exposure, Morningstar managed risk score, and portfolio sustainability risk score are significant at the 1% level. For the comparatively less significant characteristics, we find the net vs. gross expense ratio, social risk score, and governance risk score to impact the probability of a price transmission at 5% statistical significance. Several studies have shown the importance of the Morningstar rating and manager tenure to be important in investor decisions (see Blake and Morey 2000; Ben-David et al. 2022; Gormus et al. 2018; and others). Our tests provide further evidence of the importance of these “quality” characteristics in manager trading decisions and investor sentiment.

Since we expect energy funds to be especially susceptible to ESG dimensions, our study provides evidence of the impact of those characteristics on investor sentiment. It is important to note that this study only looks at energy funds. We compare the results and comment on the differences between this table and Table 8 in the next section.

Table 7. Impact of fund characteristics on the price transmission from oil prices to mutual fund flows.

Variable	Coefficient		z−Statistic	Prob.
MSR	−1.920247	***	−2.648316	0.0081
AGE	0.000421		0.689236	0.4907
TEN	−0.393242	***	−2.757079	0.0058
SIZE	−0.052588		−0.880197	0.3788

NEXP	−2.125418	*	−1.866874	0.0619
NGEXP	−6.047463	**	−2.112962	0.0346
TURN	0.005947	**	2.254171	0.0242
SUSR	−1.4155		−0.76437	0.4446
ESGEXP	−368.7428	***	−3.133504	0.0017
SCRISK	2.499112	**	2.357708	0.0184
MRS	122.8687	***	3.130596	0.0018
GOVRISK	−2.779238	**	−1.85898	0.0630
PORTSUS	92.17396	***	3.135833	0.0016
FOSINV	−0.032619		−0.411201	0.6809
C	15.46992		0.844147	0.3986

McFadden R-Square 0.430046 H-L Prob. Chi-sq 0.1399. Notes: Table 7 presents Logit regression results for a binary dependent variable which denotes whether there is any price transmission from oil prices to mutual fund flows. See Table 6 for details. *** indicates statistical significance at 1 percent. ** indicates statistical significance at 5 percent. * indicates statistical significance at 10 percent.

In the ESG factors, Morningstar sustainability rating (SUSR) is not significant for differentiating responses in either direction. All other factors, other than fossil fuel involvement, are found to significantly impact transmission from oil markets to mutual fund flows. Thus, it appears that mutual fund investors dynamically adjust their investments for broad ESG or social or governance considerations of the funds; however, they do not adjust holdings based upon fossil fuel intensity. As we previously referenced, several studies have shown the significance of general ESG related-factors on fund performance.

Evaluating the price transmission from fund flows to oil prices, we find the Morningstar rating, manager tenure, and social risk score to be not as significant. However, fossil fuel involvement, corporate ESG risk exposure, the Morningstar managed risk score, and the portfolio sustainability risk score are significant at the 1% level. There are two conclusions we can derive from these results. The first conclusion is that regardless of the transmission direction, fund managers pay very close attention to certain ESG criteria. In other words, these criteria are influential when investors act upon or react to oil price dynamics.

The second conclusion can be tied to the differences in the results for these two tables (Table 7 vs. Table 8), which could be explained by the dynamics of fund and oil market characteristics. Although we find the size factor to be significant at the 10% level, and larger energy funds will clearly have more influence on driving the oil market, the most important difference relates to the fossil fuel involvement criteria (significant at 1% level). SUSR is still insignificant, but the broad ESG factors and fossil-fuel involvement are significant. SCRISK and GOVRISK are not found to be significant. These results highlight the transmission of information from the funds to oil prices resulting from the fossil fuel exposure of the funds.

As we previously mentioned, we suspect investors to pay close attention to the portfolio structures of the funds they hold. Interestingly, while they do not pay as close attention to fossil fuel involvement when reacting to oil price shocks, investors clearly consider a fund's fossil fuel intensity when making independent investment decisions or when different sets of investors drive the performance in the two markets. In other words, the funds (or other investors) holding equities with high levels of fossil fuel involvement are likely participants in the oil market, thus trading on their information in both markets. Since we did not detect a differentiation across funds in the oil price transmission to mutual fund flows related to fossil fuel involvement, it is possible that individual investors do not differentially change allocations to energy funds based upon fossil fuel involvement in reaction to oil price changes. One additional observation from comparing Tables 7 and 8 can be the changes in the coefficient signs of some characteristics. Concentrating specifically on ESG characteristics that are statistically significant in both tables, the ESGEXP and PORTSUS coefficients change signs. For example, ESGEXP is negative when investors are reacting to shocks to oil prices and positive when oil prices are reacting to shocks in fund flows. When there is a shock to oil prices, investors pick funds with less corporate ESG risk exposure (negative coefficient). However, when capital flows to funds with a high corporate ESG risk exposure, this impacts price spillover to the oil market. PORTSUS is the opposite. The higher the portfolio sustainability score of a fund, the more sustainable it is; when there is a shock to oil prices, investors pour money into funds with a higher portfolio sustainability. In the opposite direction, when money flows to low portfolio sustainability funds, this impacts price transmission to the oil market.

Table 8. Impact of fund characteristics on the price transmission from mutual fund flows to oil prices.

Variable	Coefficient		z−Statistic	Prob.
MSR	0.197351		0.206531	0.8364
AGE	0.000896	*	1.671322	0.0947
TEN	−0.015425		−0.076454	0.9391
SIZE	0.757519	*	1.911902	0.0559
NEXP	1.607935		1.115835	0.2645
NGEXP	−19.25012	**	−2.524372	0.0116
TURN	0.002249		0.568284	0.5698
SUSR	0.715895		0.412472	0.6801
ESGEXP	373.3877	***	3.081423	0.0020
SCRISK	0.207934		0.326628	0.7439
MRS	−124.5622	***	−3.084171	0.0021
GOVRISK	0.345235		0.446559	0.6552
PORTSUS	−93.30223	***	−3.074370	0.0019
FOSINV	0.320727	***	3.224989	0.0013
C	−40.48964		−1.835314	0.0665

McFadden R-Square 0.518020 H-L Prob. Chi-sq 0.7171. Notes: Table 8 presents Logit regression results for binary dependent variable which denote whether there is any price transmission from mutual fund flows to oil prices. See Table 6 for details. *** indicates statistical significance at 1 percent. ** indicates statistical significance at 5 percent. * indicates statistical significance at 10 percent.

5. Concluding Remarks

This study evaluates the volatility and price transmission relationships between the oil market and energy funds. In light of the increasing attention ESG characteristics have been receiving, we test whether those ESG characteristics (along with other general fund characteristics) impact the price and volatility transmissions we identify.

Our results indicate a strong price transmission from energy funds to oil prices. We find a bi-directional information flow between the oil market and the funds for volatility transmission. More importantly, fund flows, which can reflect investor sentiment, exhibit interaction at varying degrees with oil in terms of price and volatility. When we test for the impact of fund characteristics on the price and volatility transmissions, our results indicate some differences depending on the direction of the transmission.

Looking at information transmission from oil prices to fund flows, our results show the Morningstar rating, manager tenure, corporate ESG risk exposure, Morningstar managed risk score, and portfolio sustainability risk score to be the most important. Evaluating the transmission from fund flows to oil prices, we find fossil fuel involvement, corporate ESG risk exposure, the Morningstar managed risk score, and the portfolio sustainability risk score to be significant in impacting those interactions.

Our results further confirm that ESG characteristics influence investor sentiment and provide additional information on the impact of a multitude of ESG dimensions. The social risk score and governance risk score influence investor flows in energy funds differently from the influence of fossil fuel involvement. These results highlight the potential for fund ESG metrics, and specifically fossil fuel involvement, in connecting financial markets and energy commodity markets and contributing to the financialization of energy markets. Our findings, which suggest some differences in investor and manager sensitivities to ESG characteristics, do not infer investors' lack of interest in ESG criteria; they simply show that investors do not always prioritize ESG dimensions when reacting to price shocks in the oil market. An alternate explanation could be that investors already prioritize certain ESG criteria when initially picking funds and then outsource further sensitivity to the fund manager. Our findings are especially important because investors should consider monitoring volatility and price changes in energy mutual funds in managing a direct exposure to oil markets.

Author Contributions: Conceptualization, A.G. and S.L.B.; methodology, S.N.; software, A.G.; validation, A.G., S.N. and S.L.B.; formal analysis, S.N.; investigation, A.G and S.L.B.; resources, S.L.B.; data curation, A.G.; writing—original draft preparation, A.G., S.N. and S.L.B.; writing—review and editing, A.G and S.L.B.; visualization, S.N.; supervision, A.G.; project administration, A.G.; funding acquisition, S.L.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding

Data Availability Statement: Data available upon request from corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Note

1. In order to save space, we omit the details of the bootstrap procedure here and refer interested readers to Balcilar et al. (2010).

References

Manuel Ammann, Christopher Bauer, Sebastian Fischer, and Philipp Müller. 2019. The impact of the Morningstar Sustainability Rating on mutual fund flows. *European Financial Management* 25: 520–53.

Anand Babu, and Sunil Paul. 2021. Oil shocks and stock market: Revisiting the dynamics. *Energy Economics* 96: 105111.

Mehmet Balcilar, Zeynal Abidin Ozdemir, and Yalcin Arslanturk. 2010. Economic growth and energy consumption causal nexus viewed through a bootstrap rolling window. *Energy Economics* 32: 1398–410.

Martin G. Becker, Fabio Martin, and Andreas Walter. 2022. The power of ESG transparency: The effect of the new SFDR sustainability labels on mutual funds and individual investors. *Finance Research Letters* 47: 102708.

Itzhak Ben-David, Jiacui Li, Andrea Rossi, and Yang Song. 2022. Ratings-driven demand and systematic price fluctuations. *The Review of Financial Studies* 35: 2790–838.

Azi Ben-Rephael, Shmuel Kandel, and Avi Wohl. 2012. Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics* 104: 363–82.

Christopher R. Blake and Matthew R. Morey. 2000. Morningstar ratings and mutual fund performance. *Journal of Financial and Quantitative Analysis* 35: 451-483.

Nicholas P.B. Bollen, 2007. Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis* 42: 683–708.

Patrick Bolton, and Marcin Kacperczyk. 2021. Do investors care about carbon risk?. *Journal of Financial Economics* 142: 517–49.

Elie Bouri and Riza Demirer. 2016. On the volatility transmission between oil and stock markets: a comparison of emerging importers and exporters. *Economia Politica: Journal of Analytical and Institutional Economics* 33(1): 63-82.

Ellie Bouri, Riza Demirer, David Gabauer, and Rangan Gupta. 2022. Financial market connectedness: The role of investors' happiness. *Finance Research Letters* 44: 102075.

Cheung Yin Wong, and Lilian K. Ng. 1996. A causality in variance test and its application to financial market prices. *Journal of Econometrics* 72: 33–48.

Da Zin, Joseph Engelberg, and Pengjie Gao. 2015. The sum of all FEARS investor sentiment and asset prices. *The Review of Financial Studies* 28: 1–32.

Stavros Degiannakis, and George Filis. 2017. Forecasting oil price realized volatility using information channels from other asset classes. *Journal of International Money and Finance* 76: 28–49.

Stavros Degiannakis, George Filis, and Vipin Arora 2018. Oil prices and stock markets: a review of the theory and empirical evidence. *The Energy Journal* 39: 85–130.

Diane Del Guercio, and Paula A. Tkac. 2002. The determinants of the flow of funds of managed portfolios: Mutual funds vs. pension funds. *Journal of Financial and Quantitative Analysis* 37: 523–57.

Davd A. Dickey and Wayne Fuller. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association* 74 (366): 427-431.

Limin Du, and Yanan He. 2015. Extreme risk spillovers between crude oil and stock markets. *Energy Economics* 51: 455–65.

Bradley Efron. 1979. Bootstrap methods: another look at the jackknife. *The Annals of Statistics* 7: 1–26.

Sadok El Ghoul, and Aymen Karoui. 2017. Does corporate social responsibility affect mutual fund performance and flows?. *Journal of Banking & Finance* 77: 53–63.

Graham Elliott, Thomas J. Rothenberg, James H. Stock. 1996. Efficient tests for an autoregressive unit root. *Econometrica* 64: 813–36.

Walter Enders, and Junsoo Lee. 2012a. A unit root test using a Fourier series to approximate smooth breaks. *Oxford Bulletin of Economics and Statistics* 74: 574–99.

Walter Enders, and Junsoo Lee. 2012b. The flexible Fourier form and Dickey-Fuller type unit root tests. *Economics Letters* 117: 196–99.

Gerald Epstein 2002. Financialization, rentier interests, and central bank policy. In *The Political Economy of Central Banking (2019).* Edgar Elgar. https://doi.org/10.4337/9781788978415

The Economist ESG. 2022. ESG: Three letters that won't save the planet: ESG should be boiled down to one simple measure: Emissions. *The Economist,* July 21.

Yanhong Feng, Xiaolei Wang, Shuanglian Chen, and Yanqiong Liu. 2022. Impact of oil financialization on oil price fluctuation: A perspective of heterogeneity. *Energies* 15. https://doi.org/10.3390/en15124294

Miguel A. Ferreira, Aneel Keswani, Antonio F. Miguel, and Sofia Brito Ramos. 2013. The determinants of mutual fund performance: A cross-country study. *Review of Finance* 17: 483–525.

Iraj J. Fooladi, and Gregory Hebb. 2022. Drivers of differences in performance of ESG-focused funds relative to their underlying benchmarks. *Global Finance Journal* 100745.

Ronald A. Gallant. 1981. On the basis in flexible functional form and an essentially unbiased form: the flexible Fourier form. *Journal of Econometrics* 15: 211–353.

Alper Gormus, John David Diltz, and Ugur Soytas. 2018. Energy mutual funds and oil prices. *Managerial Finance*. 44(3), 374-388

Alper Gormus, Saban Nazlioglu, and Ugur Soytas. 2018. High-yield bond and energy markets. *Energy Economics* 69: 101–10.

Alper Gormus, Ugur Soytas, and John David Diltz. 2014. Volatility transmission between energy-related asset classes. *Global Finance Journal* 25: 246–59.

Clive W. Granger, 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society* 37: 424–38.

Scott R. Hacker, and Abdulnasser Hatemi-J. 2006. Tests for causality between integrated variables using asymptotic and bootstrap distributions: theory and application. *Applied Economics* 38: 1489–500.

Christian M. Hafner, and Helmut Herwartz. 2006. A Lagrange multiplier test for causality in variance. *Economics Letters* 93: 137–41.

Yongmiao Hong, 2001. A test for volatility spillover with application to exchange rates. *Journal of Econometrics* 103: 183–224.

David W. Hosmer Jr., Stanley A. Lemeshow, and Rodney X. Sturdivant. 2013. *Applied Logistic Regression*, 3rd ed. Hoboken: Wiley.

Jacquelyn E. Humphrey, and Yong Li. 2021. Who goes green: Reducing mutual fund emissions and its consequences. *Journal of Banking & Finance* 126: 106098.

Marcin Kacperczyk, Clemens Sialm, and Lu Zheng. 2005. On the industry concentration of actively managed equity mutual funds. *The Journal of Finance* 60: 1983–2011.

Denis Kwiatkowski, Peter C. B. Phillips, Peter Schmidt, and Yongcheol. Shin. 1992. Testing the null hypothesis against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics* 54: 159–78.s

Thai-Ha Le, and Youngho Chang. 2015. Effects of oil price shocks on the stock market performance: Do nature of shocks and economies matter? *Energy Economics* 51: 261–74.

Junsoo Lee, and Mark C. Strazicich. 2013. Minimum LM unit root test with one structural break. *Economics Bulletin* 33: 2483–92.

Jing Li, and Walter Enders. 2018. Flexible Fourier form for volatility breaks. *Studies in Nonlinear Dynamics & Econometrics* 22: 1–19.

Li Liu, Feng Ma, and Yudong Wang. 2015. Forecasting excess stock returns with crude oil market data. *Energy Economics* 48: 316–24.

Yan-ran Ma, Qiang Ji, and Jiaofeng Pan. 2019. Oil financialization and volatility forecast: Evidence from multidimensional predictors. *Journal of Forecasting* 38: 564–81. https://doi.org/10.1002/for.2577

Walid Mensi, Makram Beljid, Adel Boubaker, and Shunsuke Managi. 2013. Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling* 32: 15–22.

Walid Mensi, Shawkat Hammoudeh, Syed Jawad Hussain Shahzad, and Muhammad Shahbaz. 2017. Modelling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance*. 75: 258–79.

Issac J. Miller, and Ronald A. Ratti. 2009. Crude oil and stock markets: Stability, instability, and bubbles. *Energy Economics* 31: 559–68.

Vikram Nanda, Zhi Jay Wang, and Lu Zheng. 2004. Family values and the star phenomenon: Strategies of mutual fund families. *Review of Financial Studies* 17: 667–98.

Saban Nazlioglu, Alper N. Gormus, and Ugur Soytas. 2016. Oil prices and real estate investment trusts (REITs): gradual-shift causality and volatility transmission analysis. *Energy Economics* 60: 168–75.

Benyza Mina Ordu, and Ugur Soytaş. 2016. The Relationship Between Energy Commodity Prices and Electricityand Market Index Performances: Evidence from an Emerging Market. *Emerging Markets Finance and Trade* 52(9), 2149-2164

Thomas I. Palley, 2007. Financialization: What It Is and Why It Matters, Levy Economics Institute, Working Paper No. 525. Available online: https://www.levyinstitute.org/pubs/wp_525.pdf (accessed on 13 March 2023).

Pierre Perron, 1989. The great crash, the oil price shock, and the unit root hypothesis. *Econometrica* 57: 1361–401.

Dinh Hong Bach Phan, Susan Sunila Sharma, and Paresh Kumar Narayan. 2016. Intraday volatility interaction between the crude oil and equity markets. *Journal of International Financial Markets, Institutions and Money* 40: 1–13.

Joshua M. Pollet, and Mungo Wilson. 2008. How does size affect mutual fund behavior? *The Journal of Finance* 63: 2941–69.

Ken Pucker, and Andrew King. 2022. ESG investing isn't designed to save the planet. *Harvard Business Review*, August 1. Available online: https://hbr.org/2022/08/esg-investing-isnt-designed-to-save-the-planet (accessed on 14 March 2023).

Arno Riedl, and Paul Smeets. 2017. Why do investors hold socially responsible mutual funds? *The Journal of Finance* 72: 2505–50.

Martin Rohleder, Marco Wilkens, and Jonas Zink. 2022. The effects of mutual fund decarbonization on stock prices and carbon emissions. *Journal of Banking & Finance* 134: 106352.

Ke Tang, and Wei Xiong. 2012. Index investment and the financialization of commodities. *Financial Analysts Journal* 68: 54–74. https://doi.org/10.2469/faj.v68.n6.5

Hiro Y. Toda, and Taku Yamamoto. 1995. Statistical inference in vector autoregression with possibly integrated processes. *Journal of Econometrics* 66: 225–50.

Baochen Yang, Yingjian Pu, and Yunpeng Su. 2020. The financialization of Chinese commodity markets. *Finance Research Letters* 34: 101438. https://doi.org/10.1016/j.frl.2020.10.101438

Yue-Jun Zhang, and Jin-Li Wang. 2019. Do high-frequency stock market data help forecast crude oil prices? Evidence from the MIDAS models. *Energy Economics* 78: 192–201.