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Plantinga, Auke; Scholtens, Bert

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Auke Plantinga
Bert Scholtens

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Research Institute SOM
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University of Groningen

Visiting address:
Nettelbosje 2
9747 AE Groningen
The Netherlands

Postal address:
P.O. Box 800
9700 AV Groningen
The Netherlands

T +31 50 363 9090/3815

www.rug.nl/feb/research

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Auke Plantinga
University of Groningen, Faculty of Economics and Business, Department Economics, Econometrics and Finance

Bert Scholtens
University of Groningen, Faculty of Economics and Business, Department Economics, Econometrics and Finance & School of Management, University of Saint Andrews
l.j.r.scholtens@rug.nl

The financial impact of divestment from fossil fuels

Auke Plantinga[a] and Bert Scholtens[a,b,c]

a Faculty of Economics and Business, Department of Economics, Econometrics and Finance, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands.

b School of Management, University of Saint Andrews, The Gateway, North Haugh, St Andrews, Fife, KY16 9RJ, Scotland, UK.

c Corresponding author. Email: l.j.r.scholtens@rug.nl; Phone: +31-503637064; Fax +31-503638252.

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Abstract

Divesting from fossil companies has been put forward as a means to address climate change. We study the impact of such divesting on investment portfolio performance. To this extent, we systematically investigate the investment performance of portfolios with and without fossil fuel company stocks. We investigate mispricing in stock returns and test for the impact of (reduced) diversification by excluding fossil fuel companies from the portfolio. While the fossil fuel industry outperforms other industries based on returns only, we show that this is due to the higher systematic risk of this industry, as there is no statistically significant difference between the risk-adjusted performance of stocks in the fossil fuel sample and the non-fossil fuel sample. We conclude that divesting from fossil fuels does not have a statistically significant impact on overall portfolio performance, and only a very marginal impact on the utility derived from such portfolios. The policy implication is that investors can divest from fossil fuels without significantly hurting their financial performance.

Keywords: Divestment, Fossil fuels, Investment management, Portfolio performance, Stock market

JEL codes: G11, Q41

1 Introduction

Allen et al. (2009) and Meinshausen et al. (2009) suggest that most fossil fuel reserves should be left unused in order not to exceed the 2°C threshold beyond which it seems impossible to avoid dramatic climate change. Griffin et al. (2015) find that investors only show a small negative reaction to news about 'unburnable carbon'. Nevertheless, public initiatives and non-governmental organizations asking investors to move their funds out of the fossil fuel industry have mushroomed (see https://campaigns.gofossilfree.org/). Their hope is this will help reduce greenhouse gas emissions. Cornell (2015) finds that divestment from fossil energy companies would be costly for US university endowments and would reduce the size of the endowment by 12.1% over a 50-year time frame. In our study, we focus on what would happen to investors' financial performance if they sold their stocks in fossil energy companies and systematically investigate the impact of such divestment at the portfolio level. In general, energy firms make up part of most individual and institutional investment portfolios. This is not a surprise, as they constitute about 7.5% of the market value of the MSCI World Index.

We take an investment perspective and focus on the impact of divestment from fossil fuel stocks on investment performance using mean-variance portfolio theory. As suggested by Cornell (2015), excluding fossil fuel stock potentially deteriorates the performance of a diversified portfolio, in particular when fossil fuel stocks show better than average returns. Additionally, excluding fossil fuel stocks from the investment universe reduces diversification opportunities, which may increase portfolio risk. In this paper we will address these issues and consider the implications of excluding fossil fuel stocks on portfolio performance in terms of expected returns and risk.

The call for divestment from fossil fuels is related to socially responsible investing (SRI). SRI focuses on how investors align ethical and financial concerns, as well as on the impact on firms' environmental, social, and governance (ESG) performance (Renneboog et al., 2008). To achieve this, the socially responsible investors have developed a variety of strategies, including "best-in-class" investing, active ownership, and ESG integration (see Eurosif, 2014). However, the original SRI practice of excluding stocks of companies involved in harmful or controversial activities (so-called *sin stocks*) remains the most common SRI strategy today (see Eurosif, 2014). But what does it actually mean for an investor to employ negative screens on the universe of potential investments, from the investment perspective? And does it matter for financial performance if a 'fossil' screen is employed? Screening limits the investment universe, which should be detrimental for the mean–variance efficiency of a portfolio. For example, Hong and Kacperczyk (2009) find that investors who ditch firms in contested industries like alcohol, tobacco and gambling forego the excess returns as these 'sin stocks' have higher expected returns than similar stocks. The former being neglected by investors who are constrained by norms and values. In contrast, Bello (2005) reports that mutual funds with an SRI strategy have the same performance as a group of non-SRI funds with similar characteristics; more recent studies (e.g. Humphrey and Tan, 2014) confirm this findings. This is in line with the literature on the minimum number of stocks needed to create a well-diversified portfolio, which claims that a limited number of stocks is sufficient. For instance, this minimum is 10 stocks according to Evans and Archer (1968), and 40 according to Statman (1987). This literature suggests that the exclusion of a small set of assets may have only a minor impact on portfolio performance.

Our paper focuses on the financial performance of fossil fuel stocks in comparison with all other industries and on the consequences of divestment from fossil fuel for portfolio construction. We address the following two research questions:

1. *Do returns from investing in fossil fuel stocks differ from those in other industries?*

2. *Are there implications for the performance of investment portfolios with and without fossil fuel stocks?*

We aim to contribute to the investment portfolio performance literature as well as the responsible investment literature, since we investigate the potential downside on portfolio choice of excluding fossil fuel stocks. This is the first study, to our knowledge, that systematically investigates the impact of excluding fossil fuel stocks at the portfolio level. To answer the research questions, we create two portfolios using standard industry indices provided by Datastream. To address the first research question, we create a portfolio with all fossil fuel stocks and one with all remaining stocks. Next, we analyze the returns of each portfolio as well as the difference between them using the Carhart (1997) extension of the Fama and French (1993) model. Since the second research question focuses on investment portfolios, we construct optimal portfolios using mean variance optimization to assess the impact of screening on fossil fuel stocks.

We find that both the fossil fuel stocks and all remaining stocks are priced consistent with the Carhart (1997) model. In addition, the difference in returns between the fossil fuel and other stocks does not generate a significant risk-adjusted return, although there are statistically significant differences in exposure to systematic risk. Further, we find that limiting the investment universe by excluding fossil fuel stocks has a marginal impact on the performance of a portfolio. The financial performance of the restricted portfolios with lower risk tends to have lower utility for the investor than the unrestricted portfolios; vice versa, the restricted portfolios with higher risk have higher utility than the unrestricted portfolios with higher risk.

This paper proceeds as follows. We describe the sampling process and the data in Section 2. We present the findings in Section 3. Here, we also discuss the implications of these results, particularly in light of the divestment and screening discussion. We set forth our conclusions in Section 4.

2 Materials and methods

We test the impact of excluding fossil fuel stocks from the investment universe by studying stock returns at the industry level. This is because such an approach is easily translated into an investment strategy, with no liquidity concerns. Many providers offer industry-level portfolios as actively managed mutual funds, passively managed mutual funds, or exchange traded funds, which makes it easy for an investor to implement the strategies that we investigate. We use the industry indices provided by Datastream, as they have a return history of more than 40 years, allowing for elaborate robustness analysis. The Datastream industry indices are based on the Industry Classification Benchmark (ICB) for classifying stocks into industries and sectors, which include four hierarchical classification levels: the top level is industry, and the remaining levels are supersector, sector, and subsector, respectively. In our study, we focus on the top level, which consists of ten industries. Industry-level classification plays an important role in the practice of investment management. Many professional investment institutions follow industry classification in their investment processes, by focusing on specific industries or by defining their asset allocations in terms of industry. We adjust the ICB classification by relocating some (sub)sectors. There are two reasons for doing so. First, companies involved in the exploration and exploitation of fossil fuels are present in two different industries, namely the ICB industries Oil and Gas and Basic Materials. Second, the ICB industry Oil and Gas also contains the sector of Alternative Energy stocks. Therefore, we create a new industry classification that replaces the initial industry Oil and Gas with the newly created industry Fossil Fuels. This Fossil Fuels index consists of the sectors Oil and Gas Producers and Oil Equipment and Services from the Oil and Gas industry and the subsector Coal Mining from the Basic Materials industry. This new index has 327 constituents. We create an adjusted Basic Materials index, which is based upon the ICB Basic Material index, excluding stocks of firms involved in coal mining activities.

We adjust the Utilities index by adding the sector Alternative Energy, which is separated from the Oil and Gas industry. Finally, we also create a new index, the All Stocks Excluding Fossil Fuel Index (ASEFFI). This index has 6,578 constituents, being the sum of all other indices except for the Fossil Fuel Index. We summarize this transformation of the industry indices in Table I. We want to point out that this approach is very well in line with what is being used in the investment industry (see e.g. FTSE Russell, 2014).

Table I. Definition of new industry indices

New industry definition	# Constituents	Link with original ICB industry	(Sub)sector
Fossil Fuels	327	Oil and Gas	Oil & Gas Producers (sector)
			Oil Equip. & Serv. (sector)
		Basic Resources	Coal (subsector)
Basic Materials	460	Basic Materials	All (sub)sectors except for coal
Industrials	1,297	Industrials	Unchanged
Consumer Goods	914	Consumer Goods	Unchanged
Health Care	402	Health Care	Unchanged
Consumer Services	900	Consumer Services	Unchanged
Telecom	153	Telecom	Unchanged
Utilities	332	Utilities	All (sub)sectors
		Oil & Gas	Alternative Energy
Financials	1,731	Financials	Unchanged
Technology	389	Technology	Unchanged
ASEFFI	6,578	All Stocks Excluding Fossil Fuels	

We collected monthly total returns for all of the indices starting from January 1973 until March 2015. Table II presents the summary statistics of the returns for all the (adjusted) industries, including the Fossil Fuels index (FFI), and the adjusted Basic Materials and

Utilities indices. The other industries (Industrials, Consumer Goods, Health Care, Consumer Services, Telecommunications, Financials, and Technology) remain unchanged. The adjusted industry indices as well as the ASEFFI are constructed as portfolios of industries and/or (sub)sectors. The weights are based on the market capitalizations of the underlying industry, sector, or subsector. Portfolios are rebalanced monthly, and the return of an index is calculated as the market capitalization weighted average return of all industries in the index. The returns for the unadjusted indices are directly retrieved from Datastream. All returns index prices are denominated in US dollars and the resulting returns are denominated in percentages.

Table II shows that the fossil fuel industry has the highest average mean return over the period 1973–2015. This supports the notion that excluding fossil fuel stocks might have a detrimental impact on portfolio performance. Moreover, if there were some index that showed better performance than this index, this would suggest that replacing the former by the latter would create financial value for the investor. We will investigate this issue in the next section. Table II shows that the consumer goods industry has the lowest performance. The difference between the best and worst performing industries is 0.22% over the period 1973–2015, thus, we may conclude that the differences in returns between individual industries are quite limited. The technology industry has the highest monthly standard deviation (6.54%) and the health care industry the lowest standard deviation (4.05%). Therefore, differences in standard deviations between individual industries are also limited, although they are somewhat bigger than the mean return differences. In Table A.1 in the Appendix, we provide the results for subperiods. These suggest that the average return for stocks in the fossil fuel index (FFI) have tended to decline over the past 20 years.

Table II. Summary statistics for returns of industry indices

This table presents average, median and standard deviations of monthly returns starting from January 1973 until March 2015.

	1973-2015		
	Mean	Median	Standard deviation
Fossil Fuels	1.06%	1.04%	5.63%
Basic Materials	0.92%	1.09%	5.85%
Industrials	0.94%	1.24%	5.09%
Consumer Goods	0.85%	1.00%	4.88%
Health Care	1.03%	1.09%	4.05%
Consumer Services	0.84%	1.03%	4.68%
Telecommunications	0.91%	0.83%	5.02%
Utilities	0.89%	0.92%	4.29%
Financials	0.94%	1.22%	5.58%
Technology	0.98%	1.04%	6.54%
ASEFFI*	0.88%	1.14%	4.57%
All industries	0.89%	1.20%	4.54%

*All Stocks Excluding Fossil Fuel Index.

To investigate the impact of divesting from fossil fuel stocks on investment performance, we must address differences in risk between industries and assess the implications for risk from creating a diversified portfolio. One of the main explanations for the differences in mean returns between industries is differences in systematic risk. At the same time, we should also consider the benefits from creating a diversified portfolio. Accordingly, we estimate an asset pricing model to address the issue of risk, and we create efficient portfolios to assess the diversification costs of excluding fossil fuel stocks.

The first research question we address regards comparison of returns from fossil fuel investing versus investing in other industries. Although the summary statistics suggest that fossil fuel stocks have higher returns than other industries, the difference could be explained by risk. We answer this question by performing Fama and French (1993) regressions extended with the momentum factor proposed by Carhart (1997); this is currently the mainstream standard asset pricing model. In this model, the return $R_{p,t}$ on a portfolio p in month t is explained by the following regression:

$$R_{p,t} = \alpha + \beta_{p,m}\left(R_{m,t} - R_{f,t}\right) + \beta_{p,smb}R_{smb,t} + \beta_{p,hml}R_{hml,t} + \beta_{p,mom}R_{mom,t} + \epsilon_{p,t} \quad (1)$$

where $R_{m,t}$ is return on the market portfolio and $R_{smb,t}$ is the return the so-called SMB factor, a long portfolio in small cap stocks and short portfolio in large cap stocks. Furthermore, $R_{hml,t}$, is the return on the HML factor, a portfolio with positive weights in stocks with a high book-to-market ratio and negative weights in a portfolio with low book-to-market ratios, and finally, $R_{mom,t}$ is the return on the momentum factor, a portfolio with positive weights in stocks with the highest returns and negative weights in stocks with the worst performance in the past 12-months. The market portfolio and factor-mimicking portfolios are global factors obtained from the website of Kenneth French.[1] Since these factors are available only starting from July 1990, equation (1) is estimated using data from November 1990 to March 2015. Using regressions of this type is frequently done in empirical research to test alternative investment strategies (see, e.g., Banerjee et al., 2007; Goyal, 2012).

The second research question investigates the impact of a limited universe on the diversification opportunities and the performance of a portfolio with and without fossil fuel stocks. With a well-diversified portfolio, it is possible to attain lower levels of risk at a given level of expected return. We compare the differences between the performance of the two portfolios using the Sharpe (1966) ratio, which provides a convenient way to compare portfolios with different levels of risk. However, this approach relies on perfect markets,

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

where investors can borrow and lend at one riskless rate without limits. In practice, investors are limited in so doing. An alternative way of addressing the second research question is to examine the return differences of investment strategies with and without fossil fuel stocks. To this extent, we choose to model a limited set of passive strategies linked closely to standard portfolio theory. We use a two-step approach in testing each strategy. In the first step, we estimate the input parameters for the strategy based on returns from the estimation period, which is a period of 60 months preceding the moment of portfolio construction. In the second step, we calculate the portfolio resulting from these parameter choices, and implement this on the first day after the estimation period. This portfolio is passively managed without being adjusted to new information for the next 60 months following the estimation period. We track the performance of the portfolio during these 60 months, while rebalancing the weights of the portfolio on a monthly basis to keep them aligned with the portfolio weights initially calculated.

Since the main benefit of diversification is risk reduction, we begin by focusing on the minimum variance portfolio. Since it represents the portfolio with the lowest risk, the minimum variance portfolio is a natural measure of the risk-reduction potential in a universe of risky assets. It is constructed without the need to estimate expected returns and is based on the covariance matrix of returns only. As a result, its composition is associated with less estimation risk than, for instance, a tangency portfolio. The tangency portfolio is constructed by optimizing the Sharpe ratio, which is the portfolio return in excess over the risk-free rate as a fraction of its standard deviation. The calculation of the composition of the tangency portfolio requires the covariance matrix and the expected returns. Among others, Best and Grauer (1991) and Chopra and Ziemba (1993) show that estimation risk is an important consideration in finding optimal portfolios, in particular when it comes to estimating expected returns. The minimum variance portfolio for period t is calculated using the following expression:

$$w_t = \frac{\Omega^{-1}\iota}{\iota'\Omega^{-1}\iota}, \tag{2}$$

where Ω is the full historical covariance matrix estimated over the estimation period $t-1$ preceding the time of portfolio construction and ι is a vector of ones.

The main analysis is an out-of-sample test using an estimation period and an evaluation period, because this represents a feasible strategy for any investor, relying only on information that is available at the time of portfolio construction. During the estimation period, we estimate the covariance matrices and use these to construct portfolios at the beginning of the evaluation period. We measure the performance of the portfolio over the evaluation period. A common approach to calculating optimal portfolios is to use five years of historical data (see Chan and Lakonishok, 1999). This pragmatic choice represents a trade-off between the idea that parameters need to be estimated on a period as long as possible, while at the same time the period can be too long because firms may change in terms of fundamental risk and return characteristics. Therefore, we divide the data into eight periods of five years each. This creates seven independent evaluation periods, since the first period is used as the estimation period. The first period includes the monthly returns from January 1973 to March 1980. As such, the first portfolio is created on April 1st 1980, based on the historical covariance matrix estimated over the period January 1973 to March 1980. The next portfolio is created on April 1st 1985, based on the historical covariance matrix estimated over the period April 1980 to March 1985, and so on.

We also construct portfolios with higher levels of risk than those implied by the minimum variance portfolios. Accordingly, we calculate the tangency portfolio for period t using the following equation:

$$w_t = \frac{\Omega^{-1}\boldsymbol{r}}{\iota'\Omega^{-1}\mathrm{r}}, \tag{3}$$

where r is the vector of excess returns. Excess returns are the difference between expected returns and the risk-free rate. We use return on US Treasury bills as the risk-free rate. We also create two more risky portfolios assuming the absence of a risk-free rate. We construct these portfolios by maximizing the following preference function, which is equivalent to maximizing an exponential utility function based on von-Neuman-Morgenstern preferences if returns are jointly normally distributed (Freund, 1956):

$$E(U) = E[R] - \frac{1}{RT}\sigma^2, \tag{4}$$

where RT is the risk tolerance of the investor. This preference function is a convenient way to model the preferences of an investor in a mean-variance framework . The resulting measure of utility is a certainty equivalent return, which can be easily compared across investment alternatives. For instance, an investor with a risk tolerance of '1' calculates a certainty equivalent of 7% for an investment opportunity with an expected return of 8% and a standard deviation of 10%. The certainty equivalent of the same investor is 6% for an investment with an expected return of 6% and a standard deviation of 20%. As a result, the investor chooses the first opportunity over the second one. Using the certainty equivalent provides a simple economic interpretation: when the utility measure is below the risk-free rate, the investment opportunity is inferior to an investment in the riskless asset.

Both approaches for calculating portfolios with higher risk levels require estimating expected returns. Among others, Chan and Lakonishok (1999) and Chopra and Ziemba (1993) argue that historical mean returns are much more difficult to predict than covariances, and erroneous estimates could lead to highly inefficient portfolios in an out-of-sample test. To mitigate the impact of estimation errors on portfolio choice, we estimate expected returns using an asset pricing model. Jorion (1991) shows that using expected returns derived from a capital asset pricing model (CAPM) is preferred over the historical mean. Preferably, we would want to use the Fama and French (1993) model extended with the momentum factor. However, due to lack of availability of global Fama and French factors for the period 1973 to 1990, we choose to use CAPM estimates as suggested by Jorion (1991). For each industry, we estimate its beta relative to the MSCI All Countries World Index for each individual subperiod:

$$E[r_p] - r_f = \alpha_p + \beta_p(E[r_m] - r_f) + \epsilon \tag{5}$$

The expected market return is calculated as the average return on the MSCI All countries World Index over the period 1973 to 2015, and the risk-free rate is the average risk-free rate downloaded from the website of Kenneth French. Following Jorion (1991), the estimated betas can be used directly to infer optimal portfolio weights. We assess the performance of all outcomes by comparing the means and standard deviations of the portfolios with and without fossil fuel stocks using a paired t-test for the means and a Bartlett test for the hypothesis of equal variances, which has an χ^2 distribution with one degree of freedom.

We also provide in-sample results, which means that we calculate the composition of the efficient portfolios at the beginning of the estimation period. This is the outcome of a strategy where the investor has prior knowledge of future return distribution. The reason we present the in-sample outcomes is that they provide an indication of the impact of limiting diversification opportunities in the absence of parameter uncertainty. Without parameter uncertainty, limiting the investment universe must, by definition, result in certainty equivalent losses because of higher risk and/or lower return.

Finally, we evaluate the increase in mean variance efficiency of having a constrained investment universe by calculating the certainty equivalent for each portfolio based on equation (4). Next, we calculate the difference between the certainty equivalent for the portfolio without fossil fuel stocks and the portfolio with all stocks. If the certainty equivalent for the portfolio without fossil fuel stocks is lower than the portfolio with all stocks, the restriction results in an efficiency loss. This procedure is in line with Chopra and Ziemba (1993), who calculate the certainty equivalent loss in a similar way. It allows us to evaluate the joint impact of a restricted investment universe on both return differences and diversification opportunities.

3 Results

3.1 Fossil fuel stocks versus other stocks

Based on the discussion above , we now present the results of our analysis and address the two research questions. We begin by investigating whether the returns from investing in fossil fuel stocks differ from those of other industries. To this extent, we show the results of estimating regression (1) using monthly returns from November 1990 through March 2015. We estimate the model to explain the excess returns on ASEFFI. We test the hypothesis that the risk-adjusted returns of both groups of stocks are similar by taking the difference between the returns of the FFI and ASEFFI and explaining these differences using regression (1). The results are presented in Table III. Panel A in this table shows that the risk-adjusted returns of fossil fuel stocks are not significantly different from those of other stocks. Further, it shows that fossil fuel stocks have significantly higher exposure to the SMB and the HML factors in the Carhart model. This implies that the higher returns for fossil fuel stocks reported in Table II are due to higher systematic risk.

Table III. Risk-adjusted returns for fossil fuel stocks versus other stocks

Panel A: OLS estimates of extended Fama and French model

This table provide Ordinary Least Squares (OLS) estimates of the regression coefficients for the Carhart (1997) model using monthly returns from November 1990 to March 2015. Values in parentheses present t-values. *, ** and *** denote significance at 10%, 5%, or 1% probability level, respectively.

	FFI	ASEFFI	FFI-ASEFFI
α	-0.000	0.001	-0.001
	(0.03)	(0.89)	(0.36)
$\beta_{p,m}$	1.042***	1.021***	0.021
	(19.23)	(50.34)	(0.39)
$\beta_{p,smb}$	0.260**	-0.039	0.299***
	(2.36)	(0.93)	(2.72)
$\beta_{p,hml}$	0.476***	-0.057	0.532***
	(4.68)	(1.49)	(5.25)
$\beta_{p,mom}$	0.029	-0.038	0.067
	(0.48)	(1.66)	(1.11)
R^2	0.58	0.91	0.10

-Table III continued-

Panel B: Estimates for the Carhart (1997) model using GARCH(1,1) model

This table provides Maximum Likelihood estimates of the regression coefficients for the mean and variance specification of the Carhart (1997) model using monthly returns and a GARCH(1,1) specification from November 1990 to March 2015. Values in parentheses present t-values. *, ** and *** denote significance at 10%, 5%, or 1% probability level, respectively.

	FFI*	ASEFFI**	FFI-ASEFFI
Mean specification: $R_{p,t} = \alpha + \beta_{p,m}\left(R_{m,t} - R_{f,t}\right) + \ \beta_{p,smb}R_{smb,t} + \beta_{p,hml}R_{hml,t} + \beta_{p,mom}R_{mom,t} + \ \epsilon_{p,t},$			
α	-0.001	0.001	-0.001
	(0.29)	(1.55)	(0.41)
$\beta_{p,m}$	1.016**	0.992**	0.005
	(18.33)	(55.62)	(0.09)
$\beta_{p,smb}$	0.171	-0.032	0.146
	(1.56)	(0.98)	(1.52)
$\beta_{p,hml}$	0.471**	-0.085*	0.429***
	(4.79)	(2.41)	(5.22)
$\beta_{p,mom}$	0.015	-0.020	0.023
	(0.25)	(0.96)	(0.39)
Variance specification: $h_t = \alpha_0 + \alpha_1\epsilon_{t-1}^2 + \alpha_2 h_{t-1}^2$			
α_0	0.000	0.000	0.000
	(1.25)	(2.04)*	(1.43)
α_1	0.133	0.192	0.194
	(2.64)**	(4.26)***	(2.84)**
α_2	0.836	0.760	0.783
	(13.09)***	(16.75)***	(12.39)***

* Fossil Fuel Index

** All Stocks Excluding Fossil Fuels

The residuals from the regression models test positive on Arch effects using the ARCH-LM test. For this reason, we also estimate a GARCH(1,1) model. The results are reported in panel B of Table III and are quite similar to those in panel A. The main conclusion from Table III is that the ten industries are priced in line with the extended Fama and French (1993) model, with none of the constants statistically significant. Fossil fuel stocks have a significantly higher loading on the HML factor relative to other stocks. The loading on the SMB is only significantly higher for the OLS regression results and not for the GARCH(1,1) model.

As a robustness check, Table IV presents the estimation results of the regression explaining the return differences between fossil fuels stocks and all other stocks in four subperiods of equal length.[2] This table supports the main conclusion, namely, that investment performance of the fossil fuel industry does not significantly differ from an investment universe without fossil fuel stocks over a prolonged period of time. However, the risk-adjusted returns on fossil fuel stocks are negative and marginally significant in the final period. Exposure to systematic risk varies over time, where fossil fuels in comparison with the other stocks have only higher exposure to the HML factor in the first two periods, higher exposure to the SMB factor in the second period, and higher exposure to momentum stocks in the third period.

[2] The first period has only 71 months, due to data availability.

Table IV. Regression results by period

This table presents the regression coefficients from regressions of the return differences between fossil fuel stocks and all other stocks on the four factors in the Carhart (1997) model for four different subperiods. Values in parentheses present t-values. *, ** and *** denote significance at 10%, 5%, or 1% probability level, respectively.

	1990m07–1996m09	1996m10–2002m11	2002m12–2009m01	2009m02–2015m03
α	-0.001	0.002	0.003	-0.007*
	(-0.38)	(0.30)	(0.53)	(-1.87)
$\beta_{p,m}$	-0.059	0.013	0.264**	0.167*
	(-0.72)	(0.10)	(2.13)	(1.87)
$\beta_{p,smb}$	-0.059	0.482**	-0.097	0.285
	(-0.36)	(2.53)	(-0.21)	(1.15)
$\beta_{p,hml}$	0.427**	0.672***	-0.137	-0.169
	(2.34)	(3.70)	(-0.33)	(-0.75)
$\beta_{p,mom}$	-0.008	-0.096	0.765***	-0.056
	(-0.06)	(-0.90)	(4.80)	(-0.57)
Adj. R^2	3.27%	22.43%	23.70%	3.11%
F-Stat.	1.58	6.280	6.65	1.59

3.2 Impact of fossil fuel divestment

Although the industries are priced in line with the extended Fama and French model, we still need to address our second research question, because the limitation of the investment universe can have adverse consequences for an investor within the context of a diversified portfolio. The question here is what are the implications for the performance of investment portfolios if investors divest from fossil fuel stocks. We answer this question by constructing several portfolios with and without fossil fuel stocks. We first present the results regarding the performance of the minimum variance portfolio. This portfolio explicitly focuses on the risk-reduction benefits of diversification, since this portfolio has the lowest risk given the covariance structure.

Table V presents the estimation results regarding the out-of-sample performance of the minimum variance portfolios. For most subperiods, the difference between the returns on portfolios based on all assets and those based on all assets excluding fossil fuel stocks is very small. There are some exceptions, however. During the period 1995–2000, the monthly return of portfolios including fossil fuel stocks exceeds that of portfolios excluding fossil fuel stocks by 0.25%, which is marginally statistically significant. This difference implies that when both portfolios have the same value at the start in 1995, the value of the portfolio excluding fossil fuel stocks is 24% lower compared to the portfolio with all stocks at the end of 2000.

While out-of-sample results are most relevant from a practical point of view, it may be instructive to see some in-sample results. We have calculated the returns from the minimum variance portfolio constructed at the beginning of the estimation window using the covariance structure from the estimation window. These results can be interpreted as being representative for a world where covariance matrices and expected returns are stationary and are known beforehand without any estimation uncertainty. These results, which are presented in Appendix Table A.2, show that restricting the investment universe indeed increases the risk of the minimum variance portfolio. However, the differences in monthly standard deviations are very small: the difference in standard deviation between other stocks and fossil fuel stocks is 3 basis points in the first period, and becomes 10 and 15 basis points, respectively, in the periods 1995–2000 and 2010–2015. Thus, even in the theoretical case where estimation errors can be avoided, the elimination of fossil fuel stocks only has a limited impact on risk reduction.

Table V. Return on minimum variance portfolios with and without fossil fuel stocks

This table presents out-of-sample average returns from investing in a minimum variance portfolio with and without stocks related to the fossil fuel industry. It also present the difference in mean return and the associated paired t-test. The monthly standard deviation of the asset returns is presented in parentheses, as is the Bartlett test statistic of equal variances. *, ** and *** denote significance at 10%, 5%, and 1% probability level, respectively.

Period	All assets	Excl. fossil fuels	Difference in mean returns	Diff. test t-test (chi^2)
1980–1985	1.73%	1.79%	0.06%	-0.74
	(3.73%)	(3.82%)		(0.04)
1985–1990	1.63%	1.64%	0.01%	-0.43
	(4.20%)	(4.24%)		(0.00)
1990–1995	1.10%	1.14%	0.03%	-0.26
	(3.01%)	(3.23%)		(0.30)
1995–2000	1.48%	1.22%	-0.25%	1.96**
	(4.30%)	(4.20%)		(0.04)
2000–2005	0.42%	0.41%	-0.01%	0.48
	(3.35%)	(3.35%)		(0.00)
2005–2010	0.64%	0.61%	-0.03%	0.65
	(3.90%)	(3.91%)		(0.00)
2010–2015	1.80%	1.64%	-0.15%	1.37
	(3.26%)	(3.08%)		(0.17)

Table VI presents the out-of-sample results for the tangency portfolios; it presents both mean returns and standard deviations. In general, the differences between both portfolios in terms of means and standard deviation tend to be small. The portfolios including fossil fuels have statistically significant higher out-of-sample returns in the period 2010–2015 and have marginally significant higher returns in the period 1995–2000. However, in economic terms, the difference in performance is very limited as it translates into only 6 basis points per month for 1995–2000 and 8 basis points for 2010–2015.

Table VI. Performance of tangency portfolios with and without fossil fuel stocks

This table presents out-of-sample average returns and standard deviations from investing in the tangency portfolio with and without stocks related to the fossil fuel industry. It also presents the difference in mean return and the associated t-test on the difference in mean returns. The monthly standard deviation of returns is presented in parentheses. The table also presents the Bartlett test statistic of equal variances in parentheses. *, ** and *** denote significance at 10%, 5%, or 1% probability level, respectively.

Period	All assets	Excl. fossil fuels	Difference in mean returns	Diff. test t-test (chi^2)
1980–1985	1.36%	1.42%	0.07%	-0.69
	(3.46%)	(3.34%)		(0.08)
1985–1990	1.79%	1.84%	0.05%	-0.48
	(4.48%)	(4.58%)		(0.03)
1990–1995	0.78%	0.78%	0.00%	0.07
	(4.05%)	(4.20%)		(0.08)
1995–2000	1.38%	1.32%	-0.06%	1.86*
	(3.91%)	(3.92%)		(0.00)
2000–2005	0.03%	0.05%	0.02%	-0.53
	(4.70%)	(4.70%)		(0.00)
2005–2010	0.72%	0.74%	0.02%	-0.60
	(5.85%)	(5.76%)		(0.01)
2010–2015	0.74%	0.67%	-0.08%	2.26**
	(4.51%)	(4.53%)		(0.00)

The risk of the portfolio excluding fossil fuel is sometimes higher (e.g., during the period 1990–1995, the portfolio without fossil fuel had 15 basis points more risk), and sometimes lower (e.g., during the period 2005–2010, the portfolio without fossil fuel had 9 basis points less risk). None of the differences between the pairs of standard deviations is statistically significant, as is indicated in the column labeled "Diff. Test," which presents the Bartlett test statistic.

Summarizing both the evidence on the minimum variance portfolios and the tangency portfolios, it is reasonable to conclude that screening for fossil fuel stocks and excluding them from the investment portfolio has almost no impact on the returns of a globally diversified portfolio of industry indices, although there is weak evidence that including fossil fuel stocks may improve a portfolio's performance.

3.3 Utility and constraining the investment universe

In the above analyses, we examine separately the impact of excluding fossil fuel stocks from the investment universe in terms or return and risk. To study the joint impact on return and risk, we calculate certainty equivalents according to equation (4). This approach also allows us to study the impact of the restriction on higher levels of risk. To provide a better understanding of the impact of excluding fossil fuel stocks on portfolios with different risk levels, we calculate two sets of portfolios using different risk tolerance (RT) coefficients, one using $\mathrm{RT} = 1$ and the other $\mathrm{RT} = 2$. The portfolios based on a $\mathrm{RT} = 1$ are less risky than the tangency portfolio, while the portfolios based on $\mathrm{RT} = 2$ are more risky than the tangency portfolio.

We calculate certainty equivalents based on the out-of-sample average returns and standard deviations of both strategies. The outcomes are presented in Table A.3 of the Appendix. These results are consistent with the previous results in the main analysis. The differences in mean return between the investment universe including all assets and the investment universe excluding fossil fuel stocks ranges between minus 8 basis points and plus 9 basis points, for a risk tolerance coefficient of 1. During the first two subperiods, excluding fossil fuel stocks increases the mean return by 8 basis points, while, in the last period, excluding fossil fuel stocks decreases the mean return by 9 basis points or less for a risk tolerance coefficient of 1. For investors with a higher level of risk tolerance, the differences are larger. The largest difference occurs in the period 1995–2000, when the portfolio excluding fossil fuel stocks outperforms, at a statistically significant level, the unrestricted portfolio by 34 basis points. However, risk, as measured using standard deviation during this period, is also higher than during other periods.

By comparing the difference in the certainty equivalents of portfolios with and without fossil fuels, we arrive at a measure of efficiency gains from excluding fossil fuels. The certainty equivalent gains are presented in Table VII. Panel A shows the results for a risk tolerance coefficient of 1. The restriction on the investment universe results in an average utility loss of 0.05% for the minimum variance portfolio and as a result of the restriction on fossil fuel stocks. Given this same risk tolerance coefficient, the utility loss for the tangency portfolio is, on average, zero, while there is actually a utility gain of 0.03% for the portfolio with risk level RT = 1. Overall, these results show that imposing a restriction on fossil fuel stocks has only a modest impact on utility. The impact is negative for investors with low risk tolerance and positive for investors with high risk tolerance.

Panel B of Table VII shows the results for an investor with a risk tolerance coefficient of 2. Although we observe the same pattern, the differences are greater than in Panel A. The investor experiences a utility loss of, on average, 0.13% for the minimum variance portfolio, and 0.07% for the tangency portfolio, while the restriction results in substantial gains for the portfolios constructed with RT = 2. At the same time, we observe that the pattern of utility gains and losses shows substantial variation over time.

Table VII. Monthly increases in certainty equivalent from restricting the investment universe

This table presents the out-of-sample monthly increases in certainty equivalent for the Minimum Variance Portfolio (MVP), the Tangency Portfolio (TP), and a risky portfolio with risk tolerance (RT) levels of 1 or 2, respectively. Panel A presents the monthly utility gain based on a risk tolerance of 1, while Panel B presents the monthly utility gains measured based on a risk tolerance of 2. The risky portfolio in panel A is constructed using a risk tolerance of 1 and the risky portfolio in panel B is constructed using a risk tolerance of 2.

Panel A: Results for RT = 1

	MVP	TP	Risky portfolio
1980–1985	0.05%	0.07%	0.09%
1985–1990	0.01%	0.04%	0.07%
1990–1995	0.02%	-0.01%	0.00%
1995–2000	-0.24%	-0.06%	0.04%
2000–2005	-0.01%	0.02%	0.03%
2005–2010	-0.03%	0.03%	0.05%
2010–2015	-0.16%	-0.08%	-0.08%
Average	-0.05%	0.00%	0.03%

Panel B: Results for RT = 2

	MVP	TP	Risky portfolio
1980–1985	-0.67%	0.90%	5.37%
1985–1990	-0.32%	-0.90%	2.60%
1990–1995	-1.35%	-1.24%	3.43%
1995–2000	0.64%	-0.18%	-0.62%
2000–2005	-0.04%	0.09%	-0.61%
2005–2010	-0.14%	1.10%	7.55%
2010–2015	0.93%	-0.27%	0.17%
Average	-0.13%	-0.07%	2.56%

3.4 Robustness analysis

Our analysis relies on the use of historical data during a period when the fossil fuel industry served an important role in the economy. The big question is to what extent the parameters used in our analysis will also hold in the future. They will probably change as a result of changes in the future role of fossil fuel in the economy. Whether or not fossil fuel stocks are essentially investments in stranded assets depends on the question of the viability of alternative sources of energy. Proponents of fossil fuel investing may argue that alternative sources of energy will be only available on a limited scale and may become available much later than might be desirable from the perspective of climate protection. They may also argue that even in a world with an abundance of alternative energy sources, oil, gas, and coal may remain important as inputs for the chemical industry.

On the other hand, opponents of fossil fuel stocks in an investment portfolio may follow the stranded assets argument. They may argue that the economic viability of alternative sources of energy will drive out fossil fuels and erode the future profitability of the fossil fuel industry. Although it will be difficult to forecast which reality will materialize, we provide an additional analysis that would enable an investor to get an impression of the impact of each scenario on a portfolio of stocks. For this reason, we consider two specific scenarios.

In the first scenario, we assume that fossil fuels will become even more important as a result of increasing scarcity. We will model this by increasing the beta of fossil fuel stocks with a factor 1.5. As result, the expected monthly return for fossil fuel stocks based on the CAPM specification increases from 0.85% to 1.09%. For the second scenario we consider a decrease in the importance of fossil fuels. We model this by decreasing the beta of fossil fuel stocks with a factor 2/3, which results in a expected monthly return of 0.7%. We compare both scenarios with a baseline scenario using historical expectations based on the full historical sample from 1973 to 2015. For all scenarios, we calculate efficient portfolios using a covariance matrix based on the single index model, using the market portfolio as the index. For each scenario, we calculate the expected return, standard deviation and Sharpe ratios. Since we cannot use our initial methodology of using realized returns as we did in the previous analysis, these results provide expectations given the parameters that we used to estimate the portfolios. Therefore, the analysis provides us with a robustness analysis of the importance of fossil fuel stocks with respect to changes in return expectations.

Table VIII: Scenario analysis

This table presents the expected return, standard deviation and the Sharpe ratio for a portfolio excluding fossil fuel stocks, and for the portfolio based on all stocks based on three scenarios. The base line scenario uses the historical estimates of beta. Scenario 1 is based on a beta that is 1.5 times the historical beta and scenario 2 is based on a beta that is 2/3 times the historical beta for fossil fuel stocks.

E[r]		Excluding fossil fuel	Baseline	Scenario 1	Scenario 2
MV	E[R]	0.664%	0.663%	0.663%	0.634%
	Std	3.416%	3.402%	3.267%	3.214%
	Sharpe	0.082	0.082	0.077	0.078
TP	E[R]	0.889%	0.888%	0.888%	0.884%
	Std	4.583%	4.568%	4.676%	4.537%
	Sharpe	0.111	0.111	0.111	0.111

Table VIII provides the results of this analysis for the minimum variance portfolio and the tangency portfolio. Since the scenarios only differ with respect to the betas of fossil fuel stocks, the outcomes for the portfolios excluding fossil fuel stocks are the same for each scenario. These results are presented in the first column (ie, excluding fossil fuels). The last three columns present the outcomes for the base line scenario, the high fuel stock beta and the low fuel stock beta scenario respectively. Table VIII shows very little variation in the outcomes between the different scenarios in terms of expected return, standard deviation or Sharpe ratios. The biggest difference in return yields a lower expected return of 0.29% for the minimum variance portfolio in the scenario with lower expected returns for fossil fuel stocks and a lower standard deviation of 0.188%. The differences in return and risk for the tangency portfolio are very small, without a noticeable impact on risk and return, resulting in a virtually unchanged Sharpe ratio.

4 Conclusion

If global warming by 2050 is not to exceed 2°C above pre-industrial levels, only a fraction of known fossil fuel reserves should be emitted (Meinshausen et al., 2009). This finding has been used to ask investors to divest from fossil fuel. We investigate the effects of divesting from fossil fuel stocks on the investors' portfolio performance. To this extent, we study the impact of a restriction on the investment universe of a global investor by excluding fossil fuel stocks from her investment portfolio. We create an industry index including fossil fuel stocks only and one excluding fossil fuel stocks. Our analysis of the returns in terms of the Carhart (1997) model shows that fossil fuel stocks do not earn risk-adjusted returns that are statistically different from zero and have significantly higher exposure to systematic risk. This suggests that the fossil fuel investment restriction as such does not seem to harm investment performance.

We also investigate the impact of the fossil fuel restriction on portfolio construction. Here, the main result is that the impact of the restriction is very small for typical investors. Portfolios with the restriction do not systematically differ in terms of risk and return from portfolios without the restriction. For investors with a preference for less risky portfolios, however, the restriction is likely to have a small and negative impact on their utility. For investors with a desire for more risky portfolios, the restriction actually appears to be beneficial. A technical explanation for this result is that for the latter investors, estimation errors are likely to become more important, since the results for these portfolios are driven more by the expected returns of individual industries. As it happens, the average return for stocks in the fossil fuel industry show a decline in average returns, which implies that the portfolios tend to be overweighed in fossil fuels relative to the return realized in the post-formation period.

Given that the impact of the restriction is sometimes positive and sometimes negative, and only statistically significant in a few cases, we conclude that imposing an investment restriction by excluding fossil fuel stocks does not have a material impact on the performance of the minimum variance portfolio and the tangency portfolio. The reason that this restriction does not have a material impact is probably due to the fact that the restriction involves the reduction of the investment universe by less than 10% on average. This is in line with the findings of Bello (2005), who studies mutual funds with self-imposed restrictions on the investment universe based on criteria with respect to socially responsible investing. Bello (2005) finds no difference between the typical returns from funds imposing responsibility screens and funds that do not impose such restrictions.

We point out that we specifically focus on the impact of fossil fuel divestment on financial performance for the investor. However, apart from "voting with your feet," there are several alternative strategies for investors to show their concern over climate change. For example, they can use their shareholder rights to convince management to change course. Or they can invest in renewable and sustainable energy technologies. It is outside the scope of this paper to assess what strategy would be best from a climate change perspective.

Our findings are more or less in line with the conclusion of Griffin et al. (2015), who report a small drop in stock market prices of about 1.5% to 2% for U.S. oil and gas firms. However, our results contrast with Cornell (2015) who reports a major negative impact of divesting from including fossil fuel stocks on the portfolio values of the endowment funds of a sample of U.S. Universities. This difference is probably due to the fact that the portfolios in the study of Cornell (2015) are actually portfolios with below optimal levels of diversification.

A practical limitation of our approach is that we study diversification benefits separately from the context of an already-existing portfolio. Divesting from fossil fuel stocks implies that the investor will incur costs by selling the stocks of firms active in the fossil fuel industry and buying stocks in other industries. Large institutional investors may face additional costs due to the liquidity impact of their trades. However, these liquidity costs can be largely avoided by slowly rebalancing the portfolio towards the new strategy. Other limitations of our approach are the use of a historical perspective to assess the impact of eliminating one asset class from a portfolio. This approach assumes that eliminating an entire asset class from the investment universe will have no impact on the other asset classes. The demand pressures arising from tastes or preferences for specific assets may actually have an impact on expected returns, as suggested in Fama and French (2007). To estimate the impact on investor expectations as a result of a massive change in investor tastes for specific assets on their returns is beyond the scope of this study. Further, one needs to realize that divesting from fossil fuel stocks as such does not guarantee that the 2°C global warming threshold will not be exceeded.

An implication of our research is that the debate should actually focus on the validity of non-financial arguments for including or excluding fossil fuel stocks. Our results do not confirm the conventional wisdom that reducing the number of stocks in a portfolio results in a less-diversified portfolio and a deterioration in portfolio performance. Nevertheless, our results are firmly grounded in modern portfolio theory.

References

Allen, M., Frame, D., Huntingford, C., Jones, C., Lowe, J., Meinshausen, M., Meinshausen, N., 2009. Warming caused by cumulative carbon emissions towards the trillionth tonne. Nature 458 (7242), 1163–1166.

Banerjee, P.S., Doran, J.S., Peterson, D.R., 2007. Implied volatility and future portfolio returns. Journal of Banking and Finance 31, 3183–3199.

Bello, Z.Y., 2005. Socially responsible investing and portfolio diversification. Journal of Financial Research 28, 41–57.

Best, M.J., Grauer, R.R., 1991. On the sensitivity of mean-variance-efficient portfolios to changes in asset means: Some analytical and computational results. Review of Financial Studies 4, 315–342.

Carhart, M.M., 1997. On persistence in mutual fund performance. Journal of Finance 30, 57–82.

Chan, L.K.C., Lakonishok, J., 1999. On portfolio optimization: Forecasting covariances and choosing the risk model. Review of Financial Studies 12, 937–974.

Chopra, V.K. Ziemba, W.T., 1993. The effects of errors in means, variances, and covariances on optimal portfolio choice. Journal of Portfolio Management 19, 6–12.

Cornell, B., 2015. The divestment penalty: Estimating the cost of fossil fuel divestment to select university endowments. Paper for the Independent Petroleum Association of America [http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2655603&download=yes].

Eurosif (2014). European SRI Study 2014. http://www.eurosif.org/semantics/uploads/2014/09/Eurosif-SRI-Study-2014.pdf (accessed: September 10, 2015).

Evans, J.L., Archer, S.H., 1968. Diversification and the reduction of dispersion: An empirical analysis. Journal of Finance 23, 761-767.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 2007. Disagreement, tastes, and asset prices. Journal of Financial Economics 83, 667–689.

Freund, R.A., 1956. The introduction of risk into a programming problem. Econometrica 24, 253-263.

Goyal, A., 2012. Empirical cross-sectional asset pricing: A survey. Financial Markets and Portfolio Management 26, 3–28.

Griffin, P.A., Jaffe, A.M., Lont, D.H., Dominguez-Faus, R., 2015. Science and the stock market: Investors' recognition of unburnable carbon. Energy Economics 52, 1-12.

Hong, H., Kacperczyk, M., 2009. The price of sin: The effect of social norms on markets. Journal of Financial Economics 93, 15–36.

Humphrey, J.E., Tan, D.T., 2014. Does it really hurt to be responsible? Journal of Business Ethics 122, 375–386.

Jorion, P., 1991. Bayesian and CAPM estimators of the means: Implications for portfolio selection. Journal of Banking and Finance 15, 717–727.

Meinshausen, M., Meinshausen, N., Hare, W., Raper, S., Frieler, K., Knutti, R., Frame, D., Allen, M., 2009. Greenhouse-gas emission targets for limiting global warming to 2 degrees C. Nature 458 (7242), 1158–1163.

Renneboog, L., ter Horst, J., Zhang, C., 2008. Socially responsible investments: Institutional aspects, performance and investment behavior. Journal of Banking and Finance 32, 1723–1742.

Sharpe, W.F., 1966. Mutual fund performance. Journal of Business 39, 119–138.

Statman, M., 1987. How many stocks make a diversified portfolio? Journal of Financial and Quantitative Analysis 22, 353–363.

Appendix

Table A.1: Average monthly returns over time

This table presents average monthly returns over individual indices for different subperiods.

	1973–1980	1980–1985	1985–1990	1990–1995	1995–2000	2000–2005	2005–2010	2010–2015
Fossil	1.39%	0.52%	1.65%	0.75%	1.44%	1.19%	0.79%	0.55%
Basic Material	0.90%	0.67%	2.05%	0.52%	0.36%	1.05%	1.47%	0.29%
Industrials	0.75%	1.04%	1.91%	0.52%	1.50%	0.15%	0.61%	1.18%
Consumer Goods	0.43%	1.10%	1.96%	0.37%	0.85%	0.36%	0.74%	1.24%
Health Care	0.28%	1.49%	2.12%	0.99%	1.41%	0.38%	0.28%	1.70%
Consumer Services	0.12%	1.46%	2.00%	0.60%	1.14%	0.07%	0.27%	1.41%
Telecommunications	0.60%	1.76%	1.41%	0.82%	2.05%	-0.75%	0.55%	0.98%
Utilities	0.67%	1.48%	1.74%	0.91%	0.60%	0.81%	0.58%	0.45%
Financials	0.59%	1.58%	2.03%	0.65%	1.01%	0.64%	0.18%	0.97%
Technologies	0.23%	1.47%	1.33%	1.21%	3.33%	-1.17%	0.46%	1.40%
ASEFFI	0.47%	1.30%	1.85%	0.69%	1.44%	-0.01%	0.43%	1.10%
ALL	0.59%	1.17%	1.82%	0.70%	1.43%	0.07%	0.46%	1.05%

Table A.2: Standard deviation on minimum variance portfolios with and without fossil fuel stocks

This table presents in-sample standard deviations from investing in a minimum variance portfolio with and without stocks related to the fossil fuel industry. The monthly standard deviation of the asset returns is presented and the Bartlett test statistic of equal variances. *, ** and *** denote significance at 10%, 5%, and 1% probability level, respectively.

Period	All assets	Excl. fossil fuels	Bartlett test (chi^2)
1980–1985	3.46%	3.49%	0.0041
1985–1990	2.46%	2.47%	0.0006
1990–1995	3.13%	3.33%	0.2334
1995–2000	2.59%	2.69%	0.0850
2000–2005	2.22%	2.22%	0.0001
2005–2010	2.65%	2.67%	0.0018
2010–2015	2.54%	2.69%	0.2012

Table A.3: Performance of portfolios with higher risk levels

This table presents average returns and standard deviations from investing in an optimal portfolio for an investor with risk tolerance of 1 and 2, respectively. The table presents out-of-sample results as well as the test statistic of a paired t-test of the difference in mean returns. The monthly standard deviation of returns is presented between parentheses, as is the Bartlett test statistic of equal variances. *, ** and *** denote significance at 10%, 5%, or 1% probability level, respectively.

	Risk tolerance 1			*Risk tolerance 2*		
Period	All assets	Excl. fossil fuels	Diff. test t-test (chi^2)	All assets	Excl. fossil fuels	Diff. test t-test (chi^2)
1980–1985	0.54%	0.64%	-0.74	-0.65%	-0.50%	-0.74
	10.15%	9.77%	0.083	21.66%	21.11%	0.038
1985–1990	2.13%	2.24%	-0.43	2.64%	-1.36%	-0.43
	8.57%	8.53%	0.002	16.45%	18.11%	0.015
1990–1995	-0.05%	-0.11%	0.26	-1.21%	-2.78%	0.26
	10.19%	9.55%	0.245	19.69%	26.41%	0.408
1995–2000	1.24%	1.44%	-1.96**	1.01%	-1.14%	-1.96**
	8.74%	8.77%	0.001	18.93%	11.70%	0.000
2000–2005	13.65%	-1.18%	-0.48	-2.97%	0.00%	-0.48
	13.65%	13.71%	0.001	26.27%	0.00%	0.002
2005–2010	0.86%	0.98%	-0.65	1.08%	21.11%	-0.65
	11.03%	10.52%	0.129	19.83%	0.00%	0.247
2010–2015	0.24%	0.25%	-1.37	-1.33%	18.11%	-1.37
	6.01%	6.03%	0.000	11.45%	11.70%	0.027

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