Complex risks and challenges for investors: On the risk of liquidity and carbon dependent assets

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Contents

1 Introduction

1.1 Motivation

During the last twenty years the mutual fund industry has experienced enormous growth. While in 1996 assets under management in US domestic equity funds totaled to only $1.44 trillion, this number meanwhile has increased almost fivefold to over $6.41 trillion in 2016.[1]

This increasing popularity among investors seems surprising as academics have repeatedly questioned the superiority of actively managed funds over passive investment strategies like ETFs. Starting with Jensen (1968), the general consensus is that the average fund manager portfolio tends to underperform passive benchmarks, especially after expenses and fees are deducted. Gruber (1996) analyzes a period between 1985 and 1994 and quantifies this underperformance as about 65 basis points per year. Carhart (1997) as well observes a negative correlation between active trading and a fund's benchmark-adjusted net return to investors. All of these studies draw a rather negative picture of the stock picking skill of mutual fund managers and conclude that investors are better off investing in low-expense index funds.

However lately, this harsh judgment has been at least partly mitigated by several more recent studies, which argue that the factor models that had been applied in previous studies, might not have been powerful enough to detect stock picking skill. They suggest a different approach and examine the performance of the individual stocks in the portfolio. These studies, e.g. Daniel et al (1997), Chen et al. (2000), and Wermers (2000), analyze the performance of the single trades in the portfolio and contradict prior findings as they find that these trades outperform their benchmark, at least before any expenses are deducted. Thus,

[1] cf. Investment Company Institute 2017.

these more recent studies provide a more encouraging picture of mutual fund managers. However, while these studies find that the average mutual fund delivers an outperformance of gross returns, but still no outperformance of net fees, they cannot fully explain the popularity of actively managed mutual funds. For this reason, it remains interesting to ask, why investors keep trusting the ability of mutual fund managers to invest their money.

One possible explanation might be that every investor is likely to think that he has picked a fund that will outperform the average fund. This confidence might be the reason why investors are not concerned that studies have not detected an outperformance of funds on average. The desire to find the most skilled and most talented manager that can outperform the benchmark, is understandable and is worth being investigated. Therefore, research that focuses on metrics which are able to detect the above-average fund manager is widespread in literature. This dissertation contributes to this stream of literature as well. Since Chordia (1996), Edelen (1999), Nanda et al. (2000) and Alexander et al. (2007) it is well known that not every trade a manager makes is voluntary and based on valuation. Studies about stock picking skill are therefore negatively biased as a certain amount of trades are solely done to provide liquidity for investors. For this reason, this dissertation presents an approach to distinguish liquidity-motivated and valuation-motivated trades. This enables investors to retain a more precise measure of stock picking skill, which can be used to improve the forecasts of future fund performance.

A further possible explanation for the popularity of actively managed funds might be that investors think fund managers can better anticipate and prepare for major social and macro-economic upheavals. To contribute to this question, this dissertation investigates how fund managers handle and deal with one of the next future challenges for investors - the carbon risk. Carbon risk is a company's risk of decreasing future cashflows as the emission of carbon becomes more expensive and regulated to meet the climate goals set forth in Paris

(2015). For this reason, it is interesting to investigate whether fund managers are good at anticipating this type of challenge, in which case it would justify the investment in their actively managed funds.

The dissertation is divided into two parts and structured as follows. Chapter II presents the innovative approach which enables researchers and investors to measure stock picking skill more precisely than in existing literature. This helps investors to choose actively managed funds that are more likely to beat their benchmark. Chapter III and chapter IV are about carbon risk. While chapter III provides an overview of the distribution of carbon risk among the different investor categories like hedge funds, mutual funds and governments etc., chapter IV explicitly investigates how mutual fund managers deal with it. The last chapter V sums up the results of this dissertation, shows some limitations and gives an understanding of research ideas that might be relevant in the future based on the insights provided in this dissertation. The rest of chapter I ends with the following brief summaries of the research articles provided in this dissertation.

1.2 Overview of papers included

Paper title	Co-authors	Journal	Date
Mutual fund stock picking skill: New evidence from valuation- versus liquidity-motivated trading	Martin Rohleder Dominik Schulte Marco Wilkens	Journal of Financial Management (B), forthcoming	2017
Who holds the carbon risk bomb? An overview of potential risk takers	Stefan Trück Julia Scherer	WP, University of Augsburg	2017
About carbon risk exposure in mutual funds - New evidence from mutual fund holdings	-	WP, University of Augsburg	2017

1.2.1 Article I - Mutual fund stock picking skill: New evidence from valuation- versus liquidity-motivated trading

If one wants to fairly assess the stock picking skill of a fund manager, it is important to consider the fact that not every trade of a manager is executed based on valuation. A considerable portion of trades are forced and flow-induced and thus only performed to provide liquidity as investors redeem their money or to work off new inflow even if there is no new investment idea. As such trades are triggered by external factors, they should not be included in the assessment of a manager's stock picking skill.

To deal with this problem and to provide a more precise measure of stock picking skill, we propose in the first article of this dissertation a novel Trade Motivation Matrix (TMM) that allows differentiating mutual funds' valuation-motivated (VM) and liquidity-motivated (LM) trades on single trade level. Analyzing over 4.7 million trades of a sample of 3,802 actively managed U.S. domestic equity funds between 2003 and 2012, we find that valuation-motivated trades significantly outperform liquidity-motivated trades and thus confirm and quantify the adverse effect of flow. Additionally, we show that valuation-motivated trades do outperform the market and thus provide clear evidence that managers have stock picking skill on average. Besides we find that this more precise measure can be used to pick stocks and funds that are more likely to outperform in the future.

1.2.2 Article II - Who holds the carbon risk bomb? An overview of potential risk takers

The 21st climate conference in Paris (2015) set itself the goal to keep the increase of global average temperature well below 2°C in comparison to pre-industrial levels. To reach this goal, regulatory requirements will tighten and companies must pay for allowances to emit carbon emissions. Companies that have high carbon emissions within their value chain are likely to face decreasing future cash flows. However, this will not only pose a challenge for the companies involved. Investors with exposure to such companies will be equally affected.

This study aims to thoroughly investigate how the ownership of carbon intensive stocks is distributed among the different investor types. To identify high-polluting stocks we provide a classification of stocks based on three different categories related to industry sectors, carbon footprints, and environmental scores. We use data from 2000 to 2015 to compare the attitude of different investor types towards investments in carbon intensive stocks. We find that institutional investors, hedge funds, individuals, investment advisors and mutual funds tend to hold less carbon polluting firms in their investment portfolios. Interestingly, in contrast, government agencies seem to have a higher exposure to carbon intensive stocks in their portfolios and typically also hold a high percentage of the total market capitalization of these firms. Thus, this study builds the foundation for a better understanding of the exposure to carbon intensive stocks for various investor types but also illustrates which parties have the ability to influence the environmental behavior of CO_2-emitting firms, e.g. by exhibiting voting rights.

1.2.3 Article III - About carbon risk exposure in mutual funds - New evidence from mutual fund holdings

The next article deals with carbon risk as well. However, this study explicitly focuses on actively managed US domestic open-end mutual equity funds. The study is the first to link the implication and meaning of carbon risk to the behavior of mutual fund managers. Investigating fund holdings of 702 mutual funds between 2007 and 2014, the article deals with the following research questions: How do stocks from carbon intensive industries differ from non-carbon intensive industries? How do the worst emitters within a carbon intensive industry differ from the lowest emitters? How did the fund manager’s carbon risk exposure vary over time? What fraction of market capitalization of carbon risk stocks is owned by the mutual fund industry? Besides, it identifies funds that are exposed to particular high carbon risk and funds that already have started to divest. Furthermore, the study investigates the relation between carbon risk and a manager's performance and risk. Here the study reveals that funds that structure their portfolio towards low emitter stocks generate more risk-adjusted performance and have less risk. Thus, this study helps investors and policy makers to get a better understanding of the opportunities and challenges for the mutual fund universe.

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2 Article I: Mutual fund stock picking skill: New evidence from valuation- versus liquidity-motivated trading

Martin Rohleder, Dominik Schulte, Janik Syryca, and Marco Wilkens

Abstract. We propose a novel Trade Motivation Matrix (TMM) that allows differentiating mutual funds' valuation-motivated (VM) and liquidity-motivated (LM) trades on single trade level. It thus enables analyses of stock picking skill on three levels: trade, stock and fund. On trade level, we find significant outperformance of VM buys and significant underperformance of VM sells indicating manager stock picking skills, especially during illiquid market periods. VM trades outperform LM trades confirming negative performance effects due to flow risk, especially when market liquidity is low. On stock level, VM trades capture size, value, liquidity and market risk premiums. LM trades are related to stock momentum. VM trading in specific stocks explains future stock returns. On fund level, higher VM trading is related to higher future fund alpha, especially during illiquid times.

JEL Classification G11, G20, G23

Keywords Mutual fund trading, valuation, liquidity, skill, flow risk, wisdom of crowds

2.1 Introduction

When assessing the stock picking skill of professional investors such as mutual funds it is of vital importance to distinguish valuation-motivated (VM) trades from liquidity-motivated (LM) trades. Only trades based on valuations allow judging managers' stock picking skill while forced trades based on fund holders' liquidity demands may be thought of as noise trading and do not represent skill (e.g., Edelen, 1999). In this paper, we propose a novel approach, the Trade Motivation Matrix (TMM), which is the first to differentiate between single (holdings-based) VM and LM trades. With the TMM it is therefore possible to run analyses on three different levels: individual trades, individual stocks and individual funds, whereas previous research remains on an aggregated trade level (e.g., Alexander et al., 2007). Thus, our model enables more precise measurement of stock picking skill and of the costs of liquidity provision to fund investors due to flow risk (e.g., Rakowski, 2010), a very relevant matter that the SEC recently turned their attention to.[2] Moreover, it allows investigating which stocks are traded based on VM and LM and whether funds' VM trading is related to future stock and fund performance.

Applying the TMM to a sample of over 4.7 million trades results in several contributions. First, on trade level, we contribute to the literature on stock picking skill by finding that VM buys have on average higher returns and VM sells have significantly lower returns than their respective benchmarks, consistent with stock picking skill. By conducting this analysis during different market liquidity regimes, we additionally contribute to the literature on market efficiency showing that VM trading decisions are more successful during times of low market liquidity. Lower market efficiency during such times (e.g., Chordia et al., 2008, 2011) increases pricing heterogeneity and consequentially creates more opportunities

[2] https://www.sec.gov/news/pressrelease/2015-201.html.

for VM trading (e.g., Sadka and Scherbina, 2007; Dong et al., 2014; Pástor et al., 2015b). It is also consistent with the finding that manager skill is time-varying and depends on the economic conditions (e.g., Kacperzyk et al., 2014).

Second, we are the first to consider different benchmark universes to measure trade performance. Specifically, we use all *CRSP* stocks to measure trade performance relative to stocks with similar characteristics (e.g., Daniel et al., 1997, henceforth DGTW). However, for sells this assumes unrestricted short selling, which is not allowed by the SEC and therefore seldom done (e.g., Chen et al., 2013). Therefore, we alternatively use the respective fund's holdings at the time of the trade to measure if trades improve portfolio quality. With this distinction, we are the first to show specifically that funds' VM trades overall improve portfolio quality while LM trades do not.

Third, we contribute to the literature on flow risk as the TMM facilitates a more detailed analysis of funds' LM trading compared to previous research. Contrasting VM and LM trades clearly shows that funds are forced to make disadvantageous trading decisions if investors' and managers' investment strategies are not aligned. This represents strong empirical evidence that mutual fund performance suffers significantly from investor-induced flow risk. It also indicates that previous trade-based approaches to measuring skill are biased by LM trading. In analyses during different liquidity regimes, we show that this adverse effect of investor flows also worsens during illiquid times.

Fourth, on stock level, we contribute to the general understanding of fund manager's trading preferences. Specifically, the TMM allows detailed analyses of the characteristics of stocks traded by mutual fund managers based on VM and LM. We show that with their VM buys fund managers prefer smaller over bigger companies and value over growth stocks, i.e. fund managers chasing size and value premiums (e.g., Fama and French, 1993). Moreover, if funds have a clear valuation, they are prepared to accept higher market risk exposure as well as higher illiquidity risk, even during times of low market liquidity. If managers are forced to trade without clear valuations (LM buys and sells), they prefer to engage in momentum trading (e.g., Jegadeesh and Titman, 1993; Carhart, 1997), sell very liquid stocks and reduce risk with their LM sells.

Fifth, we find that the collective VM trading decisions of mutual funds in single stocks, i.e. the ratio of VM buys (sells) and all buys (sells) in a specific stock during a certain quarter, represents wisdom of the fund manager crowd (e.g., Chalmers et al., 2013; Jiang et al., 2014; Sias et al., 2016). Specifically, we show that stock-specific VM buying ratios are significantly related to positive future stock performance over horizons at least up to 12 months, while VM selling ratios are significantly related to negative future stock performance.

Sixth, on fund level, we contribute to the literature on differences between mutual funds by analyzing the fund characteristics associated with a higher degree of VM trading, i.e. the ratio of VM trades to all trades by a fund during a certain quarter. We show that inflows and higher cash increase buying discretion, while outflows and low cash decrease buying discretion (e.g., Simutin, 2014). Moreover, younger and smaller funds have higher buying discretion, consistent with the prior literature on diseconomies of scale (e.g., Chen et al., 2004; Berk and Green, 2004; Pollet and Wilson, 2008; Pastor et al., 2015). Fee structures such as expense ratios and load fees have no effect on the degree of VM trading. Turnover as a measure of overall trading is positively related to VM trading, consistent with Pastor et al. (2016).

Seventh, we show that a higher degree of VM trading is significantly related to funds' future Carhart (1997) alpha and thus translates directly into benefits for investors, especially during illiquid market periods. It also confirms our previous finding that stock picking skill is valuable primarily in periods with low market efficiency and high valuation uncertainty.

Our work is thus related to various popular streams of mutual fund research. The flow-performance relation and the potentially adverse effect of investor flows on the discretion of open-end mutual fund managers, i.e. flow risk, was first empirically investigated by Edelen (1999). He finds that the general underperformance of actively managed funds compared to passive alternatives can partly be explained by flow-induced LM trading. Dubofsky (2010) as well as Fulkerson and Riley (2015) confirm the strong relation between investor gross flows and aggregated mutual fund trading during later periods.[3] Therefore, the SEC recently turned their attention to flow risk and mutual fund liquidity, considering new regulation to protect buy-and-hold investors from negative effects of LM trading caused by purchasing and redeeming investors (e.g., Hanouna et al, 2015). Within this literature, the TMM builds particularly on the study by Pollet and Wilson (2008) who investigate mutual fund behavior in reaction to growth. They argue that mutual funds may react to investor flows by means of two alternative strategies: scaling and diversification. On the one hand, a manager without new investment ideas or valuations uses investor flows to scale her existing holdings, thereby maintaining her old portfolio allocation. On the other hand, a manager possessing new investment ideas and valuations may utilize investor flows to alter her allocation and to invest in new stocks.

The TMM is also related to the fund trading literature which attempts to assess manager performance directly from the success of buying and selling decisions. The first to use such an approach are Grinblatt and Titman (1993) who show a significantly positive covariance between mutual fund holdings-weight changes and subsequent stock returns based on quarterly holdings.[4] Chen et al. (2000) use quarterly holdings and DGTW benchmark-

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[3] Further empirical studies confirming the existence of flow risk are, e.g., Coval and Staffort (2007), Frino et al. (2009), Cherkes et al. (2009), Rakowski (2010) and Rohleder et al. (2015).

[4] There are studies using actual mutual fund trades from the Abel Noser Corp. ANCERNO database (e.g., Puckett and Yan, 2011; Anand et al., 2012; Eisele et al. 2015; Busse et al., 2015). However, this database

adjusted stock returns and find that stocks bought by mutual funds significantly outperform stocks sold.[5] Using the same approach, Dyakov et al. (2015) report that the informational advantage leading to this pattern turned negative after 2001. However, none of these studies consider trade motivation and thereby potentially underestimate skill. Moreover, these studies do not consider different benchmark universes for trades and thus cannot assess the trades' effects on portfolio quality.

Alexander et al. (2007) are the first to infer trade motivation from the direction and size of trades and flows. Aggregating single trades to portfolios, they show that a higher probability of VM trading results in higher trade performance. However, our methodology is distinctively different to theirs and fixes some of its limitations. We therefore explicitly discuss the differences between the methods as well as advantages of the TMM in section 2.2.3.[6]

Another approach to consider trading motivation is provided by Da et al. (2011) who derive fund level motivation from the traded stocks' probability of informed trading (PIN). They find that mutual funds trading high PIN stocks outperform funds trading low PIN stocks. However, as they use aggregated trades their analyses remain on the portfolio level. In contrast, by assigning motivation directly to each single trade, the TMM allows additional analyses on single trades and single stocks.

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includes only 8% of total trading volume in US stocks and 10% of total trading volume by US domestic equity funds. Thus, this data is very valuable for specific types of studies like those studying the transaction costs of mutual funds (Busse et al., 2015), but inadequate for large scale studies on the mutual fund universe.

[5] Further studies using holdings-based mutual fund trades include Pinnuck (2003), Baker et al. (2010), Cullen et al. (2010), Brown et al. (2014) and Wei et al. (2014).

[6] Another approach to considering trade motivation is provided by Da et al. (2011) who derive fund level motivation from the traded stocks' probability of informed trading (PIN, Easley et al., 1996).

We proceed as follows: Section 2.2 introduces the Trade Motivation Matrix (TMM) in detail and explains how we measure trade performance against different benchmark universes. Additionally it distinguishes our model from previous approaches. Section 2.3 describes the data. Section 2.4 presents our empirical analysis on trade level, Section 2.5 on stock level and Section 2.6 on fund level. Section 2.7 presents robustness checks and further tests. Section 2.8 concludes.

2.2 Methodology

2.2.1 The Trade Motivation Matrix (TMM)

To assign each single mutual fund trade to one of the four categories of the TMM, we combine two intuitive measures: trade direction and weight change.

Figure 1: The Trade Motivation Matrix (TMM)

	Weight change in the direction of the trade	*No weight change in the direction of the trade*
Buy	**VM buy**	**LM buy**
Sell	**VM sell**	**LM sell**

As shown in Figure 1, we first categorize trades into buys and sells.[7] Following the related literature (e.g., Chen et al., 2000; Pinnuk, 2003; ACG; Dyakov et al., 2016), fund *i*'s trade in stock $j = 1, \dots N$ between quarterly holdings reports in q–1 and q is given by Eq. (1):

$$trade_{i,j,q} = shares_{i,j,q} - shares_{i,j,q-1}, \quad (1)$$

[7] In addition to VM and LM, funds may also trade due to tax motives (e.g., Bergstresser and Poterba, 2002) or for window dressing (e.g., Agarwal et al., 2014). We address those in section 7.3.

where $shares_{i,j,q}$ is the split and corporate action-adjusted number of shares that fund i holds in stock j at time q. A positive trade represents a buy while a negative trade represents a sell.

Then, we consider the weight change of stock j in fund i caused by a trade (e.g., Grinblatt and Titman, 1993). Specifically, we define weight change as the difference between the actual portfolio weight of stock j at time q and the hypothetical benchmark weight of stock j that would have occurred if the fund had not traded between times q–1 and q except for direct reinvestment of dividends.[8] The assumption underlying the hypothetical benchmark portfolio is that each holdings report represents the fund manager's efficient portfolio allocation and is based on her current valuations. If these do not change, the allocation should not change. Thus, the TMM should only consider weight changes if the manager's valuations are updated. Further, we include cash as a separate asset N+1 to control for funds managing investor flows using cash as a buffer (e.g., Simutin 2010 and 2014). Weight change is thus calculated as shown in Eq. (2) where $P_{j,q}$ is the price of stock j at time q and $r_{j,q}^{total}$ is the total return of stock j from q–1 to q including dividends.[9]

$$weight\ change_{i,j,q} = \frac{shares_{i,j,q}P_{j,q}}{\sum_{j=1}^{N+1} shares_{i,j,q}P_{j,q}} - \frac{shares_{i,j,q-1}P_{j,q-1}\left(1+r_{j,q}^{total}\right)}{\sum_{j=1}^{N+1} shares_{i,j,q-1}P_{j,q-1}\left(1+r_{j,q}^{total}\right)}, \qquad (2)$$

[8] The majority of dividends and other distributions obtained by mutual funds is usually directly reinvested into the fund. If the manager invests the dividends directly into the same stocks, this does not present a new investment idea and is thus identified by the TMM as an LM buy. If the manager invests the dividend into a different stock, the TMM identifies this as a VM buy. In unreported robustness tests, we abstract from the assumption, obtaining economically similar results.

[9] The intuitive way to consider direct reinvestment of dividends in the hypothetical benchmark portfolio is to adjust the number of shares held by a fund in the following way: $\frac{shares_{i,j,q-1}(1+D_{j,t}/P_{j,t}^{exD})P_{j,q}}{\sum_{j=1}^{N} shares_{i,j,q-1}(1+D_{j,t}/P_{j,t}^{exD})P_{j,q}}$. Here $D_{j,t}$ is the dollar amount of dividends paid per stock j at time t. This amount is instantaneously reinvested into shares of stock j at its price ex dividends $P_{j,t}^{exD}$. However, instead of considering the exact timing of t, we employ the total return conveniently provided by CRSP.

If a fund manager possesses a positive (negative) valuation regarding a stock, she will increase (decrease) its weight in her portfolio. Hence, valuation-motivated buys (VM buy) are trades where a buy in stock *j* leads to an increase of its portfolio weight. Similarly, valuation-motivated sells (VM sell) are trades where a sell transaction in stock *j* leads to a decrease in its portfolio weight. Both VM trade categories can occur during times of inflow and outflow.

$$\text{VM buy}_{i,j,q} = 1 \quad \text{if} \quad \textit{trade}_{i,j,q} > 0 \quad \& \quad \textit{weight change}_{i,j,q} > 0 \tag{3a}$$

$$\text{VM sell}_{i,j,q} = 1 \quad \text{if} \quad \textit{trade}_{i,j,q} < 0 \quad \& \quad \textit{weight change}_{i,j,q} < 0 \tag{3b}$$

Conversely, if the fund manager has no valuation, Pollet and Wilson (2008) argue that inflowing money is allocated by simply upscaling existing portfolio holdings. Since these trades lack a clear investment idea we consider them to be liquidity-motivated buys (LM buy). The same holds for disproportionately small buys in times of inflow, resulting in a decrease of stock *j*'s portfolio weight.[10]

$$\text{LM buy}_{i,j,q} = 1 \quad \text{if} \quad \textit{trade}_{i,j,q} > 0 \quad \& \quad \textit{weight change}_{i,j,q} \leq 0 \tag{3c}$$

Similarly, we argue that sell transactions that simply downscale existing portfolio holdings in times of outflows without considerably changing portfolio weights lack clear valuation-motivation and are thus defined as liquidity-motivated sells (LM sell). The same holds for sells in times of outflow that are so small in comparison to other sells that they result in an increase of the portfolio weight of stock *j*.

$$\text{LM sell}_{i,j,q} = 1 \quad \text{if} \quad \textit{trade}_{i,j,q} < 0 \quad \& \quad \textit{weight change}_{i,j,q} \geq 0 \tag{3d}$$

[10] To test against misclassifications due to imperfect scaling that can arise because only integer numbers of stocks can be sold or bought, we provide some robustness tests in section 7.2.

2.2.2 Measuring trade performance against different benchmark universes

To measure the stock picking performance of mutual fund trades, we use an approach similar to Chen et al. (2000) and calculate the stocks' cumulative monthly characteristics-based benchmark-adjusted return in the spirit of the DGTW "characteristics selectivity (CS)" measure. Specifically, we measure the cumulative DGTW-adjusted return of the trade, assuming the respective stocks are held over the subsequent 1, 3, 6 and 12 months.

Further, we consider different benchmark universes for different trade categories. As in the classic DGTW approach, we (i) use all *CRSP* stocks assuming that funds may freely choose from this benchmark universe. A positive buy trade performance thus indicates that managers buy stocks which subsequently outperform other stocks with similar stock characteristics with regard to firm size, book-to-market ratio and momentum. Similarly, a negative sell trade indicates that managers buy stocks which subsequently underperform other stocks with similar characteristics. Both are consistent with stock superior stock picking skill. However, for sells such an approach assumes unrestricted short selling. Taking into account that short selling is strictly regulated by the Investment Company Act of 1940 and thus seldom used by mutual funds (e.g., Chen et al., 2013), we use as an alternative universe (ii) only the stocks held by the fund at the time of the trade. Specifically, we measure performance of single trades against the equal-weighted DGTW benchmark-adjusted returns of all stocks held by the respective fund at time q–1. A positive buy performance thus indicates that the stock outperforms the average stock held by the fund and thus improves portfolio quality. A negative sell performance similarly indicates that a manager sells a stock that subsequently underperforms the average stock she keeps in the portfolio, also consistent with improved portfolio quality. In addition, we present results where we measure all trades against their respective relevant universes, i.e. buys against all *CRSP* stocks and sells against the funds' holdings.

2.2.3 Advantages of the TMM over previous approaches

The approach which is closest to ours is developed by Alexander, Cici and Gibson (2007), hereafter ACG. They derive degrees of VM trading from the direction and size of trades and flows. Aggregating single trades to portfolios, they show that a higher probability of VM trading results in higher trade performance. Specifically, in each period, they aggregate the trade volume of all buys (sells) of a fund and the fund's experienced flow to build a BF (SF) portfolio. Then, motivation is assigned to BFs (SFs) by sorting them into quintiles within the fund over time. While this approach is also very intuitive, it has some differences and disadvantages in comparison to the TMM.

The first difference is that ACG requires a fund to have a very long reporting history to provide reliable results. To be able to have all BF and SF quintiles occupied, a minimum of six consecutive holdings reports per fund are required (5+1 starting point). Having all quintiles balanced (to reduce noise) even requires integer multiples of this number. In contrast, TMM can be applied for every two consecutive reported fund quarters. As a result, the lower data requirement of the TMM reduces incubation and survivorship bias, allows more timely analysis and is the only alternative to assess funds that are either new or from countries with low reporting availability.

The second important difference is that sorting BFs and SFs into quintiles following ACG assumes that each fund makes as many VM trades (BF1 and SF1) as it makes LM trades (BF5 and SF5). However, this is very unlikely the case due to differential skill in the cross-section of mutual funds (Fama and French, 2010) and because funds face differential levels of flow risk (Rakowski, 2010; Rohleder et al., 2017). For example, consider a fund with a skilled manager who is excellent at flow risk management or faces overall low flow risk. It is safe to assume that this fund performs more VM trades than LM trades. The TMM adequately considers this difference. According to ACG, this fund performs 20% VM trades and 20%

LM trades.[11] Consider another fund which is unskilled and faces high flow risk. According to the TMM, this fund may have many LM trades and only few VM trades. According to ACG, it performs 20% VM trades and 20% LM trades. Thus, by construction, the ACG may mechanically lead to false classifications. While we concede that the TMM may make some false classifications, too, we argue that they are not mechanical. In sections 7.1 and 7.2, we run robustness tests controlling for potential misclassifications by the TMM.

Moreover, once assigned to, e.g., the BF1 quintile, all of the fund's buys during that period are considered VM, while the TMM allows for VM and LM buys of the fund within the same period which may also be the more realistic case. Furthermore, the TMM allows for VM buys and VM sells during the same period. Conversely, with ACG, which conditions on the flow direction, a simultaneous occurrence of VM buys and VM sells is very unlikely by definition. However, especially during phases of high overall pricing heterogeneity we consider it very realistic that funds have over- and under-valuations of different stocks at the same time.

In addition, due to the sorting approach, the ACG method may lead to unstable classifications of BFs and SFs into the quintiles when the sample period is extended, e.g. by incorporating new holdings reports, or shortened, e.g. for sub-period analyses. Conversely, the TMM results in a stable classification of trades independent of the sample period. Thus, we consider our TMM the more reliable method.

Furthermore, the direct assignment of motivation to single trades by the TMM guarantees that 100% of the trades made by the sample funds over the sample period are considered. Conversely, ACG base their interpretations only on the extreme portfolios and thus ignore >90% of the trades. While one may argue that looking only at the extremes

[11] 4% each if we take into account that ACG additionally sort by trade size within the BFs and base all interpretations on the corner portfolios of the resulting 5x5-matrix.

reduces noise in motivation assignment, it does not allow for any conclusions regarding the average skill of mutual fund managers or regarding the profit and loss resulting from average mutual fund trading with different motivations. With the TMM this is possible.

As a consequence of the direct assignment of motivation to single trades, the TMM facilitates further analyses on fund level as in Section 6 by utilizing, e.g., in each period the ratio of VM trades to overall trades. Here, a higher ratio may proxy for more investment ideas, higher skill or lower exposure to flow risk. Moreover, the variation of the ratio over time may be used to link fund behavior to macro influences such as market illiquidity and other economic or market crises. With the ACG method, similar analyses are not possible because for each fund in the cross-section the ratio of VM trades to overall trades is 20% by definition (respectively 4% when combined with trade size). Over time within the fund, the ratio may only be 1 or 0, and the assignment is dependent on the sample period also aggravating such analyses.

The ACG puts more focus on a trade's absolute trade volume while TMM attaches more attention to the trade's weight change. This can result in different categorizations. Consider a fund manager who experiences high outflows and scales down the existing holdings to maintain her old allocation. Unless the fund holds an equal-weighted portfolio, some trades have a larger dollar volume than others. According to the TMM, all trades are clearly categorized as LM sells. According to ACG, larger trades will be assigned a higher probability of VM than smaller trades, despite both having no impact on portfolio composition. Overall, we therefore think that the TMM fixes some of the limitations of the ACG approach and offers further applications.

2.3 Data

Fund characteristics and information on mutual fund holdings are from the *CRSP* Survivorship-Bias-Free Mutual Fund Database. As fund data from *CRSP* are mostly at the share class level, we aggregate them to fund level by value weighting with the respective total net assets (TNA) of each share class. Only TNA is exempt from this procedure, as it is defined as the sum of individual share class TNA. We only include funds that are listed as domestic equity style or cap based funds (EDY or EDC). We follow Amihud and Goyenko (2013) and exclude index funds by eliminating those with names containing words like index, 'S&P', 'Dow', 'WILSHIRE', 'RUSSELL'. We further exclude funds before they first surpass the threshold of 5 million in TNA as in Fama and French (2010). In line with Kacpercyk et al. (2008), we delete fund periods with less than 10 reported holdings as this is an indication of bad reporting quality.

Information on stock returns and characteristics are obtained from the *CRSP* Stock Database and from Compustat. We include only equity holdings with share codes 10 and 11 and delete all stocks with a price below $1. Following ACG, we account for stock splits when computing quarterly fund trades by using the cumulative adjustment factors from the *CRSP* stock return file. The final sample consists of 79,814 quarterly[12] fund observations for 3,802 active U.S. domestic equity funds in the period from 2003 to 2012.

To measure the performance of stocks bought and sold by mutual funds, we use the returns of the DGTW characteristics-based benchmark portfolios developed by Daniel et al.

[12] During our sample period, mutual funds are obliged to report portfolio holdings to the SEC on a quarterly basis. Empirically however, actual reporting frequencies deviate from strictly quarterly reports, even within individual funds, and may be as high as monthly or as low as semiannually in few cases. As the average time between reporting frequency is close to 3 months, we simplify by referring to reporting periods as quarterly.

(1997) and kindly provided by Russ Wermers.[13] Further, we use the market liquidity factor from Pastor and Stambaugh (2003) which is kindly provided on Lubos Pastor's homepage.[14] To measure fund performance, we use the Fama/French/Carhart factors from Kenneth R. French's data library.[15]

Table I: Mutual fund characteristics

This table presents pooled summary statistics of fund characteristics for 3,802 actively managed US domestic equity funds in the period 2003-2012.

	Mean	Median	Standard Deviation
Net excess return (% p.a.)	9.36	16.44	16.66
Net Carhart alpha (% p.a.)	-1.6879	-1.2136	4.7937
TNA ($mil)	1,159.9	200.3	4,853.9
Expense ratio (% TNA, p.a.)	1.20	1.17	0.45
Max. front load (%)	2.96	3.77	2.43
Max. rear load (%)	1.10	1.00	1.11
Turnover ratio (% TNA, p.a.)	90.73	67.00	110.49
Cash (% TNA)	3.19	1.79	6.16
Age (years)	12.9	10.3	10.8
Net flow (% TNA)	0.66	-0.74	9.89
Abs. net flow (% TNA)	5.42	2.56	8.31

Table I displays descriptive statistics of the fund characteristics in our sample of 3,802 funds. Overall, the statistics are in line with previous mutual fund research. Especially important for our analysis are the cash positions of funds, as these may serve as a potential liquidity buffer. On average, funds hold 3.19% of their TNA in cash, however there is substantial variation in the cross section indicated by the standard deviation of 6.16%. This is consistent with statistics in Simutin (2014) and Hanouna et al. (2015). Even more importantly,

[13] We thank Russ Wermers for providing the data. For details on benchmark construction, please refer to Daniel et al. (1997) and Wermers (2004). http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.html.

[14] We thank Lubos Pastor for providing the data. For details on factor construction, please refer to Pastor and Stambough (2003). http://faculty.chicagobooth.edu/lubos.pastor/research/.

[15] We thank Kenneth R. French for providing the data. For details on benchmark construction, please refer to Fama and French (1993) and http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

the funds in our sample experience substantial investor flows with absolute monthly net percentage flows of about 5.42% of TNA on average. Over the period 2003-2012, the funds experience monthly net inflows of 0.66% of TNA on average, while the median represents an outflow of -0.74% of TNA, indicating that a few funds experienced extreme inflows.

Table II: Fund stock holdings

This table provides year-end summary statistics on stock holdings of 3,802 actively managed US domestic equity funds in the period 2003-2011. It contains statistics on all stocks with available returns over the following 12 months.

Year	Funds	Stocks held by all funds	Mean number of stocks per fund and quarter		
			Held	Bought	Sold
2003	1,747	3,935	82	58	26
2004	1,658	3,806	108	96	54
2005	1,711	3,657	114	91	50
2006	1,731	3,631	83	105	54
2007	2,020	3,474	86	123	61
2008	2,326	3,129	125	110	78
2009	2,232	3,274	180	108	72
2010	2,876	3,152	199	90	69
2011	2,876	3,122	221	96	76
Average	2,131	3,464	133	98	60
Total	3,802	5,246	3,368,497	2,458,616	2,277,088

Table II provides year-end summary statistics on the funds’ stock holdings. Overall, funds report holdings in 5,246 distinct stocks over our sample period, which makes up a substantial portion of all stocks available in the *CRSP* stock database.

Table III: TMM sorting

This table displays numbers (N) and fractions (%) of trades sorted into valuation-motivated buys (VM buys), liquidity-motivated buys (LM buys), valuation-motivated sells (VM sells) and liquidity-motivated sells (LM sells) according to the Trade Motivation Matrix (TMM).

	N	in %
All Trades	4,735,704	100.00
Buys	2,458,616	51.92
VM buys	1,710,743	36.12
LM buys	747,873	15.79
Sells	2,277,088	48.08
VM sells	2,111,743	44.59
LM Sells	165,345	3.49

Table III illustrates the number of trades assigned to the different categories according to the TMM. Our sample includes more than 4.7 million trades. 52% of these trades are buys and 48% are sells. 36% of all trades are VM buys, 16% are LM buys, 45% are VM sells and only 3.5% of all trades are LM sells.[16] As a rough comparison, Edelen (1999, Table 3) reports that 29% of the buying volume and 27% of the selling volume was liquidity-motivated during the late 1980s, documenting high flow risk. This effect seems to decrease over time as Dubofsky (2010, Table 3) reports that 13.2% of the buying volume and 7.5% of the selling volume was liquidity-motivated in the late 1990s and early 2000s. Thus, our fractions of 16% LM buys and 3.5% LM sells for 2003 to 2012 are in line with the related literature. Involuntary noise trading is thus more prevalent in buys than in sells, as the number of LM buys is nearly five times the number of LM sells.

2.4 Trade level analysis

2.4.1 Mutual fund stock picking skill and the costs of liquidity provision

In this section, we analyze the performance of single trades regarding the existence of stock picking skill and flow risk. Whether mutual fund managers are skilled should show most prominently in their VM trading activities. Hence, we argue that if managers exhibit significant stock picking skills, their VM buys should subsequently outperform and their VM sells should underperform. If, on the other hand, mutual fund managers possess no stock picking skill, there should be no significant outperformance of VM buys and no significant underperformance of VM sells.

Panel A of Table IV presents pooled single trade performance for the overall period against the *CRSP* universe, which is the standard approach in the literature (e.g., DGTW;

[16] The number of LM sells is very small and may stem from imperfect downscaling by mutual funds in an attempt to reduce transaction costs. We consider such gray cases in robustness section 8.1.

Table IV: Pooled single trade performance - Overall period

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6- and 12-months periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003-2012. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

		Cumulative DGTW-adjusted performance (in %) over the next			
	N	1 month	3 months	6 months	12 months
Panel A. Benchmarked against the *CRSP* stock universe - *unlimited short selling*					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM sells	2,111,743	0.029***	0.088***	0.148***	0.194***
VM buys – VM sells		0.148***	0.152***	0.204***	0.168***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.228***	0.358***	0.599***	0.621***
VM buys – LM buys		0.132***	0.146***	0.126***	-0.030
VM sells – LM sells		-0.199***	-0.270***	-0.451***	-0.427***
Panel B. Benchmarked against the holdings - *no short selling*					
VM buys	1,710,743	0.055***	0.013	-0.026	-0.153***
VM sells	2,111,743	-0.077***	-0.105***	-0.144***	-0.178***
VM buys – VM sells		0.131***	0.118***	0.118***	0.025
LM buys	747,873	-0.023**	-0.038**	-0.011	0.014
LM sells	165,345	0.001	0.034	-0.053	-0.143*
VM buys – LM buys		0.078***	0.051**	-0.014	-0.167***
VM sells – LM sells		-0.077***	-0.139***	-0.091	-0.035
Panel C. Benchmarked against the relevant universe (buys: *CRSP*, sells: holdings)					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM sells	2,111,743	-0.077***	-0.105***	-0.144***	-0.178***
VM buys – VM sells		0.254***	0.344***	0.496***	0.540***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.001	0.034	-0.053	-0.143*
VM buys – LM buys		0.132***	0.146***	0.126***	-0.030
VM sells – LM sells		-0.077***	-0.139***	-0.091	-0.035

Chen et al., 2000). On the one hand, the cumulative performance of VM buys is positive and statistically significant over all tested investment horizons (e.g., 0.240% over the first 3 months), indicating that the stocks bought based on VM subsequently outperform other stocks with similar stock characteristics, consistent with stock picking skill. On the other hand, the performance of VM sells is also positive and statistically significant against the *CRSP* universe indicating that funds sell stocks which subsequently outperform other stocks with similar stock characteristics, counterintuitive to stock picking skill.

However, the *CRSP* universe is not relevant for sells due to short selling restrictions (e.g., Chen et al., 2013). Therefore, Panel B shows trade performance against the respective fund's holdings. Here, VMB buys are positive and significant only over the first month indicating that VM buys slightly increase portfolio quality in the short run. More interestingly, the cumulative performance of VM sells is negative and statistically significant over all tested horizons (e.g., -0.105% over the first 3 months), indicating that the stocks sold based on VM subsequently underperform the stocks held. Hence, funds sell the right stocks on average revealing that selling-skill is a valuable contributor to fund performance which has widely been ignored in the literature so far.

Panel C considers all *CRSP* stocks for buys and the holdings for sells. The difference between VM buys and VM sells, the "value added" compared to the relevant benchmark universe, is thus positive and statistically significant over all tested horizons (e.g., 0.344% over the first 3 months), Overall, all our findings regarding VM trades are consistent with the existence of stock picking skill in active mutual fund management.

Next, we analyze the existence of flow risk based on single trades. In this context, Edelen (1999) argues that a fund manager holding a - from her perspective - optimal portfolio is moved away from this allocation by investor flows. To regain an optimal portfolio, the fund is forced to trade. In a standard expectations model, this investor flow is interpreted as exogenous supply noise trading which faces expected losses in comparison to informed trading. In the TMM model, this should show in significant outperformance of VM buys over LM buys and in significantly higher avoided losses through VM sells compared to LM sells.

In Panel A of Table IV, the cumulative performance of LM buys is positive and statistically significant over all tested horizons (e.g., 0.094% over the first 3 months), indicating that even with less discretion, managers may make good decisions on average compared to the overall market. However, VM buys still significantly outperform LM buys, leading to a positive and statistically significant difference at least over the first 6 months (e.g., 0.146% over the first 3 months) and indicating that the restricted trading discretion caused by investor flows is costly. After 12 months, we see no significant difference between VM buys and LM buys. In Panel B, measured against the respective fund's holdings, the performance of LM buys is negative over all tested horizons and statistically significant over the first 3 months, indicating that liquidity-motivated buys - despite showing positive performance in Panel A - cannot improve portfolio quality on average and thus hurt performance.

LM sells in Panel A are positive, high and statistically significant over all tested horizons (e.g., 0.358% over the first 3 months). We interpret this so that funds selling without a clear valuation consider the relative liquidity of the stocks, thereby generating "losses" to informed traders. Moreover, it is consistent with our previous assumption that mutual funds hold a positive selection of the *CRSP* universe on average. However, the difference between VM sells and LM sells are very large and significant (e.g., -0.270% over the next 3 months) indicating high illiquidity costs caused by flow risk.

Contrasting VM sells and LM sells using the more relevant holdings benchmark universe in Panel B, the cumulative performance of LM sells is insignificant over the first 6 months before turning slightly negative after 12 months indicating that LM sells cannot improve portfolio quality. The difference between VM sells and LM sells is negative and statistically significant over the first 3 months and then becomes insignificant indicating that higher discretion leads to better selling decisions and that flow-induced LM selling is costly. The results in Panel C using the respective relevant benchmarks confirm the previous panels and show that both LM buys and LM sells are detrimental to performance at least in the short run, consistent with the existence of flow risk.

To investigate why outperformance of VM buys over LM buys turns negative after 12 months, we additionally analyze the average duration of a trade's motivation, i.e. the time period until the same stock is traded with a different motivation. Table V shows that for all trades the average motivation duration is well below the hypothetical 12-month holding period in Table IV. This indicates that the result in Table IV that LM buys outperform VM buys over the 12-month horizon is of minor relevance compared to 3-month and 6-month holding periods, for which we find strong evidence of flow risk.

Table V: Motivation duration of TMM trade categories

This table shows the average and median motivation duration of trades categorized by the TMM of US domestic equity mutual funds during the period from 2003 to 2012. We define the motivation duration of a trade as the time period until the same stock is traded by the fund in another direction or in the same direction with a different motivation.

	Motivation duration (months)			Motivation duration (months) in illiquid times		
	N	Average	Median	N	Average	Median
VMB	1,659,887	5.85	3.00	373,105	6.62	4.00
LMB	737,687	4.94	3.00	160,613	5.94	3.00
VMS	2,020,433	6.43	4.00	449,869	7.06	5.00
LMS	160,843	3.02	2.00	30,267	3.76	3.00

2.4.2 Skill in illiquid market periods, liquidity costs and market efficiency

In this section, we perform additional analyses which focus on the interplay between stock picking skill, flow risk and market illiquidity. Regarding stock picking skill in illiquid times, prior research (e.g., Sadka and Scherbina, 2007; Chordia et al., 2008, 2011; Dong et al., 2014; Pastor et al., 2015) indicates that market efficiency is lower and pricing uncertainty is higher during periods of low market liquidity. Thus, these periods frequently present more opportunities for VM trades and the potential gains from such trades should be higher. In the TMM, this should show in higher returns to VM buys, in higher avoided losses through VM sells and ultimately in a wider performance spread between VM buys and VM sells compared to non-illiquid times. Moreover, during illiquid times, the mispricing may be more fundamental and thus provide long-term opportunities to informed traders, while mispricing during non-illiquid times may present only short-term opportunities. In the TMM this should show in clearer patterns over longer holding periods during illiquid market periods.

Table VI presents pooled single trade performance separately for illiquid and non-illiquid periods.[17] Panel A presents results for illiquid times, defined as the bottom 10% of the Pastor and Stambaugh (2003) aggregated market liquidity factor, against the holdings benchmark.[18] With slightly over 1 million trades, about 22.5% of all trades occur during the 10% illiquid times, indicating higher trading activity during such phases consistent with, e.g., Pastor et al. (2016). The performance of VM buys is positive over all tested periods and significant in 3 of 4 cases (e.g., 0.373% over the first 12 months). This clearly indicates that VM buys improve portfolio quality. The performance of VM sells is negative and statistically significant for all tested periods (e.g., -0.735% over the first 12 months), so that the difference between VM buys and VM sells is statistically significant and economically relevant with, e.g., 1.107% over the first 12 months. It also confirms that VM sells improve portfolio quality more strongly than VM buys.

Panel B shows results against the respective relevant benchmarks for buys and sells. The results are even stronger with a performance of VM buys of 2.007% over the first 12 months and the difference to VM sells, the "value added", increasing to 2.742%. Overall these finding confirm our expectation that stock picking skill is more valuable during times of low market efficiency. Moreover, the results support our assumption that this informational advantage allows outperformance over longer periods as all figures are statistically and economically significant over all tested horizons.

[17] In TableVI, we drop the Panel using all CRSP stocks as a benchmark for sells as it is economically irrelevant due to short selling restrictions.

[18] For robustness, we also test a 20% Pastor and Stambaugh (2003) cutoff to identify illiquid periods, for economic contractions following the definition of the NBER, and stock market crises following Ben-David et al. (2012). The results are economically similar and available upon request.

Table VI: Pooled single trade performance - Illiquid vs. non-illiquid market periods

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6- and 12-months periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003-2012. Non-illiquid (Illiquid) market periods are defined as periods with Pastor and Stambaugh's (2003) aggregated market liquidity factor above (below) the 10%-percentile. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

		Cumulative DGTW-adjusted performance (in %) over the next			
	N	1 month	3 months	6 months	12 months
Panel A. Illiquid market periods (Bottom 10%), benchmarked against holdings					
VM buys	387,368	0.091***	0.049	0.188***	0.373***
VM sells	479,154	-0.149***	-0.202***	-0.453***	-0.735***
VM buys – VM sells		0.240***	0.251***	0.641***	1.107***
LM buys	165,761	-0.039	-0.032	-0.030	-0.198**
LM sells	31,991	-0.001	0.041	-0.252	-0.322
VM buys – LM buys		0.130***	0.081	0.218***	0.571***
VM sells – LM sells		-0.148*	-0.243**	-0.201	-0.413*
Panel B. Illiquid market periods (Bottom 10%), benchmarked against relevant universe					
VM buys	387,368	0.476***	0.739***	1.462***	2.007***
VM sells	479,154	-0.149***	-0.202***	-0.453***	-0.735***
VM buys – VM sells		0.625***	0.941***	1.915***	2.742***
LM buys	165,761	0.217***	0.495***	0.906***	0.725***
LM sells	31,991	-0.001	0.041	-0.252	-0.322
VM buys – LM buys		0.259***	0.244***	0.556***	1.282***
VM sells – LM sells		-0.148*	-0.243**	-0.201	-0.413*
Panel C. Non-illiquid market periods (Top 90%), benchmarked against holdings					
VM buys	1,323,375	0.044***	0.003	-0.088***	-0.307**
VM sells	1,632,589	-0.056***	-0.076***	-0.053***	-0.014
VM buys – VM sells		0.100**	0.079***	-0.035	-0.293***
LM buys	582,112	-0.019*	-0.039**	-0.006	0.075*
LM sells	133,354	0.001	0.032	-0.005	-0.100
VM buys – LM buys		0.063***	0.042*	-0.083**	-0.382***
VM sells – LM sells		-0.057**	-0.109***	-0.048	0.085
Panel D. Non-illiquid market periods (Top 90%), benchmarked against relevant universe					
VM buys	1,323,375	0.089***	0.094***	0.027	-0.119***
VM sells	1,632,589	-0.056***	-0.076***	-0.053***	-0.014
VM buys – VM sells		0.145***	0.170***	0.080***	-0.105***
LM buys	582,112	-0.004	-0.020	0.032	0.297***
LM sells	133,354	0.001	0.032	-0.005	-0.100
VM buys – LM buys		0.094***	0.114***	-0.005	-0.417***
VM sells – LM sells		-0.057**	-0.109***	-0.048	0.085

Comparing the results for illiquid times with those for non-illiquid times in Panels C (holdings universe) and D (relevant universe) shows that VM buys have positive but rather low returns only over the first 6 months and then turn negative after 12 months. Similarly, VM sells are only slightly negative compared to illiquid times. The value added from VM trading during non-illiquid times is thus comparably low (e.g. Panel D, 0.170% over the first 3 months) and turns negative after 12 months. Clearly therefore, the results for the overall period presented in Table IV are driven by the strong positive VM trading performance during illiquid times. This is also consistent with the efficient markets hypothesis (e.g., Fama, 1970) that during non-illiquid times there exists no informational advantage even for skilled managers, at least not over long horizons.

Regarding the interplay between flow risk and market illiquidity, it should be more costly to provide liquidity to investors while facing illiquidity on the stock market. In the TMM model, this should show in inferior performance of LM trades during illiquid times compared to non-illiquid times. To test this, we first look at LM buys in illiquid times. In Panel A, LM buys show insignificant but slightly negative performance which turns significantly negative after 12 months (-0.198%) and thus cannot improve portfolio quality. Compared to VM buys, LM buys clearly underperform with 0.571% over the first 12 months which represents economically significant liquidity "costs" and confirms increased flow risk. In Panel B, LM buys show positive performance over all tested periods (e.g., 0.725% over the following 12 months) but still clear, significant and economically relevant underperformance compared to VM buys with statistically significant differences of, e.g., 1.282% over the following 12 months.

Similar interpretations apply to LM sells, which are negative but statistically insignificant for most tested periods (e.g., -0.252% over the following 6 months). However, they are significantly less negative compared to VM sells with differences of, e.g., -0.413% over the first 3 months. This supports our assumption that the "costs" of providing liquidity to investors are higher during illiquid times. Interestingly, the liquidity costs from capital inflows (VM buys minus LM buys) are higher and show higher statistical significance than the costs from capital outflows (VM sells minus LM sells). One explanation of this result could be that during illiquid times, those funds that provide liquidity to other market participants (LM sellers) gain a liquidity premium while funds demanding liquidity (LM buyers) pay the premium. This may at least partly offset the disadvantages of LM selling compared to VM selling while increasing the disadvantages of LM buying compared to VM buying.

Finally, looking at the costs of liquidity provision during non-illiquid times (Panels C and D) we see that VM buys outperform LM buys only by a small margin and only for the first 6 months before turning negative. This is also consistent with an efficient market where the disadvantage of low trading discretion is not too harmful after all.

2.5 Stock level analysis

2.5.1 Manager preferences and characteristics of stocks

After showing that mutual funds' VM trades generally outperform their LM trades in the previous section, we now analyze whether the stocks that funds trade due to VM are significantly different from the stocks they trade based on LM. Table VII therefore shows average stock characteristics for the TMM categories during illiquid (Panel A) and non-illiquid times (Panel B). Overall, the table shows clearer patterns during illiquid times, which is consistent with our previous finding that there exist clearer valuations in illiquid markets. Therefore, we concentrate on the respective results in Panel A and comment on the results of non-illiquid times in Panel B only if they follow a different pattern.

As measures for stock liquidity, we use monthly trading volume and the Amihud (2002) illiquidity ratio. With their VM trading, funds tend to buy illiquid stocks and sell non-

Table VII: Average stock characteristics for TMM trade categories

This table reports pooled average characteristics of the stocks traded by 3,802 actively managed US domestic equity funds in the period 2003-2012 sorted according to the Trade Motivation Matrix (TMM). Panel A presents results for illiquid market periods defined as the bottom 10% of the Pastor and Stambaugh (2003) market liquidity measure at the time of the trade. Panel B reports the results for all trades in the remaining periods (top 90%). +Compustat firm characteristics are filtered at the 1% and 99% percentiles to control for extreme outliers. ***, **, * indicate statistical significance of the differences in means at the 1%, 5% and 10% level, respectively.

	N (tsd)	VM buy	VM sell	VM buy – VM sell	LM buy	LM sell	LM buy – LM sell	VM buy – LM buy	VM sell – LM sell
Panel A. Illiquid market periods - Bottom 10%									
Trading volume ($mil p.m.)	1,064	134.500***	139.900***	-5.318***	112.800***	139.800***	-26.940***	21.709***	0.086
Amihud illiquidity ratio	1,064	0.124***	0.052***	0.073***	0.065***	0.031***	0.034***	0.060***	0.020***
Market capitalization ($bil)	1,064	19.409***	22.797***	-3.387***	21.241***	20.470***	0.770***	-1.831***	2.327***
Book-to-market ratio+	810	0.956***	0.844***	0.112***	0.864***	0.872***	-0.008	0.092***	-0.028
Prior 1y DGTW-adj. return (% p.a.)	997	-2.919***	1.825***	-4.743***	2.850***	-11.619***	14.469***	-5.768***	13.444***
CAPM beta	1,064	1.179***	1.121***	0.057***	1.139***	1.159***	-0.021***	0.040***	-0.038***
Return standard deviation (% p.a.)	1,064	3.402***	3.258***	0.144***	3.062***	3.657***	-0.596***	0.341***	-0.399***
Return skewness	1,064	0.114***	0.115***	-0.001	0.117***	0.129***	-0.012***	-0.003	-0.015***
Return kurtosis	1,064	3.379***	3.343***	0.036***	3.343***	3.304***	0.039***	0.037***	0.039***
Short interest (mil)+	620	9.845***	10.098***	-0.253***	9.202***	10.105***	-0.904***	0.644***	-0.007
Price-to-earnings ratio+	491	16.721***	17.656***	-0.934***	17.622***	15.782***	1.840***	-0.901***	1.874***
Price-to-cash flow ratio+	446	12.137***	12.712***	-0.574***	12.629***	11.082***	1.547***	-0.492***	1.630***
Return on equity (% p.a.) +	610	9.898***	11.495***	-1.597***	10.761***	9.668***	1.092***	-0.863***	1.826***
Return on investment (% p.a.) +	611	7.348***	8.479***	-1.131***	7.931***	7.162***	0.769***	-0.583***	1.317***
S&P short-term credit rating+	107	102.575***	102.552***	0.023***	102.562***	102.577***	-0.015	0.013**	-0.025**
S&P long-term credit rating+	281	10.566***	10.458***	0.107***	10.461***	10.348***	0.113***	0.104***	0.111***
Total assets to total equity ratio+	512	3.380***	3.260***	0.120***	3.424***	3.586***	-0.162***	-0.044***	-0.326***
Retained earnings ($bil) +	392	2.266***	2.402***	-0.136***	2.218***	2.414***	-0.196***	0.047*	-0.012

Table VII: continued.

	N (tsd)	VM buy	VM sell	VM buy – VM sell	LM buy	LM sell	LM buy – LM sell	VM buy – LM buy	VM sell – LM sell
Panel B. Non-illiquid market periods - Top 90%									
Trading volume ($mil p.m.)	3,671	119.400***	123.000***	-3.576***	95.939***	132.500***	-36.525***	23.465***	-9.484***
Amihud illiquidity ratio	3,671	0.045***	0.020***	0.025***	0.039***	0.024***	0.015***	0.006	-0.004
Market capitalization ($bil)	3,671	20.831***	23.052***	-2.221***	20.261***	23.562***	-3.301***	0.570***	-0.509***
Book-to-market ratio+	2,939	0.697***	0.631***	0.066***	0.687***	0.659***	0.028**	0.009	-0.028***
Prior 1y DGTW-adj. return (% p.a.)	3,596	22.312***	26.273***	-3.961***	22.022***	20.318***	1.704***	0.289***	5.955***
CAPM beta	3,671	1.190***	1.173***	0.016***	1.154***	1.163***	-0.010***	0.036***	0.010***
Return standard deviation (% p.a.)	3,671	2.211***	2.158***	0.052***	2.050***	2.231***	-0.181***	0.161***	-0.073***
Return skewness	3,671	0.106***	0.118***	-0.011***	0.107***	0.102***	0.004*	0.000	0.015***
Return kurtosis	3,671	3.469***	3.458***	0.011***	3.466***	3.369***	0.097***	0.004***	0.089***
Short interest (mil)+	2,192	9.137***	9.312***	-0.174***	8.173***	9.883***	-1.710***	0.965***	-0.571***
Price-to-earnings ratio+	1,826	18.334***	18.972***	-0.639***	18.743***	17.697***	1.046***	-0.410***	1.275***
Price-to-cash flow ratio+	1,705	13.135***	13.527***	-0.392***	13.345***	12.521***	0.823***	-0.210***	1.005***
Return on equity (% p.a.) +	2,178	12.067***	13.236***	-1.169***	12.285***	13.127***	-0.842***	-0.218***	0.108**
Return on investment (% p.a.) +	2,186	8.827***	9.652***	-0.825***	8.981***	9.420***	-0.439***	-0.155***	0.232***
S&P short-term credit rating+	407	102.594***	102.577***	0.017***	102.592***	102.614***	-0.021***	0.002	-0.037***
S&P long-term credit rating+	1,055	10.685***	10.610***	0.075***	10.661***	10.456***	0.205***	0.024***	0.154***
Total assets to total equity ratio+	1,884	3.331***	3.249***	0.081***	3.406***	3.402***	0.004	-0.075***	-0.153***
Retained earnings ($bil) +	1,711	3.083***	3.231***	-0.148***	2.854***	3.929***	-1.074***	0.229***	-0.698***

illiquid stocks (e.g., Cao et al., 2013, Dong et al., 2014). This difference is most striking in the Amihud illiquidity ratio which is 0.124 for VM buys and 0.052 for VM sells on average. Moreover, VM buys have a distinctly higher illiquidity ratio than LM buys. This is consistent with funds capturing illiquidity premiums during times of low market liquidity if they have a clear valuation regarding the stock. With their LM trading, funds tend to sell highly liquid stocks. Overall, their LM sells have the highest level of liquidity, even in times of low market liquidity, which is consistent with funds reacting to investor outflows by selling off the assets with the lowest liquidity-related transaction costs (e.g., Clarke et al., 2007).

Next, we consider the stock characteristics accounted for by the DGTW benchmarks (Daniel et al., 1997). Regarding market capitalization, funds tend to buy smaller stocks and sell larger ones with their VM trades, consistent with a small cap premium strategy (e.g., Fama and French, 1993). Conversely, with their LM trades, funds buy larger stocks and sell smaller ones. During non-illiquid times (Panel B) we see a similar pattern for VM trades but a reversed one for LM trades, as funds sell larger and buy smaller stocks, as is also consistent with a small cap premium strategy.

Regarding the book-to-market ratio, we observe that funds capture the value premium with their VM trades, as they generally buy stocks with high book-to-market ratios and sell stocks with low ratios. LM trades do not differ in their average book-to-market ratios. Regarding momentum we compute the stocks' prior year's DGTW-adjusted return based on daily returns. With their VM buys, funds buy stocks with moderately negative prior returns which might be an indication of current undervaluation. Similarly, VM sells show moderately positive prior returns, potentially indicating current overvaluation. The clearer pattern, however, can be observed in funds' LM trades, as they buy stocks with prior positive returns and sell stocks with very high negative returns, consistent with a classic momentum strategy (e.g., Jegadeesh and Titman, 1993; Carhart, 1997). Thus, if they have no clear fundamental valuation, funds strongly rely on technical analysis when forced to trade by investors' liquidity needs.

Concerning measures of risk, the market beta is significantly higher for VM buys than for LM buys, suggesting that mutual funds are prepared to take more systematic risk if they have a positive fundamental valuation of a stock. Comparing VM sells with LM sells shows the opposite pattern, suggesting that if funds have no clear valuation, they tend to sell stocks with higher systematic risk exposure. This pattern is also observable but less pronounced for the standard deviation of daily returns to reduce risk. As further risk characteristics, the skewness and kurtosis of returns show no clear patterns between VM and LM trading.

The short interest of the stocks, represented by the number of shares sold short by investors and not yet covered, is generally higher for sells than for buys, consistent with the interpretation as a measure of the market's sentiment regarding the stock (e.g., Lamont and Stein, 2004). For LM trades this pattern is stronger than for VM sells, especially during non-illiquid times. Thus, if funds have no clear valuations and especially during times with low overall investment opportunities, funds tend to follow market sentiment in their LM selling decisions.

Regarding commonly used multiples, the price-to-earnings ratio and the price-to-cash flow ratio show different patterns between VM and LM trades. Specifically, with their VM trades funds buy stocks with lower ratios on average. Such stocks may be considered undervalued and offer each unit of earnings or cash flow at a cheaper price. With their LM buys, on the other hand, funds tend to buy stocks with higher ratios, which may be interpreted as the market having higher growth expectations and positive sentiment regarding these stocks.

Regarding measures of firm's operating profitability, funds tend to buy stocks with lower return on equity (ROE) and with lower return on investment (ROI) and sell stocks with higher measures. This is against the intuition used by Fama and French (2015) in creating the profitability factor RMW which is long in firms with robust profitability and short in firms with weak profitability. The only exception is the pattern of LM trading during illiquid times, when funds buy stocks with higher profitability as they sell, which is consistent with the Fama and French (2015) intuition.

Regarding the credit worthiness of the firms, we see no relevant differences between the S&P short-term or long-term credit ratings. Moreover, we see no relevant differences in the firm's ratio of total assets to total equity which we interpret as the leverage of the firms playing no important role for the trading decisions of mutual funds.

Lastly, we look at the retained earnings of the firms as indicators of past profitability but also of the stocks' tendency to withhold earnings from the investors instead of paying profits out as dividends. While during illiquid times there seem to be no clear tendencies we observe that during non-illiquid times, LM buys are in stocks with low retained earnings and LM sells are in stocks with high retained earnings. This may be explained by the lack of investment ideas and growth expectations so that funds rely on the tendency of firms to at least pay a dividend (e.g., Harris et al., 2015).

Overall, we find that funds tend to display rather different trading patterns with their VM and LM trades. These can be rationalized in many cases with the funds capturing risk premiums and following fundamental valuations with their VM trades versus relying on common multiples, sentiment and technical valuations such as momentum with their LM trades.

2.5.2 Explaining stock performance with collective mutual fund trading - Wisdom of crowds

Considering the findings in the previous sections, we find it reasonable to assume that the collective valuations of all mutual funds may have explanatory power over the future performance of single stocks. In this context, several recent papers analyzing the "wisdom of crowds" in financial markets indicate that the collective trading decisions of mutual fund managers (e.g., Chalmers et al., 2013) and hedge fund managers (Sias et al., 2016) predict future raw and risk-adjusted stock returns. However, these studies do not consider trading motivation.

Therefore, we define two new stock-specific variables based on the TMM: $VMB\ ratio_{j,q}$ is defined as the number of funds buying stock j due to VM during quarterly reporting period q divided by the total number funds buying stock j during q. Similarly, $VMS\ ratio_{j,q}$ is defined as the number of funds selling the stock due to VM divided by the total number funds selling the stock. A higher VMB ratio thus indicates a stronger positive consensus valuation of a stock and a higher VMS ratio indicates a stronger negative consensus valuation of a stock. Thus, our VM ratios reverse the approach by Da et al. (2011), who use the stocks' probability of informed trading (PIN) based on stock characteristics to derive fund level motivation from the funds' trades.

To test our expectation that the VM ratios represent wisdom of the (fund manager) crowd, we run panel regressions for the overall period with stock- and time-fixed effects to explain future stock performance, measured by the DGTW-adjusted returns over up to 12 months going forward, with the stocks' VM ratios controlling for the stock characteristics presented in Table VII[19] following Eq. (4). To ease interpretation, all variables are

[19] We use only those fund characteristics as control variables which have a high number of observations available to retain a high number of observations in our regression analysis.

standardized to mean zero and unit standard deviation. Standard errors are 2-dimensionally clustered by stock and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

$$performance_{i,q+x} = \varphi_0 + \varphi_1 VM\ ratio_{j,q} + \sum_{c=2}^{C} \varphi_c\ stock\ characteristics_{j,c,q} + \eta_{j,q} \quad (4)$$

The results are presented in Table VIII. Panel A reports results for mutual fund VM buying. Univariate (1) as well as multivariate regression results (2) indicate that a higher degree of VM buying is significantly related to positive future DGTW-adjusted stock returns over all tested time horizons. Thus, the collective VM buying decisions of mutual fund managers represent wisdom of the crowd. Moreover, as the pattern can be observed over long horizons, this shows that our finding is not driven by a potential price impact by funds' collective trading.

Similarly, Panel B reports results for mutual fund VM selling. As expected, the coefficients of the VMS ratio are negative and in most cases statistically significant for all tested horizons. Thus, also the collective VM selling decisions of mutual fund managers represent wisdom of the crowd.[20] Further, the coefficients on the stock characteristics indicate that trading volume has an overall negative effect and market beta has a positive effect on DGTW-adjusted stock returns. The fund characteristics explicitly controlled for by the DGTW benchmarks - size, book-to-market ratio and momentum - still have significant effects on DGTW-adjusted returns, similar to findings on fund level by Busse et al. (2016).

[20] Unreported additional panel regressions using future cumulative raw returns as independent variables lead to qualitatively similar results which are available upon request.

Table VIII: Prediction of future stock performance with the stocks' degree of valuation-motivated trading

This table reports panel regressions with stock- and time-fixed effects (within) of future cumulative DGTW-adjusted stock performance with the amount of collective valuation-motivated mutual fund trading in 5,246 common US stocks in the period 2003-2012. VMB ratio (VMS ratio) is the number of VM buying (selling) funds divided by the number of total buying (selling) funds. All independent variables are measured over quarterly reporting period *q* except "Prior 1y DGTW-adjusted return" which is measured over year *y*-1. P-values are given in parentheses. All variables are standardized to mean zero and unit standard deviation. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by stock and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

	Cumulative DGTW-adjusted performance over the next							
	1 month		3 months		6 months		12 months	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A. Collective VM mutual fund buying								
VMB ratio	0.0073**	0.0065*	0.0120***	0.0110***	0.0100***	0.0089**	0.0163***	0.0149***
	(0.04)	(0.05)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Trading volume		-0.0046*		-0.0054		-0.0080		-0.0141***
		(0.09)		(0.24)		(0.13)		(0.01)
Amihud illiquidity ratio		0.0039		-0.0006		0.0068		0.0059
		(0.21)		(0.90)		(0.16)		(0.32)
Market capitalization		-0.0242***		-0.0412***		-0.0550***		-0.0739***
		(0.00)		(0.00)		(0.00)		(0.00)
Book-to-market ratio		-0.0116**		-0.0154**		-0.0142*		-0.0100
		(0.04)		(0.04)		(0.08)		(0.19)
Prior 1y DGTW adjusted return		-0.0460***		-0.0795***		-0.1116***		-0.1424***
		(0.00)		(0.00)		(0.00)		(0.00)
Market beta		0.0269*		0.0213		0.0197		0.0216*
		(0.08)		(0.12)		(0.13)		(0.07)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.03
N	154,565	154,565	154,565	154,565	154,565	154,565	154,565	154,565

Table VIII *continued*.

	Cumulative DGTW-adjusted performance over the next							
	1 month		3 months		6 months		12 months	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel B. Collective VM mutual fund selling								
VMS ratio	-0.0072*	-0.0053	-0.0092**	-0.0062*	-0.0107***	-0.0067**	-0.0099***	-0.0049
	(0.07)	(0.16)	(0.02)	(0.09)	(0.00)	(0.03)	(0.01)	(0.13)
Trading volume		-0.0042*		-0.0042		-0.0070		-0.0132***
		(0.09)		(0.32)		(0.16)		(0.01)
Amihud illiquidity ratio		0.0072		0.0093*		0.0194**		0.0183*
		(0.29)		(0.08)		(0.05)		(0.10)
Market capitalization		-0.0233***		-0.0390***		-0.0525***		-0.0713***
		(0.00)		(0.00)		(0.00)		(0.00)
Book-to-market ratio		-0.0068		-0.0139**		-0.0126*		-0.0090
		(0.14)		(0.02)		(0.08)		(0.25)
Prior 1y DGTW adj. return		-0.0500***		-0.0849***		-0.1168***		-0.1495***
		(0.00)		(0.00)		(0.00)		(0.00)
Market beta		0.0334**		0.0290**		0.0287**		0.0299**
		(0.05)		(0.05)		(0.05)		(0.02)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.03
N	143,143	143,143	143,143	143,143	143,143	143,143	143,143	143,143

2.6 Fund level analysis

2.6.1 Determinants of mutual funds' extent of VM trading

This section analyzes which fund characteristics are associated with discretionary trading. Hence, similar to our stock level analysis, we define three fund-specific variables based on the TMM: $VM\ ratio_{i,q}$ is defined as the number of VM trades of fund i during quarterly reporting period q divided by the number of fund i's total trades during q. Similarly, $VMB\ ratio_{i,q}$ ($VMS\ ratio_{i,q}$) is defined as the number of VM buys (sells) divided by the total number of buys (sells).[21] To determine which fund characteristics are associated with a higher degree of VM trading, Table IX shows the results of panel regression (5) with fund- and time-fixed effects (within) of the VM ratios on the fund characteristics reported in Table I. To ease interpretation, all variables are standardized to mean zero and unit standard deviation. Standard errors are 2-dimensionally clustered by fund and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

$$VM\ ratio_{i,q} = \varphi_0 + \sum_{c=1}^{C} \varphi_c\ fund\ characteristics_{i,c,q} + \eta_{i,q}. \tag{5}$$

As our previous findings on the value of funds' VM trading are more pronounced during illiquid market periods, Panels A and B report results separately for the different liquidity regimes. The first overall impression is that fund characteristics explain VM trading quite well with R^2 of 18% overall and of 32% for VM buying. However, the R^2 for VM selling is only 2%, possibly due to the low overall number of LM sells compared to LM buys documented in Table III..

[21] In unreported tests, we use similar VM ratios based on trading (buying/selling) volume. The results are economically similar and available upon request.

Table IX: Determinants of extent of valuation-motivated mutual fund trading

This table reports panel regressions with fund- and time-fixed effects (within) of the extent of valuation-motivated mutual fund trading for 3,802 actively managed US domestic equity funds in the period 2003-2012. VM ratio is the number of VM trades divided by the number of total trades per fund in quarterly reporting period *q*, VMB ratio (VMS ratio) is the number of VM buys (sells) divided by the number of total buys (sells). Alpha is the intercept from the Carhart (1997) 4-factor model calculated using daily net returns. All dependent and independent variables are measured over quarterly reporting period *q* except $Alpha_{q-1}$ and VM $ratio_{q-1}$ which are lagged one reporting period. P-values are given in parentheses. All variables are standardized to mean zero and unit standard deviation. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are 2-dimensionally clustered by fund and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

	VM ratio			VMB ratio			VMS ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A. Illiquid market periods - Bottom 10%									
Net flow	-0.4142***	-0.4144***	-0.4180***	-0.5555***	-0.5532***	-0.5673***	0.1370***	0.1348***	0.1403***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cash	-0.0317**	-0.0307**	-0.0290**	-0.0502***	-0.0469***	-0.0481***	0.0427***	0.0398***	0.0436***
	(0.02)	(0.03)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log-Size	-0.0110	-0.0083	-0.0103	-0.0242**	-0.0224*	-0.0233*	0.0008	0.0040	0.0109
	(0.46)	(0.58)	(0.53)	(0.04)	(0.08)	(0.06)	(0.96)	(0.83)	(0.54)
Age	-0.0115	-0.0127	-0.0143	0.0275***	0.0273**	0.0212*	-0.0574***	-0.0591***	-0.0620***
	(0.33)	(0.34)	(0.26)	(0.01)	(0.02)	(0.07)	(0.00)	(0.00)	(0.00)
Expense ratio	-0.0090	-0.0079	-0.0094	-0.0108	-0.0096	-0.0113	-0.0042	-0.0036	-0.0061
	(0.45)	(0.51)	(0.51)	(0.38)	(0.44)	(0.43)	(0.74)	(0.78)	(0.62)
Front load	0.0005	0.0036	-0.0027	0.0107	0.0147	0.0080	-0.0073	-0.0084	-0.0109
	(0.98)	(0.84)	(0.88)	(0.58)	(0.45)	(0.70)	(0.56)	(0.49)	(0.37)
Rear load	-0.0181	-0.0222	-0.0189	-0.0111	-0.0162	-0.0134	-0.0058	-0.0046	-0.0089
	(0.30)	(0.20)	(0.29)	(0.54)	(0.39)	(0.45)	(0.65)	(0.68)	(0.50)
Turnover ratio	0.0098	0.0111	0.0045	0.0184**	0.0174**	0.0153	-0.0014	0.0005	-0.0020
	(0.43)	(0.35)	(0.74)	(0.03)	(0.05)	(0.12)	(0.88)	(0.96)	(0.84)
$Alpha_{q-1}$		0.0007			0.0072			-0.0102	
		(0.95)			(0.56)			(0.42)	
VM $ratio_{q-1}$			-0.0167			0.0061			-0.0535
			(0.53)			(0.81)			(0.29)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.18	0.18	0.18	0.32	0.33	0.32	0.02	0.02	0.03
N	5,785	5,467	5,486	5,583	5,277	5,170	5,646	5,334	5,248

Table IX *continued*.

	VM ratio			VMB ratio			VMS ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel B. Non-illiquid market periods - Top 90%									
Net flow	-0.4520***	-0.4537***	-0.4220***	-0.5508***	-0.5522***	-0.5134***	0.1405***	0.1405***	0.1440***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cash	-0.0199***	-0.0204***	-0.0146**	-0.0313***	-0.0318***	-0.0209***	0.0292***	0.0284***	0.0271***
	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log-Size	-0.0233**	-0.0245***	-0.0129	-0.0414***	-0.0428***	-0.0259***	0.0392***	0.0388***	0.0377***
	(0.01)	(0.01)	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.0223***	0.0219***	0.0156***	0.0279***	0.0273***	0.0187***	-0.0116**	-0.0113**	-0.0115**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)	(0.04)	(0.03)
Expense ratio	-0.0012	-0.0013	0.0007	-0.0153**	-0.0159**	-0.0114*	0.0152**	0.0163**	0.0139*
	(0.87)	(0.86)	(0.92)	(0.05)	(0.04)	(0.07)	(0.04)	(0.03)	(0.06)
Front load	0.0098	0.0091	0.0121*	0.0161**	0.0150**	0.0190***	-0.0086*	-0.0094*	-0.0093*
	(0.17)	(0.21)	(0.06)	(0.02)	(0.03)	(0.00)	(0.09)	(0.07)	(0.07)
Rear load	0.0045	0.0043	0.0047	-0.0054	-0.0051	-0.0055	0.0065	0.0067	0.0070
	(0.58)	(0.59)	(0.51)	(0.52)	(0.54)	(0.46)	(0.36)	(0.34)	(0.31)
Turnover ratio	0.0123*	0.0128*	0.0088	0.0004	0.0014	0.0001	0.0214***	0.0210**	0.0219***
	(0.07)	(0.06)	(0.14)	(0.95)	(0.82)	(0.98)	(0.01)	(0.01)	(0.00)
Alpha$_{q\text{-}1}$		-0.0018			-0.0059			0.0021	
		(0.78)			(0.37)			(0.72)	
VM ratio$_{q\text{-}1}$			0.1469***			0.1711***			0.0376***
			(0.00)			(0.00)			(0.01)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.21	0.21	0.23	0.31	0.31	0.34	0.02	0.02	0.02
N	35,072	34,623	33,661	33,565	33,143	31,421	33,703	33,275	31,511

As expected, investor flows are negatively related to the degree of VM trading at all times. Specifically, higher net inflows are associated with a significantly lower degree of discretionary buying. Conversely, higher net inflows are positively associated with significantly higher discretionary selling. This is consistent with previous studies showing that mutual funds face flow risk (e.g., Edelen, 1999; Rakowski, 2010; Rohleder et al., 2015). The same applies to higher cash holdings which are negatively related to VM buying and positively related to VM selling at all times. This is in accordance with the related literature (e.g., Simutin, 2014) and indicates that holding cash can be an efficient buffer against flow risk.[22]

Fund size, measured by the natural logarithm of TNA, is negatively related to the degree of VM trading, especially to VM buying for which the coefficients are significant. Comparing different liquidity regimes, the relation is especially prevalent during non-illiquid times. This is consistent with diseconomies of scale in general (e.g., Chen et al., 2004; Pastor et al., 2015) and especially with the findings in Pollet and Wilson (2008) that larger funds hold more different assets than smaller funds and thus may have greater difficulties generating new investment ideas. This leads to a tendency of larger funds towards scaling instead of diversification. In illiquid times, however, these difficulties are less severe due to lower market efficiency and more opportunities of VM trading. Moreover, when explaining VM selling, size shows positive coefficients during non-illiquid times, which may also be consistent with larger funds holding more different assets and thus having a larger selling universe to choose from − once again assuming that short sales are scarcely used by mutual funds (e.g., Chen et al., 2013).

[22] In unreported tests, we confirm the findings in this paragraph by conducting trade level analyses analogue to Table IV where we distinguish trades occurring when funds have (i) high vs. low absolute flows and (ii) high vs. low cash holdings. The results are available upon request.

Fund age is positively related to VM buying and negatively related to VM selling. The former result may be explained by older funds having more mature and sophisticated structures and overall experience. Moreover, more successful managers may get promoted to older and thus more prestigious funds (e.g., Kempf and Rünzi, 2008; Evans, 2009). The negative relation with selling discretion, however, may indicate that selling-skill is not equally recognized as buying-skill when it comes to promoting fund managers.

Concerning mutual fund fee structures, the coefficients of expense ratio, front load and rear load are unrelated to VM trading during both liquidity regimes. A possible explanation is that many mutual funds recently stopped charging front loads to become more attractive to increasingly well-informed and fee-sensitive investors (e.g., Barber et al., 2005).

In terms of the overall trading behavior of funds, the turnover ratio is positively related to VM buying in illiquid times and with VM selling in non-illiquid times. This is in accordance with findings by Pastor et al. (2016), who argue that abnormal turnover may proxy for a higher degree of valuations and new investment ideas, especially during times with high valuation uncertainty.

Finally, we also include past performance in our panel regressions (2) to control for endogeneity. However, the coefficients are insignificant during illiquid and non-illiquid times so that there is no endogeneity in our results. Moreover, we include lagged VM ratio in our panel regressions (3) to control for persistence in discretionary trading. While there is no significant effect during illiquid times, the results for non-illiquid times show significantly positive coefficients, so that the trading discretion of funds is persistent in such periods.

2.6.2 Explaining fund performance with the extent of VM trading

The findings in previous sections indicate that managers generally possess stock picking skill and that collective VM trading represents wisdom of the (fund manager) crowd. These findings may be in contrast to the majority of mutual fund studies beginning with Jensen (1968) which consistently show that funds deliver negative risk-adjusted performance to investors. Thus it remains questionable whether the skill we find on trade and stock level actually translates into investor benefits via higher fund performance. However, following Pastor et al. (2016) we argue that VM trading may have a direct effect on performance rather than a cross-sectional one.

Therefore, Table X shows the results of panel regressions (Eq. 6) with fund- and time-fixed effects of future investor performance $alpha_{i,q+1}$, measured by applying the Carhart (1997) 4-factor model on daily fund net returns during quarter q+1, on the VM ratios defined in subsection 6.1 and controlling for the fund characteristics reported in Table I. To ease interpretation, all variables are standardized to mean zero and unit standard deviation. Standard errors are 2-dimensionally clustered according to fund and reporting period, following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.[23]

$$alpha_{i,q+1} = \varphi_0 + \varphi_1 VM\ ratio_{i,q} + \sum_{c=2}^{C} \varphi_c\, fund\ characteristics_{i,c,q} + \eta_{i,q} \qquad (6)$$

The results for the univariate panel regressions (1) in Panel A for illiquid times show significantly positive coefficients for all three VM ratios. Thus, a higher degree of trading discretion during illiquid market periods is significantly related to higher investor performance in the following quarter. This is in line with the observation that under crisis conditions, the overall pricing heterogeneity creates an environment in which managers more easily identify over- and underpriced stocks and discipline themselves more strongly in both their buying and selling decision (e.g., Jin and Taffler, 2016).

[23] In unreported tests, we use similar VM ratios based on trading (buying/selling) volume. The results are economically the same but statistical significance is a bit lower.

Table X: Predicting future fund performance by extent of valuation-motivated mutual funds trading

This table reports panel regressions with fund- and time-fixed effects (within) of future risk-adjusted performance $Alpha_{q+1}$ by the extent of valuation-motivated mutual fund trading for 3,802 actively managed US domestic equity funds in the period 2003-2012. VM ratio is the number of VM trades divided by the number of total trades per fund during reporting period *q*, VMB ratio (VMS ratio) is the number of VM buys (sells) divided by the number of total buys (sells). Alpha is the intercept from the Carhart (1997) 4-factor model calculated using daily net returns. All independent variables are measured over quarterly reporting period *q*. P-Values are given in parentheses. All variables are standardized to mean zero and unit standard deviation. ***, **, * indicate statistical significance on the 1%, 5%, and 10% level, respectively. Standard errors are clustered by fund and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

	$Alpha_{q+1}$ explained by VM ratio			$Alpha_{q+1}$ explained by VMB ratio			$Alpha_{q+1}$ explained by VMS ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A. Illiquid market periods - Bottom 10%									
VM ratio	0.0407***	0.0393***	0.0326**	0.0261*	0.0256*	0.0116	0.0296**	0.0292***	0.0338***
	(0.00)	(0.00)	(0.01)	(0.07)	(0.07)	(0.39)	(0.01)	(0.00)	(0.00)
Net flow			-0.0034			-0.0100			-0.0239
			(0.85)			(0.59)			(0.13)
Cash			0.0012			0.0020			0.0008
			(0.93)			(0.89)			(0.96)
Log-Size			-0.1140***			-0.1114***			-0.1133***
			(0.00)			(0.00)			(0.00)
Age			0.0049			0.0047			0.0044
			(0.77)			(0.79)			(0.81)
Expense ratio			-0.0072			-0.0051			-0.0076
			(0.64)			(0.75)			(0.62)
Front load			-0.0266			-0.0262			-0.0230
			(0.20)			(0.20)			(0.30)
Rear load			0.0230			0.0242			0.0207
			(0.12)			(0.11)			(0.20)
Turnover ratio			0.0473**			0.0517***			0.0482**
			(0.01)			(0.01)			(0.02)
Alpha		-0.0931**	-0.0968**		-0.0949**	-0.0984***		-0.0859**	-0.0898**
		(0.02)	(0.01)		(0.01)	(0.01)		(0.03)	(0.02)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.00	0.01	0.03	0.00	0.01	0.03	0.00	0.01	0.02
N	5,434	5,239	5,239	5,246	5,059	5,059	5,306	5,118	5,118

Table X *continued*.

	Alpha$_{q+1}$ explained by VM ratio			Alpha$_{q+1}$ explained by VMB ratio			Alpha$_{q+1}$ explained by VMS ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel B. Non-illiquid market periods - Top 90%									
VM ratio	0.0065	0.0064	-0.0056	0.0135**	0.0128*	-0.0007	-0.0177***	-0.0170***	-0.0132**
	(0.25)	(0.29)	(0.39)	(0.04)	(0.05)	(0.92)	(0.00)	(0.01)	(0.03)
Net flow			-0.0269***			-0.0245***			-0.0227***
			(0.00)			(0.00)			(0.00)
Cash			0.0072			0.0042			0.0099
			(0.37)			(0.61)			(0.24)
Log-Size			-0.0659***			-0.0654***			-0.0677***
			(0.00)			(0.00)			(0.00)
Age			-0.0220***			-0.0220***			-0.0241***
			(0.00)			(0.00)			(0.00)
Expense ratio			0.0051			0.0056			0.0031
			(0.51)			(0.47)			(0.69)
Front load			-0.0128**			-0.0117*			-0.0129**
			(0.04)			(0.05)			(0.03)
Rear load			-0.0037			-0.0033			-0.0024
			(0.59)			(0.63)			(0.73)
Turnover ratio			0.0054			0.0046			0.0044
			(0.46)			(0.52)			(0.54)
Alpha		0.0148	0.0116		0.0139	0.0106		0.0151	0.0117
		(0.37)	(0.48)		(0.40)	(0.52)		(0.36)	(0.48)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01
N	33,238	32,760	32,760	31,838	31,387	31,387	31,956	31,505	31,505

This relation also holds for the inclusion of alpha in specification (2) as a control variable for short-term persistence (e.g., Bollen and Busse, 2004). However, we find significant evidence for short-term reversal during illiquid times, which may be a result of performance chasing (Gruber, 1996). When we include the other fund characteristics as controls in specification (3), the coefficients for overall VM trading and VMS trading remain significantly positive while the positive effect of VM buying on future performance seems to be subsumed by the other fund characteristics. With regard to the fund characteristics, size is negatively related to future performance, consistent with diseconomies of scale (e.g., Chen et al., 2004; Pastor et al., 2015) and turnover is positively related to future performance, consistent with the findings in Pastor et al. (2016).

The results in Panel B for non-illiquid market periods are less pronounced compared to the results for illiquid times. This could be expected from the previous sections, as under non-crisis conditions, there is low pricing heterogeneity which aggravates the identification of over- and underpriced stocks. Consequentially, the coefficients of the overall VM trading ratio on alpha are insignificant. However, VM buying still positively predicts future alpha which is in line with the higher overall buying discipline found by Jin and Taffler (2016).

As for the control variables, higher net flows during non-illiquid times result in significantly lower future performance, consistent with flow risk. Log size and age are negatively related to future performance as in Panel A. Turnover loses its predictive power over performance in non-illiquid times. Finally, there is no significant relation between current and future alpha indicating no performance persistence, consistent with an efficient market (e.g., Fama, 1970).

2.7 Further tests and robustness checks

2.7.1 Considering heavy and light valuation motivation

One of the advantages of the TMM is its limited set of assumptions and hence its intuitiveness and clarity. However, the assignment of single trades to TMM categories may be further enhanced by additionally considering that within all valuation-motivated trades, there might exist different degrees of valuation. Therefore, we consider an extended TMM (eTMM) which further distinguishes VM buys and VM sells into "heavy" and "light."

Figure 2: The Extended Trade Motivation Matrix (eTMM)

	Weight change in the direction of the trade	*No weight change in the direction of the trade*
Buy	**Heavy VM buy** / **Light VM**	**LM buy**
Sell	**Heavy VM sell** / **Light VM sell**	**LM sell**

The first intuitive approach to further differentiate the degree of valuation is based on the magnitude of the weight increase. This makes sense, as one would assume that, e.g., VM buys with high weight increases contain more valuation than VM buys with only small weight increases. For this reason, the first test with the eTMM separates VM trades at the median weight change, i.e. their influence on portfolio allocation. The results are presented in Table XI. They are as expected in that more influential VM buys clearly outperform less influential VM buys for up to 6 months (overall), respectively 12 months (illiquid). Similarly, the mitigated losses from heavy VM sells are higher than those from light VM sells in most cases.

The second test with the eTMM takes into account that in some scenarios a clear assignment of trade motivation is not always possible. Imagine a fund that experiences outflow and does not sell every holding in proportion but only sells some of its holdings to

Table XI: Pooled single trade performance - Valuation separated by weight change (overall and illiquid market period)

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6- and 12-months periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003-2012. VM trades are further categorized as heavy (weight increase above 50 percentile within all VM trades) and light (weight increase below 50 percentile within all VM trades). ***, **, * indicate statistical significance at the 1, 5 and 10 level, respectively.

		Cumulative DGTW-adjusted performance (in %) over the next			
	N	1 month	3 months	6 months	12 months
Panel A. Overall period - Benchmarked against the relevant universe (buys: *CRSP*, sells: holdings)					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM buys (heavy)	855,371	0.203***	0.269***	0.377***	0.311***
VM buys (light)	855,372	0.151***	0.210***	0.326***	0.409***
VM buys (heavy) – VM buys (light)		0.052***	0.059**	0.051	-0.099*
VM sells	2,111,743	-0.077***	-0.105***	-0.144***	-0.178***
VM sells (heavy)	1,055,871	-0.078***	-0.098***	-0.159***	-0.276***
VM sells (light)	1,055,872	-0.077***	-0.114***	-0.132***	-0.084***
VM sells (heavy) – VM sells (light)		-0.001	0.016	-0.028	-0.192***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.001	0.034	-0.053	-0.143*
Panel B. Illiquid market period - Benchmarked against the relevant universe (buys: *CRSP*, sells: holdings)					
VM buys	387,368	0.476***	0.739***	1.462***	2.007***
VM buys (heavy)	193,672	0.518***	0.898***	1.832***	2.488***
VM buys (light)	193,673	0.434***	0.577***	1.088***	1.511***
VM buys (heavy) – VM buys (light)		0.083**	0.321***	0.745***	0.977***
VM sells	479,154	-0.149***	-0.202***	-0.453***	-0.735***
VM sells (heavy)	239,550	-0.120***	-0.203***	-0.491***	-0.793***
VM sells (light)	239,551	-0.179***	-0.207***	-0.422***	-0.690***
VM sells (heavy) – VM sells (light)		0.059*	0.004	-0.069	-0.103
LM buys	165,761	0.217***	0.495***	0.906***	0.725***
LM sells	31,991	0.684***	0.986***	1.856***	2.561***

save transaction costs. Such trades would be identified as VM sells whereas on the other hand, one could argue that it is a grey case because the transactions are triggered by flow. For this reason we use the direction of the flow to separate heavy (clear valuation) and light (vague valuation) VM trades. Specifically, heavy VM sells occur during periods with net inflow and light (vague) VM sells as in the example occur during periods with net outflow. A similar logic applies to VM buys. This approach of distinguishing valuation clearness is also closest to the BF and SF definitions of ACG. The results are presented in Table XII. Overall,

Table XII: Pooled single trade performance - Valuation separated by valuation clearness (overall and illiquid market period)

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6- and 12-months periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003-2012. VM trades are further categorized as heavy (if buy despite of outflow and sell despite of inflow) and light (up-scaling buy in case of inflow and down-scaling sell in case of outflow). ***, **, * indicate statistical significance at the 1, 5 and 10 level, respectively.

		Cumulative DGTW-adjusted performance (in %) over the next			
	N	1 month	3 months	6 months	12 months
Panel A. Overall period - Benchmarked against the relevant universe (buys: *CRSP*, sells: holdings)					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM buys (heavy)	954,939	0.201***	0.250***	0.355***	0.366***
VM buys (light)	755,804	0.146***	0.227***	0.349***	0.357***
VM buys (heavy) – VM buys (light)		0.055***	0.023	0.006	0.008
VM sells	2,111,743	-0.077***	-0.105***	-0.144***	-0.178***
VM sells (heavy)	543,736	-0.095***	-0.129***	-0.229***	-0.302***
VM sells (light)	1,568,007	-0.070***	-0.096***	-0.114***	-0.135***
VM sells (heavy) – VM sells (light)		-0.025*	-0.033	-0.115***	-0.168***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.001	0.034	-0.053	-0.143*
Panel B. Illiquid market period - Benchmarked against the relevant universe (buys: *CRSP*, sells: holdings)					
VM buys	387,368	0.476***	0.739***	1.462***	2.007***
VM buys (heavy)	228,868	0.557***	0.782***	1.616***	2.363***
VM buys (light)	158,500	0.359***	0.677***	1.240***	1.493***
VM buys (heavy) – VM buys (light)		0.198***	0.105	0.377***	0.870***
VM sells	479,154	-0.149***	-0.202***	-0.453***	-0.735***
VM sells (heavy)	126,737	-0.126***	-0.154***	-0.528***	-0.812***
VM sells (light)	352,417	-0.157***	-0.219***	-0.426***	-0.707***
VM sells (heavy) – VM sells (light)		0.030	0.065	-0.102	-0.105
LM buys	165,761	0.217***	0.495***	0.906***	0.725***
LM sells	31,991	0.684***	0.986***	1.856***	2.561***

the results are as expected in that heavy trades outperform light trades, however less clear than in the test using the median weight change (see Table XI)).

In summary, we consider the results from the eTMM as valuable additional insights into the effects of heavy and light VM. However, by considering only heavy VM trades as in ACG ignores a significant proportion of trades and thus makes inferences on average manager skill impossible. As the overall difference to our main analysis is not substantial, we conclude that the simple classification method is robust.

2.7.2 Imperfect scaling

Another possible source of imprecise categorization by the TMM can arise from imperfect scaling. This occurs if a manager wants to scale, i.e. trade liquidity-motivated without new investment idea, but fails to keep the weight change of the stock perfectly at zero, e.g. due to integer numbers of stocks. If such a trade (e.g. a buy) involuntarily results in a weight increase (even if it is only slightly higher than 0), the TMM falsely classifies this trade as valuation-motivated buy. To mitigate the influence of such possible imprecise classifications, we control for "marginal" weight changes from imperfect scaling by weighting trade performance with the respective weight-changes in Panel A in Table XIII (overall) and Table XIV (illiquid). As a result, the performance of VM buys increases while the performance of VM sells decreases as expected, resulting in a higher difference between VMB and VMS which is significant for all tested horizons.

In addition, in Panel B (C), we reclassify VM trades as LM trades if the respective absolute weight change is below 5% (below 10%) of the previous portfolio weight. This clearly increases the proportions of LM trades and especially of the LM sells. The results are very similar to those presented in Panel A in that the outperformance of VM trades over LM trades increases for all holding periods. We therefore conclude that our findings in the previous sections are not driven by these possible misclassifications.

Table XIII: Pooled single trade performance adjusted for marginal weight changes (overall period)

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6- and 12-months periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003-2012. The benchmark universe for buys consists of all *CRSP* stocks. The benchmark universe for sells consists of all stocks currently held by the respective fund, assuming no short selling. In Panel A, the performance is weighted by the underlying weight changes. Weights below the 1% percentile and above the 99% percentile were excluded from this analysis to account for outliers. In Panel B (C), trades with absolute weight changes below 5% (10%) of the previous weight are reclassified as LM trades. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively, based on bootstrapped standard errors.

		Cumulative DGTW-adjusted performance (in %) over the next			
	N	1 month	3 months	6 months	12 months
Panel A. Weight change-weighted trades					
VM buys	1,613,953	0.190***	0.258***	0.383***	0.385***
VM sells	2,019,455	-0.091***	-0.129***	-0.169***	-0.189***
VM buys – VM sells		0.281***	0.387***	0.552***	0.575***
LM buys	747,368	0.044***	0.094***	0.229***	0.401***
LM sells	165,304	0.002	0.037***	-0.050***	-0.138***
VM buys – LM buys		0.146***	0.165***	0.154***	-0.016***
VM sells – LM sells		-0.093***	-0.165***	-0.119***	-0.052***
Panel B. Reclassification of trades with absolute weight changes below 5% as LM trades					
VM buys	1,435,856	0.191***	0.245***	0.346***	0.341***
VM sells	1,659,298	-0.091***	-0.113***	-0.171***	-0.247***
VM buys – VM sells		0.282***	0.358***	0.517***	0.587***
LM buys	1,022,760	0.060***	0.126***	0.268***	0.415***
LM sells	617,790	-0.019*	-0.045**	-0.047	0.017
VM buys – LM buys		0.131***	0.120***	0.079***	-0.074*
VM sells – LM sells		-0.071***	-0.068***	-0.124***	-0.264***
Panel C. Reclassification of trades with absolute weight changes below 10% as LM trades					
VM buys	1,345,131	0.191***	0.246***	0.350***	0.345***
VM sells	1,419,339	-0.088***	-0.105***	-0.166***	-0.257***
VM buys – VM sells		0.279***	0.351***	0.516***	0.602***
LM buys	1,113,485	0.071***	0.135***	0.269***	0.403***
LM sells	857,749	-0.043***	-0.077***	-0.090***	-0.040
VM buys – LM buys		0.120***	0.111***	0.082***	-0.058
VM sells – LM sells		-0.046***	-0.029	-0.076**	-0.217***

Table XIV: Pooled single trade performance adjusted for marginal weight changes (illiquid periods)

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6- and 12-months periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003-2012. The benchmark universe for buys consists of all *CRSP* stocks. The benchmark universe for sells consists of all stocks currently held by the respective fund, assuming no short selling. In Panel A, the performance is weighted by the underlying weight changes. Weights below the 1% percentile and above the 99% percentile were excluded from this analysis to account for outliers. In Panel B (C), trades with absolute weight changes below 5% (10%) of the previous weight are reclassified as LM trades. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively, based on bootstrapped standard errors.

		Cumulative DGTW-adjusted performance (in %) over the next			
	N	1 month	3 months	6 months	12 months
Panel A. Weight change-weighted trades					
VM buys	357,641	0.511***	0.794***	1.590***	2.156***
VM sells	448,490	-0.183***	-0.239***	-0.507***	-0.840***
VM buys – VM sells		0.693***	1.033***	2.096***	2.996***
LM buys	165,368	0.222***	0.505***	0.945***	0.763***
LM sells	31,982	0.002	0.048	-0.243***	-0.315***
VM buys – LM buys		0.289***	0.289***	0.645***	1.394***
VM sells – LM sells		-0.185***	-0.286***	-0.263***	-0.524***
Panel B. Reclassification of trades with absolute weight changes below 5% as LM trades					
VM buys	346,443	0.492***	0.741***	1.498***	2.092***
VM sells	417,617	-0.166***	-0.222***	-0.507***	-0.802***
VM buys – VM sells		0.658***	0.963***	2.005***	2.894***
LM buys	206,686	0.241***	0.540***	0.957***	0.837***
LM sells	93,528	-0.020	-0.031	-0.144	-0.291**
VM buys – LM buys		0.251***	0.201***	0.541***	1.255***
VM sells – LM sells		-0.145***	-0.190**	-0.363***	-0.511***
Panel C. Reclassification of trades with absolute weight changes below 10% as LM trades					
VM buys	327,801	0.497***	0.762***	1.534***	2.156***
VM sells	370,214	-0.165***	-0.227***	-0.521***	-0.821***
VM buys – VM sells		0.662***	0.989***	2.055***	2.977***
LM buys	225,328	0.254***	0.527***	0.949***	0.848***
LM sells	140,931	-0.073**	-0.082	-0.228***	-0.415***
VM buys – LM buys		0.243***	0.235***	0.585***	1.308***
VM sells – LM sells		-0.092**	-0.145**	-0.293***	-0.405***

2.7.3 Window dressing, portfolio pumping and tax motivated trading

Apart from pure valuation-motivation and liquidity-motivation, mutual fund trades may also be driven by other motives such as window dressing, portfolio pumping and tax optimization (e.g., ACG). Specifically, regarding window dressing (e.g., Agarwal et al., 2014), mutual funds might alter their portfolio composition prior to reporting to disguise their true holdings

Table XV: Pooled single trade performance - Window dressing and tax motivated trades

This table reports cumulative DGTW benchmark-adjusted performance over the next 1, 3, 6 and 12 months periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 4,002 actively managed US domestic equity funds in the period 2003-2012. The benchmark universe for buys are all *CRSP* stocks. The benchmark universe for sells are all stocks currently held by the respective fund assuming no short selling. To control for window dressing and tax motivated trading, we drop all trades in the last quarter of each year. Due to the large number of observations, all figures are statistically significant at conventional levels. For readability, we do not report test statistics in the table.

		Cumulative DGTW adjusted performance (in %) over the next			
	N	1 month	3 months	6 months	12 months
Panel A. Overall single trade analysis					
VM buys	1,246,547	0.160	0.153	0.254	0.255
VM sells	1,533,962	-0.071	-0.100	-0.161	-0.159
VM buys – VM sells		0.232	0.253	0.415	0.414
LM buys	557,122	0.049	0.125	0.182	0.384
LM sells	117,834	-0.024	-0.044	-0.084	-0.157
VM buys – LM buys		0.112	0.028	0.072	-0.130
VM sells – LM sells		-0.048	-0.056	-0.077	-0.002
Panel B. Illiquid market periods - Bottom 10%					
VM buys	288,272	0.663	0.881	1.117	1.635
VM sells	352,310	-0.191	-0.251	-0.414	-0.619
VM buys – VM sells		0.854	1.132	1.531	2.254
LM buys	122,492	0.293	0.606	0.718	0.721
LM sells	23,535	-0.055	-0.046	-0.365	-0.441
VM buys – LM buys		0.370	0.275	0.399	0.915
VM sells – LM sells		-0.136	-0.205	-0.049	-0.178
Panel C. Liquid market periods - Top 90%					
VM buys	958,275	0.009	-0.066	-0.006	-0.161
VM sells	1,181,652	-0.036	-0.055	-0.086	-0.023
VM buys – VM sells		0.045	-0.011	0.080	-0.138
LM buys	434,630	-0.020	-0.011	0.031	0.289
LM sells	94,299	-0.016	-0.043	-0.014	-0.086
VM buys – LM buys		0.029	-0.055	-0.036	-0.450
VM sells – LM sells		-0.020	-0.012	-0.071	0.064

and prevent copycat funds from hurting their performance (e.g., Phillips et al., 2014) as well as to make their portfolio look more attractive to investors. Similarly, mutual funds might artificially try to inflate performance by placing large bets on existing holdings (e.g., Patel and Sarkissian, 2013). The reason for tax-motivated trading is to realize capital losses in order to lower the tax base of investors (e.g., Sialm and Starks, 2012; Bergstresser and Pontiff, 2013). Thus, efficient tax management by mutual funds is another service provided to investors and often credited as performance (e.g., Sialm and Zhang, 2015). Moreover, mutual fund flows might be affected by after-tax returns (e.g., Bergstresser and Poterba, 2002).

To rule out the possibility that such trades drive our findings, we utilize the fact that most of these trades occur in the fourth calendar quarter and replicate our pooled single trade performance analysis using only trades from the first three quarters (e.g., ACG). Table XV reports the results analog to Table IV and Table VI with the fund’s holdings as the relevant benchmark universe for sells assuming no short selling. Panel A shows results for the overall period while Panels B and C show results for illiquid and liquid market periods, respectively. They are economically similar to the findings in our main analysis. Therefore, we conclude that our findings are not driven by alternative trade motives.

2.8 Conclusion

We propose a novel approach to distinguishing VM trades from LM trades of mutual funds. The TMM is the first to allow the direct classification of single trades whereas previous approaches remain on the aggregated portfolio level. This allows more accurate measurement of stock picking skill than previous approaches not considering motivation and thus underestimating skill as well as previous approaches considering motivation only for aggregated trades. Moreover, we are the first to consider different benchmark universes for trades thereby distinguishing the success of VM and LM trading compared to all stocks with similar characteristics from their actual effects on portfolio quality. Based on funds’ VM trading according to the TMM, we thus find clear evidence for the existence of stock picking skill which is significantly related to future stock and fund performance. This is especially the case during illiquid market periods with low market efficiency. Based on funds’ LM trading, we find clear evidence for the existence of flow risk, i.e. negative performance effects due to investors’ liquidity demand. This is also especially pronounced during illiquid market periods and overall driven more strongly by inflows than outflows, probably due to liquidity premiums earned by LM sellers and paid by LM buyers when overall liquidity is low.

Overall, due to these clear and novel findings, we deem it very important to consider trading motivation in future analyses of stock picking skill and flow risk. Therefore, the TMM provides an intuitive, easy-to-apply way to accurately distinguishing between single VM and LM trades. Future research should also concentrate on the differential effects of buys and sells relative to their relevant benchmark universes when measuring the performance of active mutual fund management.

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3 Article II: Who holds the carbon risk bomb? An overview of potential risk takers[24]

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Abstract. Economic growth is one of the major reasons for increasing levels of CO_2 emissions that have the potential to accelerate climatic change and threaten our environment. However, many investors still support CO_2-heavy companies financially, even though there are various associated risks for these assets with respect to climate policies and stranded assets. This study aims to thoroughly examine which investor types tend to hold a higher proportion of carbon intensive stocks. To identify high-polluting stocks we provide a classification of stocks based on three different categories related to industry sectors, carbon footprints and environmental scores. Data on year-end holdings from 2000-2015 is used to investigate whether different investor types prefer or try to avoid carbon intensive stocks in comparison to investments in peer companies. We find that institutional investors, hedge funds, individuals, investment advisors and mutual funds tend to hold less carbon intensive firms in their investment portfolios. Interestingly, in contrast, government agencies seem to have a higher exposure to polluting stocks in their portfolios (approximately 50%) and typically also hold a high percentage of the total market capitalization of these firms. Our results are robust against different specifications of carbon intensive companies and measures of ownership. Overall, our study provides a better understanding of the exposure to carbon intensive stocks for various investor types, but also illustrates which parties have the ability to influence environmental behavior of CO_2-emitting firms, e.g. by exhibiting voting rights.

Keywords Carbon Risk, GHG Emissions, Ownership Structure, Mutual Fund Behavior

[24] This research article is joint work of Julia Scherer, Janik Syryca and Prof. Stefan Trueck. Major parts of this article were authorized to the use in the master thesis of Julia Scherer.

3.1 Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), Carbon Dioxide (CO_2) accounts for about three-quarter of global greenhouse gas (*GHG*) emissions and is likely to be the main driver for anthropogenic global warming (Pachauri et al. (2014)). As a result, policy makers around the world are considering various plans to reduce carbon emissions and aim to mitigate the possible consequences of rising temperature. Even though there have been achievements like the recent Paris agreement (European Commission (2015)), the implementation process of the agreed measures for carbon emission reductions is typically rather lengthy, difficult to enforce and subject to regular changes. The uncertainty about how upcoming measures will impact a firm's future cash flow is often referred to as carbon risk (Dupré et al. (2015)). This risk is particularly relevant for companies with exposures to carbon emissions in any part of their business. It has been argued that the exposure to carbon risk for businesses and industries could be quite substantial (Stern (2007), Carbon Tracker Initiative (2013)). On the one hand, companies face potential extra costs due to taxes or the requirement to provide allowances based on their carbon emissions. On the other hand, they also need to handle possible changes in customer demand and reputational risks related to being classified as unsustainable or high-polluting businesses. Furthermore, estimates suggest that in order to achieve the 2°C-goal set in Paris, about three-quarters of all remaining coal, oil and gas reserves should not be exploited (Global Carbon Budget (2014)), which will create so-called stranded assets, i.e. assets losing their economic value well ahead of their anticipated useful lifetime. Assuming that this situation could create a "Carbon Bubble" in the valuation of carbon intensive companies, there is an increasing interest in who invests in firms with high operational carbon risk. It is also important for policy makers to understand the ownership structure of these firms in order to develop appropriate measures.

This paper aims to analyze the exposure of different investor types to carbon intensive stocks as well as to identify possible recent changes in investment behavior, using an extensive ownership database for a large universe of stocks. In particular we combine information on firms with high carbon risk exposure based on the Asset4 database with a Global Ownership database that provides year-end holdings of these stocks for different types of investors for the sample period 2000-2015. This allows us to thoroughly examine the ownership of carbon intensive stocks for various ownership and investors types.

Our study provides important information on investor behavior with regards to high-polluting firms and is highly relevant for different strands of existing literature. First, our work is related to carbon risk research. So far, academic literature has not contributed much to help investors with the costly challenge of cutting through the complexity of identifying an asset's exposure to carbon risk. An exception includes the study by Hoffmann and Busch (2008) who develop four different indicators that help to assess a company's contribution to climate change and its effort to manage its use of carbon emissions in a better way. Second, this study relates to research investigating the relationship between environmental and financial performance. In environmental science, scholars have illustrated that companies with higher pollution are typically less efficient in their operations, which harms their competitiveness and consequently minimizes their firm value. In addition to that, the eco-efficiency concept suggests that modern and environmentally friendly production methods lead to developmental advantages (Ulshöfer and Bonnet (2009)). Based on this rationale, the expected relation between environmental performance, especially with respect to *GHG* emissions, and financial performance would be positive. However, the literature studying this relationship provides rather mixed conclusions. Using factor-model regression analysis, Derwall et al. (2005) and Oestreich and Tsiakas (2015) find conflicting results, with the first one suggesting an outperformance of good environmental performers and the second one better risk-return characteristics for bad ones. In earlier years Cohen et al. (1997) find neither a penalty nor a reward for investing in green portfolios. Studies performed by Ziegler et al. (2011) and Liesen (2015) use the willingness of a company to disclose responses on climate change and *GHG* emissions, respectively, to set up different portfolios. As a result, they find a financial performance of disclosing firms. Summarizing the findings from event studies it seems that qualitative signals like companies' attitude towards climate change have a significant influence on stock returns, see, e.g., Jacobs et al. (2010), Flammer (2013), Griffin and Sun (2013), Hsu and Wang (2013), Murguia and Lence (2015) and Veld-Merkoulova and Viteva (2016). However, the direction of the observed impact is not consistent. Another popular research method applies using regression models, with financial performance of firms as the dependent variable and environmental performance as the key explanatory variable. Most of these studies find that high emissions of greenhouse gases have a negative effect on market value and return on equity, see, Konar and Cohen (2001), King and Lenox (2001), Matsumura et al. (2011), Aggarwal and Dow (2011), Saka and Oshika (2014), Misani and Pogutz (2015) and Gallego-Álvarez et al. (2015). Kim et al. (2015) and Chen and Silva Gao (2012) confirm this effect on the cost side, when associating higher *GHG* emissions with a higher cost on equity. An exception to these results is provided by Wang et al. (2014), who find a positive effect of high *GHG* emissions on Tobin's Q for Australian firms. This could be explained by the importance of the mining industry for the Australian economy. Lastly, academics examine whether decarbonization and the support of green investments are worth striving for with regards to the performance of investment portfolios. Like SRI-research, see, e.g., Mallin et al. (1995), Schumacher-Hummel (2005) and Derwall et al. (2011), existing studies on green funds make use of different data sources, observation periods, methodological approaches and definitions. The findings of these studies either suggest empirical evidence in favor of (Climent and Soriano (2011), Chang et al. (2012)) or against

(Labatt and White (2002), Mallett and Michelson (2010), Muñoz et al. (2014)) the superior performance of green investments.

The existing literature is mainly focused on examining which incentives, i.e. higher performance investors might have to invest in carbon intensive stocks. However, it often fails to provide investors and policy makers with an appropriate approach to identify carbon risk exposure. Furthermore, scholars have not yet explored the question of who actually 'holds the carbon risk bomb', i.e. which investors types are most invested in carbon intensive stocks and, therefore, exposed to potential carbon risks. Our study contributes to the literature by thoroughly analyzing both of these aspects. Firstly, we define three different categories of carbon intensive stocks that help to identify which companies can be considered as being 'dirty'. Secondly, we are the first to work with an extensive dataset of ownership structures from 2000-2015 in order to analyze investor behavior related to carbon intensive stocks. Therefore, with our study, we contribute to carbon risk research by showing in which portfolios the risks are bundled and which investor types are more likely to hold high proportions of carbon intensive stocks. In particular, our study contributes to answering the following important research questions: How much carbon risk exposure can be observed in the portfolios of different investor types? What level of ownership - measured by the percentage of the total market capitalization of a stock - do different investor types typically hold for the companies in their portfolios? How is the (CO_2-intensive) stock universe split between different owner types and how are the different owner types invested in 'dirty' stocks in comparison to their normal investment behavior and portfolio allocation?

Our findings show that from an owner type perspective, it is typically governments who have the highest exposures to carbon intensive stocks in their portfolio (approximately 50%), whereas institutionals, hedge funds, individuals, investment advisors and mutual funds hold much lower exposures in these stocks (between 15% and 30%). Interestingly, governments also hold the highest percentage of shares of ‘dirty’ stocks in their portfolio, holding on average around 40% of the total market capital of these firms. Regarding the overall ownership distribution of stocks in the CO_2-intensive universe, we find that mainly mutual funds, but also hedge funds and investment advisors form the biggest owner groups, having an ownership between 10% and 20% each. Moreover, we provide more detailed information about the preferences and behavior of each investor type. For example, we find that hedge funds, individuals, investment advisors and mutual funds own statistically significant less carbon intensive stocks in comparison to non-carbon intensive stocks. Government agencies in contrary typically have more ownership in carbon intensive stocks (even though not statistically significant).

The remainder of the paper is set up as follows. Section 3.2 describes the methodology applied to identify carbon intensive stocks and holdings. This is followed by section 3.3, which describes available and selected data for our empirical analysis. Section 3.4 presents the results of our analysis, while section 3.5 concludes and provides possible direction of future work in the area.

3.2 Methodology and definitions

To examine which investors are most exposed to carbon intensive firms, it is necessary to identify the companies with the highest carbon risk exposure. So far, academic research has not contributed much to help investors with cutting through the complexity of identifying an asset’s exposure to carbon risk. An exception is the study by Hoffmann and Busch (2008) who define considerable indicators based on the amount of CO_2-emissions. However, the Portfolio Carbon Initiative (PCI) set up by the United Nations Environment Finance Initiative (UNEP FI) develops a rather practical framework and argues that carbon risk does not only comprise quantifiable but also non-quantifiable components. In our study, we aim to gather a comprehensive picture of a firm's exposure to carbon risk by including quantitative and qualitative aspects. Therefore, we define three metrics to classify carbon intensive stocks: Industry-based carbon risk definition (industry affiliation), the carbon footprint of a company as well as a measure related to climate scoring.

3.2.1 Industry-based carbon risk definition (industry affiliation)

To break down the complexity of identifying carbon risk exposure, we start with the most intuitive approach. In a first step, we use the Thomson Reuters Business Classification (TRBC) to classify all stocks based on the industry they belong to. This is reasonable as sectors are affected differently by the transformation into a carbon-constrained world, see e.g., Labatt and White (2002). This method has also been used in recent studies by Gallego-Álvarez et al. (2015) and Misani and Pogutz (2015) to select *GHG* sensitive firms. The sector that is typically considered to be the most sensitive to carbon risk is the energy industry, including oil, gas, coal and power utilities[25] (Labatt and White (2002) and (2007)).

However firms that belong to energy-intensive industries such as chemicals, iron, steel, cement, and metallurgy[26] are nearly equally effected. The reason is that these sectors have a high consumption of fossil fuels and are represented by Basic Resources (Dell'Aringa and van Ast (2009)). Besides direct *GHG* emissions, it is also relevant how much carbon is emitted during downstream activities. Hence, we additionally categorize producers and users of energy-consuming products like the automobile and transportation industry[27] as carbon intensive industry. These companies are also very vulnerable, especially to technology risk (e.g. fuel efficiency), see, e.g., Labatt and White (2007) and Goodstein (2011).

[25] Corresponding to the Thomson Reuters industry groups oil & gas, oil & gas related equipment and services, natural gas utilities, coal, electric utilities & ipp and multiline utilities.
[26] Corresponding to the Thomson Reuters industry groups chemicals, metals & mining and construction materials.
[27] Corresponding to the Thomson Reuters industry groups aerospace & defense, automobile & parts, freight & logistics services, passenger transportation and transport infrastructure.

We additionally include the sector “Paper and Forest Products” into the list of CO_2-heavy industries. This takes into account that deforestation does not only lead to releases of CO_2 stored in the terrestrial biosphere, but also reduces the ability to absorb emitted greenhouse gases (Pachauri et al. (2014)). Therefore, the industry also has the potential to worsen global warming and is subject to possible regulatory measures. This leaves us with the 15 CO_2-heavy industries that are presented in Table XVI.

Table XVI: CO_2-intensive industries

This table includes 14 industries from three categories which are most sensitive to carbon risk. In addition to the sectors provided, we also include the “Paper & Forest Products” industry into the list of CO_2-intensive industries. Every company in Asset4 that belongs to one of these 15 industries is categorized as carbon intensive in our analysis.

Energy industry	Energy-intensive industry	Energy-consuming products
Coal	Chemicals	Aerospace and Defense
Electric Utilities and IPPs	Construction Materials	Automobile and Parts
Natural Gas Utilities	Metals and Mining	Freight and Logistics Services
Multiline Utilities		Passenger Transportation Services
Oil and Gas		Transport Infrastructure
Oil and Gas Related Equipment and Services		
	Paper and Forest Products	

3.2.2 Carbon Footprint

By using the industry affiliation of a company, the underlying assumption is that all companies which belong to the 15 defined CO_2-heavy industries face the same degree of carbon risk exposure. However not all companies within the same industry face the exact amount of carbon risk as they emit different amounts of *GHG*.

To achieve a finer distinction, we therefore follow Hoffmann and Busch (2008) and the PCI and additionally compute a company’s footprint. The carbon footprint is defined as a company’s total *GHG* emissions[28] standardized by some proxy of size. In line with Aggarwal

[28] To overcome the problem of an imperfect time series, we calculate the averages of all normalized CO_2e-emissions from 2008-2015 for each firm. Working with a limited period allows us to create a static sample of

and Dow (2011), Balkissoon and Heaps (2014), Saka and Oshika (2014), Kim et al. (2015), Misani and Pogutz (2015), we use the market capitalization, *EBITDA* and sales as proxies for our ranking:

$$Carbon\ Footprint_M = \frac{Total\ GHG\ Emissions}{Market\ capitalization} \quad (1a)$$

$$Carbon\ Footprint_E = \frac{Total\ GHG\ Emissions}{EBITDA} \quad (1b)$$

$$Carbon\ Footprint_S = \frac{Total\ GHG\ Emissions}{Sales} \quad (1c)$$

Total GHG emissions include CO_2-emissions from Scope 1 (emissions from sources directly owned and controlled by the company) and Scope 2 (indirect emissions from the generation of purchased electricity). Emissions from Scope 3, which occur in upstream as well as in downstream activities are not included in this definition as the company has no influence over them. Besides their reporting is optional and available data therefore not very reliable (Carbon Trust (2012)).

However only a few regulators require mandatory *GHG* disclosure and if they do, these disclosures are only imposed on companies with specific features (Nitoiu (2013)). As a result, the coverage of total CO_2e-emissions data is sparse, especially in the early 2000's. However, Figure 3 shows that coverage has lately increased. In 2015 more than 400 companies (more than 50% of all companies) from carbon intensive industries provide data for total CO_2e-emissions.

To differentiate the best and worst carbon risk stocks, we use a "worst-in-class" approach, i.e. we rank all companies within each carbon intensive industry based on their

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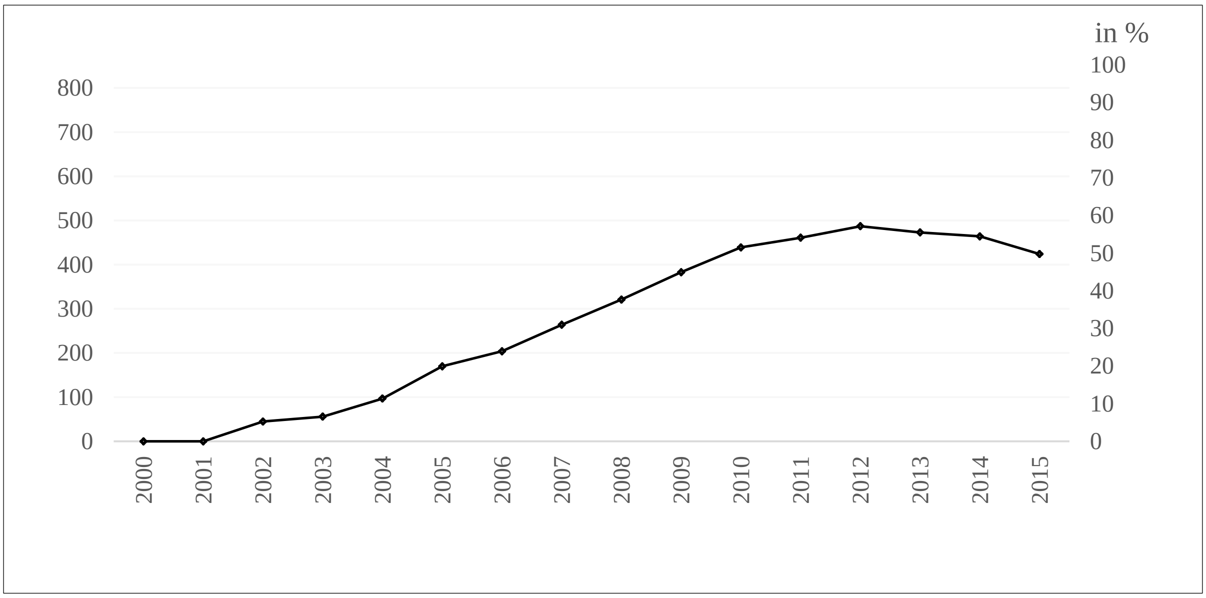
CO_2-heavy firms, which can be analyzed over time. Thereby we assume that the average behavior is representative for the whole time period of 2000-2015. We exclude companies without any emission data.

carbon footprint (Labatt and White (2002)). Firms with carbon footprint values in the highest 50% of an industry are classified as worst emitters.[29]

Figure 3: Firms with available CO2e emission data

This figure presents the number (left *y*-axis) and percentage (right *y*-axis) of firms from CO_2-intensive industries with available CO_2e-emission reportings. The observed period ranges from 2000 to 2015.



3.2.3 Climate Scoring

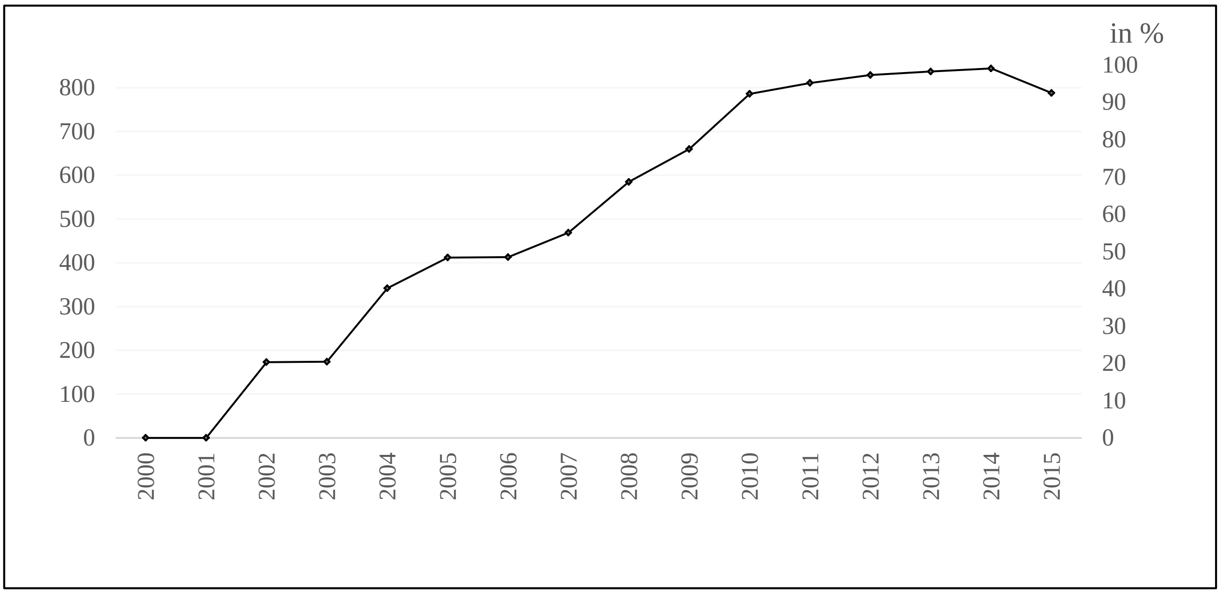
Earlier academic studies have mainly neglected the fact that a firm's carbon risk exposure is not only a question of its quantifiable carbon footprint. If a company wants to reduce its risk, cutting down carbon emissions is only one step. In addition to that, there must be initiatives to develop improvements in dealing with natural resources, see, e.g., Calvello (2009). This is why we also identify firms with high carbon risk exposure through ranking their Climate Scoring. Hereby, we offer a more comprehensive and forward-looking picture about how a company deals with carbon risk exposure that also includes qualitative factors. Scoring data can be received from third-party providers like Thomson Reuters. But here again, coverage in

[29] We acknowledge that one disadvantage of the „worst-in-class“ approach is that in sectors with generally low standards, not all companies with high pollution are classified as bad environmental performers (Ulshöfer and Bonnet (2009)).

the early 2000's is spare. However Figure 4 shows that after 2009 nearly 100% of all stocks from carbon intensive industries have E-Score available.

Figure 4: Firms with available E-Score data

This figure presents the number (left *y*-axis) and percentage (right *y*-axis) of firms from CO_2-intensive industries with available E-Score (Thomson Reuters). The observed period ranges from 2000 to 2015.



Similar to the approach taken to compute the worst carbon footprint based emitters, we average all of a company's reported E-scores from 2008 to 2015 and classify the lowest 50% in each industry as worst E-Score based emitters.

3.3 Data

3.3.1 Firms with highest carbon risk exposure

The following section provides summary statistics about the databases used in this study. We obtain data about CO_2-emission and E-Score from the Asset4 database (provided by Thomson Reuters). This database covers the most important shares traded on global stock markets[30] and therefore serves as a good proxy for the worldwide investment universe. Data about sales, *EBITDA* and market capitalization stem from the data provider Worldscope.

[30] MSCI Emerging Markets, MSCI World, CAC40, DAX, FTSE250, S&P 500, NASDAQ 100, STOXX 600, ASX 300, SMI and Bovespa.

Since Asset4 sources its CO_2-data inter alia from the Carbon Disclosure Project, we have to work with voluntarily reported data that might possibly be unreliable, inconsistent and not validated by a third party according to Calvello (2009). Furthermore, it poses the risk of a self-selection bias, where e.g. bad environmental performers consciously do not report emissions in order to minimize their reputational risks. However, the Asset4 database is currently the best available source for *ESG* data without considerable alternatives (Thomson Reuters (2012)). Hence, this analysis has to proceed with the mentioned limitations similar to earlier studies (Aggarwal and Dow (2011), Matsumura et al. (2011), Wang et al. (2014), Saka and Oshika (2014), Misani and Pogutz (2015)) that have also worked with voluntarily disclosed data.

In total, we obtain 875 stocks from carbon intensive industries which have been active for the whole period between 2000 and 2015. Companies that have entered the stock market later or were delisted due to mergers or bankruptcy are excluded. By doing so, we create an Asset4 universe where investors could theoretically have been invested in every year throughout the considered sample period. Due to the smaller coverage of available data, we have 291 firms that are ranked as the worst emitters according to their carbon footprint and 424 which have the worst climate scoring.

An overview of the industry and country distribution of these subsamples can be found in Table XVII. This summary also shows that the selected 875 firms correspond to approximately 21% of the total market capitalization of all Asset4 companies in the sample. Besides, more than 20% of all companies are from the United States.

Table XVII: Number of firms in Asset4 which are categorized as carbon intensive stocks

Panels A and B include the number of firms which are covered in the subsample after selecting 875 Asset4 companies that belong to the 15 most CO_2-sensitive industries and after applying the "worst-in-class" approach for carbon footprint (with three different normalization metrics) and climate scoring. Panel A shows how many of the remaining Asset4 firms belong to each of the defined CO_2-intensive industry. Furthermore, it includes the equivalent market capitalization for the defined stocks and how big their proportion of the total Asset4 universe is. Panel B shows where these firms have their headquarters. Countries marked with * have emission regulations (trading scheme or carbon tax) that have either already been implemented, are scheduled or currently under consideration.

Panel A: Distribution by industry

Industry	**carbon intensive industry**	**worst carbon footprint normalized by**			**worst E-Score**
		Market Capitalization	***EBITDA***	**Sales**	
Aerospace & Defense	27	11	11	11	12
Automobiles & Auto Parts	85	31	31	31	42
Chemicals	95	37	37	37	47
Coal	16	2	2	2	7
Construction Materials	34	12	12	12	16
Electric Utilities & IPPs	84	36	36	36	41
Freight & Logistics Services	49	16	16	16	24
Metals & Mining	179	49	49	49	88
Multiline Utilities	22	8	8	8	10
Natural Gas Utilities	16	5	5	5	7
Oil & Gas	123	39	39	39	60
Oil & Gas Related Equipment and Services	59	14	14	14	29
Paper & Forest Products	17	8	8	8	8
Passenger Transportation Services	43	15	15	15	21
Transport Infrastructure	26	8	8	8	12
Total # of firms	875	291	291	291	424
Total market capitalization in bn.$	8,331	3,545	3,875	3,335	1,241
% of total Asset4 market capitalization	21%	9%	10%	8%	3%

Panel B: Distribution by country

Country	**carbon intensive industry**	**worst carbon footprint normalized by**			**worst E-Score**
		Market Capitalization	**EBITDA**	**Sales**	
Australia	73	9	11	18	48
Brazil*	19	5	6	7	6
Canada	106	20	22	27	73
Chile*	10	1	2	3	7
China*	20	2	2	2	14
EU*	122	55	51	36	25
Hong Kong	24	5	3	6	13
India	26	13	14	12	12
Japan*	106	51	47	35	36
Kazakhstan*	0	0	0	0	0
Mexico*	6	1	2	0	2
New Zealand*	9	1	1	2	7
Others	70	20	20	24	51
Russian Federation	9	3	2	2	0
South Africa*	24	17	14	17	9
South Korea*	21	11	10	10	6
Thailand*	5	1	0	1	1
Turkey*	8	2	3	1	6
United Kingdom	26	11	11	12	7
United States	191	63	70	76	101
Total # of firms	875	291	291	291	424
% of firms with headquarter in *countries	40%	51%	47%	39%	28%

3.3.2 Ownership holdings

Our data on ownership structure is sourced from the Thomson Reuters' Global Ownership database. We use year-end holdings from 2000 to 2015. We focus on institutional investors (incl. banks, trusts, insurances, pension and endowment funds and foundations), hedge funds, mutual funds, investment advisors, as well as individuals and government agencies. Since mutual funds report on an aggregated level (e.g. as "Fidelity Asset & Research Company") as well as on a single fund level (e.g. for "Fidelity High Income Fund" or "Fidelity Value Fund") there is the risk of duplicates. This is why in our empirical analysis we examine mutual funds and aggregated mutual funds separately.

Table XVIII shows how the holdings of the companies in our specified Asset4 subsample are distributed amongst the different owner groups in the Global Ownership database. We find that the value of all stocks held by all owners in the sample varies from 13,716 billion dollars in 2000 to 27,755 billion dollars in 2015. As mutual funds hold constantly more than 30% of this value, they form the largest group regarding their number of total investment volume, while governments and individuals form the smallest investor types.

3.4 Results

The analysis in this paper is divided into two major parts. Part I investigates owners and their investment behavior with regards to carbon intensive stocks in general, and examines the following two key questions: (i) How much carbon risk exposure do portfolios of different owner types contain? (ii) What is the fraction of ownership (i.e. the percentage of the total market capitalization) for the companies in the portfolio of different ownership types? Note that the analysis in part I only considers stocks that are held in the owners' portfolio, whereas

Table XVIII: Comparison of the different investor types

This table shows on a yearly basis the number of different investors for each investor type. Besides it reports the number of stocks this group holds at the end of year *t*. Additionally, it shows how big the seven groups are regarding their percentage of the total investment volume in our Asset4 universe.

		Investor Types							Total investment volume in bn.	
		Institutionals	Hedge Funds	Individuals	Government	Inv. Advisor	Mutual Funds	aggregated	units of shares	value of shares
2000	# of owners	506	843	1,625	43	1,443	17,659	910		
	# of reported holdings	50,469	102,254	1,672	110	109,506	870,907	111,458	1,413	13,716
	% of investment volume in units/value	14.7% / 10.3%	21.5% / 23.4%	3.2 / 3.9%	7.1% / 2.1%	13.7% / 21.4%	32.1% / 31.6%	7.7% / 7.2%		
2001	# of owners	506	906	2,366	28	1,415	16,204	980		
	# of reported holdings	54,069	119,288	2,435	87	110,402	874,814	128,501	686	9,522
	% of investment volume in units/value	6.1% / 8.3%	19.3% / 24.8%	7.1% / 2.7%	6.0% / 1.4%	16.6% / 27.9%	31.2% / 28.0%	13.7% / 6.8%		
2002	# of owners	545	1,013	2,381	29	1,422	18,409	1,130		
	# of reported holdings	61,927	127,713	2,467	101	111,993	1,050,105	140,812	910	8,357
	% of investment volume in units/value	6.2% / 8.1%	24.6% / 25.8%	4.5% / 3.1%	3.5% / 2.1%	14.7% / 26.5%	36.3% / 28.9%	10.2% / 5.4%		
2003	# of owners	582	1,133	3,528	33	1,479	18,753	1,115		
	# of reported holdings	65,740	139,347	3,652	103	123,821	1,127,696	137,886	1,075	12,133
	% of investment volume in units/value	5.7% / 8.0%	22.6% / 26.5%	5.4% / 2.8%	5.4% / 2.1%	13.3% / 25.6%	38.6% / 29.3%	9.0% / 5.8%		
2004	# of owners	592	1,283	3,870	36	1,562	19,101	1,210		
	# of reported holdings	66,107	146,259	4,012	103	129,039	1,148,571	139,938	1,129	14,004
	% of investment volume in units/value	5.0% / 7.1%	21.1% / 25.3%	4.6% / 3.1%	9.4% / 2.0%	14.2% / 25.8%	36.9% / 31.5%	8.7% / 5.1%		
2005	# of owners	663	1,458	4,838	37	1,717	20,078	1,283		
	# of reported holdings	69,452	163,565	5,049	94	139,908	1,215,343	142,279	1,248	16,902
	% of investment volume in units/value	4.9% / 6.6%	20.9% / 25.4%	5.0% / 2.9%	7.8% / 1.7%	13.9% / 23.3%	40.9% / 35.4%	6.7% / 4.7%		
2006	# of owners	691	1,647	4,831	42	1,823	21,728	1,353		
	# of reported holdings	71,629	186,982	5,038	98	155,468	1,318,032	155,280	1,309	20,723
	% of investment volume in units/value	4.6% / 6.4%	22.7% / 26.1%	3.75 7 2.95	7.55% / 1.65%	13.0% / 22.6%	41.6% 35.8%	6.9% / 4.6%		
2007	# of owners	666	1,768	5,251	43	1,913	22,028	1,563		
	# of reported holdings	71,858	226,978	5,482	104	166,835	1,408,210	184,511	1,111	21,301
	% of investment volume in units/value	5.9% / 6.1%	20.1% / 25.6%	6.2% / 3.6%	3.9% / 2.4%	14.7% / 23.0%	35.3% / 31.9%	13.9% / 7.3%		
2008	# of owners	607	1,698	6,291	62	1,904	18,007	1,436		
	# of reported holdings	66,618	212,675	6,628	134	169,994	1,282,063	161,112	1,142	12,076
	% of investment volume in units/value	4.9% / 5.9%	18.7% / 25.1%	7.7% / 3.4%	11.0% / 2.4%	15.5% / 25.1%	31.0% / 32.0%	11.3% / 6.2%		
2009	# of owners	603	1,605	6,892	68	1,932	18,199	1,413		
	# of reported holdings	68,300	216,605	7,222	161	168,261	1,272,460	145,820	1,211	16,815
	% of investment volume in units/value	4.8% / 6.1%	18.2% / 24.5%	7.5% / 4.2%	11.3% / 3.3%	15.2% / 24.4%	32.0% / 31.8%	10.9% / 5.7%		
2010	# of owners	606	1,645	6,461	66	2,013	18,843	1,446		
	# of reported holdings	72,906	220,763	6,773	159	176,934	1,298,089	155,585	1,288	18,877
	% of investment volume in units/value	4.7% / 6.3%	17.7% / 24.7%	7.8% / 4.2%	10.5% / 3.0%	15.3% / 23.8%	32.8% / 32.4%	11.2% / 5.6%		
2011	# of owners	612	1,723	6,880	64	2,112	21,123	1,640		
	# of reported holdings	72,230	226,511	7,178	150	184,848	1,410,596	161,486	1,346	17,697
	% of investment volume in units/value	5.3% / 6.6%	17.4% / 24.5%	7.9% / 4.0%	10.2% / 2.5%	15.3% / 24.2%	33.1% / 33.1%	10.7% / 5.1%		
2012	# of owners	586	1,691	6,698	67	2,231	21,365	1,599		
	# of reported holdings	77,238	240,460	6,985	159	203,126	1,498,424	163,192	1,430	20,908
	% of investment volume in units/value	5.6% / 6.6%	17.6% / 24.0%	6.9% / 4.0%	9.5% / 2.2%	13.4% / 23.2%	35.4% / 34.6%	11.6%/5.4%		
2013	# of owners	602	1,788	6,995	69	2,418	23,144	1,678		
	# of reported holdings	82,117	256,324	7,310	155	222,322	155,841	196,156	1,493	26,375
	% of investment volume in units/value	5.5% / 6.2%	17.6% / 24.2%	6.4% / 3.6%	9.4% / 1.9%	13.1% / 23.4%	35.6% / 34.7%	12.5% / 6.0%		
2014	# of owners	608	1,877	7,306	66	2,645	22,806	1,739		
	# of reported holdings	89,699	271,439	7,603	153	249,578	1,558,897	211,522	1,600	28,672
	% of investment volume in units/value	5.9% / 6.2%	17.6% / 24.2%	6.5% / 3.1%	8.7% / 1.7%	13.2% / 23.9%	35.2% / 35.1%	12.9% / 5.8%		
2015	# of owners	628	1,860	9,441	66	2,745	22,452	1,802		
	# of reported holdings	90,200	274,820	9,719	155	267,901	1,650,714	219,468	1,616	27,755
	% of investment volume in units/value	5.2% / 5.8%	17.7% / 24.0%	6.2% / 3.3%	9.3% / 1.6%	13.4% / 24.2%	35.4% / 35.3%	12.8% / 5.9%		
TOTAL	total # of different owners	1,380	3,248	26,417	105	4,691	57,037	3,546		
	total # of reported holdings	1,130,559	3,131,983	89,225	2,026	2,689,936	20,543,662	2,555,006		

in part II the analysis is augmented to the full investment universe of all stocks that are potentially available for purchase. Part II answers the following questions: How is the (CO_2-intensive) stock universe split between different owner types? How are the different owner types invested in ‘dirty’ stocks in comparison to their normal investment habits and portfolio allocations?

3.4.1 Part I: About the owners and the stocks in their portfolio

3.4.1.1 Exposure of ‘dirty’ stocks in investor portfolios

In this section we investigate the carbon risk exposure in portfolios of different owner types. Hereby, we examine institutionals, hedge funds, individuals, government agencies, investment advisors, mutual funds and aggregated mutual funds - and compute the following variables to measure the exposure:

The carbon risk exposure $CRE_{i,t}$ of investor *i* in *t* is computed as

$$CRE_{i,t} = \frac{\sum_{s \in P_{DS_{i,t}}} value\ held_{i,s,t}}{\sum_{k \in P_{DS_{i,t}} + P_{NDS_{i,t}}} value\ held_{i,k,t}} \qquad (1)$$

where $value\ held_{i,s,t}$ is the value of stock *s* that investor *i* has in her portfolio at time *t,* and $k \in P_{DS_{i,t}}$ describes all ‘dirty’ stocks DS in the portfolio P of investor *i* at time *t.* $k \in P_{NDS_{i,t}}$ analogously describes all ‘non-dirty’ stocks NDS in this portfolio.

The average carbon risk exposure $CRE_{j,t}(\emptyset)$ of owner type *j* (e.g. all hedge funds) in *t* is then computed as

$$CRE_{j,t}(\emptyset) = \frac{1}{n_{O_j}} \sum_{i \in O_j} CRE_{i,t} \qquad (2)$$

where $i \in O_j$ contains all investors *i* that belong to owner type *j* and n_{O_j} is the number of these investors in owner type *j*.

Additionally to our analysis about the average carbon exposure behavior of the single owner types, we aggregate all investors within one owner type and compare the exposure of this hypothetical aggregated portfolio. For this purpose, we sum up all corresponding stocks of all investors *i* that belong to owner type *j*.

$$CRE_{j,t}(aggr) = \frac{\sum_{i \in O_j} \sum_{s \in P_{DS_{i,t}}} value\ held_{i,s,t}}{\sum_{i \in O_j} \sum_{s \in P_{DS_{i,t}} + P_{NDS_{i,t}}} value\ held_{i,s,t}} \quad (3)$$

Thus, a $CRE_{j,t}(aggr)$ value of 30% indicates that all investors of owner type *j* (e.g. all hedge funds) have 30% of their total money invested in carbon intensive stocks.

Figure 5 displays the development of average carbon risk exposure $CRE_{j,t}(\emptyset)$ and the aggregated carbon risk exposure $CRE_{j,t}(aggr)$ for the various investor types over time.

In our description of the results we focus on the average carbon risk exposure that is displayed in the left graphs since the described tendencies are qualitatively the same for the aggregated exposure on the right.

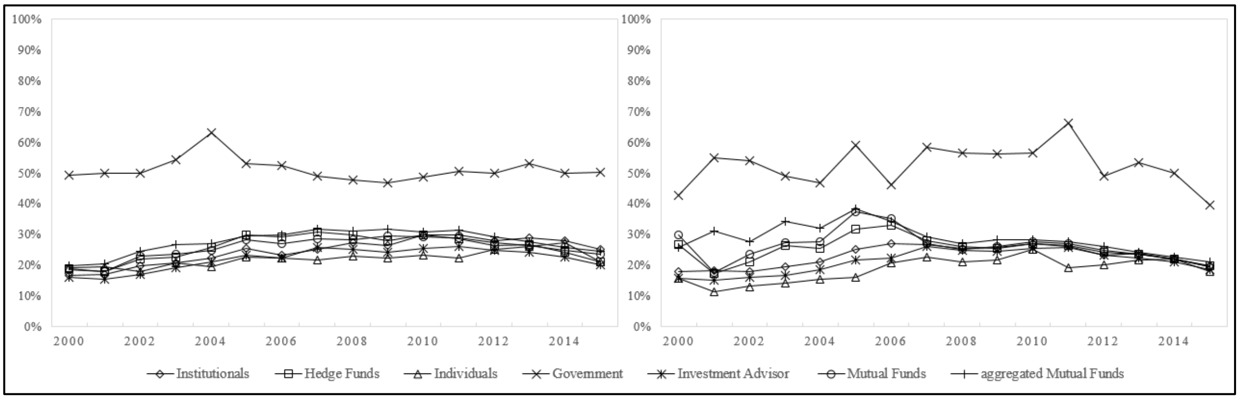
Interestingly, the most significant difference in investment preferences among the different investor types can be observed within government agencies. Panel A shows that the average portfolio of government agencies consists of about 50% carbon intensive stocks while the average portfolio of all other owner or investor types is relatively stable over time and ranges from 15% to 30%. Values between 15% and 30% lie within the expected range since carbon intensive stocks account for approximately 21% of the market capitalization in our sample (see Table XVII). However, the high investment of government agencies in carbon intensive stocks is remarkable. Main driver is probably the high occurrence of state-ownership within CO_2-heavy sectors like Utilities and Oil & Gas. This hypothesis is supported by a report published by PwC in 2015 that shows that petroleum refining, utilities

Figure 5: Carbon risk exposure of different investor types

The following graphs show the carbon risk exposure in the portfolios of the following investor types: Institutionals, Hedge Funds, Individuals, Government Agencies, Investment advisors, Mutual Funds and aggregated Mutual Funds. Graphs on the left present the average exposure $CRE_{j,t}(\emptyset)$ within one owner group, while the graphs on the right illustrate the aggregated value of CO_2-intensive stocks $CRE_{j,t}(aggr)$ as a proportion of the aggregated total assets of each investor type.

The results in each panel vary due to the different categories of CO_2-intensive stocks. Panel A shows the carbon risk exposure for 'dirty' stocks from CO_2-intensive industries. Panel B, C and D represent the results for the worst emitters according to the ranking of their carbon footprint (CO_2e-emissions normalized by Market Capitalization, *EBITDA* and Sales, respectively). Finally, Panel E includes the exposures in stocks with the worst ranking in climate scoring.

Panel A: Carbon risk exposure for stocks from CO_2-intensive industries



Panel B: Carbon risk exposure for stocks with worst carbon footprint ranking (Business metric: Market Capitalization)

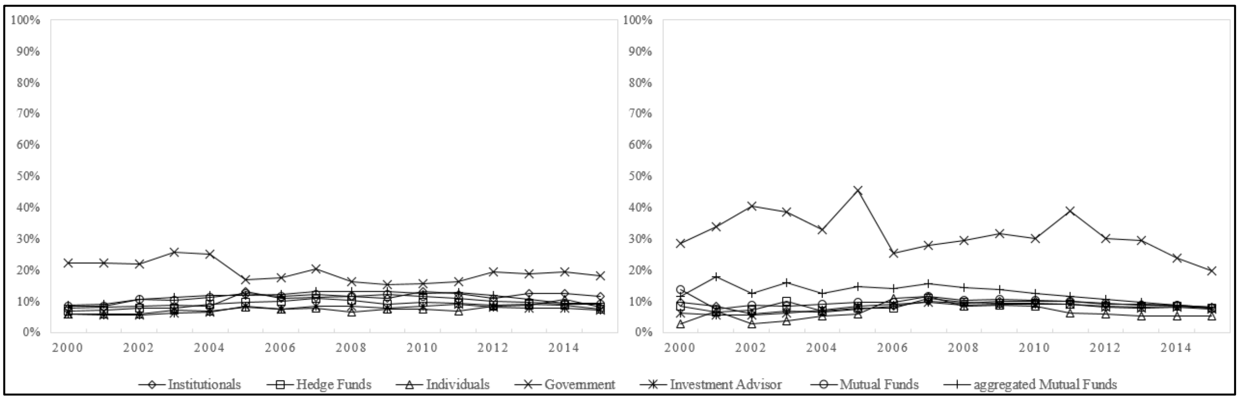
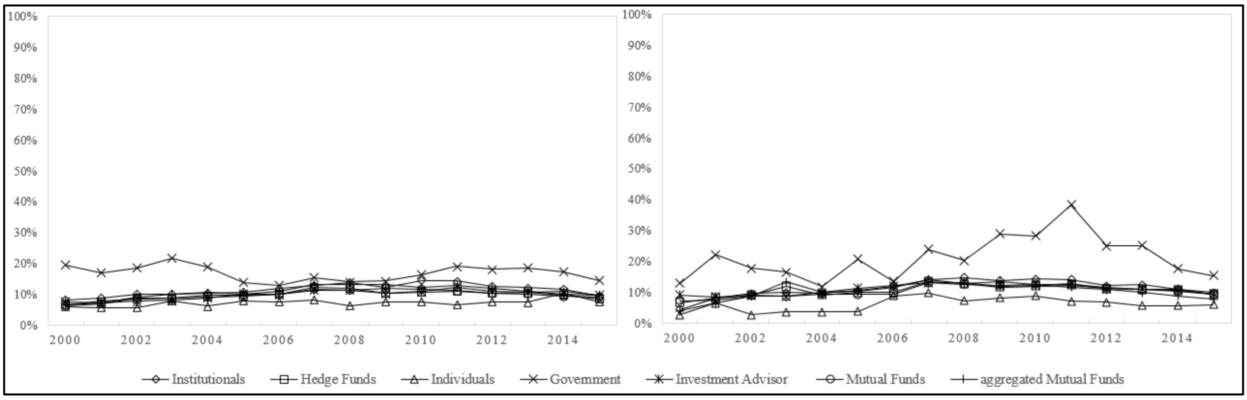
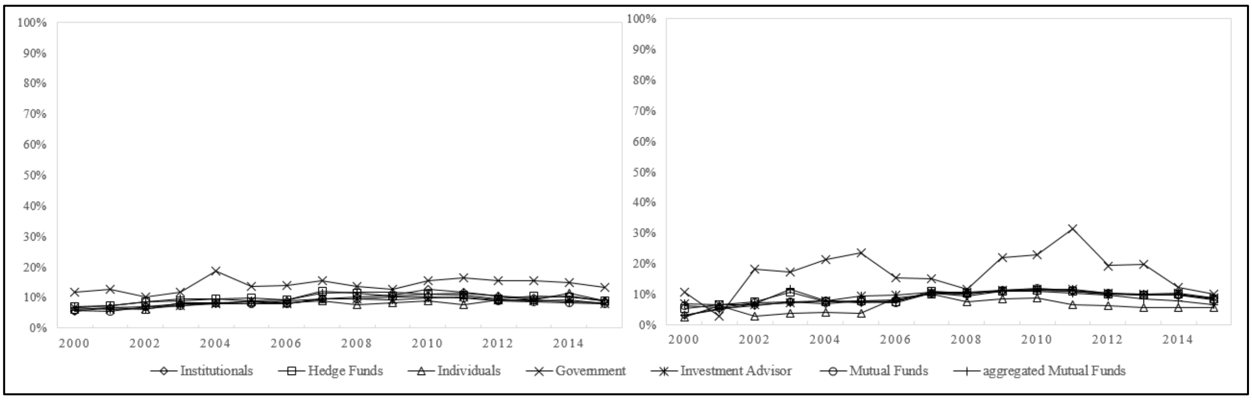


Figure 5 (continued):

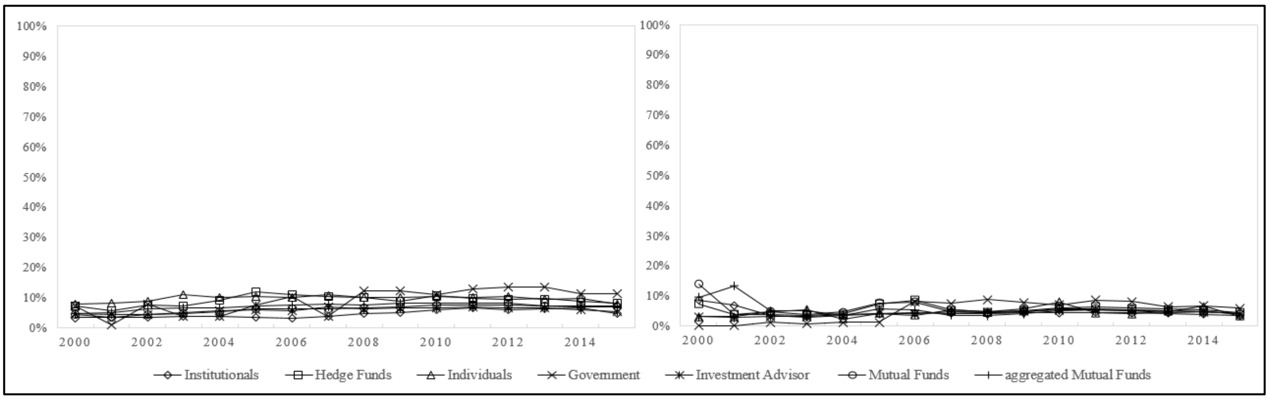
Panel C: Carbon risk exposure for stocks with worst carbon footprint ranking (Business metric: *EBITDA*)



Panel D: Carbon risk exposure for stocks with worst carbon footprint ranking (Business metric: Sales)



Panel E: Carbon risk exposure for stocks with worst ranking regarding climate scoring



and financial services are dominant sectors among state-owned enterprises in the Fortune Global 500, with metals and motor vehicles being the most emerging sectors (Sturesson et al. (2015)). In Panels B-E, the exposure to carbon intensive stocks is further disentangled by examining investments into the 'dirtiest' stocks within the carbon intensive stock category. For this purpose, the worst emitters are defined as the 50% companies with the highest carbon footprint measured by CO_2e-emissions divided by market capitalization (Panel B), carbon emission divided by *EBITDA* (Panel C) and carbon emission divided by sales (Panel D). Furthermore, Panel E includes investments into 50% of the firms in each CO_2-intensive industry with the worst climate scores.

Recall that in terms of market capitalization, Table XVII shows that companies classified as worst emitters make up only slightly more than 40% (based on the different business metrics in Panel B-D) and 15% (based on the climate scoring in Panel E) of all CO_2-intensive stocks[31]. This means that without any exposure preferences between worst and best emitters within the 'dirty' stocks category - one would expect the investment of government agencies in Panel B-D to equally decrease to slightly more than 20% (40% of 50% exposure) and 7.5% (15% of 50% exposure) in Panel E. As the values of the exposure of government agencies are within the expected range, we can conclude that portfolio allocation is made irrespective of the ranking within the CO_2-intensive stocks universe.

3.4.1.2 Ownership of stocks in the portfolio

In this section we target the following question: How much ownership of the carbon intensive stocks in their portfolio (in terms of percentage of the total market capitalization or total shares outstanding) do the different owner types possess?

[31] Total market capitalization of all stocks from carbon intensive stocks is 8,331 billion dollars. The total market capitalization of all stocks that are classified as worst emitter is 3,545 (3,875 / 3,335 / 1,241) billion dollars. Notice that due to limited data availability not all stocks from the carbon intensive industry could be ranked according to their footprint.

For this purpose we define for each owner type *j* (e.g. all hedge funds), the ownership that this group possess in all 'dirty' stocks in their portfolios.

$$OWNERSHIP\_P_{j,t}^{shares}(aggr.) = \frac{\sum_{i \in O_j} \sum_{s \in P_{DS_{i,t}}} shares\ held_{i,s,t}}{\sum_{s \in P_{DS_{j,t}}} shares\ outstanding_{s,t}} \qquad (4a)$$

Therefore, an $OWNERSHIP\_P_{j,t}^{shares}(aggr.)$ of 20% indicates that all investors of owner type *j* together (e.g. all hedge funds) possess 20% of the shares outstanding of all 'dirty' stocks *DS* in their portfolios *P*.

Additionally as robustness, we use a similar variable that is not based on shares held but on value that is owned.[32]

$$OWNERSHIP\_P_{j,t}^{value}(aggr.) = \frac{\sum_{i \in O_j} \sum_{s \in P_{DS_{i,t}}} value\ held_{i,s,t}}{\sum_{s \in P_{DS_{j,t}}} market\ cap_{s,t}} \qquad (4b)$$

Figure 6 displays the amount of carbon intensive stocks in the portfolios possessed by the different owner types. The left panel describes ownership in terms of owned shares, while the right panel describes ownership in terms of market value held by the investors. The results show that if investors - again with the exception of governments - invest in carbon intensive companies they hold on average less than 10% in terms of stocks and less than 20% in terms of market capitalization of these firms. However, it is remarkable that government agencies typically have a considerably higher share of ownership that is greater than 40%. This again might indicate a high occurrence of state-ownership within CO_2-intensive sectors as it reveals that when governments are invested in these companies, they hold proportions far above the

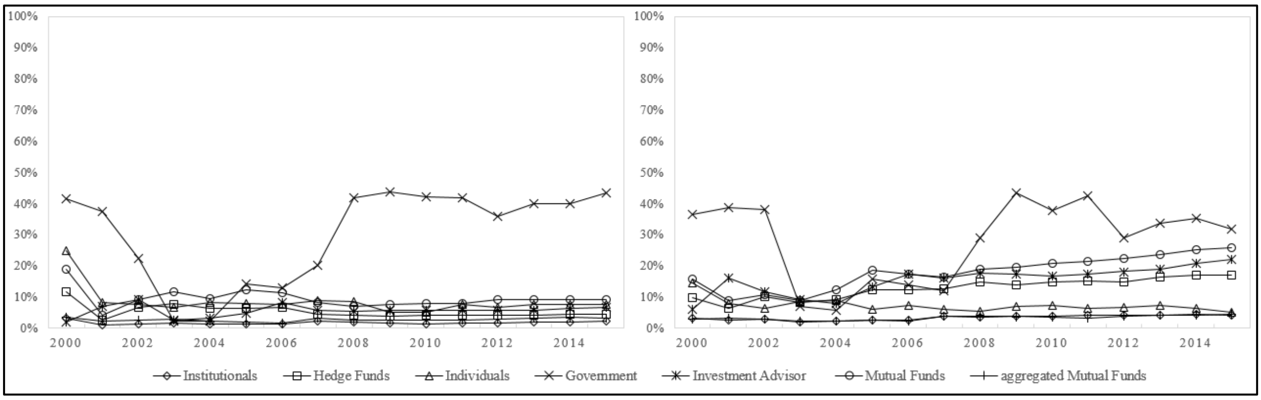
[32] Both approaches might be justified depending on the purpose of investigation as they can lead to different interpretations: Imagine that there are only two CO_2-intensive stock companies which have the same market capitalization. One is a penny stock, the other is not. (e.g. company A has a market capitalization of 100 and 100 shares outstanding (penny stock); company B has a market capitalization of 100 and only 10 shares outstanding (no penny stock)). If all hedge funds altogether possess 10 stocks of each company, its $OWNERSHIP_{j,t}^{shares}(aggr.)$ is 18% ($\frac{10+10}{100+10}$), but the $OWNERSHIP_{j,t}^{value}(aggr.)$ is 55% ($\frac{10+100}{100+100}$).

average. Since governments usually do not primarily invest for financial gain, but to provide services to their citizens, holding higher shares provides them with more shareholder rights which can be used to get a stronger position to control the targeted companies.

Figure 6: Carbon stock ownership of the different investor types

The following graphs show the fraction of carbon intensive stocks that is owned by the different investor types. Carbon intensive stocks that do not occur in the investors' portfolios are not considered. The left graph presents the aggregated ownership of each owner group measured in units of shares outstanding $OWNERSHIP\_P_{j,t}^{shares\ held}(aggr.)$. The right one constitutes the aggregated ownership measured in value held of the market capitalization $OWNERSHIP\_P_{j,t}^{value}(aggr.)$.
The results in each panel vary due to the different categories of CO_2-intensive stocks. Panel A shows the ownership share for 'dirty' stocks from CO_2-intensive industries. Panel B, C and D represent the results for the worst emitters according to the ranking of their carbon footprint (CO_2e-emissions normalized by Market Capitalization, *EBITDA* and Sales, respectively). Finally, Panel E includes ownerships in stocks with the worst ranking in climate scoring.

Panel A: Ownership development for stocks from CO_2-intensive industries



Panel B: Ownership development for stocks with worst carbon footprint ranking (Business metric: Market Capitalization)

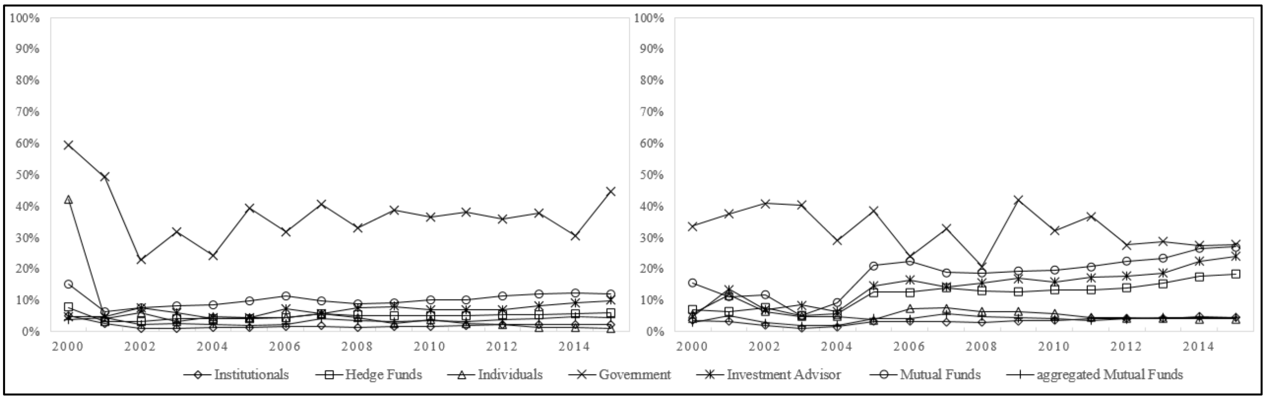
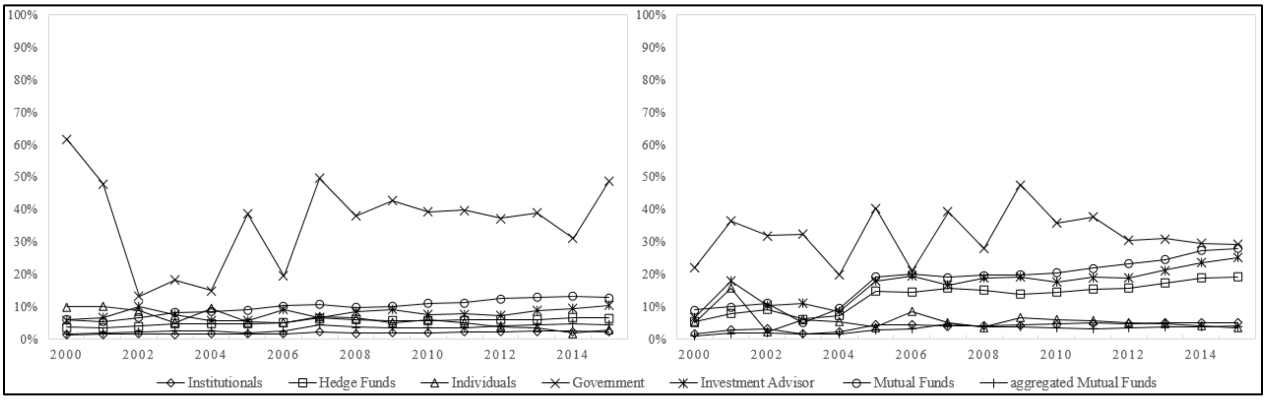
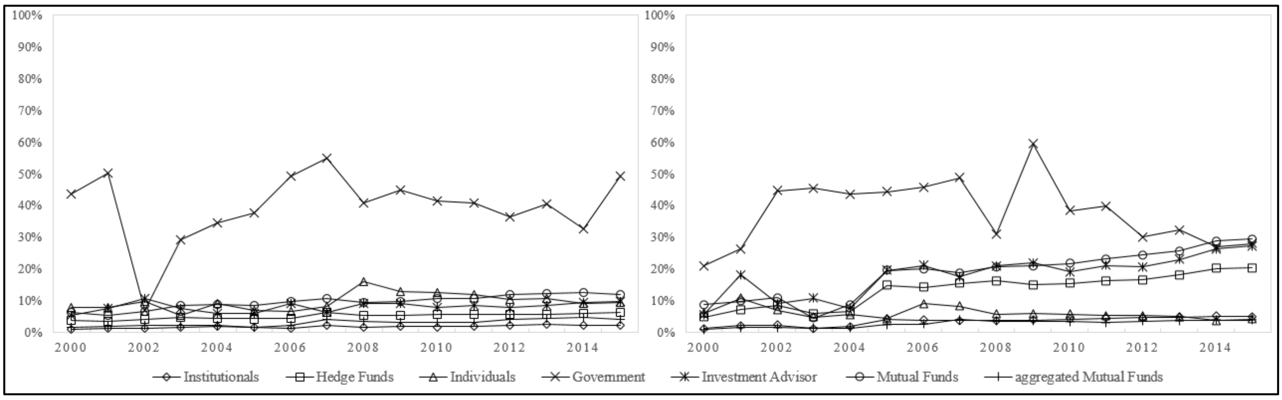


Figure 6 (continued):

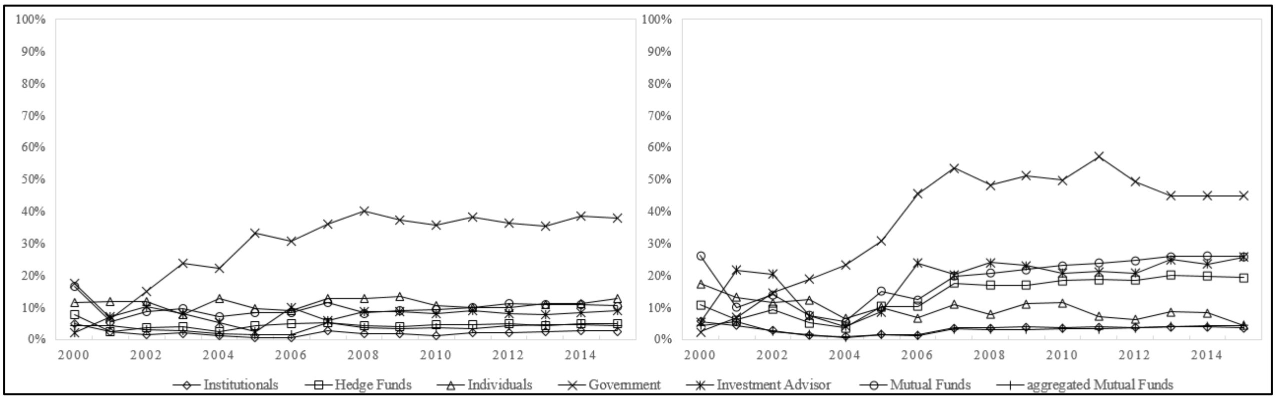
Panel C: Ownership development for stocks with worst carbon footprint ranking (Business metric: *EBITDA*)



Panel D: Ownership development for stocks with worst carbon footprint ranking (Business metric: Sales)



Panel E: Ownership development for stocks with worst ranking regarding climate scoring



3.4.2 Part II: About the owners and the full investment universe

So far our analysis only considers stocks that are held in the owners' portfolio. However, it does not take into account that some of the carbon intensive stocks might be completely ignored by the different investor types. To illustrate this difference, imagine a universe with 100 CO_2-intensive stocks. If hedge funds only invest in one of these companies (e.g. with ownership = 100%), our analysis in part I correctly detects that they possess 100% of the 'dirty' stocks in their portfolio. However, it does not take into account that there are 99 further carbon intensive companies in which their share is 0%. To draw inferences about ownership of different investor types in the CO_2-intensive stock universe, in the following we consider the full investment universe of all stocks that are potentially available for purchase. Such an analysis will then allow us to answer the following questions: How is the whole (carbon intensive) stock universe split between the different owner types? How are the different owner types invested in the 'dirty' stocks universe in comparison to their usual investment habits and portfolio allocations?

For this analysis, we rely on the $OWNERSHIP_{j,t}(aggr.)$ measures that are developed in the previous section. Clearly, the main difference to the analysis previously conducted is in the denominator: we no longer consider only shares outstanding (or market capitalization) of CO_2-intensive stocks in the portfolios of the different owners ($s \in P_{DS_{j,t}}$), but the whole investment universe of all carbon intensive stocks. Thus, we consider all 'dirty' stocks ($s \in DS_t$) that could have been bought by the different investor types. We define

$$OWNERSHIP_{j,t}^{shares}(aggr.) = \frac{\sum_{i \in O_j} \sum_{s \in P_{DS_{i,t}}} shares\ held_{i,s,t}}{\sum_{s \in DS_t} shares\ outstanding_{s,t}} \qquad (5a)$$

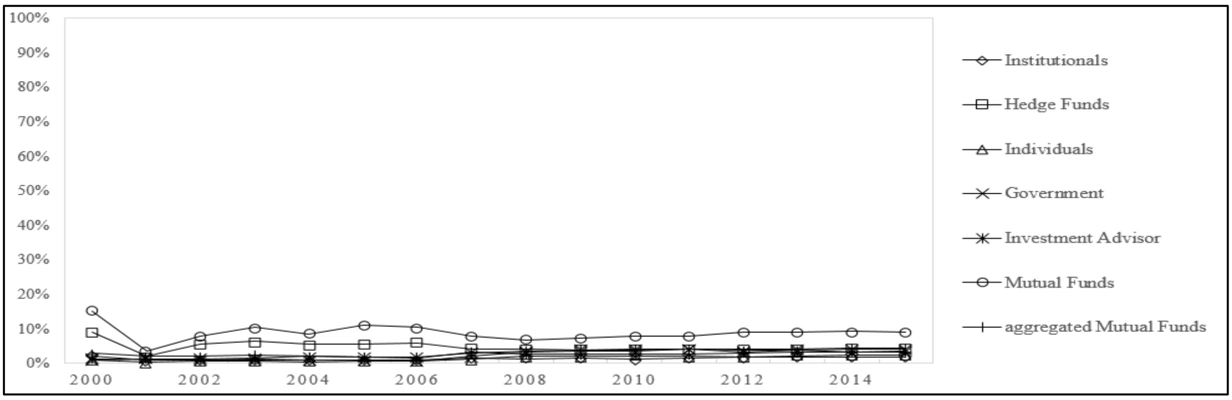
and $$OWNERSHIP_{j,t}^{value}(aggr.) = \frac{\sum_{i \in O_j} \sum_{s \in P_{DS_{i,t}}} valueheld_{i,s,t}}{\sum_{s \in DS_t} marketcap_{s,t}} \qquad (5b)$$

where $s \in DS_t$ contains all stocks in the carbon intensive stock universe (available in Asset4) at time *t*.

Figure 7: Carbon stock ownership of the different investor types - full investment universe

Following graphs show how the full carbon stock universe is split between different owner groups. It shows the ownership distribution of carbon intensive stocks according to their affiliation to 15 CO_2-intensive industries. Panel A presents the aggregated ownership of each owner group measured in units of shares outstanding $OWNERSHIP_{j,t}^{shares}(aggr.)$. Panel B constitutes the aggregated ownership measured in value held of the market capitalization $OWNERSHIP_{j,t}^{value\ held}(aggr.)$.

Panel A: Development of ownership distribution of CO_2-intensive stocks - units of shares outstanding



Panel B: Development of ownership distribution of CO_2-intensive stocks - value of shares outstanding

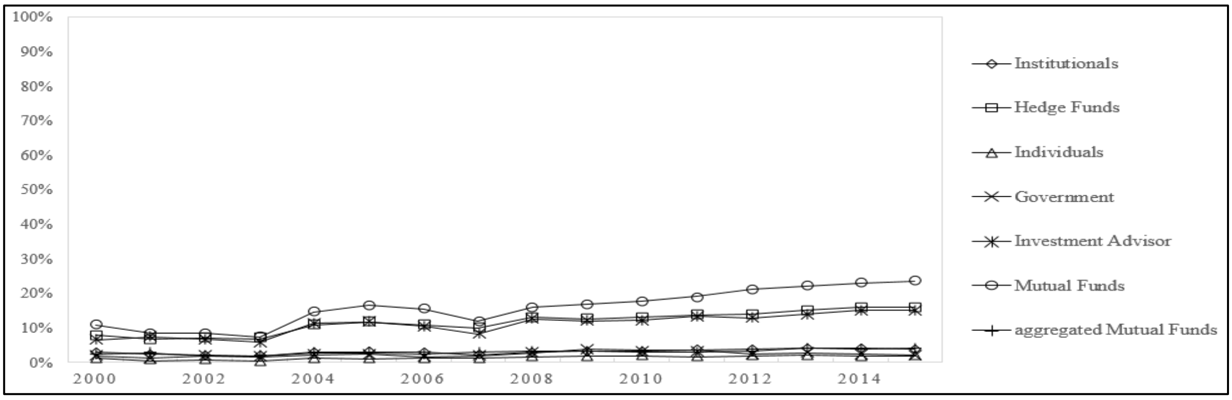


Figure 7 shows how ownership of carbon intensive stocks is distributed among the different investor types. It illustrates that mutual funds are the strongest owner group, holding around 10% of all outstanding shares (Panel A) and 20% of market capitalization (Panel B) of all carbon intensive stocks in our sample. In total, Figure 7 reveals that mutual funds, hedge funds and investment advisors hold the highest proportion of the carbon risk bomb. This might not only be interesting for clients of these investor types, but also for policy makers, who are thinking of controlling the sponsors of ‘dirty’ companies. Governments, which had more than 50% carbon intensive stocks in their portfolio (see Figure 5) have only about 2% ownership in all carbon intensive stocks in total. Therefore, governments belong to the weakest investor types. Overall, we see their role as a carbon risk taker mainly stemming from state-ownership of selected CO_2-intensive firms.

One might argue that different owner types have different amounts of money to invest. For this reason it is self-evident that owner types with more assets under management are generally able to have higher ownership in companies. Therefore, solely relying on aggregated measures of ownership might lead to misleading results. To draw conclusions about the different owners’ investment preferences in carbon intensive stocks, we now conduct an analysis that puts the owners’ ownership of one individual stock in relation to their average ownership in other stocks. Let

$$OWNERSHIP_{j,s,t}^{shares} = \frac{\sum_{i \in o_i} shares\ held_{i,t}}{sharesoutstanding_{s,t}} \quad (6)$$

denote the ownership of an investor type *j* of a specific stock *s* at time *t* as the sum of shares held of stock *s* by all investors *i* of group *j* divided by the number of shares outstanding of stock *s* at time *t.* In order to evaluate how much this single investment differs from the owner group’s *j* usual investment behavior, we adjust the ownership in stock *s* of owner type *j* by the owner type’s *j* average ownership in all other stocks, which yields

$$\Delta OWNERSHIP_{j,s,t} = OWNERSHIP_{j,s,t}^{shares} - \frac{1}{n_{DS_t+NDS_t}} \sum_{s \in s \in DS_t+NDS_t} OWNERSHIP_{j,s,t}^{shares} \quad (7)$$

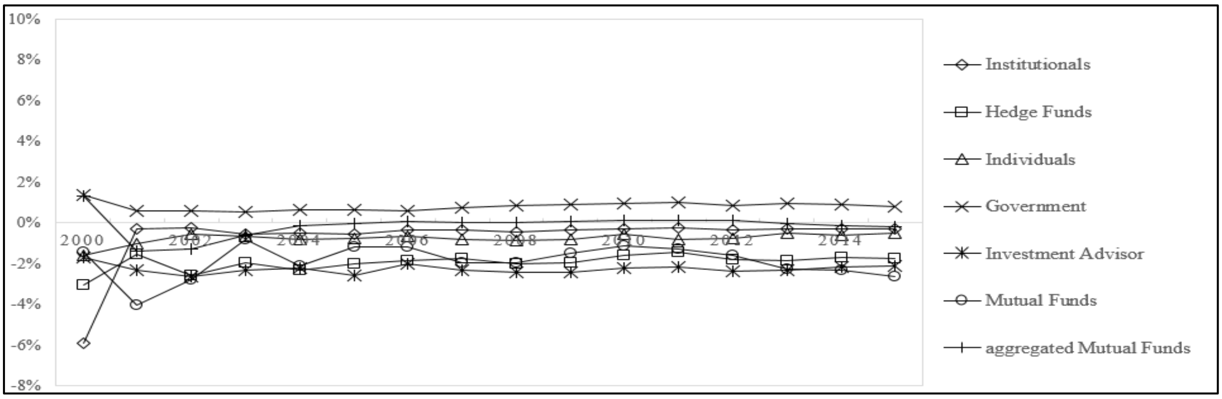
Thus, a value of 1% for the variable $\Delta OWNERSHIP_{j,s,t}$ indicates that investor type *j* (e.g. hedge funds) holds 1 percentage point (pp) more of this particular company *s* than she holds on average in any other carbon intensive and non-carbon intensive companies.

Panel A in Figure 8 focuses on the ownership preference in carbon intensive companies. It displays how the average $\Delta OWNERSHIP$ for every investor type for all carbon intensive stocks of the Asset4 universe has developed over time. It is observable that governments are the only owner group with a constantly positive value of $\Delta OWNERSHIP$. This indicates that on average governments have a higher share of ownership in a specific 'dirty' company than they average ownership in all other Asset4 companies. This inferred preference for carbon intensive firms is in line with our findings from part I of our empirical analysis. All remaining investor types have negative values of $\Delta OWNERSHIP$, which means that they typically hold less of a specific CO_2-intensive stock in comparison to their usual investment behavior.

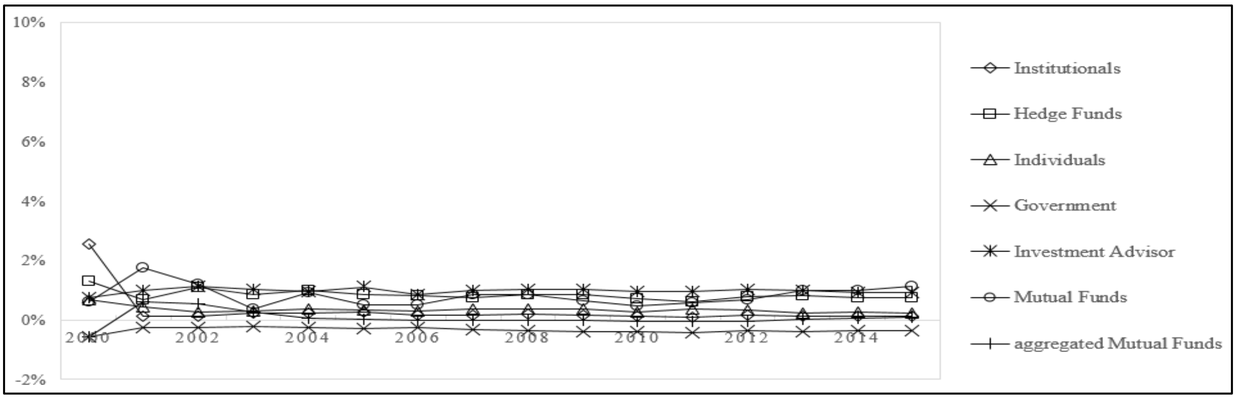
Figure 8: Delta ownership development

In order to evaluate how much a single investment differs from the owner group's usual investment behavior, we adjust the ownership in a specific stock of an owner type by the owner type's average ownership in all other stocks. This is expressed by the variable $\Delta OWNERSHIP$. Panel A displays for every investor type how their average $\Delta OWNERSHIP$ for all carbon intensive stocks of the Asset4 universe has developed over time. As a comparison, Panel B shows the development for $\Delta OWNERSHIP$ of an average stock that does not belong to one of the 15 CO_2-intensive industries identified earlier.

Panel A: Development of delta ownership distribution of CO_2-intensive stocks



Panel B: Development of delta ownership distribution of non-CO_2-intensive stocks



Analogous to this, Panel B shows that governments are less invested in non-carbon intensive companies while all other investor types seem to favor non-carbon intensive stocks and have a higher ownership in these companies.

To further test how significant these differences are, we use year-end observations and run for each stock *s*, each investor type *j* and each year *t* the following regression model.

$$\Delta OWNERSHIP_{j,s,t} = a_0 + \sum_{j\in\{1,2,..,J\}} a_j D_{DIRTY\,j,s,t} + a_{J+1} LOGSIZE_{s,t} + a_{J+2} VOLA_{s,t} + a_{J+3} RET_{s,t} + \varepsilon_{j,s,t} \quad (8)$$

The dummy variables $D_{DIRTY\,j,s,t}$ equal one if the stock s is categorized as a carbon intensive stock and held by the corresponding investor type j, and zero otherwise. It is computed for each different owner type (*J* indicates the number of different owner types). In line with Hong and Kacperczyk (2009) who conduct a similar analysis based on sin stocks, we use the following control variables: We compute $LOGSIZE_{s,t}$ as the natural logarithm of the market capitalization of the company at the end of year *t*, $VOLA_{s,t}$ as the daily stock return standard deviation during the year *t* and $RET_{s,t}$ as the arithmetic average of monthly returns of year *t*. All variables are calculated at the end of the year.

The coefficients of interest however are the coefficients of the dummy variables a_1 to a_J, which measure whether different sets of carbon intensive stocks cause a change in investment habits of the corresponding owner group. For example, assume that hedge funds are owner type number 1, and the estimation yields a_1=0.01. This result would then correspond to hedge funds having a $\Delta OWNERSHIP$ for carbon intensive firms that is higher than for non-carbon intensive firms by 1 percentage point. Hence, for our example, on average this owner group would own 1 percentage point more of a ‘dirty’ company in comparison to a ‘clean’ company based on all Asset4 firms.

Table XVIV reports the results of the regression. Panel A contains a specification without control variables. We find that all signs for the estimated coefficients of the owner

Table XVIV: Regression estimation results

This table shows the estimation results for a pooled panel regression for ownership data from 2000 to 2015. It only includes $D_{DIRTY\,s,t}(j)$ as the independent variable. The dummy variable $D_{DIRTY\,s,t}(j)$ equals one if the stock s is categorized as a CO_2-intensive stock and held by a specific investor type j, and zero otherwise. The categorization can either be based on "Industry Affiliation", "Carbon Footprint" or "Climate Scoring". Thereby, the carbon footprint for "$\text{Carbon Footprint}_\text{M}$" is normalized by market capitalization, the one for "$\text{Carbon Footprint}_\text{E}$" by $EBITDA$ and the one for "$\text{Carbon Footprint}_\text{S}$" by net revenues/sales. $LOGSIZE$ is the logarithm of the market capitalization of the company. $VOLA$ is the daily stock return standard deviation during the past year. $PRINV$ is the inverse of the stock price. RET is the arithmetic average of the last year's monthly returns. All variables are calculated at the end of the year

	ΔOWNERSHIP				
Dirty stocks identification based on:	Industry affiliation	Carbon $\text{Footprint}_\text{M}$	Carbon $\text{Footprint}_\text{E}$	Carbon $\text{Footprint}_\text{S}$	Climate Scoring
Panel A: Pooled panel regression without control variables					
D_{DIRTY} (Institutional)	-0.012	-0.005	-0.006	-0.006	-0.009
	(2.00)**	(0.54)	(0.57)	(0.62)	(1.09)
D_{DIRTY} (HF & Inv. Adv./HF)	-0.024	-0.033	-0.028	-0.021	-0.012
	(4.18)***	(3.34)***	(2.83)***	(2.18)**	(1.53)
D_{DIRTY} (Individuals)	-0.012	-0.017	-0.016	-0.012	-0.006
	(2.13)**	(1.79)*	(1.65)*	(1.25)	(0.69)
D_{DIRTY} (Governments)	0.003	0.010	0.008	0.001	-0.002
	(0.60)	(1.03)	(0.86)	(0.12)	(0.30)
D_{DIRTY} (Inv. Advisor)	-0.027	-0.026	-0.018	-0.006	-0.020
	(4.73)***	(2.62)***	(1.81)*	(0.58)	(2.45)**
D_{DIRTY} (Mutual Funds)	-0.023	-0.046	-0.032	-0.042	0.003
	(4.07)***	(4.75)***	(3.27)***	(4.32)***	(0.31)
D_{DIRTY} (aggr. Mutual Funds)	-0.006	-0.008	-0.007	-0.012	0.001
	(1.00)	(0.80)	(0.71)	(1.24)	(0.15)
R^2	0.00	0.00	0.00	0.00	0.00
N	326,480	326,480	326,480	326,480	326,480
Panel B: Pooled panel regression incl. control variables					
D_{DIRTY} (Institutional)	-0.014	-0.007	-0.008	-0.007	-0.010
	(2.65)***	(0.81)	(0.87)	(0.84)	(1.34)
D_{DIRTY} (HF & Inv. Adv./HF)	-0.024	-0.032	-0.027	-0.019	-0.011
	(4.49)***	(3.63)***	(3.09)***	(2.17)**	(1.48)
D_{DIRTY} (Individuals)	-0.016	-0.021	-0.020	-0.015	-0.009
	(3.07)***	(2.39)**	(2.25)**	(1.72)*	(1.18)
D_{DIRTY} (Governments)	-0.002	0.007	0.004	-0.002	-0.006
	(0.29)	(0.75)	(0.50)	(0.23)	(0.82)
D_{DIRTY} (Inv. Advisor)	-0.028	-0.026	-0.018	-0.005	-0.018
	(5.26)***	(2.95)***	(2.08)**	(0.52)	(2.41)**
D_{DIRTY} (Mutual Funds)	-0.023	-0.044	-0.030	-0.039	0.004
	(4.29)***	(5.01)***	(3.35)***	(4.36)***	(0.59)
D_{DIRTY} (aggr. Mutual Funds)	-0.011	-0.010	-0.010	-0.014	-0.002
	(1.99)**	(1.17)	(1.09)	(1.61)	(0.33)
log(Marketcap)	0.004	0.004	0.004	0.004	0.004
	(8.55)***	(8.78)***	(8.78)***	(8.73)***	(8.17)***
Vola	0.001	0.001	0.001	0.001	0.001
	(12.97)***	(12.39)***	(12.35)***	(12.36)***	(12.61)***
Mthl. Return	0.054	0.053	0.054	0.054	0.056
	(1.95)*	(1.91)*	(1.95)*	(1.95)*	(2.01)**
R^2	0.00	0.00	0.00	0.00	0.00
N	303,352	303,352	303,352	303,352	303,352

dummies are in line with the results reported earlier: we obtain negative coefficients for institutional investors, hedge funds, individuals, investment advisors, and mutual funds, while the coefficients for government agencies are typically positive. However, there is no statistically significant support for our earlier findings with regards to governments holding a higher share in carbon intensive firms in comparison to other stocks. For institutionals, hedge funds, individuals, investment advisors and mutual funds it can be statistically proven that these investor types have a smaller $\Delta OWNERSHIP$ if a firm is considered 'dirty' according to its industry affiliation. This indicates that they hold a smaller portion of a carbon intensive firm than they would usually do in any other stock. However this does not hold for every specification of 'dirty' stock.

Panel B reports the results for the pooled panel regression including the control variables. We find economic effects that are similar to that reported in Panel A. Although the sign for governments becomes negative for some specifications, this investor type remains the investor with the highest $\Delta OWNERSHIP$. All control variables have positive significant loadings, indicating that all investor types generally favor stocks with higher market capitalization, volatility and higher historical returns.

Overall, the results of the conducted regression analysis confirm our findings from previous sections on investor behavior with respect to carbon intensive stocks: hedge funds, individuals, investment advisors and mutual funds own statistically significant less carbon intensive stocks in comparison to non-carbon intensive stocks. On the other hand, government agencies are found to typically hold more carbon intensive stocks in comparison to the overall Asset4 investment universe. We note, however that while the latter results seem to be relatively robust across different classifications of carbon intensive stocks as well as size of the considered firms, they are not statistically significant in our regression analysis.

3.5 Conclusion

We provide one of the first studies to examine the exposure of various investor types to carbon intensive stocks, using a large universe of stocks. In particular, we combine different metrics to classify carbon intensive stocks with Thomson Reuters' Global Ownership database that provides year-end holdings for these stocks for the time period 2000 to 2015. The applied approach allows us to thoroughly examine the ownership structure of carbon intensive stocks for various ownership types such as institutional investors, hedge funds, individuals, investment advisors, mutual funds or government agencies.

The conducted analysis allows us to examine important questions related to carbon risk and ownership structure. We define three different categories of carbon intensive stocks that help to identify companies that are particularly exposed to carbon risk, i.e. to possible regulatory changes with regards to *GHG* emissions. We argue that investors have a strong interest in understanding which firms could be particularly affected by new policies restricting carbon emissions, due to the possible detrimental effects of such policies on the financial performance of these companies. Moreover, we are the first to work with an extensive dataset of ownership structures in order to analyze investor behavior related to carbon intensive stocks. In particular, we examine portfolios of different owner types, with regards to their investment in the classified high-polluting firms. Interestingly, we find that it is actually government agencies who have the highest exposure to carbon risk, with approximately 50% of their portfolios invested in carbon intensive stocks. Comparable numbers for all other investor types are significantly lower and lie between 15% and 30% of their total investments.

Another area of interest is what percentage of the total market capitalization of high-polluting firms are held by the different investor groups. The results show that governments typically hold around 40% of a 'dirty' stock in their portfolio, whereas institutionals, hedge funds, individuals, investment advisors and mutual funds hold a significantly lower share, corresponding to approximately 10% of the total market capitalization of these stocks. In this context, it is also interesting to investigate how the whole CO_2-intensive stock universe is divided between different owner types. We find that mainly mutual funds, but also hedge funds and investment advisors form the biggest investor groups which have an ownership between 10% and 20% each. Both aspects help to understand how influential the different owner types are for the carbon intensive sector overall as well as for specific stocks that have a high share of government agencies as investors.

Moreover, we provide more detailed information on the preferences of each owner type, by examining how they are invested in carbon intensive stocks in comparison to their overall investment behavior. Our findings suggest that hedge funds, individuals, investment advisors and mutual funds own statistically significant less carbon intensive stocks in comparison to non-carbon intensive stocks. At the same time, government agencies typically have more ownership in carbon intensive stocks in comparison to their holding in other stocks, although the results are not statistically significant. These results are at least somehow surprising, given that it is typically government at all levels claiming to expedite the transition to a low-carbon and climate resilient economy. We believe that the information provided in this study can help policy makers tailoring incentives for each investor type to support the goal of reducing emissions. Based on our results, this might either happen through encouraging investors to de-invest in carbon intensive firms or particularly for government agencies through executing voting rights to influence emission levels of carbon intensive firms.

Our findings also suggest directions for future research. One possible direction is to further explore the importance different investor types assign to carbon risk exposure and how much it influences their investment decisions in real life. Furthermore, given that it is typically government agencies holding the highest shares in carbon intensive firms, it might be worthwhile to investigate the relationship between shareholder activism and carbon intensive companies, especially in the context of state-ownership.

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4 Article III: About carbon risk exposure in mutual funds - New evidence from mutual fund holdings

Janik Syryca

Abstract. Since the 21st climate conference in Paris (2015), the goal is precisely defined: The global average temperature may not exceed to more than 2°C above pre-industrial levels. To reach this goal, regulatory requirements will tighten and companies must pay for allowances to eject carbon emissions. This will not only pose a challenge for the companies involved. Asset managers and investors with exposure to such companies will be equally affected. This study is the first to demonstrate the implication and meaning of the so-called carbon risk to actively managed US domestic open-end mutual funds. It describes the asset allocation, exposure preference and ownership structure in carbon intensive stocks within the fund universe. In doing so, both, funds exposed to particular high carbon risk and funds that already have started to divest will be identified. Furthermore, the study reveals that funds that structure their portfolio towards low emitter stocks generate more risk-adjusted performance and have less risk.

Thus, the study not only helps investors to better assess the carbon risk, they involuntarily might be invested in, but equally provides support to policy makers that want to tailor fund-customized measures to facilitate the transformation into a carbon-constrained world.

JEL Classification G11, G18

Keywords Carbon Risk, GHG Emissions, Green Finance, Mutual fund behavior

4.1 Introduction

Carbon dioxide (CO_2) accounts for about three-quarter of global greenhouse gas (*GHG*) emissions and is considered to be the main cause of anthropogenic global warming (Pachauri et al. (2014)). However, governments are slowly starting to counteract. Recent initiatives as the 21st Conference of the Parties (COP 21) in Paris 2015 proof that policy makers are determined to put a stop to further rise in global temperature[33]. Consequently, companies need to transform into a carbon-constrained world and will be affected by many structural changes. Extra costs due to tighter regulatory requirements, taxes or forced payment for carbon emission certificates will negatively influence future cash flows of all companies involved. To meet the goals set forth in Paris, approximately only one-quarter of all worldwide coal, oil and gas reserves will be allowed to be exploited (IPCC (2014), Carbon Tracker Initiative (2013)). Resources that become suddenly no longer useable to its full potential, experience a decrease in value. Companies that own such “stranded assets” will suffer from significant future economic losses. As to this moment, this future loss is not all considered in the current balance sheets of the companies, their value might currently be severely overestimated - a situation known as “carbon bubble”. Additionally, rising ecological awareness in society will cause high carbon polluters to be exposed to reputational risk.

These changes will come and not only influence the corresponding companies. Asset manager and investors will equally be affected. As Carrington (2013) expects a possible burst of this “Carbon Bubble” to have similar consequences as the financial crisis in 2008, insights about the influence and meaning of carbon risk for different investor types is all the more of vital importance.

[33] The precise goal is to limit the increase in the global average temperature to well below 2° C above pre-industrial levels (United Nations Framework Convention on Climate Change (2015)).

This paper contributes to this question as it is the first study at all that links the implication and meaning of carbon risk to one of the largest investor group - the actively managed domestic open end mutual funds.

As a foundation for the subsequent mutual fund related analyses, this study starts by comparing several characteristics on stock level and answers the following questions: How do companies from carbon-heavy industries and carbon light industries differ? How are high CO_2 emitters within the carbon-heavy industries different from low emitters? The main finding is that between 2007 and 2014 stocks from carbon intensive industry have less performance (6.6% p.a. in terms of Carhart alpha). Low emitter stocks, i.e. stocks that belong to the lowest emission ejectors within their industry, outperformed high emitter stocks by 0.5% p.a. and significantly experienced less risk. Thus, this paper confirms the majority of studies as Aggarwal and Dow (2011), Gallego-Alvarez et al. (2015), Saka and Oshika (2014) and Misani and Pogutz (2015) which find that reduction and lower usage of carbon emissions are associated with a better positive performance. In this context, only Delmas and Narin-Birch (2011) deliver mixed results. They confirm that low emission has a positive effect on Tobin's Q, but find a negative relation to corporate financial performance.

The next aspect, investigated in this study, targets the fund manager's portfolio allocation and exposure preference. Additionally, it investigates the mutual fund's ownership structure in carbon risk stocks. This section is of interest for both, policy makers as well as investors in mutual funds, as it provides insights of to which extent the fund universe is invested in carbon risky stocks and therefore affected by the future changes to come. In concrete terms, the following questions will be answered: How much carbon risk exposure is within the fund universe? How can these values be interpreted? How did exposure change over time? Which percentage of all dirty stock companies does the mutual fund universe possess? The study finds that the average fund portfolio - with decreasing tendency - consists of 23.49% carbon risk stocks. This is nearly 10% more than the weight of all carbon risk in the *CRSP* universe. However with an average ownership of 2.14%, actively managed US domestic open end funds only possess a small fraction of the US carbon risk companies in the *CRSP* universe.

To help policy makers tailor customized measures, it is important to let them know the characteristics of funds that face high carbon risk exposure. The study contributes to this question by finding that it is especially old funds with high expense ratio and low 12b1 fees that are exposed to a higher amount of carbon risk. In the broader sense, this part of the study can be linked to Scherer et al. (2017), which provide a broad overview of the worldwide exposure and ownership structures of different owner types as institutionals, hedge funds, individuals, investment advisors and mutual funds. However, their focus is not on the US and not on actively managed open-end mutual funds.

The fourth contribution of this paper breaks new ground and is the first to deliver a link between a manager's performance/risk and his preference of structuring the portfolio towards low emitter stocks. Confirming the commonly known fact that between 2007 and 2014 stocks from carbon-heavy industries like oil, coal, etc. have suffered from a bad performance in comparison to other industry sections, the study interestingly reveals that there seems to be a difference on how strong a portfolio was balanced towards low emitter stocks. Investors who gave money to funds with a focus on only the lowest emitters within each carbon intensive industry could benefit from more performance and less risk.

If one considers the ecological aspect of carbon risk, this study can be connected to research about social investments as well. Hong and Kacperczyk (2009) provide evidence that social considerations of the players in the financial markets can no longer be neglected. They show that many large investors, such as public pension funds, have started to avoid companies that are involved with tobacco, alcohol, gambling or weapons. Bollen (2007) additionally finds deviant behavioral patterns of social retail investors as he reports that all other things being equal, socially responsible mutual funds (SRI) experience less outflow after a negative performance in comparison to their peer group of regular funds.

With regard to performance, however, research is split. Even though there exist many studies on stock level that find that social stock portfolios generate lower risk-adjusted returns (Fabozzi et al. (2008), Hong and Kacperczyk (2009), Statman and Glushkov (2009), Derwall et al. (2011) and Salaber (2013))[34], their findings often cannot be transferred to fund level. The common conclusion of studies as e.g. Hamilton et al. (1993), Bauer et al. (2005), Derwall et al. (2011), Leite and Cortez (2014) is that SRI funds do not underperform regular funds. Only Climent et al. (2011) and Chang et al. (2012) find that green funds have significant lower alphas - the first one, however, only for the first period in his study.

Last but not least, as high carbon emitting companies are likely to face decreasing profits in the future, it is of interest for investors to see what kind of funds already started in anticipation to engage in divesting trading strategies. Here the study reveals that it is especially small and young funds that are taking lead to the way to a carbon - constrained world.

To summarize, this study is the first to link carbon risk and mutual funds. It therefore helps investors and policy makers to get a better understanding of the opportunities and challenges for this important group of investors.

[34] From a theoretical point of view, socially controversial stocks are expected to have higher expected returns. The reason is that stocks that are avoided by investors due to social considerations, experience less demand and lower stock prices (see Angel and Rivoli (1997), Heinkel et al. (2001) and Hong and Kacperczyk (2009)).

The remaining of this paper is structured as follows: Section 4.2 introduces definitions and methodology used in this study. Section 4.3 gives a description of the data. Section 4.4 presents the empirical results followed by a conclusion in section 4.5.

4.2 Methodology

This study deals with carbon risk and its implications and meaning for mutual fund managers. The following section aims to give precise definitions and differentiations of the terms that occur in the context of this study.

4.2.1 Definition of carbon risk stock

Correct measurement and identification whether a stock is a carbon risk stock or not are of vital importance for a study of a mutual fund's carbon risk exposure. However, this process can be arbitrarily deep and complex and strongly depends on the respective application. For the sake of simplicity, I use a very simple but intuitive approach to identify carbon risk stocks - a categorization based on the carbon emission of the industry the stock is affiliated to. This idea is not new and similar to Gallego-Álvarez et al. (2015), Misani and Pogutz (2015) and Scherer et al (2017). A stock is classified as carbon risk stock if it belongs to an industry with high carbon emissions. To divide the stock universe into different industrial sectors, I use French's suggested industry classification, where each stock is assigned to one of 30 different industries.[35] To select the most carbon intensive industries I refer to many different sources (Labatt and White (2002), Labatt and White (2007), Pachauri et al. (2014)). According to these studies, steel, fabricated products and machinery, autos, carry (aircraft ships and railroad equipment), mines, coal, oil, utilities, and paper belong to the industries with the highest

[35] French assigns each NYSE, AMEX, and NASDAQ stock to one of 30 different industry portfolios based on its four-digit SIC code at that time. I thank Kenneth R. French for providing these data. For more details, please refer to http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port.html.

carbon emissions. For this reason, I categorize a stock as carbon risk stock, if it belongs to one of the above-mentioned industries.

4.2.2 Definition of carbon footprint and worst / medium / light emitter stock

The above-mentioned categorization based on industry affiliation is basic but useful and correct. However, it neglects the fact that different companies within the same industry are likely to vary in terms of their carbon emission. For this reason, I further disentangle each carbon risk stock in a second step by additionally applying a more precise measure of its carbon intensity - the carbon footprint. The carbon footprint of a company indicates all of its total *GHG* emissions. This measure includes emissions from both, Scope 1 and Scope 2, i.e. it takes into account all emissions from sources directly owned and controlled by the company (Scope 1) as well as all emissions that arise indirectly by the purchase and use of electricity, heat or steam (Scope 2). Emissions of activities that are not controlled by the company, e.g. waste disposal (Scope 3), have very low reporting requirements, are not very reliable and are therefore not included in the measure (Carbon Trust (2012)).

To take into account that big companies are more likely to have more carbon emissions than smaller ones - even if they have equal environmental awareness - I follow Hoffmann and Busch (2008) and Busch (2010) and make carbon emissions comparable by normalizing them by net sales, one of the suggested proxies for company size. This yields the following formula of carbon footprint $CFP_{i,t}$.[36]

[36] Please note that there a further related studies to the measure of carbon footprint. Pandey et al (2011) suggest measurement of carbon emissions in the carbon footprint from the point of view of the products. Andrew and Cortese (2011) evaluate the carbon footprint with regard to reliability and usability for climate change related decision making.

$$CFP_{i,t} = \frac{Total\ GHG\ Emissions_{i,t}}{Net\ sales_{i,t}} \qquad (1)$$

Another aspect to be investigated in this study is the comparison of carbon risk stocks that have relatively low carbon emissions (low emitters) and carbon risk stocks with high carbon emitting values (high emitters). The comparison is interesting as it compares companies that are rather progressive in terms of environmental awareness with those, who will probably be more severely affected by the transformation into a carbon-constrained world. As value chains strongly vary across the different industrial sectors, a simple comparison of carbon footprint among different industries is not expedient. For this reason, I choose to apply the best in class approach. This means I rank each stock based on its average carbon footprint for each industry separately.

Thus, a company is defined to be a low emitter (*LE*) if its average carbon emission / net sales values belong to the bottom 33% in the corresponding industry. Similarly, a medium emitter (*ME*) stock lies in the range between 33% and 66%. High emitter (*HE*) stocks have average carbon emission / net sales values that are higher than 66% of all other companies within the same industry.

4.2.3 Definition of a fund's carbon risk exposure

The focus of this study is the impact and meaning of carbon risk for the mutual fund manager. For this reason, I develop a new but basic measure, which represents the carbon risk exposure of a manager's portfolio. To compute the carbon risk exposure $CRE_{i,t}$ of fund i at quarter t I simply sum up the holding weights of all stocks that have been categorized as carbon risk stock.

$$Carbon\ Risk\ Exposure\ CRE_{i,t} = \sum_{j=1} weight_{j,t} \cdot D_{CarbonStock_{j,t}} \qquad (2)$$

where $D_{CarbonStock_{j,t}}$ is a dummy that equals 1 if stock j is a carbon risk stock

4.2.4 The degree of investment in low emitter - the *DILE* factor

For some research questions, it might be interesting to not only consider the absolute carbon risk exposure but to specifically compare the differences between fund managers that prefer low emitter stocks in their portfolio with those, who do not. For this purpose, I develop a new measure which is able to capture the manager's preference for low emitter stocks in his portfolio - the degree of investment in low emitters (*DILE*).

The *DILE*-measure is calculated as the difference between the exposure in low emitter stocks and high emitter stocks. It has the following formula:

$$DILE_{i,t} = \sum_{j=1} weight_{j,t}\, D_{LowEmitterStock_{j,t}} - \sum_{j=1} weight_{j,t}\, D_{LowEmitterStock_{j,t}} \quad (3)$$

where $D_{LowEmitterStock_{j,t}}$ ($D_{HighEmitterStock_{j,t}}$) is a dummy that equals 1 if stock j in the portfolio is a low emitter stock LE (high emitter stock HE) .

The advantage of this measure is that it takes more information into account than a measure that only includes the exposure of the low emitter stocks. The reason for this is that it indirectly considers exposure in medium emitter stocks (*ME*) as well.

Figure 9: Example *DILE* factor

This figure illustrates the computation of a fund's *DILE* factor. *DILE* indicates the degree of investment in low emission and is the difference between exposure in low emitter minus exposure in high emitter stocks.

Fund	Low emitter exposure	Medium emitter exposure	High emitter exposure	$DILE_{i,t}$
A	100 %	0 %	0 %	100 %
B	80 %	0 %	20 %	60 %
C	80 %	10 %	10 %	70 %
D	0 %	0 %	100 %	- 100 %

Figure 9 is meant to illustrate this relation: Fund *A* obviously possesses the highest degree of investment in low emitters. A distinction between fund *B* and *C* based on solely regarding the exposure to low emitters is not possible. However, the *DILE* factor enables to provide a more precise differentiation between those both funds, as it takes into account that fund *C* has more *ME* exposure and less *HE* exposure than fund *B*.

4.3 Data

The study uses information on mutual fund holdings from Morningstar where all holdings with more portfolio weight than 0.006% are reported. [37] I delete holdings reports if the weight of all equities is less than 75% of the fund's *TNA*. Fund characteristics are obtained from the *CRSP* Survivorship-Bias-Free Mutual Fund Database and mostly only available at the share class level. To aggregate them to fund level, I value weight them with the corresponding total net assets of each share class. Only the fund's total net assets are computed as the sum of each share class. Furthermore, I delete all funds that are not listed as domestic equity style or cap based funds (EDY or EDC).

In line with Amihud and Goyenko (2013), I exclude index funds by removing those with names containing words like index, 'S&P', 'Dow', 'WILSHIRE', 'RUSSELL'. Additionally, I exclude funds with less than 5 million TNA as in Fama and French (2010). Following Kacpercyk et al. (2008), I eliminate fund periods with less than 10 reported holdings as this is an indication of bad reporting quality. [38]

Information on stock returns and characteristics are from the *CRSP* Stock Database. I only include common equity holdings (share codes 10 and 11) and delete all penny stocks with a price below $1. Information on a company's carbon emission characteristics is

[37] For a more detailed description of the Morningstar holdings data, see Elton (2012).

[38] The approach applied is similar to Rohleder et al. (2017).

obtained from voluntary reports of the Asset4 database. It is important to note that the Asset4 database suffers from two major limitations as firstly, their reports are only voluntary and therefore potentially be affected by a reporting bias and secondly, their coverage among all companies is not very high. However - due to the lack of alternatives - the Asset4 database is nevertheless considered to be one of the best possible data sources available for research related to carbon emissions. To make inferences in my study more reliable, I use a subsample of funds and require their holding reports to have at least more than 30% of equities available in the Asset4 database. However restricted availability of carbon emission values limits the sample period to be from 2007 to 2014. The final sample consists of 15,946 quarterly[39] fund observations of 702 active U.S. domestic equity funds.

Table XX: Completeness of the Asset4 database

This table demonstrates how many funds exist in each year if a certain percentage of holdings availability in the Asset4 database is required. The percentage of holdings availability is measured in market value of all equities available in the Asset4 database / *TNA* of the fund.

	% (equity / *TNA*) matchable with *CRSP* and available in Asset4				
Year	Full sample	over 20%	over 30%	over 40%	over 50%
2007	1,102	440	139	4	20
2008	1,128	481	154	8	10
2009	1,111	621	480	195	29
2010	1,033	601	448	145	30
2011	995	607	455	208	9
2012	992	614	484	227	1
2013	978	539	317	81	20
2014	943	424	183	13	10

Table XX demonstrates the availability of data in the Asset4 database and indicates the number of funds existing in each year. In the full sample, the number of funds declines

[39] During my sample period, mutual funds are obliged to report portfolio holdings to the SEC on a quarterly basis. Empirically however, actual reporting frequencies deviate from strictly quarterly reports, even within individual funds, and may be as high as monthly or as low as semiannually in few cases. As the average time between reporting frequency is close to 3 months, I simplify by referring to reporting periods as quarterly.

from 1,102 to 943. The other columns indicate how many different funds remain if a certain percentage of holdings availability in the Asset4 database is required.

A reliable study about carbon emissions and funds requires, on the one hand, a fund sample as big as possible, but on the other hand, a sample with sufficient coverage in the Asset4 database. Having these conflicting goals, I decided to use the subsample of funds in which at least more than 30% of equities is covered in the Asset4 database. This allows analysis of 139 funds in 2007 and 183 funds in 2014. To mitigate the suspicion that funds in the subsample do differ systematically from the full sample, Table XXI is intended to compare the fund's main characteristics of each sample. It demonstrates that funds in the full sample are only slightly smaller (1.3 billion vs. 1.7 billion) and younger (214 months vs. 237 months) and that they have quite similar expense ratio (0.012 vs. 0.011), 12b1 fee (0.003 vs. 0.002), rear load (0.009 vs. 0.008), front load (0.031 vs. 0.030) and flows (-0.002 vs. -0.004). This militates in favor of the subsample being representative for the full sample.

Table XXI: Comparison of the subsamples

This table displays fund characteristics of the different subsamples. *TNA* is denoted in million $. Expense ratio, 12b1 fee, rear load, front load are yearly (and denoted in relation to a fund's *TNA*). Age is declared in months. Flow / *TNA* is based on quarterly observations.

	TNA	Exp. ratio	12b1 fee	Rear load	Front load	Age	Flow/*TNA*
full sample	1,341.733	0.012	0.003	0.009	0.031	213.671	-0.002
over 20%	1,740.739	0.011	0.003	0.008	0.030	233.210	-0.002
over 30%	1,667.789	0.011	0.002	0.008	0.030	236.806	-0.004

Table XXII displays descriptive statistics of the fund characteristics in my sample. Funds have on average 1.7 billion of *TNA* and have increased from 1.7 billion to 3.3 billion on average. Overall, the size of the characteristics is in line with previous mutual fund research.

Table XXII: Fund characteristics of the subsample

This table displays the average fund characteristics of the subsample where equity value available in Asset4 is more than 30% of the *TNA*. *TNA* is denoted in million $. Flow / *TNA* is based on quarterly observations. Expense ratio, 12b1 fee, rear load, front load are yearly (and denoted in relation to a fund's *TNA*). Age is declared in months. Fund reports indicate the number of different available holdings reports. The column "funds" shows the number of different funds.

	TNA	Age	Flow/*TNA*	Expense ratio	12b1 fee	Front load	Rear load	Fund reports	Funds
2007	1,727	159.1	0.002	0.012	0.003	0.034	0.011	492	139
2008	810	201.5	-0.007	0.012	0.002	0.030	0.010	672	154
2009	1,173	218.5	-0.004	0.011	0.003	0.030	0.009	2,939	480
2010	1,345	231.7	-0.006	0.011	0.002	0.030	0.008	2,645	448
2011	1,582	241.6	-0.004	0.011	0.002	0.031	0.007	2,937	455
2012	1,705	249.7	-0.006	0.011	0.002	0.030	0.007	3,141	484
2013	2,273	260.5	0.003	0.010	0.002	0.030	0.007	2,043	317
2014	3,295	261.3	-0.002	0.010	0.002	0.030	0.006	1,077	183
2007 - 2014	1,668	236.8	-0.004	0.011	0.002	0.030	0.008	15,946	702

Table XXIII: Fund performance and risk characteristics

This table displays average performance and risk characteristics of the subsample where equity value available in Asset4 is more than 30% of the *TNA*. Returns are monthly. Standard deviation is monthly based on daily return data. For each month, Carhart alpha, beta market, beta *smb*, beta *hml* and beta *mom* are computed based on daily data. Carhart alpha is annualized. *CRSP vw* indicates the monthly returns of the *CRSP* value-weighted market Index.

Year	*CRSP vw*	Return	Carhart alpha	Beta market	Beta *SMB*	Beta *HML*	Beta *MOM*	Std	Fund reports	Funds
2007	0.006	0.000	-0.001	1.029	-0.134	0.212	0.002	0.011	492	139
2008	-0.037	-0.036	-0.073	0.902	-0.095	0.081	0.018	0.019	672	154
2009	0.025	0.024	-0.031	0.973	-0.054	0.003	0.014	0.015	2,939	480
2010	0.015	0.012	-0.032	1.001	-0.083	0.042	0.015	0.011	2,645	448
2011	0.000	0.001	-0.014	1.002	-0.078	-0.015	-0.020	0.013	2,937	455
2012	0.013	0.012	-0.015	0.999	-0.078	0.016	-0.038	0.008	3,141	484
2013	0.023	0.024	-0.015	0.994	-0.101	0.124	-0.025	0.007	2,043	317
2014	0.009	0.009	-0.015	0.991	-0.088	0.135	-0.005	0.007	1,077	183
2007-2014	0.007	0.011	-0.022	0.991	-0.081	0.043	-0.009	0.011	15,946	702

For the sake of completeness, Table XXIII adds further performance and risk characteristics of the fund sample. As expected funds have a negative Carhart alpha of -2.2% p.a., but positive monthly returns (1.1% p.m). The other characteristics are as well in line with existing literature.

4.4 Empirical Analysis

4.4.1 Carbon stock characteristics

This section serves as the basis for the subsequent fund related analyses to come. It describes the most important characteristics of the stocks that are held at least once by the mutual fund managers in my sample.

Table XXIV demonstrates the stocks' distribution across the different industries and gives an overview of the availability of the Asset4 database. The funds in the sample hold 8,235 different stocks. 404 different stocks are prevalent in the Asset4 database whereas 138 belong to carbon-heavy industries (as indicated by being below the black line). Applying the approach described in section 4.2.4 I divide all carbon risk stocks - based on their average carbon footprint within their industry - into worst, medium and low carbon emitters. This procedure yields 48 worst emitters *WE,* 47 medium emitters *ME* and 43 lowest emitters *LE.*

Table XXV compares common characteristics of carbon risk and non-carbon risk stocks. As described in section 4.2.1, all stocks from carbon-heavy industries are carbon risk stocks. The table shows that carbon stocks have more market beta and a higher *HML* loading. This is in line with the fact that carbon-heavy stocks tend to belong to the production industry which is known to be more cyclical and volatile around the market. The high amount of production facilities is also reflected in a high book value and therefore a higher *HML* loading. Besides carbon-heavy stocks tend to be bigger and more liquid. However, they have

Table XXIV: Distribution of stocks across the different industries

This table demonstrates the stocks' distribution across the different industries and gives an overview of the availability of the Asset4. The black line separates non-carbon risk stocks (above) and carbon risk stocks (below). Carbon risk stocks that are available in the Asset4 can be ranked within their industry based on their average carbon footprint and assigned to be high (*HE*), medium (*ME*) and low (*LE*) emitter stocks.

Industry	Distinct stocks	in %	Distinct stocks in Asset4	in %	*HE*	*ME*	*LE*
Non classified	820	10.0%	10	2.5%	0	0	0
Apparel	80	1.0%	4	1.0%	0	0	0
Banking, Insurance, Real Estate, Trading	1,824	22.1%	69	17.1%	0	0	0
Beer	22	0.3%	1	0.2%	0	0	0
Business Equipment	615	7.5%	40	9.9%	0	0	0
Chemicals	107	1.3%	20	5.0%	0	0	0
Construction	158	1.9%	9	2.2%	0	0	0
Consumer Goods	71	0.9%	4	1.0%	0	0	0
Electrical Equipment	93	1.1%	2	0.5%	0	0	0
Food	118	1.4%	9	2.2%	0	0	0
Healthcare	631	7.7%	13	3.2%	0	0	0
Other	22	0.3%	3	0.7%	0	0	0
Personal and Business Services	1,374	16.7%	27	6.7%	0	0	0
Printing and Publishing	62	0.8%	2	0.5%	0	0	0
Recreation	118	1.4%	4	1.0%	0	0	0
Restaurants, Hotels, Motels	113	1.4%	8	2.0%	0	0	0
Retail	249	3.0%	7	1.7%	0	0	0
Telecommunication	225	2.7%	4	1.0%	0	0	0
Textils	15	0.2%	2	0.5%	0	0	0
Tobacco Products	12	0.1%	0	0.0%	0	0	0
Transportation	190	2.3%	20	5.0%	0	0	0
Wholesale	217	2.6%	8	2.0%	0	0	0
Aircraft, ships etc.	39	0.5%	2	0.5%	1	1	0
Auto and Trucks	77	0.9%	3	0.7%	1	1	1
Coal	21	0.3%	3	0.7%	1	1	1
Fabricated Products and Machinery	164	2.0%	8	2.0%	3	3	2
Mines	130	1.6%	20	5.0%	7	7	6
Oil	346	4.2%	41	10.1%	14	14	13
Paper	65	0.8%	9	2.2%	3	3	3
Steel	74	0.9%	3	0.7%	1	1	1
Utilities	183	2.2%	49	12.1%	17	16	16
Total	8,235		404	2.5%	48	47	43

Table XV: Comparison of stock characteristics - carbon risk stock vs. non-carbon risk stock

This table compares the stock characteristics of carbon risk stocks (i.e. stocks that are from carbon intensive industries) and non-carbon risk stocks. Market capitalization is denoted in million $. Momentum indicates aggregated discrete returns over the last 12 months. Turnover is the number of stocks traded during a month divided by the stock's shares outstanding, return is monthly, Carhart alpha, beta market, beta *HML*, beta *SMB* and beta *MOM* are estimated for each month with the Carhart (1997) model based on daily data. Carhart alpha is annualized. Standard deviation is monthly and computed based on daily returns.

	Carbon risk stock		Non-carbon risk stock		Carbon – non-carbon
	mean	N	mean	N	
Market capitalization	12,759***	20,552	12,169***	70,808	590**
	(0.000)		(0.000)		(0.029)
Momentum	0.167***	18,683	0.179***	64,300	-0.012***
	(0.000)		(0.000)		(0.007)
Turnover	0.255***	20,552	0.251***	70,807	0.004**
	(0.000)		(0.000)		(0.026)
Return	0.014***	20,552	0.016***	70,802	-0.002**
	(0.000)		(0.000)		(0.045)
Carhart alpha	-0.012	20,851	0.054***	71,873	-0.066***
	(0.156)		(0.000)		(0.000)
Beta market	1.089***	20,851	0.997***	71,873	0.092***
	(0.000)		(0.000)		(0.000)
Beta *HML*	0.242***	20,851	0.035***	71,873	0.207***
	(0.000)		(0.000)		(0.000)
Beta *SMB*	0.296***	20,851	0.420***	71,873	-0.124***
	(0.000)		(0.000)		(0.000)
Beta *MOM*	-0.033***	20,851	-0.044***	71,873	0.011
	(0.001)		(0.000)		(0.330)
Standard deviation	0.023***	20,851	0.023***	71,873	0
	(0.000)		(0.000)		(0.210)

less return and less momentum, consistent with the observation that these industries have performed not very well in the period of the sample between 2007 and 2014. The standard deviation of returns is quite similar.

Comparing worst *WE* and lowest emitters *LE* as in Table XXVI, it is remarkable that *WE* stocks are smaller and more liquid than *LE* stocks. Low emitter stocks have an economically significant higher Carhart alpha by 0.5% p.a. (-0.6% vs. -1.1%). Thus this study shows a tendency to support literature that finds a positive relationship between environmental and financial performance[40] and rather contradicts literature that finds either no relationship[41] or a negative relationship[42].

Table XXVI: Comparison of stock characteristics - low emitter stocks vs. high emitter stocks

This table disentangles carbon risk stocks (i.e. stocks that are from carbon intensive industries) into high emitter stocks (*HE)*, medium emitter stocks (*ME)*, low emitter (*LE)* and carbon risk stocks that are not available in the Asset4. High emitter stocks are carbon risk stocks that have carbon/emissions that belong to the top 33% of their corresponding industry. Medium emitter and low emitter belong to the medium and lowest tercile.
Market capitalization is denoted in millions $. Momentum indicates aggregated discrete returns over the last 12 months. Turnover is the number of stocks traded during a month divided by the stock's shares outstanding, return is monthly, Carhart alpha, beta market, beta *HML*, beta *SMB* and beta *MOM* are estimated for each month with the Carhart (1997) model based on daily data. Carhart alpha is annualized. Standard deviation is monthly, and computed based on daily returns.

	High emitter (*HE)*		Medium emitter (*ME)*		Low emitter (*LE)*		*HE - LE*	Carbon risk stock (not in Asset4)	
	mean	N	mean	N	mean	N		mean	N
Market cap.	15,349***	2,564	28,319***	2,597	21,340***	2,545	-5,991***	7,396***	12,846
	(0.000)		(0.000)		(0.000)		(0.000)	(0.000)	
Momentum	0.127***	2,311	0.107***	2,360	0.132***	2,281	-0.005	0.193***	11,731
	(0.000)		(0.000)		(0.000)		(0.702)	(0.000)	
Turnover	0.313***	2,564	0.218***	2,597	0.239***	2,545	0.074***	0.254***	12,846
	(0.000)		(0.000)		(0.000)		(0.000)	(0.000)	
Return	0.010***	2,564	0.009***	2,597	0.011***	2,545	-0.001	0.016***	12,846
	(0.000)		(0.000)		(0.000)		(0.788)	(0.000)	
Carhart alpha	-0.011	2,564	0.008	2,598	-0.006	2,665	-0.005	-0.017	13,024
	(0.614)		(0.654)		(0.765)		(0.860)	(0.133)	
Beta market	1.015***	2,564	0.974***	2,598	1.041***	2,665	-0.026	1.136***	13,024
	(0.000)		(0.000)		(0.000)		(0.197)	(0.000)	
Beta *HML*	0.310***	2,564	0.366***	2,598	0.296***	2,665	0.014	0.192***	13,024
	(0.000)		(0.000)		(0.000)		(0.711)	(0.000)	
Beta *SMB*	0.030	2,564	-0.006	2,598	0.001	2,665	0.029	0.468***	13,024
	(0.111)		(0.746)		(0.947)		(0.271)	(0.000)	
Beta *MOM*	-0.008	2,564	-0.004	2,598	-0.011	2,665	0.003	-0.049***	13,024
	(0.760)		(0.855)		(0.665)		(0.948)	(0.000)	
Standard deviation	0.021***	2,564	0.018***	2,598	0.020***	2,665	0.001***	0.025***	13,024

[40] E.g. Ulshöfer and Bonnet (2009), Derwall et al. (2005), Konar and Cohen (2001), King and Lenox (2001), Matsumura et al. (2011), Aggarwal and Dow (2011), Misani and Pogutz (2015), Saka and Oshika (2014) and Gallego-Álvarez et al. (2015), Kim et al. (2015) and Chen and Silva Gao (2012), Climent and Soriano (2011) and Chang et al. (2012).
[41] E.g. Cohen et al. (1997).
[42] E.g. Wang et al. (2014), Labatt and White (2002), Mallett and Michelson (2010) and Muñoz et al. (2014).

Table XXVI shows as well that carbon stocks that are not reported in the Asset4 database even perform worse than those, classified as high emitters.

4.4.2 Mutual fund carbon risk exposure preference and ownership

Until now there is no study investigating the extent to which fund managers are engaged in carbon risk investments. To fill this gap, this section targets, on the one hand, the fund manager's portfolio allocation and exposure preference, and on the other hand, the mutual fund's ownership structure in carbon risk stocks. For this reason, this section might be of interest for both, policy makers as well as investors in actively managed mutual funds, as it allows insights of to which extent the fund universe might be affected by the possible burst of the carbon bubble.

Table XXVII shows the carbon risk exposure within the fund universe and how it changes over time. Additionally, it displays the share of carbon risk stocks in the market capitalization of the whole *CRSP* stock universe. Table XXVII indicates that the average carbon risk exposure in mutual funds' portfolios decreases from 28.26% in 2007 to 23.49% in 2014, while carbon risk exposure in the *CRSP* stock universe is 19.97% in 2007, has its peak in 2011 (23.49%) and declines back to 19.59% in 2014. Thus, in every year, exposure in mutual fund portfolios is on average higher than exposure in the *CRSP* universe. The difference is highest in 2007 (fund portfolios have 42% more exposure than the *CRSP* universe), decreases to only 1% in 2012, followed by an increase to 17% in 2014. Disentangling carbon risk stock exposure into high, medium and low emitter exposure (the remaining part belongs to carbon intensive industries, but is not available in Asset4) provides the following insights: Mutual fund exposure in low emitter stocks is 7.72% in 2007 and declines to 5.23% in 2014, while exposure in high emitter stocks is always lower, ranging from 3.91% in 2007 to 3.53% in 2014. Table XXVII additionally shows that the difference

Table XXVII: Descriptive statistics carbon risk exposure

This table displays the average carbon risk exposure (*CRE*) of a fund and the percentage of the carbon risk exposure that is available in the *CRSP* universe. The average fund carbon risk exposure is split into exposure in high emitter stocks (*HE)*, medium emitter stocks (*ME)*, low emitter stocks (*LE)* and exposure in carbon risk stocks that could not be assigned into of these categories as there were not emission values available in the Asset4. The column fund / *CRSP* indicates the ratio of a fund's carbon risk exposure and the *CRSP* carbon risk exposure.

		Funds' carbon risk exposure *(CRE)*						*CRSP* carbon risk exposure	Fund / *CRSP*
Year	N Fund	Mean	*HE*	*ME*	*LE*	Not in Asset4	*LE - HE*	Mean	
2007	139	28.26	3.91	9.07	7.72	7.56	3.81	19.97	1.42
2008	154	28.37	4.95	8.25	7.42	7.75	2.47	23.84	1.19
2009	480	22.70	4.38	5.25	5.84	7.23	1.46	21.99	1.03
2010	448	23.51	4.44	5.22	5.39	8.46	0.95	21.65	1.09
2011	455	24.42	4.58	5.31	5.55	8.98	0.97	23.49	1.04
2012	484	22.09	4.07	4.66	4.99	8.37	0.92	21.91	1.01
2013	317	23.00	3.94	5.04	5.47	8.55	1.53	20.69	1.11
2014	183	22.95	3.53	5.25	5.23	8.94	1.7	19.59	1.17
Total	702	23.49	4.26	5.36	5.58	8.29	1.32	21.64	1.09

between the low emitter and high emitter exposure decreases from 3.81 percentage points in 2007 to 1.7 percentage points in 2014. To sum up, the table indicates the following. First, mutual funds' seem to lower their carbon risk exposure over time, second, their exposure is still high in comparison to the exposure within the *CRSP* stock universe and third, within their carbon risk exposure portfolios, funds tend to be relatively more invested in low emitter stocks than in high emitter stocks over time.

Table XXVIII provides insights into the ownership structure of the carbon risk stocks, i.e. more specifically it answers the question what fraction of market capitalization is owned by the mutual fund industry. The total market capitalization of all carbon risk stocks is 13,500 billion dollar in 2007 and 14,200 billion dollars in 2014. The fraction owned by mutual funds, however, is only rather low, ranging between 0.30% and 1.36%. The total market capitalization of all companies belonging to industries that are not assigned to be carbon risk industries is significantly lower. It is 3,370 billion dollar in 2007 and 4,170 billion dollars in 2014. As those companies are smaller, it is more likely for mutual funds to achieve a higher percentage of ownership. Ownership of mutual funds thus can rise up to more than 15%. As actively managed mutual funds only possess a relatively small fraction of carbon risk stocks, they are likely to have only few voting rights and therefore are only limitedly suitable to put pressure on companies to cut down emissions. Governments trying to tailor incentives for different investor types should keep this in mind.

A more detailed overview of the ownership structure of carbon risk companies is provided by Scherer et al. (2017) who are the first to investigate ownership for the different investor types as institutional investors (e.g. banks, trusts, insurances, pension and endowment funds and foundations), hedge funds, mutual funds, investment advisors, as well as individuals and government agencies.

Table XXVIII: Descriptive statistics ownership

This table displays the amount of market capitalization of all stocks, being either categorized as carbon risk stock or non-carbon risk stock that are available in the *CRSP* universe and compares it with the amount of market capitalization that is owned by the mutual fund universe in my sample.

		Market capitalization carbon risk stocks (in billion $)			Market capitalization non-carbon risk stocks (in billion $)			Total market capitalization (in billion $)		
Year	N Fund	*CRSP* universe	Fund universe	%	*CRSP* universe	Fund universe	%	*CRSP* universe	Fund universe	%
2007	139	13,500	41	0.30%	3,370	97	2.87%	16,870	138	0.82%
2008	154	10,700	40	0.38%	3,370	92	2.72%	14,070	132	0.94%
2009	480	8,070	106	1.31%	2,270	328	14.45%	10,340	434	4.20%
2010	448	9,950	135	1.36%	2,750	428	15.56%	12,700	563	4.43%
2011	455	11,200	151	1.35%	3,440	486	14.13%	14,640	637	4.35%
2012	484	11,900	144	1.21%	3,330	509	15.29%	15,230	653	4.29%
2013	317	14,200	143	1.01%	3,700	483	13.05%	17,900	626	3.50%
2014	183	17,100	100	0.58%	4,170	356	8.54%	21,270	456	2.14%

4.4.3 Determinants of carbon exposure

To support policy makers tailor customized measures, knowledge about the characteristics of funds that face high carbon risk exposure might be helpful. Until now the analysis about carbon risk exposure only considered average mutual fund exposure without taking into account that different funds might have a differing exposure behavior. To identify which fund characteristics are associated with a higher degree of carbon exposure, I run a panel regression with fund-, style, and time-fixed effects to explain the determinants of carbon exposure with the common fund characteristics reported in Table XXII.

I use the following formula to explain a fund's carbon risk exposure $CRE_{i,t}$:

$$CRE_{i,t} = b_0 + b_1 \log(TNA_{i,t}) + b_2\, expense\ ratio_{i,t} + b_3\ 12b1_{i,t} + b_4\, front\ load_{i,t} + b_5\, rear\ load_{i,t} + b_6\, age_{i,t} + b_7\, flow_{i,t} + \epsilon_{i,t} \qquad (4)$$

Table XXIX shows the results of the regression.[43]

Results are robust, no matter whether the panel regression specification contains time, style or fund fixed effects or whether it is controlled for limited boundaries by using tobit regression. The coefficient on expense ratio is positive and significant at the 10% significance level, indicating that funds with higher expense ratio tend to have higher carbon risk exposure. Additionally, high 12b1 fees are correlated with lower carbon risk exposure. One possible explanation for this might be that having low carbon risk exposure (i.e. being a rather green fund) is in line with current trends that are well received in the society and therefore heavily advertised by the corresponding fund managers. Besides, older funds are more likely to have high carbon risk exposure, because younger funds might tend to invest in modern new

[43] Funds do not always report perfectly at equal intervals. However, this model assumes that these inequalities are not systematically.

industries as e.g. media and older funds tend to stick to the "older" production intensive industries that are assigned to be a carbon intensive industry.

Table XXIX: Analysis of the determinants of carbon risk exposure

This table shows the determinants of a mutual fund's carbon risk exposure (*CRE*). *TNA* is denoted in million $. Flow / *TNA* is the ratio between flow and the fund's total net assets *TNA*. Expense ratio, 12b1 fee, rear load, front load are denoted in relation to a fund's *TNA*. Age is declared in months. The first three models are estimated by panel regression and include different specifications with time, style, and fund fixed effects. The fourth specification is estimated by tobit regression. P-values are given in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Carbon risk exposure (*CRE*).			
Log(*TNA*)	0.2158	0.2173	0.2158	0.2116
	(0.36)	(0.36)	(0.36)	(0.37)
Expense ratio	218.0367*	218.2753*	218.0367*	218.3085**
	(0.05)	(0.05)	(0.05)	(0.05)
12b1 fee	-587.9821**	-586.7484**	-587.9821**	-595.9921**
	(0.01)	(0.01)	(0.01)	(0.01)
Front load	-3.8922	-4.2042	-3.8922	-3.6804
	(0.85)	(0.84)	(0.85)	(0.86)
Rear load	-22.7439	-22.6347	-22.7439	-22.9147
	(0.48)	(0.48)	(0.48)	(0.47)
Age	0.0540***	0.0539***	0.0540***	0.0540***
	(0.00)	(0.00)	(0.00)	(0.00)
Flow/*TNA*	0.6876	0.6705	0.6876	0.7405
	(0.46)	(0.47)	(0.46)	(0.43)
Intercept	2.0171	0.3318	8.8826**	20.1532***
	(0.67)	(0.95)	(0.02)	(0.00)
Time fixed	*Yes*	*Yes*	*Yes*	*Yes*
Style fixed	*No*	*Yes*	*No*	*No*
Fund fixed	*No*	*No*	*Yes*	*Yes*
Model	*Panel*	*Panel*	*Panel*	*Tobit*
R^2	0.15	0.15	0.15	.
N	15,946	15,946	15,946	15,946

4.4.4 Carbon risk exposure and the relation to performance and risk

Investors are particularly interested in performance and risk characteristics of the fund in which they intend to invest. For this reason, studies that investigate the driver of these two parameters belong to one of the most frequently investigated research questions in the fund literature. However, until now there is no study investigating, how manager portfolios with high carbon risk exposure $CRE_{i,t}$ respectively a high degree of investment in low emitter stocks (*DILE*) differ in terms of performance and risk. The following analysis is intended to close that gap.

For each fund *i* and every month *t* I estimate the Carhart (1997) alpha $\alpha_{i,t}$ based on daily data. I explain alpha by common control variables, the fund's carbon risk exposure *CRE* and the *DILE* factor (see section 4.2.3 and 4.2.4). Additionally I add the fund's weighted carbon footprint *WCFP* of all carbon risk stocks in the portfolio as further explanatory variable.

This yields

$$\alpha_{i,t} = b_0 + \sum_{k=1}^{K} b_k X_{i,t} + \mathrm{b}_{K+1} CRE_{i,t} + \mathrm{b}_{K+2} DILE_{i,t} + b_{K+3} WCFP_{\mathrm{i,t}} + \epsilon_{i,t} \quad (5)$$

where $WCFP_{i,t} = \sum_{j=1} weight_{j,t}\, CFP_{j,t}\; D_{CarbonStock_{j,t}}$

Again, I run panel estimation with the different specifications that contain time, style and fund fixed effects.[44]As expected, bigger funds have significantly lower performance. This is in line with Chen et al. (2004) and Pastor et al. (2015) and might partly be explained by the fact that big funds suffer through price impact while investing their money. The coefficient of *CRE* is significant and negative (-0.0015). This finding is in line with section 4.4.1, which demonstrated that carbon risk stock performed worse than non-carbon risk stocks in the observed period between 2007 and 2014. As the categorization of carbon risk stocks is based on industry affiliation, *CRE* in this context can be interpreted as industry index which captures characteristics of the carbon intensive sectors. So the negative sign only states that these industries have on average performed worse in the observed period between 2007 and 2014. Consequently, fund managers with high exposure to these sectors were only able to generate a lower alpha than others. For this reason, impact on alpha until this point might rather be due to industry characteristics than carbon risk effects.

[44] Funds do not always report perfectly at equal intervals. However, this model assumes that these inequalities are not systematically.

Table XXX: Analysis of the determinants of fund manager performance

This table shows the determinants of fund manager performance. Fund manager performance is measured for each fund and each month by the monthly Carhart (1997) alpha based on daily data. *TNA* is denoted in million $. Flow / *TNA* is the ratio between flow and the fund's total net assets *TNA*. Expense ratio, 12b1 fee, rear load, front load are denoted in relation to a fund's *TNA*. Age is declared in months. *CRE* is a fund's carbon risk exposure and indicates the weight of all carbon risk stocks in the portfolio. *DILE* indicates the degree of investment in low emitter stocks and is computed by the difference of exposure in low emitter stocks minus exposure in high emitter carbon risk stocks. *WCFP* is the weighted carbon footprint of all carbon risk stocks in the portfolio. P-values are given in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. The model includes specifications with time, style, and fund fixed effects.

	Carhart alpha											
Log(*TNA*)	-0.0077***	-0.0077***	-0.0075***	-0.0076***	-0.0077***	-0.0077***	-0.0076***	-0.0076***	-0.0077	-0.0077***	-0.0075***	-0.0076***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)**	(0.00)	(0.00)	(0.00)
Expense ratio	3.7477***	3.6256***	3.4981***	3.6475***	3.7212***	3.6002***	3.4488***	3.5979***	3.7477	3.6256***	3.4981***	3.6475***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)**	(0.01)	(0.01)	(0.01)
12b1 fee	-3.3582	-3.3577	-2.5100	-2.5507	-3.3923	-3.3893	-2.5986	-2.6417	-3.3582	-3.3577	-2.5100	-2.5507
	(0.21)	(0.20)	(0.34)	(0.33)	(0.20)	(0.20)	(0.32)	(0.32)	(0.21)	(0.20)	(0.34)	(0.33)
Front load	0.1290	0.1144	0.0983	0.1106	0.1312	0.1155	0.0999	0.1136	0.1290	0.1144	0.0983	0.1106
	(0.48)	(0.53)	(0.59)	(0.54)	(0.47)	(0.53)	(0.58)	(0.53)	(0.48)	(0.53)	(0.59)	(0.54)
Rear load	-0.4272	-0.4178	-0.4011	-0.4158	-0.4327	-0.4221	-0.3956	-0.4115	-0.4272	-0.4178	-0.4011	-0.4158
	(0.43)	(0.44)	(0.47)	(0.45)	(0.43)	(0.44)	(0.48)	(0.46)	(0.43)	(0.44)	(0.47)	(0.45)
Age	-0.0003	-0.0003	-0.0004	-0.0004	-0.0003	-0.0003	-0.0004	-0.0004	-0.0003	-0.0003	-0.0004	-0.0004
	(0.25)	(0.22)	(0.14)	(0.18)	(0.25)	(0.22)	(0.15)	(0.18)	(0.25)	(0.22)	(0.14)	(0.18)
Flow / *TNA*	0.0048	0.0046	0.0059	0.0061	0.0050	0.0048	0.0063	0.0065	0.0048	0.0046	0.0059	0.0061
	(0.83)	(0.83)	(0.79)	(0.78)	(0.82)	(0.83)	(0.77)	(0.77)	(0.83)	(0.83)	(0.79)	(0.78)
CRE	-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0015	-0.0015***	-0.0015***	-0.0015***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)**	(0.00)	(0.00)	(0.00)
DILE		0.0007*	0.0008**			0.0007*	0.0008**			0.0007*	0.0008**	
		(0.09)	(0.04)			(0.09)	(0.04)			(0.09)	(0.04)	
WCFP			0.0039	0.0022			0.0039	0.0022			0.0039	0.0022
			(0.20)	(0.47)			(0.19)	(0.46)			(0.20)	(0.47)
Intercept	0.1240*	0.1229*	0.1329*	0.1344*	0.1517**	0.1441**	0.1766**	0.1617**	0.0971	0.0951*	0.1020*	0.1344*
	(0.09)	(0.07)	(0.06)	(0.09)	(0.05)	(0.04)	(0.02)	(0.04)	(0.09)	(0.08)	(0.07)	(0.09)
Time fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41
N	15,946	15,946	15,733	15,733	15,946	15,946	15,733	15,733	15,946	15,946	15,733	15,733

To measure the influence of carbon risk effects and to control at the same time for industry-specific characteristics I use the following approach: First, I rank the companies based on their carbon footprint within their industry. Afterward, I use this ranking to classify each company as either low, medium or high emitter stock (see section 4.2.2). To aggregate this information on a portfolio level, I develop the *DILE* factor (see section 4.2.4) which is computed by the difference of exposure in low emitter stocks and high emitter stocks. Thus, the *DILE* factor indicates, how much a manager has balanced his portfolio towards low emitter stocks.

The coefficient on the *DILE* factor is positive and significant, i.e. the more the fund manager's portfolio was structured towards the lowest emitters of each industry sector, the more performance the manager were able to generate. Investing in the best in class companies (in terms of carbon footprint) seemed to be rewarding in the investigated period of time. This tendency was already observable in section 4.4.1 where low emitter and high emitter were compared (however not statistically signficant). Therefore it cannot be completely ruled out that outperformance of managers with a preference for low emitter stocks is due to skill and their more progressive mindset.

Is there a general relationship (i.e. regardless of the industries) between exposures to stocks with high carbon footprint and performance? The insignificance of the carbon footprint variable *WCFP* suggests that there is not. Mixing carbon footprint values across different industries does not seem to provide further explanatory power.

In analogy to above, the following section investigates the relationship of carbon risk and a fund manager's portfolio risk.

$$\sigma_{i,t} = b_0 + \sum_{k=1}^{K} b_k X_{i,t} + \mathrm{b}_{K+1} CRE_{i,t} + \mathrm{b}_{K+2} DILE_{i,t} + b_{K+3} WFP_{\mathrm{i,t}} + \epsilon_{i,t} \quad (6)$$

As a proxy of risk, I compute for each fund *i* and every month *t* the fund's standard deviation $\sigma_{i,t}$ of its daily fund returns. The interpretation of the results is analogously to the analysis of the fund's alpha.

The coefficient of *CRE* is significantly positive. This indicates that managers with high exposure to carbon intensive industries have been exposed to higher variation in the observed period between 2007 and 2014.

The coefficient on the *DILE* factor is negative and significant. Fund managers who have balanced their portfolio towards the lowest emitters of each industry sector faced significantly less risk in terms of variation. This is in line with section 4.4.1 as low emitter stocks face less risk than high emitter stocks. However, a possible additional explanation might be as well that funds with the more progressive attitude towards environmental awareness are simply more risk averse in general.

In contrast to the analysis of the performance, I find a positive relation between exposure to stocks with high carbon footprint and risk. Stocks with high emissions seem to have experienced - irrespective of the industry they belong to - more variation and thus cause more variation in the fund manager's portfolio.

To conclude, this section empirically confirms the fact that portfolios with stocks from carbon-heavy industries like oil, coal, etc. suffered from bad performance and more risk in comparison to other industry sections. However, interestingly, there seemed to be a difference on how strong a portfolio was balanced towards low emitter stocks. Investors who gave money to funds with a more environmental awareness could benefit from more performance and less risk.

Table XXXI: Analysis of the determinants of a fund manager risk

This table shows the determinants of fund manager risk. Fund manager risk is measured by the monthly standard deviation based on daily fund returns. *TNA* is denoted in million $. Flow / *TNA* is the ratio between flow and the fund's total net assets *TNA*. Expense ratio, 12b1 fee, rear load, front load are denoted in relation to a fund's TNA. Age is declared in months. *CRE* is a fund's carbon risk exposure and indicates the weight of all carbon risk stocks in the portfolio. *DILE* indicates the degree of investment in low emitter stocks and is computed by the difference of exposure in low emitter stocks minus exposure in high emitter carbon risk stocks. *WCFP* is the weighted carbon footprint of all carbon risk stocks in the portfolio. P-values are given in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. The model includes specifications with time, style, and fund fixed effects.

	Standard Deviation											
Log(*TNA*)	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001**	0.0001	0.0001**	0.0001**	0.0001**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)*	(0.02)	(0.03)	(0.03)
Expense ratio	0.0100	0.0136	0.0165	0.0110	0.0089	0.0125	0.0155	0.0099	0.0100	0.0136	0.0165	0.0110
	(0.66)	(0.55)	(0.46)	(0.62)	(0.69)	(0.58)	(0.49)	(0.66)	(0.66)	(0.55)	(0.46)	(0.62)
12b1 fee	0.0140	0.0140	-0.0064	-0.0049	0.0128	0.0127	-0.0075	-0.0059	0.0140	0.0140	-0.0064	-0.0049
	(0.79)	(0.79)	(0.90)	(0.93)	(0.81)	(0.81)	(0.89)	(0.91)	(0.79)	(0.79)	(0.90)	(0.93)
Front load	0.0047	0.0051	0.0053	0.0048	0.0046	0.0051	0.0053	0.0048	0.0047	0.0051	0.0053	0.0048
	(0.26)	(0.22)	(0.18)	(0.22)	(0.26)	(0.22)	(0.18)	(0.22)	(0.26)	(0.22)	(0.18)	(0.22)
Rear load	-0.0042	-0.0045	-0.0043	-0.0038	-0.0047	-0.0050	-0.0050	-0.0044	-0.0042	-0.0045	-0.0043	-0.0038
	(0.59)	(0.57)	(0.58)	(0.63)	(0.56)	(0.53)	(0.53)	(0.58)	(0.59)	(0.57)	(0.58)	(0.63)
Age	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.51)	(0.47)	(0.49)	(0.54)	(0.51)	(0.47)	(0.48)	(0.53)	(0.51)	(0.47)	(0.49)	(0.54)
Flow / *TNA*	-0.0011***	- 0.0011***	-0.0012***	-0.0012***	-0.0011***	-0.0011***	-0.0012***	-0.0012***	-0.0011	-0.0011***	-0.0012***	-0.0012***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)**	(0.00)	(0.00)	(0.00)
CRE	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000	0.0000***	0.0000***	0.0000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)**	(0.00)	(0.00)	(0.00)
DILE		-0.0000**	-0.0000***			-0.0000**	-0.0000***			-0.0000**	-0.0000***	
		(0.01)	(0.00)			(0.01)	(0.00)			(0.01)	(0.00)	
WCFP			-0.0003***	-0.0002***			-0.0003***	-0.0002***			-0.0003***	-0.0002***
			(0.00)	(0.00)			(0.00)	(0.00)			(0.00)	(0.00)
Intercept	0.0100***	0.0100***	0.0101***	0.0101***	0.0137***	0.0095***	0.0096***	0.0138***	0.0082	0.0083***	0.0085***	0.0101***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)**	(0.00)	(0.00)	(0.00)
Time fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
N	15,946	15,946	15,733	15,733	15,946	15,946	15,733	15,733	15,946	15,946	15,733	15,733

4.4.5 Divestment in mutual funds

As policy makers have to tighten up regulatory constraints on the use of carbon to target the 2°C goal as set in Paris (2015), it is very like for carbon consuming companies to experience decreasing profits in the future. For this reason, it is of interest for investors to identify the funds that have anticipated this development and have already started to divest, i.e. lower their exposure to carbon risk stocks.

So, the last analysis in this study investigates what kind of funds already started to divest during my sample between 2007 and 2014. For this purpose, I compute the divestment proxy $DIV_{i,t}$ as the difference between carbon risk exposure in time *t*-1 and *t*.

This yields:

$$DIV_{i,t} = CRE_{i,t-1} - CRE_{i,t} \qquad (7)$$

respectively

To identify the determinants of divestment, I run - similar to the previous sections - the following panel regressions:[45]

$$DIV_{i,t} = b_0 + b_1 \log\left(TNA_{i,t}\right) + b_2\, expense\ ratio_{i,t} + b_3\, 12b1_{i,t} + b_4\, front\ load_{i,t} + b_5\, rear\ load_{i,t} + b_6\, age_{i,t} + b_7\, flow_{i,t} + \epsilon_{i,t} \qquad (8)$$

The coefficient on log(*TNA*) is negative and statistically significant. Big funds tend to do less divestment. Similarly, the coefficient on age is negative, meaning that old funds as well do not divest a lot.

To sum up, I find that new funds (small and young) tend to divest, i.e. become less invested in carbon-heavy industries over the observed period of time between 2007 and 2014.

[45] Funds do not always report perfectly at equal intervals. However, this model assumes that these inequalities are not systematically.

The fact that young funds i.e. more recently founded funds engage in divestment might indicate that they follow a trend to become greener, as this is a trend that is well received in the population.

Table XXXII: Analysis of divestment behavior

This table displays characteristics of funds that engage in divesting trading behavior. Divestment is measured as the difference between $CRE_{i,t-1}$ and $CRE_{i,t}$. TNA is denoted in million $. Flow / TNA is the ratio between flow and the fund's total net assets TNA. Expense ratio, 12b1 fee, rear load, front load are denoted in relation to a fund's TNA. Age is declared in months. P-values are given in parentheses. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. The model includes specifications with time, style, and fund fixed effects.

	Divestment $DIV_{i,t}$		
Log(*TNA*)	-0.0599*	-0.0567*	-0.0599*
	(0.05)	(0.06)	(0.05)
Expense ratio	0.7978	4.1144	0.7978
	(0.97)	(0.83)	(0.97)
12b1fee	36.2309	40.7758	36.2309
	(0.44)	(0.38)	(0.44)
Front load	3.3400	2.9911	3.3400
	(0.52)	(0.56)	(0.52)
Rear load	-3.8783	-2.3808	-3.8783
	(0.54)	(0.71)	(0.54)
Age	-0.0239***	-0.0238***	-0.0239***
	(0.00)	(0.00)	(0.00)
Flow / *TNA*	0.2835	0.2679	0.2835
	(0.40)	(0.43)	(0.40)
Intercept	7.2976***	3.2785**	3.4945***
	(0.00)	(0.04)	(0.00)
Time fixed	*Yes*	*Yes*	*Yes*
Style fixed	*No*	*Yes*	*No*
Fund fixed	*No*	*No*	*Yes*
R^2	0.09	0.09	0.09
N	15,786	15,786	15,786

4.5 Conclusion

Carbon dioxide (CO_2) accounts for about three-quarter of global greenhouse gas (*GHG*) emissions and is considered to be the main driver for anthropogenic global warming (Pachauri et al. (2014)). However recent initiatives as the Paris agreement 2015 proof that awareness in society increases and that policymakers are determined to put a stop to further rise in global temperature. This has the consequence that companies will be severely affected by structural changes in a carbon-constrained world. Extra costs due to tighter regulatory requirements, taxes or forced payment for carbon emission certificates will not only influence future cash flows of the companies involved but will have as well a direct impact on asset manager and investors. For this reason, analysis of the influence of carbon risk on different investor types is of vital importance.

This paper contributes to this question by being the first study, investigating the implication and meaning of carbon risk for one of the largest investor group - actively managed domestic open end mutual funds.

The study starts - as a foundation for the fund related analyses - with a comparison of stock characteristics and answers the following questions: How do companies from carbon-heavy industries and carbon light industries differ? How are high CO_2 emitters within the carbon-heavy industries different from low emitters? The main finding is that stock from carbon intensive industries had less performance between 2007 and 2014 (yearly Carhart alpha -0.0012 vs. 0.054) but similar monthly standard deviation (0.023 vs. 0.023). Low emitter stocks, i.e. stocks that belong to the lowest emission ejectors within their industry, performed better than high emitter stocks (Carhart alpha: -0.005 vs. -0.011) and experienced less risk (standard deviation 0.020 vs. 0.021).

The second aspect investigated in this study targets on the fund industry and is of interest for both, policy makers as well as investors of mutual funds. It provides an overview about the fund manager’s portfolio allocation and exposure preference. Additionally, it investigates the mutual fund’s ownership structure in carbon risk stocks. This section enables the reader to get to know the extent of which the fund universe is invested in carbon risky stocks and therefore is affected by the future changes to come. In concrete terms, the following questions will be answered: How much carbon risk exposure is within the fund universe? How can these values be interpreted? How did exposure change over time? Which percentage of all dirty stock companies does the mutual fund universe possess? One of the key findings is that the average fund portfolio - with decreasing tendency - consists of 23.49% carbon risk stocks. This is nearly 10% more than all carbon risk stocks make up in the CRSP universe. With an average ownership of 2.14%, actively managed US domestic open end funds only possess a small fraction of the US carbon risk companies in the *CRSP* universe.

If policy makers want to tailor customized measures to facilitate the transformation into a carbon-constrained world, it is of advantage to know, what kind of funds face high exposure to carbon risk. So, this study contributes additionally to this question by finding that it is especially old funds with high expense ratio and low 12b1 fees that are exposed to a higher amount of carbon risk.

The fourth contribution of this paper is a better understanding of how carbon risk and the manager's preference of structuring the portfolio towards low emitter stocks is related to the manager's performance and risk structure. Here the study describes the commonly known fact that stocks from carbon-heavy industries like oil, coal, etc. have suffered from bad performance and more risk in comparison to other industry sections between 2007 and 2014. However, the study interestingly reveals that there seem to be differences on how strong a portfolio was balanced towards low emitter stocks. Investors who gave money to funds with a focus on only the lowest emitters within each carbon intensive industry could benefit from more performance (0.8% Carhart alpha difference p.a.) and less risk.

Last but not least, as high carbon emitting companies are likely to face decreasing profits in the future, it is of interest for investors to see what kind of funds already started in anticipation to engage in divestment. Here the study reveals that especially small and young funds are taking lead to the way to a carbon -constrained world.

To summarize, this study is the first to link carbon risk and mutual funds. It therefore helps investors and policy makers to get a better understanding of the opportunities and challenges for the mutual fund universe.

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5 Conclusion

The first contribution of this dissertation is the development of an approach that enables investors to assess fund manager stock picking skill more precisely than was possible in prior existing literature.

In order to achieve this, we take into account that a fund manager is not always allowed to trade voluntarily based on valuation, but is sometimes forced to trade to meet investors' liquidity demands. The TMM approach is the first to allow differentiation of both different trade categories. This not only facilitates assessment of the magnitude of the adverse effect of flow, but additionally allows a more precise evaluation of stock picking skill. Having this more accurate measure of skill provides several applications:

First, it could be used within fund families to find suitable manager compensation or to help promote only the most skilled managers.

Secondly, the results of the TMM can provide direct economic value for investors as we find that stocks that are bought based on valuation by a lot of managers tend to outperform their benchmark. The same holds true for funds that are able to execute a high proportion of valuation-motivated trading. Thus, identification of these stocks and funds is useful for investors to find investment opportunities that are more likely to outperform their benchmark in the future.

The TMM is based on holdings data which are available because the SEC obliges all mutual funds to report their holdings at a quarterly frequency. Approaches based on holdings data have many advantages in comparison to fund-level analyses as they allow a less diluted look at a manager's trading activity. However, Elton et al. (2010) name the following limitations. First, quarterly holdings data lack round-trip transactions, i.e. transactions that open and close positions within the reporting period are not observable in the data. Second, the exact timing of the trades remains concealed as they could have occurred at any time within the quarter.

However, on October 13, 2016, the SEC adopted a new portfolio form, obliging (among other things) all registered management investment companies (other than money market funds and small business investment companies) to file monthly instead of quarterly reportings.[46] As of now, only every third of these monthly reportings becomes available to the public. However, it may be that in the near future, the SEC will give in to the pressure from the public demanding more transparency by granting access to the monthly reportings.

Elton et al. (2010) estimate that quarterly reportings miss 18.5% of trades, all of which could be revealed with access to monthly data. Therefore, these monthly data could tremendously improve the accuracy of the TMM and the transparency of manager behavior in general in the future. For this reason it remains exciting to await new decisions from the SEC.

The second issue addressed in this dissertation is carbon risk which is a topic that is more current than ever. When, at the beginning of June 2017, the current president of the US, Donald Trump, decided in a quite spectacular way, to step back from the Paris Agreement (2015), the world public refocused its attention back to climate protection and the corresponding reduction of greenhouse gases. In this context, paper two and three seem more relevant than ever.

Paper two provides an overview of how the different investor groups are engaged in carbon intensive companies. This knowledge could help policymakers to tailor customized measures as well as investors to better locate the risk and extent of a possible burst of the carbon risk bomb.

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[46] https://www.sec.gov/rules/final/2016/33-10231.pdf

Paper three, in contrast, puts more focus on US domestic actively managed mutual funds. One of the key findings of this study is that investors who gave money to funds with a focus on only the lowest carbon emitters within each carbon intensive industry could benefit from more performance and less risk.

However, one limitation of these studies is the data quality of carbon emissions that is provided by the Asset4 database. The database is available for free but based on voluntary reportings of the corresponding companies. Thus, the coverage is sparse and a selection bias cannot be completely ruled out. Data availability could be improved by additionally complementing further data providers such as CDP, South Pole, and MSCI. However, as these data providers do not have full coverage of all companies either, an even more promising approach is suggested by Görgen et al. (2017) who calibrate a risk factor that is applicable to companies without emission data as well. In any case, as the quality and availability of carbon-related company specific data will increase due to more public focus on this field, the potential of further research in this field is huge.

Overall, this dissertation makes a contribution to a better understanding of two important challenges investors face - the risk of liquidity and the risk of carbon dependent assets. New data sources will improve the accuracy of existing studies. The potential to close further research gaps is huge.

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