Essays on Derivative Pricing and Mutual Fund Manager Behavior

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The President:

Prof. Dr. Thomas Bieger

To my Mum.

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Summary

This dissertation consists of three papers, each of which represents an individual research topic. In the first paper, *The Valuation of Derivatives on Carbon Emission Certificates*, we analyze three different models for the pricing of derivative products based on carbon dioxide (CO_2) futures. By using a Monte Carlo simulation, we find that a mean-reverting jump diffusion (MRJD) model outperforms the GARCH(1,1) and t-GARCH(1,1) models. The MRJD model is the most appropriate model for reproducing the observed future dynamics in- and out-of-sample especially for short time horizons. Our results show that the MRJD model is the most accurate in pricing the down-and-out calls and up-and-out puts as well as index trackers.

The second paper, *Selling Winners, Holding Losers: The Relation between the Disposition Effect and Investment Characteristics*, studies the disposition effect for a large sample of U.S. mutual fund managers between 1980 and 2010. The disposition effect is a well-known behavioral bias referring to the tendency that investors sell winner stocks too early and hold on to loser stocks for too long. Previous literature documents that the disposition effect is related to fund characteristics (e.g. Cici (2012)), fund manager characteristics (e.g. Scherbina and Jin (2011)), and fund flows (e.g. Singal and Xu (2011)). The goal of this paper is to analyze the unexplored link between the disposition effect and investment characteristics. In the first part, our results suggest that the disposition effect is present in our sample. In the second part, we find that the disposition effect is more prevalent for fund managers who invest in stocks that are more difficult to value using different measures

of stock and market uncertainty. In addition, we discover that trading of attention-grabbing stocks as well as less profitable and riskier stocks amplify the disposition effect. To sum up, this paper suggests that the level of the disposition effect can partly be explained by stock characteristics of mutual fund managers' holdings.

In the third paper, *Momentum, Reversal and the Disposition Effect: An Empirical Investigation of Mutual Fund Managers' Behavior*, we study the relationship between the disposition effect and the momentum effect in stock returns. The goal of this paper is to test whether the disposition effect can induce short-term underreaction to news and thereby be a possible explanation for the momentum effect and reversal as predicted by the theoretical model of Grinblatt and Han (2005). Our empirical results show that less disposition prone fund managers earn higher momentum profits which is contrary to the proposed theory. We do find support for stronger reversals for stocks held by less disposition prone fund managers. Our main findings hold even when controlling for risk or known drivers of momentum (firm size, book to market ratio, and turnover). Our results suggest that it is likely that the story of momentum needs further investigation and cannot be explained by the disposition effect.

Zusammenfassung

Die vorliegende Dissertation besteht aus drei einzelnen Aufsätzen, die jeweils ein in sich geschlossenes Forschungsthema darstellen. Im Rahmen des ersten Aufsatzes, *The Valuation of Derivatives on Carbon Emission Certificates*, werden drei verschiedene Modelle für die Preismodellierung von Derivaten auf Kohlenstoffdioxid (CO_2) Futures untersucht. Im Rahmen einer Monte Carlo Simulation haben wir festgestellt, dass ein Modell mit Mean-Reversion und Sprüngen (mean-reverting jump diffusion (MRJD) Modell) eine bessere Performance als ein GARCH(1,1) und ein t-GARCH(1,1) Model zeigt. Des Weiteren wurde festgestellt, dass sich das MRJD Modell am besten eignet, um die beobachtete Dynamik des Futurepreises in der in-sample und out-of-sample Periode nachzubilden, insbesondere für kürzere Zeitperioden. Unsere Ergebnisse haben ergeben, dass die Preismodellierung mittels des MRJD Prozesses für die untersuchten Produkte (down-and-out Calls, up-and-out Puts und Index Tracker) die kleinsten Bewertungsfehler aufweist.

Der zweite Aufsatz, *Selling Winners, Holding Losers: The Relation between the Disposition Effect and Investment Characteristics*, analysiert den Dispositionseffekt für Fondsmanager von amerikanischen Investmentfonds zwischen 1980 und 2010. Der Dispositionseffekt beschreibt eine verhaltensbezogene Verzerrung bei der Investoren dazu tendieren Gewinneraktien zu früh zu verkaufen und Verliereraktien zu lange zu halten. Die bisherige Literatur hat den Dispositionseffekt auf Fondscharakteristika (z.B. Cici (2012)), auf Eigenschaften der Fondsmanager (z.B. Scherbina and Jin (2011)), und auf die

Zu- und Abflüsse von Geldmitteln (z.B. Singal and Xu (2011)) zurückgeführt. Das Ziel dieser zweiten Arbeit ist es, den bisher noch unerforschten Zusammenhang zwischen dem Dispositionseffekt und Investmentcharakteristika, zu untersuchen. Die Ergebnisse im ersten Teil dieses Aufsatzes weisen darauf hin, dass die untersuchten Fondsmanager nach dem Dispositionseffekt handeln. Im zweiten Teil, belegen wir, dass der Dispositionseffekt für diejenigen Fondsmanager stärker ausgeprägt ist, die in Aktien investieren, welche schwieriger zu bewerten sind. Dabei wird die Bewertung von Aktien anhand verschiedener Massstäbe für die Unsicherheit auf der Aktien- und der Marktebene untersucht. Darüber hinaus hat sich gezeigt, dass das aufmerksamkeitsgetriebenen Handeln von Aktien sowie das Handeln von weniger profitablen und risikoreicheren Aktien den Dispositionseffekt verstärkt. Zusammenfassend lässt sich feststellen, dass die vorliegenden Ergebnisse Evidenz erbringen, welche konsistent mit der Hypothese sind, dass Aktiencharakteristika eine mögliche Erklärung für den Dispositionseffekt sind.

Im dritten Aufsatz, *Momentum, Reversal and the Disposition Effect: An Empirical Investigation of Mutual Fund Managers' Behavior*, wird der Zusammenhang zwischen dem Dispositionseffekt und dem Momentumeffekt untersucht. Hierbei wurde der Hypothese nachgegangen, ob der Dispositionseffekt für eine zu geringe Reaktion (underreaction) auf neue Informationen verantwortlich ist und ob dieses Verhalten für das Entstehen des Momentumeffekts sowie den Reversaleffekt herangezogen werden kann. Diese Idee basiert auf dem theoretischen Modell von Grinblatt and Han (2005). Die Ergebnisse weisen auf eine entgegengesetzte Beziehung hin: Aktien, die von Fondsmanager mit einem geringeren Dispositionseffekt gehalten werden, erzielen höhere Momentumrenditen. Die Resultate deuten zudem darauf hin, dass der Reversaleffekt für Fondsmanager mit einem geringeren Dispositionslevel stärker ist. Selbst unter Einbezug von Risiken oder bekannten Einflussgrössen des Momentumeffekts (Firmengrösse, Buch-Marktwert Verhältnis, Aktienhandelsvolumen), verändern sich unsere Ergebnisse nicht. Zusammenfassend haben unsere Ergebnisse gezeigt, dass es wahrscheinlich ist, dass der Dispositionseffekt nur einen Teilaspekt der "Momentum-Story" erklären kann.

Part I.
Valuation of Derivatives on Carbon Emission Certificates

Joint paper with Philipp Isenegger and Rico von Wyss. This paper is accepted for publication and forthcoming in the Journal of European Financial Management.

Abstract

We evaluate three different models for the pricing of derivative products based on carbon dioxide (CO_2) futures. The methods considered include a standard GARCH model, a t-GARCH model as well as a mean-reverting jump diffusion (MRJD) model. The MRJD model performs best in appropriately reproducing the observed future dynamics in- and out-of-sample. The simulation and subsequent valuation of structured products on CO_2 futures yields quite precise outcomes for short time horizons. Comparing the three models, the MRJD model has the best accuracy in pricing down-and-out calls and up-and-out puts as well as index trackers.

1. Introduction

In January 2005 the European Union Emission Trading Scheme (EUTS) came into force to reach the climate goals of the EU set by the Kyoto protocol in 1997. This has been supported by the introduction of trading platforms for carbon dioxide (CO_2) certificates, CO_2 futures, as well as related derivative products. The trading scheme is characterized by different phases (phase I from 2005 until 2007, phase II from 2008 until 2012 and phase III from 2013 until 2020) and a banking prohibition between the first and the second phase. Therefore, emission allowances became worthless at the end of phase I. Due to this particularity two kinds of contracts exist: those beginning and ending within the same period (intra-period contracts) and those written in one period and maturing in a subsequent period (inter-period) contracts (e.g. Daskalakis et al. (2009)). By being able to trade CO_2 certificates on specialized exchanges (e.g. European Climate Exchange (ECX), acquired by Intercontinental Exchange (ICE) ; BlueNext) and by placing a price tag, CO_2 emissions have been commoditized as if they were a barrel of oil or coal (Daskalakis et al. (2009), ECX (2008)).

The objective of this article is to investigate the dynamics of the CO_2 futures prices and to find an appropriate pricing model for derivatives with CO_2 futures as an underlying. Our paper is based on the ICE EUA (European Union Allowance) futures from the first and second compliance period. There are two main contributions: First, we propose and compare three types of models that have the potential to generate predictions of the CO_2 futures price behavior. We achieve this by including a GARCH and a t-GARCH component in modeling the return volatility as well as by allowing for jumps in the return process. By the evaluation of the empirical in- and out-of-sample performance of GARCH, t-GARCH and mean-reverting jump diffusion models to capture the stylized facts of EUA futures' log returns, we derive an approach for a more accurate pricing of CO_2 futures options. The second contribution is, therefore a comparison of the model performance in pricing derivatives. The empirical analysis is conducted for down-and-out calls, up-and-out puts and index trackers. Our main result shows that a mean-reverting model including jumps performs best in- and out-of-sample, and yields the smallest pricing errors for the derivatives.

Since the ECX has introduced derivative instruments in October 2006, the pricing of options on spot and carbon futures received increased attention. Grüll and Taschini (2011) provide a summary of theory and empirical evidence on emission permit price dynamics. A number of empirical studies identify certain characteristics of the CO_2 price and investigate different models for the dynamics of the short-term spot price (e.g. Paolella and Taschini (2008)), two-factor models (Cetin and Verschuere (2009)) as well as regime-switching models (Benz and Trück (2009), Uhrig-Homburg and Wagner (2009)). The following classes of stochastic processes are applied to the CO_2 prices: jump diffusion models (Daskalakis et al. (2009)), GARCH models as well as mix-normal GARCH models (Benz and Trück (2009)). Daskalakis et al. (2009), Paolella and Taschini (2008), Seifert et al. (2008), and Uhrig-Homburg and Wagner (2009) incorporate the most important characteristics of the EU ETS spot price dynamics in a stochastic equilibrium model. Paolella and Taschini (2008) find a GARCH type model to be appropriate for the conditional dynamics of the spot market price, whereas Benz and Trück (2009) document different phases of return and volatility, and hence they argue in favor of a regime-switching model. Moreover, Paolella and Taschini (2008) analyze the future-sport parity of CO_2, and develop a forecasting model based on the analysis of key fundamentals. Daskalakis et al. (2009) as well as Benz and Trück (2009) additionally compare the performance of different pricing models. GARCH based models are used by Paolella and Taschini (2008) who suggest a t-GARCH approach while Chevallier et al. (2011) choose an asymmetric threshold-GARCH model. Other studies, such as Dannenberg and Ehrenfeld (2011) assume mean reversion of the underlying price process.

Daskalakis et al. (2009) additionally address the presence of jumps in the underlying price process. Jumps are motivated by the strong influence of regulatory announcements in the carbon market, e.g. the decision about the absolute supply or the allocation of certificates to different sectors (Yang et al. (2008)). Borovkov et al. (2011) discuss the theoretical implications of continuous time diffusion and jump diffusion models followed by a small numerical study. Sanin and Violante (2010) find a model of combining the underlying price process of the December 2008 futures with a time varying jump component to fit the data best.

The two papers closest to ours are Daskalakis et al. (2009) and Uhrig-Homburg and Wagner (2009) who investigate the relation between emission allowance prices and derivative products. Daskalakis et al. (2009) identify extreme discontinuous variation in the CO_2 futures prices. The authors fit several diffusion and jump diffusion processes. They compare the in- and out-of-sample performance of the different pricing models for vanilla options. However, using a constant variance jump diffusion process, the models fail to capture the dynamics of the underlying process when comparing to a GARCH approach as e.g. in Benz and Trück (2009). Uhrig-Homburg and Wagner (2009) analyze futures expiring within the first compliance period and argue for a cost-of-carry pricing relationship. The authors use a GARCH(1,1) model to value barrier call options on carbon futures. Borak et al. (2006) find a highly significant and dynamic convenience yield. Also Chevallier (2009) reports a time-varying convenience yield that is best captured by an AR(4) process. In a recent article, Chang et al. (2013) try to explain convenience yield, and find mean reversion as well as an asymmetric effect of market information. Chesney and Taschini (2012) model the CO_2 dynamics and provide an application to option pricing. Chevallier et al. (2011) study the effects of option trading on market volatility. They find evidence that the introduction of derivatives in the EU ETS market changed observed volatility. Frunza and Guegan (2010) suggest a normal-inverse Gaussian process to model the underlying price behavior, and find lower pricing errors for options compared to a geometric Brownian motion model.

Our study has two key advantages to the above mentioned papers: First, we differ from the analysis by comparing the in- and out-of-sample performance of different models with respect to their forecasting accuracy for the pricing of derivatives on CO_2 futures. To include discrete events such as regulatory decisions, our empirical models allow for GARCH effects as well as jumps. Second, we do not limit ourselves to a certain type of derivative. We consider barrier calls and puts as well as index trackers and, therefore extend the investigated range of derivative products on CO_2.

Our focus is on the second trading period of the EUTS, i.e. we only look at intra-period futures. According to Linacre et al. (2011), in 2009 about 22% of carbon trading was in spot market transactions, 73% in futures contracts and only 5% in other derivatives. Although the overall carbon derivatives market is still rather small, it has experienced a significant growth of almost 70% in 2009.

The suggested models can be used for short- and long-term forecasting and subsequent evaluation of derivatives. Thus, our paper could be of interest for traders or risk managers operating in the CO_2 market as well as other participating industries. Market participants may use our findings for speculative, hedging or risk management purposes. In addition, there is little correlation between emission allowance prices and stock market returns. Thus, diversification aspects are an important reason for incorporating derivatives on carbon emission rights in a portfolio. Also, our results might help banks to better price their CO_2-related derivatives and might reduce mispricing in the market.

The remainder of the article is organized as follows. In the next section, we present the three different stochastic approaches for modeling the dynamics of CO_2 futures, namely a GARCH, a t-GARCH, and a mean-reverting jump diffusion model. In Section 3, we provide a short overview of our data. We also explain the methodology for the valuation of the different derivatives considered in this paper. Details on the model estimation are shown in Section 4. In Section 5, we discuss the results of the performance of the different model types in- and out-of-sample as well as their accuracy concerning the valuation of the certificates. In the last section, we summarize the main findings, and provide a conclusion.

2. Methodology

Motivated by the descriptive statistics, we identify different stochastic models which are adequate in capturing the various phases of return and volatility behavior of the carbon price process. To account for autocorrelation and heteroscedasticity, we suggest a GARCH, as well as a *t*-GARCH model. A third model comprises of a mean-reverting and a jump component reflecting the observed CO_2 future's return pattern. After having identified the appropriate model types, we compare the in- and out-of-sample performance of the models by the valuation of different derivatives.

2.1. Modeling the Price Dynamics of CO_2 Futures

GARCH Model

Motivated by the descriptive statistics previously discussed, we apply a GARCH (1,1) model (Bollerslev (1987)) to capture the volatility clustering apparently present in the time series of the carbon futures. The variance σ_n^2 consists of a long term average variance rate, V_L, of the past realization of the return series y_{n-1} and of an additional lagged variance term:

$$\sigma_n^2 = \gamma V_L + \alpha y_{n-1}^2 + \beta \sigma_{n-1}^2 \tag{2.1}$$

The respective weights have to sum to unity:

$$\gamma + \alpha + \beta = 1 \tag{2.2}$$

The variance estimated by the GARCH(1,1) model is based on the most recent observation of y^2 as well as the most recent observation of the variance rate. Defining $\omega = \gamma\ V_L$ we can rewrite the model as:

$$\sigma_n^2 = \omega + \alpha y_{n-1}^2 + \beta \sigma_{n-1}^2. \tag{2.3}$$

After having estimated ω, α and β, we calculate the long run variance V_L by dividing ω by γ, where γ is 1 - α - β. To ensure stationarity as well as the long term variance's non-negativity, the condition $\alpha + \beta < 1$ must hold.

t-GARCH Model

The GARCH model accounts for the conditional volatility of a time series assuming normal distribution of the noise term, whereas the *t*-GARCH model is based on a student-*t* distribution accounting for fat tails. As the futures' log returns exhibit more observations in the tails, the *t*-distribution model is expected to perform better in the pricing of the derivatives.

Mean-Reverting Jump Diffusion Model (MRJD)

We use the jump diffusion model of Merton (1976), which is essentially constructed by adding a jump (or Poisson) component to a standard Geometric Brownian motion (GBM). In addition, we consider mean-reversion in the return series.

Mean-reverting jump diffusion processes are employed for different asset classes, e.g. for electricity spot price dynamics (e.g. Cuaresma et al. (2004), Knittel and Roberts (2005)), stock price behavior (e.g. Chernov et al. (2003)), and exchange rates (e.g. Ball and Roma (1993)). But, to our best knowledge, mean-reverting jump diffusion models have not yet been used in the carbon finance area. The mean-reverting jump diffusion process is a popular choice in price modeling because it shows some flexibility as far as including multiple jumps, time-varying means, and stochastic volatility in different forms.

We follow the idea of Weron and Misiorek (2008) who successfully suggest a jump diffusion model for financial times series data in the electricity market. Jumps seem relevant when new information comes into the market very quickly which is the case in the CO_2 market e.g. announcements concerning the national allocation plans (NAP). In addition, a jump component is useful in modeling excess kurtosis which is present in the distribution of CO_2 returns. Due to their promising characteristics of modeling the observed features of mean-reversion combined with a jump-component, we suggest the approach also for modeling CO_2 futures log returns.

A mean-reverting jump diffusion model for returns is characterized by a diffusion part which follows an Ornstein-Uhlenbeck process, whereas the jump component has normally distributed absolute values of jump size, with the intensity of the jumps determined by a Poisson process. The mean-reverting jump diffusion model is defined by the following equation:

$$dr_t = (\alpha - \beta r_t)dt + \sigma dW_t + J_t dq_t \tag{2.4}$$

$$J_t \sim N(\mu_j, \sigma_j^2) \tag{2.5}$$

$$q_t \sim Poisson(\lambda dt) \tag{2.6}$$

where α is the instantaneous expected return, β is the mean-reversion level, $\frac{\alpha}{\beta}$ is the long-term mean, W_t is a standard Brownian motion with $dWt \sim N(0, dt)$ for an infinitesimal time interval dt. W_t is responsible for small (proportional to σ) fluctuations around the long term mean $\frac{\alpha}{\beta}$. An independent jump process is defined by a compound Poisson process q_t which produces jumps with size J_t (here: Gaussian with mean μ_j and variance σ_j^2) and intensity λ. The underlying assumption is Markov and pairwise independence between the Brownian motion, the Poisson process, and the random jump amplitude λ.

In summary, given the stylized facts about the behavior of CO_2 futures log returns, applying a mean-reverting jump diffusion model may be a promising approach for the valuation of derivatives. It reflects the mean-reverting nature usually present in commodity prices as well as jumps induced by discontinuities in political decision making in the CO_2 market.

2.2. Valuation of Derivatives on CO_2 Futures

We model the futures price directly, and do not rely on the relationship between futures and spot rate. This relationship was heavily distorted by the market friction and the following price deterioration of the spot price. Details on the valuation are given in the appendix.

The futures price in a risk-neutral world exhibits the same behavior as a stock paying a dividend yield at the risk-free rate r. Therefore, the drift of the futures price in a risk-free world is zero. The assumption for the process followed by a futures price in a risk-neutral world where σ is constant is the following equation:

$$\delta F = \sigma F \delta z. \tag{2.7}$$

It follows according to Myers and Hanson (1993) that the important restriction of risk-neutral pricing holds, namely that the futures price at t_0 is an unbiased predictor of the futures price at maturity. This is consistent with the result of Uhrig-Homburg and Wagner (2009) who also find that the risk-neutral pricing methodology is applicable to the ICE EUA December 2008 futures contract. The incorporation of time-varying volatility does not violate the restriction placed upon risk-neutral pricing when for the change of measure to a risk-neutral setting, the risk premium is assumed to be zero. As mentioned above, we can assume that the distribution has fatter tails than the normal. Bollerslev (1987) proposes a student-t distribution for the innovations, but, if the number of the degrees of freedom is high, it converges to a normal distribution.

However, according to Myers and Hanson (1993) it can be shown that there is no closed form solution for the pricing formula. Nonetheless, using numerical procedures, the option can be priced. The futures prices are forecasted using Monte Carlo simulation.

It is important to note that the payoffs have to be adjusted to satisfy the risk-neutral valuation conditions. The risk-neutral valuation approach places a restriction on the development of the futures price. The futures price at t_0 is deemed to be an unbiased predictor of the futures rate at time T, meaning that the drift is equal to zero. In the GARCH(1,1) model specification, the returns are simulated by a constant plus a random error term. As a result the simulations of the futures returns have a mean that is different from zero as in Table 7. Thus, it is reasonable that there is a drift in the Monte Carlo simulation, as well. Myers and Hanson (1993) suggest adjusting each terminal realization of the futures price simulation by multiplying the rate by the initial futures price, and subsequently dividing it by the terminal realizations' average value. This adjustment has the effect (as shown by the column "Mean $\hat{F}_T$" in Table 9), that the mean of the terminal futures price realizations just equals the initial futures price. This satisfies the risk-neutral valuation which requires the initial futures price to be an unbiased predictor of the futures rate at maturity.

In order to assess the empirical outcomes of the suggested models, we evaluate their in- and out-of-sample pricing performance using real derivatives data. The different pricing models are compared according to the mean squared error (MSE) and the relative mean absolute error (MAE). In addition, we analyze the distributional properties of the forecasted and real returns using point estimates and density forecasts.

3. Data

3.1. Futures Data

The data considered is the December 2008 EUA futures contract traded on the Intercontinental Exchange (ICE) which has also been used in previous papers (e.g. Chevallier et al. (2011), Daskalakis et al. (2009), Sanin and Violante (2010)). Futures contracts on CO_2 certificates are based on 1,000 allowances with annual maturity, adding up to 1,000 tons of CO_2. The futures contract with maturity date December 2008 is used as the underlying with respect to all derivatives presented in this article. The quality of price discovery should be best with respect to the December 2008 futures contract due to its high liquidity. Moreover, liquid contracts generally facilitate building up and clearing positions in the underlying, if necessary. In the futures market, yearly maturities are available with the nearest contract being the most liquid. In Figure 1, we plot the December 2008 contract (nearest futures maturing in the second compliance period) as well as the 2007 futures contract maturing within the first compliance period together with the spot quotes.

Figure 1 about here

The time series used to model the ICE December 2008 futures includes observations from April 22, 2005 until April 24, 2008, and comprises 770 daily settlement prices. However, we exclude nine data points due to extreme movements in the time series. As we observe in Figure 1, the returns around the market friction in spring 2006 exhibit excessively high volatility which has never occurred again. Therefore, we conclude that this abnormality was only due to the market friction and does not contain essential information regarding the general behavior of the ICE December 2008 EUA futures price. However, one can argue that these extreme events driven by politics and regulatory adjustments also give an idea about how strongly the EU-ETS market reacts. To gain more insights, we report the descriptive statistics and the parameter estimation based on the full and reduced sample.

The log returns of the December 2008 futures show stylized facts which are typical for commodities' data such as a volatility clustering, leverage effect, skewness, excess kurtosis and presence of spikes. Also, the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller (1979)) and partial autocorrelation function (PACF)[1] show that heteroscedasticity and autocorrelation are present in the data.

Table 1 about here

The composition of the in-sample and the out-of-sample data set is given in Table 1. The in-sample data set is based on the full and the reduced sample period. The full in-sample data set included 599 data points and the reduced in-sample data set contains 590 data points from April 22, 2005 until August 22, 2007. The reduction in volatility and kurtosis is evident both in the full

[1]Results are unreported.

and reduced sample. The out-of-sample data set contains one fifth of the sample, comprising observations from August 23, 2007 until April 24, 2008.

In order to analyze the relationship between spot and future prices, Black (1976) states that we can express the relation generally by the no-arbitrage relationship in equation (3.1) assuming no income and storage costs:

$$F_t(T) = e^{r(T-t)} S_t \tag{3.1}$$

where $F_t(T)$ is the forward or futures contract with delivery date at T, S_t is the spot price and r the risk free rate. We assume that EUAs are not subject to storage costs and that the great majority of the investments in EUAs are made to comply with the regulations imposed by the EUTS. Thus, futures on EUAs should yield no income. However, in many commodity markets a convenience yield exists, meaning that holding a physical commodity generates not only costs but also yields benefits. Assuming a constant flow of benefits, we can rewrite equation (3.1) according to Geman (2006) assuming a cost-and-carry relationship as:

$$F_t(T) = e^{(r-c)(T-t)} S_t \tag{3.2}$$

where c represents a constant convenience yield without storage costs. Daskalakis et al. (2009) and Uhrig-Homburg and Wagner (2009) confirm that the relationship between spot prices and CO_2 future contracts can be described by a standard cost-of-carry approach. As a proxy for the risk free interest rate r, we use the six and nine month Euribor rate from the Deutsche Bundesbank.

3.2. Derivatives Data

For the time being, two generic types of derivatives on EUA futures contracts are offered: participation certificates and leveraged products. Table 2 displays the sample properties of the derivatives considered in the empirical analysis of this paper. We retrieve daily settlement prices from the European Warrant Exchange (EUWAX) in Stuttgart for the period from August 23, 2007 until April 24, 2008. This time horizon corresponds to the out-of-sample time period which allows us to compare the out-of-sample simulated terminal values of the certificates with real data observed in the market. Thereby, we are able to assess the correctness of our pricing models. The emission date is not the same in every case. This implies that the initial futures price changes and that we have to simulate different numbers of days.

Table 2 about here

Several banks offer certificates in order to enable retail investors to take part in the CO_2 emission market which allows the investor to participate on a 100% basis in the development of the EUA ICE December 2008 futures. Generally, the underlying of one certificate equals one thousandth part of a future, i.e. one ton of CO_2. The certificates in question are all open-end certificates with a yearly roll over procedure. Because of differences in prices between the maturing future and the next nearby future, possible losses or gains during the roll over may occur. We can derive the value of the certificate as:

$$F_T^A \cdot PR \cdot 1 \tag{3.3}$$

where F_T^A is the current futures price and PR the participation rate. Because of the above mentioned losses or gains associated with the roll over of the contracts, the participation rate is liable to changes. If the new futures price is less than the current price the investor will participate more than 100% in the development of the new futures and vice versa.

The second type, leveraged products, has in general maturities up to one year. By being long or short in such a leveraged products, the holder participates in the performance of the underlying in a option-like manner. The leverage effect stems from the small initial investment requirement. If the underlying moves in the unanticipated direction the leveraged product may be knocked out. In the case of the futures, there would be a margin call. The knock-out happens when the products' margin is used up which is implicitly made by the initial investment (Wilkens and Stoimenov (2007)). The payoff of long or index certificates, also known as turbo-certificates, is given in the following equation:

$$max(S_t - K; 0) \tag{3.4}$$

where S_t denotes the underlying quote and K is the strike price. In addition, a fixed barrier B represents either the knock-in level where the option gets activated, or the knock-out level where the option vanishes if crossed. If B equals K, the barrier can be interpreted as the point in time when a margin call would be executed. According to Wilkens and Stoimenov (2007), the knock-out feature of such certificates is mainly due to the impossibility to collect a margin call on an OTC traded product. Therefore, those leveraged certificates have convex payoff structures, because the only loss that can be incurred is the difference between S_t and B. This is contrary to a normal futures contract that has a linear payoff structure and therefore unlimited losses can occur if the underlying moves in the unanticipated direction. Turbo-certificates can be valued like down-and-out calls or up-and-out puts. Short certificates are treated analogously, yet the payoff is equal to $K - S_t$ and the certificate would be knocked out if $S_t > B$.

4. Model Estimation

To gain insights in the statistical properties of the time series of the December 2008 future contract, we employ various tests. First, to investigate the stationary properties of the log returns we perform an Augmented Dickey-Fuller test (ADF) (Dickey and Fuller (1979)) and the Phillips-Perron test (PP) (Phillips and Perron (1988))[2] which can be rejected at all significance levels for the log returns as well as for the squared log returns. Both tests indicate a clear rejection of the null hypothesis of a unit root in the data.

Second, we test for autocorrelation. Although the errors themselves do not seem to be heavily correlated, the squared errors show some autocorrelation up to lag 12. Therefore, we infer some serial dependence in the second moments meaning that we cannot assume constant variance. This is consistent with the observed leptokurtic return distribution in the December 2008 future returns. In addition, the Ljung-Box-Pierce test of innovations and squared

[2] Results are unreported.

innovations and the ARCH-test[3] clearly indicate serial correlation in the innovations.

Third, we analyze whether the CO_2 data have the skewness and kurtosis matching a normal distribution. The Jarque-Bera test (Carlos M. Jarque and Bera (1987)) which is reported in Table 1 confirms that we can reject the null hypotheses of normally distributed ICE EUA future log returns at a significance level of 5%. However, there might be a trend towards normality in log returns.

4.1. GARCH(1,1) Model

Given the strong evidence of autocorrelation and heteroscedasticity, the deployment of a GARCH model is appropriate for the modeling of the CO_2 futures' dynamics. This is confirmed by previous papers which implemented GARCH based models (e.g. Alberola and Chevallier (2009), Borak et al. (2006), Uhrig-Homburg and Wagner (2009)) to estimate the underlying dynamics. Our first model estimation is a simple GARCH(1,1) model which is based on a constant mean with a conditional variance (GARCH). The GARCH parameters are estimated by maximum likelihood estimation, subject to the constraints $\alpha > 0$, $\beta > 0$, $\omega > 0$, and $\alpha + \beta < 1$ to ensure stationarity and a strictly positive conditional variance.

We also estimate GARCH models with higher lags in p and q and compare them based on the Akaike (AIC; Akaike (1974)) and Bayesian information criteria (BIC) Schwarz (1987)).

[3]Results are unreported.

In order to test our pre-estimation results, we compare the modeling results against the raw return data (Figure 2).

Figure 2 about here

4.2. *t*-GARCH(1,1) Model

In addition, we estimate several t-GARCH models, where $\varepsilon \sim \mathrm{t}(0,h,v)$, in order to model the underlying return series. We also compare t-GARCH models with higher lags using the AIC and BIC values. Figure 3 shows the innovations, conditional standard deviations and returns for the t-GARCH(1,1) model.

Figure 3 about here

4.3. MRJD Model

The Augmented Dickey-Fuller (ADF) test (Dickey and Fuller (1979)) and Phillips Perron test (PP)(Phillips and Perron (1988))[4] for independence, normality and unit roots in the historical data confirm the use of a mean-reverting jump diffusion model. To calibrate the jump diffusion model, we follow the approach of Ball and Torous (1983). In order to estimate the parameters of a continuous-time jump process from discretely sampled data, we use a model with a mixture of normals. In this setting the future dynamics is discretized ($dt \longrightarrow \triangle t$) and we assume $\triangle t = 1$. In addition, λ is assumed to be small, therefore the arrival rate for two jumps within one period is negligible (during

[4] Results are unreported.

dt, $dI_t = 1$ if there is a jump, and $dI_t = 0$ otherwise). In this case, the Poisson process is well approximated by a simple binary probability: λ in case of a jump and $(1 - \lambda)$ in case of no jump.

Hence, (2.4) can be expressed as an AR(1) process with mean and variance of the noise term being conditional on the arrival of a jump within a given time interval. This results in:

$$r_t = \phi_1 r_{t-1} + \varepsilon_{t,i} \tag{4.1}$$

where the subscript i is 1 (if no jump occurred in this interval) or 2 (if there was a jump), $\varepsilon_{t,1} \sim N(0, \sigma^2)$ and $\varepsilon_{t,2} \sim N(\mu_j, \sigma^2 + \sigma_j^2)$.

The following six parameters have to be estimated from the given futures series:

$$\Theta = [\alpha, \beta, \sigma^2, \lambda.\mu_j, \sigma_j^2] \tag{4.2}$$

The jump diffusion model parameters are estimated by maximum likelihood (e.g. Ball and Torous (1983), Ball and Torous (1985). To gain insights in our pre-estimation results, we plot innovations, conditional standard deviations and returns for the mean-reverting jump diffusion model in Figure 4.

Figure 4 about here

5. Empirical Analysis

The empirical results are organized as follows. First, we discuss the estimation results for all three model types based on the reduced and the full sample. Comparing different GARCH models, we argue in favor of a GARCH(1,1) and t-GARCH(1,1) model as compared to higher lagged models. Second, we adopt graphical and formal methods to gain insights in the distributional fit of the three models. Third, we present the out-of-sample pricing results as well as the valuation results up to maturity.

5.1. Estimation Results

We present the estimation results for the full and reduced samples for the GARCH(1,1) model in Table 3, for the t-GARCH(1,1) model in Table 4, and for the mean-reverting jump diffusion model in Table 5. For the GARCH(1,1) model and the t-GARCH(1,1) model the values of the t-statistics indicate that all estimated parameters are significantly different from zero, with exception of the value of the constant C for the GARCH model in the reduced sample. The t-statistics for all estimated parameters of the mean-reverting jump diffusion model are significant, except for σ_j, the volatility of the jump process.

Tables 3, 4 and 5 about here

Since we do not observe any large differences between the full and reduced in-sample data set, the following analyses are based on the reduced sample only. In addition, supporting information comes from practitioners showing that in practice professionals also exclude extreme data points when estimating these kinds of models.

To compare the estimation results of the different models, we calculate AIC and BIC values for the reduced sample for all three models looked at. In a first step, we analyze GARCH and t-GARCH models with different lags in

Table 6. The relative BIC value favors the t-GARCH(1,1) model over a t-GARCH(3,1) model. We have evaluated the incorporation of a second ARCH term, but there was no statistical significance in the estimation. AIC as well as BIC values do not favor a GARCH(2,2) model over a GARCH(2,1) model (see Table 6). Thus, we conclude that a higher-lagged ARCH term does not improve the fit of the model. When looking at different t-GARCH models, the comparison of the relative BIC values indicates that the best fit should be reached deploying a simple t-GARCH(1,1) model, although it is not favored over an t-GARCH(3,1) model by the AIC value. We also compare the AIC and BIC values for the parameter estimates of the GARCH models with those for the mean-reverting jump diffusion model. The GARCH based models are favored in terms of AIC and BIC values compared to the jump based model.

Table 6 about here

5.2. Forecasting Performance

To generate an estimate of the distributional moments of the in-sample period, we simulate the time series over 170 days using one-day-ahead forecasts based on the estimated GARCH(1,1), t-GARCH(1,1) and the mean-reverting jump diffusion model to get out-of-sample estimates. We compare the Monte Carlo simulation results using 100,000 runs of the in-sample and out-of-sample data to asses the predictive power of the models using the observed data in the market. The forecast accuracy is assessed by comparing the distributional moments and interval forecasts of the simulation with the moments of the in- and out-of-sample period as well as performing interval forecasts. The distributional moments of the simulation are listed in Table 7.

Table 7 about here

5.2.1. Point Forecasts

The forecasted conditional return for the simulated in-sample period is 0.0013 for the GARCH(1,1) model, 0.0019 for the t-GARCH(1,1) model, and 0.0005 for the mean-reverting jump diffusion model. This is the case because the expected value of the ϵ_t is zero as the simulated returns are evenly distributed around the mean forecast. Comparing the three models, the mean of the mean-reverting jump diffusion model is closest in reproducing the mean of the observed log returns in the in-sample period, and hence delivers the most accurate result. With respect to the out-of-sample mean, the GARCH model performs best. With regards to producing the observed volatility, all model specifications perform equally well. The amount of the in-sample data's kurtosis cannot be reproduced by the GARCH models, especially not by the t-GARCH model. In contrast, the mean-reverting jump diffusion model seems to best capture the kurtosis in the in-sample time period whereas the GARCH(1,1) model reproduces a kurtosis that is closest to the observed kurtosis in the out-of-sample period. In contrast, the t-GARCH(1,1) model generates too many realizations around the mean, leading to an excessively high kurtosis in the in- and out-of-sample period. Moreover, there are also a few outliers as observed in the root mean squared error (RMSE) comparison (see Table 8).

Overall, the mean-reverting jump diffusion model seems to have better simulation results as the GARCH based models. Comparing the two GARCH models, we conclude that incorporating t-distributed residuals in the model has not the intended effect regarding the fit of the model, even though the t-GARCH model performs better with respect to the AIC and BIC information criteria.

Next we perform an out-of-sample comparison. We calculate the root mean squared error as $\sqrt{\frac{1}{N}\Sigma_{t=1}^{N}\hat{e}^2}$ where $\hat{e} = \frac{\hat{y}_T - y_T}{y_T}$ is the deviation of the observed futures rate from the forecasted mean return. In addition to the root mean squared error comparison, the mean of the relative absolute errors of the terminal simulated errors is listed in Table 8. The relative mean absolute error can be calculated as $\frac{1}{N}\Sigma_{t=1}^{N}|\hat{e}|$. Contrary to the root mean squared error where the mean of the forecasted returns is compared to the observed returns over the whole time horizon, in the case of the relative mean absolute error calculation only the simulated terminal values of the futures contracts are compared to the very last observation of the out-of-sample data. By doing this, we get an estimate about the relative errors in the last realizations of the simulated futures prices which are used to calculated the derivatives' payoff.

Table 8 about here

Results for the GARCH, t-GARCH and mean-reverting jump diffusion model can be found in Table 8. With an overall root mean squared error of 0.97% and a mean absolute error of 0.94%, the mean-reverting jump diffusion model performs best.

5.2.2. Interval Forecasts

For all models, we perform a kernel density estimation by computing a probability density estimate of the December 2008 future log returns as well as for the simulated models by using the Bowman and Azzalini filter (Bowman and Azzalini (1997)). By graphical inspection of Figure 5, the non-normal distribution of the CO_2 futures' log returns is evident. This indicates that a Gaussian fit of the data would not be capable of capturing the stylized facts of the log return series. The figure also shows that the fat tail characteristics in the empirical distribution is best reflected by the mean-reverting jump diffusion model. This confirms the similarity of results of the higher distributional moments between the future log returns and the returns simulated by the mean-reverting jump diffusion model.

Figure 5 about here

In order to get more detailed information on the simulated result, we show QQ (quantile-quantile plot) plots in Figure 6 of the actual data and a simulated time series generated from the fitted models for the same length in time. The comparison of the QQ plots shows that the mean-reverting jump diffusion model is best in capturing the mean and volatility of the underlying log returns. The t-GARCH model produces an extremely leptokurtic distribution. The QQ plots on the top of Figure 6, produced by the GARCH model, show distinct deviations, particularly in the tails. In addition, all three models fail in producing the tail behavior observed in the CO_2 futures' log return series. This graphical approach is in line with the results of the distributional statistics reported in Table 7. The QQ plots confirm the non-normality of the CO_2 return series, and that the jump model performs better than both GARCH based models. The graphical approach also reveals that the fitted mean-reverting jump diffusion model best reflects the distributional properties of the CO_2 future log return series.

Figure 6 about here

We further investigate the ability of the models to provide interval forecasts. We evaluate the appropriateness of our three different models by evaluating interval forecasts based on one-day-ahead return distributions as suggested by Christoffersen (1998). We first estimate the parameters of the models based on the in-sample data. Second, we form three different forecasts based on the out-of-sample one-step-ahead forecast evaluation based on the last 170 observations.

Figure 7 about here

Figure 7 shows three different panels for the conditional coverage (LR_{CC}), unconditional coverage (LR_{UC}) and independence statistics (LR_{IND}) for each of the competing forecasts. We display test values for coverage rates ranging between 70% and 95% (as robustness, we also checked coverage ratios from 50% to 70%). The dashed-dotted line shows the GARCH(1,1)-forecast, the short dashed line is the t-GARCH(1-1) forecast and the solid line is the mean-reverting jump diffusion forecast. The solid horizontal line represents the 5% significance level of the appropriate χ^2 distribution. By the decomposition property of these statistics, the sum of the values of LR_{UC} and LR_{IND} is equal to the value in the top panel, LR_{CC}.

The top panel of Figure 7 shows the values of the LR_{CC} statistics which is the test of complete coverage. We find complete coverage for all three models in the range of coverage between 70% and 85%. In addition, the mean-reverting jump diffusion model also passes the test across all coverage rates indicating the best forecasting performance compared to the two GARCH models. The middle panel of Figure 7 shows the LR_{UC} statistic which tests for unconditional coverage. All models pass the test for unconditional coverage in the range between 70% and 80%, but fail in the case of 85%. The GARCH and t-GARCH models do not pass the test of the unconditional coverage in the ranges of 85% to 90%. This result indicates that the unconditional distribution seems to change over the course of the sample. The bottom panel of Figure 7 shows the LR_{IND} statistic testing for independence. We find that the test for independence is passed for all coverage rates and for all models analyzed in this paper.

Overall, comparing the empirical distribution with the simulated results using density forecasting methods, the mean-reverting jump diffusion model performs best with respect to point and interval forecasts.

5.3. Valuation Results

In this section, we carry out the valuation of the certificates according to equation (A.8) in the appendix. We simulate the futures rate over the out-of-sample period from August 23, 2007 until April 24, 2008, which is equal to 170 days. During the simulation process, the futures prices are tested against the knock-out barrier. This has the effect that all price realizations which have hit the barrier are not incorporated in the calculation of the payoff. This procedure is repeated 100,000 times to get a reliable estimate of the derivative's payoff. At the end of the simulation process, we discount the average value of the payoffs back to t_0 at the risk free rate (Euribor adjusted for 8.16 months). The outcome of this procedure is an estimate of the derivative's price at the beginning of the out-of-sample period or at the beginning of the life of the option, respectively.

5.3.1. Out-of-Sample Valuation

In Table 9, we present the valuation results. We compare the pricing performance of the GARCH, t-GARCH and the mean-reverting jump diffusion model and their ability to price the given derivatives. To evaluate the models' performance, we calculate the mean squared error as well as the relative mean absolute error. Overall, the average value of the absolute errors amounts to roughly 5.5% for all three models. The mean absolute error values show that, with exception of a few derivatives, the deviation of most of the simulated prices from the market prices range between less than 1% and 2%. If we were to exclude the case of options with a deviation of more than 10% from the calculation, the relative mean absolute error of the GARCH model would be 1.4%, the relative mean absolute error of the t-GARCH model would be 2.1% and the mean-reverting jump diffusion model would be 3.1%. This means that the relative mean absolute error of the GARCH model would be reduced by 75%, the t-GARCH model by 62% and the mean-reverting jump diffusion model by 36%. The case for the rather small reduction of pricing error in the mean-reverting jump diffusion model compared to the two GARCH models is that only one option has a relative mean absolute error of more than 10% (whereas three options in the GARCH and two options in the t-GARCH model). Hence, looking at the average relative mean absolute error, the mean-reverting jump diffusion model seems to have the best forecasting power with respect to the prices of the given derivatives. This result is further confirmed by the overall mean squared error. The mean-reverting jump diffusion model has the lowest mean squared error value of 0.7% compared to 8% for the GARCH and 5.8% for the t-GARCH model. Overall, the outcomes of the valuation provide strong evidence that risk-neutral valuation is applicable to situations when heteroscedasticity is present in the returns.

Table 9 about here

However, the pricing performance of the models is not beyond doubt. In case of the down-and-out call options, all models tend to overprice calls with a small intrinsic value. There is a pricing error of almost 40% in the case of the call with a strike price of 20 and a respective futures price of 21.48. These outcomes could be due to the large number of knocked-out simulation runs which differ to a great extent from the other derivatives' knock-out figures. Too many low realizations of the futures rate might not be considered in the payoff calculation. However, the fact that the barrier is close to the actual futures rate makes this outcome reasonable. Looking at the pricing performance of the mean-reverting jump diffusion model, one can infer the same picture: the mean squared erros are between 0.9% and 4% for almost all call options. However, there is a significant pricing deviation in the case of calls with a strike price of 18 and 20. The mean squared errors are 31% and 11%, respectively and the relative mean absolute errors are 43% and 10%, respectively. These results can also be explained by the barrier level being close to the future rate level. If the barrier is not set close to the current futures price, e.g. deep-in-the-money options, this effect has not such a big weight and the valuation yields good results. However, the number of the available derivatives with the EUA futures 2008 as an underlying is too small to draw a final and valid conclusion about which type of option is priced wrongly by the model. Looking at the average mean squared error, the t-GARCH model has the lowest average mean squared error of 6.8% for all call options. When comparing the relative mean absolute error, the t-GARCH and the mean-reverting jump diffusion model have the same average of about 7.95%. Overall, the t-GARCH model has the best pricing performance for the down-and-out call options.

For the up-and-out puts the picture is different. Looking at the overall performance of the three models, the mean-reverting jump diffusion model has the lowest overall average mean squared error (9.59%) as well as the lowest relative mean absolute error (3.55%). There is a striking difference to the GARCH models which have an average mean squared error of 226% for the GARCH model and 157% for the t-GARCH model. The GARCH models are inclined to misprice deep-in-the-money puts in comparison to puts with a strike price closer to the actual futures rate. Here, the specific pricing errors are not as large as in the case of the calls previously analyzed but yet substantial. This effect is reduced in the mean-reverting jump diffusion model resulting in much lower pricing errors. The most likely explanation for this can be found in the specification of the valuation process. As stated above, the options labelled with two stars were issued February 22, 2008. Because of this, we model the futures rate only for a period of 43 days. Consequently, the modeling was initiated at a different rate, i.e. EUR 21.48, instead of EUR 18.81. Because of the longer time horizon, more simulated futures crossed the barrier and their rate was not included in the payoff calculation which leads to a underpricing of the derivative. However, this explanation does not hold true in any case. Regarding the calls, we could not observe such an effect. Overall, the mean-reverting jump diffusion model is by far producing the best pricing performance for the given up-and-out puts. This further confirms the results of the forecasting section (c.f. 5.2).

The simulated values for the index trackers are the same for three different models. Overall, the average mean squared error is 9.1% and is roughly as high as the average mean squared error for the call options. The first index tracker (DR98G8) has the lowest pricing error in our whole analysis (0.06%), where the others are between 4 and 36%. Assuming that the modeled price reflects the true value of the futures, we consider the index tracker DR98G8 as fairly priced by the bank, with a very small deviation in its price. These deviations might only be due to the simulation error. Theoretically, there should be no difference in the prices because all of the four certificates track the December 2008 futures price on a 100% basis. However, in case of the three open-end certificates, the rolling-over process should be reimbursed but this is generally covered by the commission when purchasing the product. However, due to the limited amount of index tracking certificates available in the market, it is not possible to significantly assess whether the price differences among those products are technically justifiable or intended.

5.3.2. Valuation up to Maturity

In the second valuation analysis, we price the derivatives up to their maturity with a start date on April 24, 2008. This equals a time period of 160 days. As the risk free rate we use the Euribor adjusted for 7.68 months. The results are listed in Table 10. Introducing a time horizon of 160 days for all given options results in an increase in overall averages. The mean squared error of the GARCH model increases from roughly 8% to more than 300%, mainly coming from increasing pricing errors for the put options. The same is true for the t-GARCH and the mean-reverting jump diffusion model. A different picture is observed for the relative mean absolute error: the overall relative mean absolute error triples for both GARCH models compared to the results in Table 9, whereas the pricing error for the mean-reverting jump diffusion model only slightly increases from 4.7% to 8.2%. Yet, inference about the valuation power of the used model may be derived based on the comparison of the outcomes when different time horizons are simulated. Analyzing the valuation outcomes under scrutiny, we conclude that the relatively large total mean absolute error is mainly due to the increase of the put option price simulation's mean absolute error.

Table 10 about here

For the down-and-out call prices, setting the time horizon equal to 160 days for all simulations, the overall relative mean absolute error in Table 10 is roughly halved to between 4% and 5% for all three models compared to Table 9. This is due to the fact that the pricing errors are now more homogeneously distributed across strike prices, meaning that the range of the deviations could be reduced. The absolute errors are generally smaller, but some big pricing errors distort the total of mean squared error and mean absolute error. Referring to the mean squared error figures the deviation of the model prices from the market prices grew substantially. As a consequence, the relative absolute pricing error is now roughly 35% for the GARCH and t-GARCH model and 31% for the mean-reverting jump diffusion model for the period from April 24, 2008 until December 3, 2008 which is the maturity date of all knock-out options. All three models have an improved mean squared error for the call options with strike prices 20 and 18, but show a substantially increased pricing error for calls with strike prices of 10, 12 and 14. This means that a longer simulation horizon for short-term calls with strike prices close to the future price (DRQQSR and DRQQSS) seems to result in better pricing performance in terms of mean squared error and relative mean absolute error. This is not the case for call options with lower strike prices: looking at the call with strike price 16 (DRQQST), one observes a reduction of the relative mean absolute error for all three models compared to the results in Table 9.

For the puts, using a simulation period of 160 days for all options, increases the respective mean absolute error figures substantially for all three models. The pricing performance of the valuation regarding the up-and-out puts is undesirable with an mean absolute error of 33% for the GARCH model and 37% for the t-GARCH model. In contrast, the mean-reverting jump diffusion model seems to capture the put prices better resulting in a lower relative pricing error of 17%. This result is mainly driven by the enhanced performance for the puts with strike price 28, 30 and 32. In these cases the GARCH models fail. However, comparing the results in Table 10 for put option with the results in Table 9, it is evident that the simulation of a longer time period has a negative effect on the pricing performance of the different models. The practitioner's approach as several interviews have revealed is to inflate the bid-ask spread in order to take the model uncertainty into account.

The pricing performance of the models regarding the index trackers in the second valuation run is not as good as in the out-of-sample setting. All results differ from the observed rates with an average relative mean squared error of roughly 100% for all models. The two open-end certificates issued by ABN Amro (AA0G6VI) and Hypo Vereinsbank (HV2C02) show the largest pricing error of the index trackers. The large deviation might be explained by the rolling-over process. However, due to the limited amount of index trackers available in the market, we cannot distinguish between a simulation based or bank-intended pricing deviation.

6. Summary and Conclusion

In this paper, we investigate the short-term forecasting power of three different models with the aim to find an appropriate valuation procedure for derivatives on EUAs. Second, we assess the pricing of those certificates and leveraged products. To achieve the first objective we analyze the EUA futures' price dynamics. The ICE December 2008 EUA futures returns exhibit stylized features of financial data as excess kurtosis and evidence of heteroscedasticity. Furthermore, we observe the presence of jumps in the return series which are partly due to the immaturity of the CO_2 market. The model estimation and the subsequent performance analysis of the models suggest a mean-reverting jump diffusion model to appropriately reproduce the futures dynamics. In a next step, we have tested whether a valuation of derivatives in a risk-neutral framework by employing a Monte Carlo simulation leads to reasonable outcomes.

For short time horizons, the valuation results are quite precise. With an increased time period in the simulation the valuation's accuracy is still sufficient for calls and index trackers. Overall, the mean-reverting jump diffusion model yields the best results in an in-sample and out-of-sample setting. In pricing the given derivatives, the mean squared error is significantly reduced when comparing the mean-reverting jump diffusion model to the two GARCH models (0.7% vs. 8.0% for the GARCH and 5.8% for the t-GARCH model). However, looking at the overall relative mean absolute error that is roughly 5.6% for all three models, one cannot observe a significant difference in the models. The models differ significantly in the ability to price call and put options: while the average mean squared error for all three models for call options is 7.6%, the put option's mean squared error is roughly 17 times higher. To better assess the performance of the models, we implement an additional valuation up to maturity. Comparing the overall pricing performance, this results in increasing mean squared error and relative mean absolute error for all three model types.

Due to the results of the out-of-sample and up-to-maturity valuation, we infer that the risk-neutral pricing framework is applicable to derivatives on EUA futures even in situations when heteroscedasticity is present. Our paper suggests that a mean-reverting jump diffusion prices the derivatives best.

A. Appendix: Risk-Neutral Valuation of Carbon Derivatives

We assume the futures price to follow the process in equation (2.7). This GARCH process is only dependent on the volatility. The conditional mean equation is a simple constant and does not contain a drift term:

$$\Delta F = C + \varepsilon_t \tag{A.1}$$

with

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{A.2}$$

where C and ω are constants and h is the conditional volatility, both estimated in the GARCH model. The current value V_f of a futures contract which matures in T is $V_f = e^{-r(T-t)}[F_t^T - F_0^T]$, according to Geman (2006). Assuming time-varying variance, the formula results in:

$$\Delta V_f = e^{-r(T-t)}[(C + \varepsilon_t) - (C + \varepsilon_0)] \tag{A.3}$$

with

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{A.4}$$

In the present case where the future returns exhibit ARCH effects as well as excess kurtosis, Myers and Hanson (1993) propose to generalize the probability model of the futures log return distribution of Black (1976) to account for those requirements, as in the equations (A.5) to (A.7) for the option valuation:

$$\Delta f_t = \mu + \varepsilon_t \tag{A.5}$$

with

$$\varepsilon | \Omega_{t-1} \sim t(0, h, v) \tag{A.6}$$

and

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{A.7}$$

where Ω is the distribution of the innovations, h is the conditional variance of futures price changes which is estimated by the GARCH model and v the degrees of freedom of the t-distribution. According to Myers and Hanson (1993), the risk-neutral option valuation formula can be rewritten as:

$$P_t = e^{-r_t(T-t)} \int_k^{\infty} [e^{f_T} - K] g(f_t) df_t \tag{A.8}$$

where $f_T = ln(F_t)$, K is the strike price and $g(\cdot)$ the density of f_t conditional on Ω (which includes f). Under the assumption that we can express the process followed by f_t by a GARCH model, f_T equals f_t and a sum of weakly dependent and heterogeneously distributed GARCH innovations. Thus, although each innovation is drawn from an i.i.d. normal random sample, the property that the GARCH model allows for autocorrelation in the innovations, $g(\cdot)$ cannot be assumed to be normal (Engle (1982)). Yet, this does not imply that the unconditional distribution of the innovations is normal as well.

7. Tables and Figures

Table 1 – Summary Statistics of Futures' Data

The table contains the summary statistics for the ICE ECX December 2008 future daily log returns for the in-sample (IS, April 22, 2005 to August 22, 2007) and the out-of-sample (OOS, August 23, 2007 to April 24, 2008) period. We distinguish between a full sample and reduced sample during our in-sample period where the full sample also includes the nine extreme data points that occurred during spring 2006. The table displays the number of observations (Obs.), mean, standard deviation (St.Dev.), skewness, kurtosis and the Jarque-Bera test. We take daily closing prices from ICE to compute the log returns.

	Obs.	Mean	St.Dev.	Skewness	Kurtosis	Jarque-Bera
IS (full sample)	599	0.0016	0.0285	0.4354	12.37	1884.34
IS (reduced sample)	590	0.0009	0.0278	-0.6406	6.85	399.37
OOS	171	0.0016	0.0187	0.2300	4.57	17.84

Table 2 – Certificates' Data

The table displays the sample properties of the derivatives considered in the empirical analysis of this paper. NSIN refers to the National Securities Identifying Number of the securities. We retrieve daily settlement prices from the EUWAX in Stuttgart for the period from August 23, 2007 until April 24, 2008. This time horizon corresponds to the out-of-sample time period. H denotes the barrier, X denotes the strike price. Value describes the value on Apr 24, 2008. The emission date varies. Simulation horizon refers to the length of the simulation for the valuation of the certificate. It depends on the emission date.

Type	H	X	Value	Emission Date	Maturity	Futures Price	Simulation Horizon
NSIN Calls							
DR5C9Z	7	5	19.83	Mar 23, 2007	Dec 03, 2008	18.81	171
DR5C90	12	10	14.83	Mar 23, 2007	Dec 03, 2008	18.81	171
DROQSR[a]	20	20	4.8	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQSS	18	18	6.8	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQST	16	16	8.8	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQSU	14	14	10.8	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQSV	12	12	12.8	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQSW	10	10	14.8	Feb 22, 2008	Dec 03, 2008	21.48	43
NSIN Puts							
DR5C9Y	33	35	9.87	Mar 23, 2007	Dec 03, 2008	18.81	171
DR98G7	40	45	20.96	Oct 11, 2006	Dec 03, 2008	18.81	171
DROQSZ[b]	26	26	0.9	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQS0	28	28	2.9	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQS1	30	30	4.9	Feb 22, 2008	Dec 03, 2008	21.48	43
DROQS2	32	32	6.9	Feb 22, 2008	Dec 03, 2008	21.48	43
NSIN Index Tracker							
DR98G8	0	0	24.14	Oct 11, 2006	Dec 03, 2008	18.81	171
DR1WBM	0	0	24.4	Oct 26, 2007	open end	22.72	125
AA0G6VI	0	0	25	Apr 25, 2007	open end	18.81	171
HV2C02	0	0	25.15[c]	Feb 27, 2007	open end	18.81	170

[a] The denomination of the following options is to the ratio 1:10. Therefore, the actual price was multiplied by ten.
[b] The denomination of the following options is to the ratio 1:10. Therefore, the actual price was multiplied by ten.
[c] As of Apr 23, 2008

Table 3 – GARCH(1,1) Parameters

The table displays the results of the maximum likelihood estimation of the parameters, standard errors and t-statistics of the GARCH(1,1) model for the full and the reduced sample where the full sample additionally includes the nine extreme data points that occurred during the spring 2006.

	Full Sample			Reduced Sample		
Parameter	Value	Std.Error	t-statistic	Value	Std.Error	t-statistic
C	0.0019	0.0009	2.14	0.0015	0.0011	1.30
ω	0.0001	0.0000	5.96	0.0001	0.0000	4.99
GARCH(1)	0.6722	0.0295	22.80	0.6947	0.0434	15.99
ARCH(1)	0.2591	0.0247	10.50	0.1884	0.0314	5.99

Table 4 – t-GARCH(1,1) Parameters

The table displays the results of the maximum likelihood estimation of the parameters, standard errors and t-statistics of the t-GARCH(1,1) model for the full and reduced sample where the full sample additionally includes the nine extreme data points that occurred during the spring 2006.

	Full Sample			Reduced Sample		
Parameter	Value	Std.Error	t-statistic	Value	Std.Error	t-statistic
C	0.0019	0.0008	2.48	0.0020	0.0009	2.11
ω	0.0001	0.0000	2.64	0.0001	0.0000	2.37
GARCH(1)	0.7412	0.0593	12.49	0.7268	0.0756	9.61
ARCH(1)	0.2038	0.0529	3.85	0.1790	0.0593	3.01

Table 5 – **MRJD Parameters**

The table displays the estimated parameters, the standard errors and t-statistics of the mean-reverting jump diffusion model for the full sample and the reduced sample where the full sample additionally includes the nine extreme data points that occurred during the spring 2006. Parameters are estimated with maximum likelihood estimation, where α is the instantaneous expected return, β is the mean-reversion level, σ is the volatility, μ_j is the expected jump size and σ_j the volatility of the jump process. Standard errors are calculated as the squared of the inverse of the Hessian.

	Full Sample			Reduced Sample		
Parameter	Value	Std.Error	t-statistics	Value	Std.Error	t-statistics
α	0.0029	0.5426	0.00	0.0027	0.0013	2.07
β	0.8817	0.0558	15.80	0.9118	0.0369	24.71
σ	0.0226	0.3954	0.05	0.0206	0.002	10.30
λ	0.0552	0.1545	0.35	0.1216	0.0043	28.27
μ_j	-0.0186	0.1933	-0.09	-0.0206	0.0045	-4.57
σ_j	0.0794	0.0672	1.18	0.0499	0.0967	0.51

Table 6 – **AIC and BIC Values of the Estimated Models**

The table displays the AIC and BIC information criterion for all three estimated models based on the reduced sample. GARCH(p,q) and t-GARCH(p,q) models are displayed with p ranging from 1 to 3 and q including 1 and 2.

Model	AIC ($*1.0e+003$)	BIC ($*1.0e+003$)
GARCH(1,1)	-2.6049	-2.5874
GARCH(2,1)	-2.6071	-2.5852
GARCH(2,2)	-2.6051	-2.5788
GARCH(3,1)	-2.6126	-2.5863
t-GARCH(1,1)	-2.6506	-2.6287
t-GARCH(2,1)	-2.6492	-2.6229
t-GARCH(3,1)	-2.6496	-2.6190
MRJD	-0.0121	-0.0399

Table 7 – **Distributional Moments of the Estimated Models**

The table shows the distributional moments for the in-sample data (IS), the out-of-sample data (OOS) as well as the simulations by GARCH, t-GARCH and mean-reverting jump diffusion models for the corresponding periods based on one-day-ahead forecasts.

	Mean	Std.Dev.	Skewness	Kurtosis
IS data	0.0009	0.0278	-0.6406	6.8458
Simulated GARCH IS	0.0013	0.0295	0.0109	4.4526
Simulated t-GARCH IS	0.0019	0.0300	0.3554	12.1844
Simulated MRJD IS	0.0005	0.0280	-0.7802	7.2006
OOS data	0.0016	0.0187	0.2283	4.5856
Simulated GARCH OOS	0.0017	0.0290	-0.0594	4.2330
Simulated t-GARCH OOS	0.0021	0.0310	-1.2551	41.2495
Simulated MRJD OOS	0.0003	0.0278	-0.8319	7.1524

Table 8 – Simulation Errors of the Estimated Models

The table shows the root mean squared errors (RMSE) and the mean absolute errors (MAE) in percent between the simulated (100,000 runs) and the observed returns for the GARCH(1,1) model, the t-GARCH(1,1) model and mean-reverting jump diffusion model.

Model	RMSE	MAE
GARCH	1.07%	0.96%
t-GARCH	1.15%	0.97%
MRJD	0.97%	0.94%

Table 9 – Certificate Valuation Results Out-of-Sample

The table shows the valuation results for the certificates in the out-of-sample period. H denotes the barrier, X denotes the strike price. Market values are taken for * as of August 23, 2007, for ** as of February 22, 2008, and for *** as of October 26, 2007. The corresponding futures prices were EUR 18.81, 21.48, 22.72, respectively. We calculate the mean squared error (MSE) as well as the relative mean absolute error (MAE) for the different certificates for all three models

	H	X	Market Value	Simulated Values			MSE			Relative MAE			Mean $\hat{F}_T$
Type				GARCH	t-GARCH	MRJD	GARCH	t-GARCH	MRJD	GARCH	t-GARCH	MRJD	
KNOCK OUT													
Calls													
DR5C9Z*	7	5	13.55	13.39	13.37	13.39	0.0239	0.0295	0.0248	0.0114	0.0127	0.0116	18.81
DR5C90*	12	10	8.55	8.50	8.48	8.35	0.0020	0.0048	0.0396	0.0053	0.0081	0.0233	18.81
DROQSR**	20	20	1.30	1.90	1.90	1.85	0.3702	0.3637	0.3068	0.4680	0.4639	0.4261	21.48
DROQSS**	18	18	3.30	3.65	3.61	3.62	0.1265	0.0980	0.1077	0.1078	0.0949	0.0995	21.48
DROQST**	16	16	5.30	5.49	5.46	5.49	0.0389	0.0258	0.0369	0.0372	0.0303	0.0362	21.48
DROQSU**	14	14	7.30	7.43	7.39	7.43	0.0188	0.0099	0.0180	0.0188	0.0136	0.0184	21.48
DROQSV**	12	12	9.30	9.41	9.37	9.41	0.0124	0.0052	0.0121	0.0120	0.0078	0.0118	21.48
DROQSW**	10	10	11.30	11.39	11.35	11.39	0.0089	0.0028	0.0089	0.0084	0.0047	0.0083	21.48
MSE/MAE Calls							0.0752	0.0675	0.0693	0.0836	0.0795	0.0794	
Puts													
DR5C9Y*	33	35	15.95	13.15	13.54	15.71	7.8109	5.8038	0.0570	0.1752	0.1510	0.0150	18.81
DR98G7*	40	45	26.00	23.60	24.12	25.41	5.7399	3.5055	0.3379	0.0921	0.0720	0.0224	18.81
DROQSZ**	26	26	4.20	4.20	4.31	4.52	0.0000	0.0142	0.1028	0.0012	0.0284	0.0764	21.48
DROQS0**	28	28	6.30	6.28	6.41	6.48	0.0003	0.0138	0.0326	0.0025	0.0187	0.0287	21.48
DROQS1**	30	30	8.30	8.35	8.47	8.45	0.0026	0.0311	0.0251	0.0062	0.0212	0.0191	21.48
DROQS2**	32	32	10.30	10.38	10.49	10.44	0.0066	0.0379	0.0198	0.0079	0.0189	0.0137	21.48
MSE/MAE Puts							2.2601	1.5677	0.0959	0.0475	0.0517	0.0291	
INDEX TRACKER													
DR98G8*	0	0	18.28	18.20	18.25	18.25	0.0053	0.0006	0.0006	0.0040	0.0013	0.0013	18.81
DR1WBM***	0	0	22.65	22.18	22.05	22.88	0.2158	0.3589	0.0542	0.0205	0.0265	0.0103	22.72
AA0G6VI*	0	0	18.55	18.20	18.25	18.25	0.1199	0.0864	0.0864	0.0187	0.0158	0.0158	18.81
HV2C02*	0	0	18.47	18.20	18.25	18.24	0.0690	0.0444	0.0508	0.0142	0.0114	0.0122	18.81
MSE/MAE Trackers							0.1025	0.1226	0.0480	0.0143	0.0138	0.0099	
Total MSE/MAE							0.8095	0.5798	0.0734	0.0562	0.0556	0.0472	

Table 10 – Certificate Valuation Results Up to Maturity

The table shows the valuation results for the certificates in the out-of-sample period as of April 24, 2008. H denotes the barrier, X denotes the strike price. The market values are as of April 24, 2008, the corresponding futures prices was EUR 24.51.

	H	X	Market Value	Simulated Values			MSE			relative MAE			Mean $\hat{F}_T$
Type				GARCH	t-GARCH	MRJD	GARCH	t-GARCH	MRJD	GARCH	t-GARCH	MRJD	
KNOCK OUT													
Calls													
DR5C9Z	7	5	19.83	18.93	18.92	18.97	0.8026	0.8109	0.7377	0.0452	0.0454	0.0433	24.51
DR5C90	12	10	14.83	14.06	14.05	14.07	0.5832	0.5966	0.5764	0.0515	0.0521	0.0512	24.51
DROQSR	20	20	4.80	5.37	5.33	4.98	0.3254	0.2838	0.0331	0.1188	0.1110	0.0379	24.51
DROQSS	18	18	6.80	6.96	6.98	6.74	0.0263	0.0346	0.0031	0.0239	0.0274	0.0082	24.51
DROQST	16	16	8.80	8.60	8.62	8.51	0.0371	0.0293	0.0796	0.0219	0.0195	0.0321	24.51
DROQSU	14	14	10.80	10.35	10.37	10.33	0.1977	0.1842	0.2179	0.0412	0.0397	0.0432	24.51
DROQSV	12	12	12.80	12.19	12.20	12.20	0.3624	0.3512	0.3522	0.0470	0.0463	0.0464	24.51
DROQSW	10	10	14.80	14.09	14.10	14.11	0.4928	0.4855	0.4625	0.0474	0.0471	0.0460	24.51
MSE/MAE Calls							0.3534	0.3470	0.3078	0.0496	0.0486	0.0385	
Puts													
DR5C9Y	33	35	9.87	6.20	5.92	9.05	13.4095	15.5733	0.6637	0.371	0.3998	0.0825	24.51
DR98G7	40	45	20.96	15.81	15.17	18.83	26.4751	33.5206	4.5152	0.2455	0.2762	0.1014	24.51
DROQSZ	26	26	0.90	0.65	0.62	1.52	0.0587	0.0760	0.3874	0.2692	0.3062	0.6916	24.51
DROQS0	28	28	2.90	1.72	1.59	3.23	1.3903	1.6965	0.1102	0.4066	0.4491	0.1144	24.51
DROQS1	30	30	4.90	3.06	2.86	5.05	3.3746	4.1596	0.0231	0.3749	0.4162	0.031	24.51
DROQS2	32	32	6.90	4.67	4.42	6.92	4.9484	6.1172	0.0006	0.3324	0.3584	0.0037	24.51
MSE/MAE Puts							8.2761	10.1905	0.9500	0.3316	0.3677	0.1708	
INDEX TRACKER													
DR98G8	0	0	24.14	23.75	23.78	23.83	0.1473	0.1238	0.0936	0.0159	0.0146	0.0127	24.51
DR1WBM	0	0	24.40	23.75	23.78	23.83	0.4145	0.3743	0.3204	0.0264	0.0251	0.0232	24.51
AA0G6VI	0	0	25.00	23.75	23.78	23.83	1.5470	1.4685	1.3596	0.0498	0.0485	0.0466	24.51
HV2C02	0	0	25.15	23.75	23.78	23.83	1.9427	1.8545	1.7319	0.0554	0.0541	0.0523	24.51
MSE/MAE Trackers							1.0129	0.9553	0.8764	0.0369	0.0356	0.0337	
Total MSE/MAE							3.1409	3.7634	0.6482	0.1408	0.1520	0.0815	

Figure 1 – Development of the EUA Spot and Futures Prices
The figure compares the spot price to the futures prices. We refer to the December 2007 contract as the "intra-period future" because it matures within the first compliance period when the spot is still traded. The December 2008 contract is the "inter-period future", since its maturity is longer than the first compliance period.

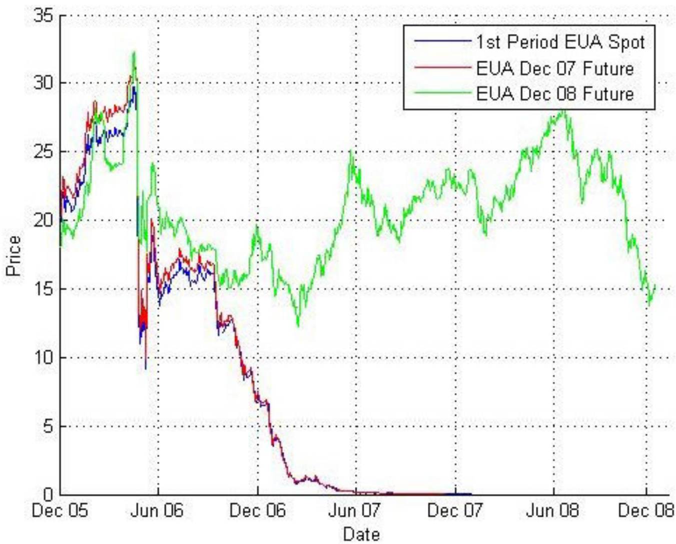


Figure 2 – GARCH Plots

The figure displays the innovations of the GARCH(1,1) model in the upper Panel. The middle panel shows the conditional standard deviations while the lower panel gives the comparison to the raw return data.

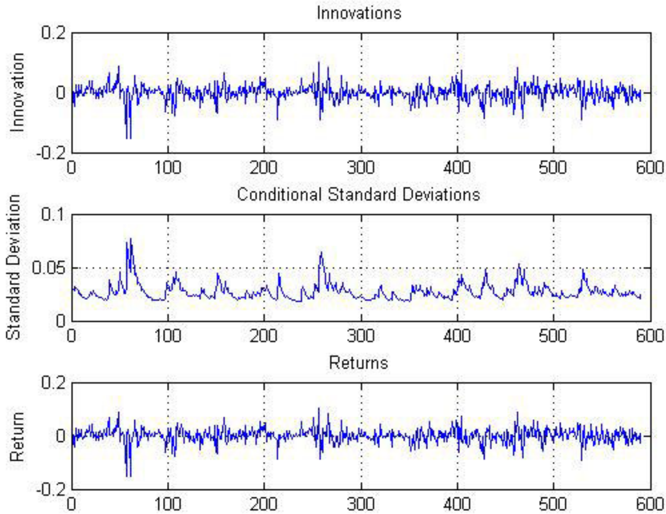


Figure 3 – t-GARCH Plots

The figure displays the innovations of the t-GARCH(1,1) model in the upper panel. The middle panel shows the conditional standard deviations while the lower panel gives the comparison to the raw return data.

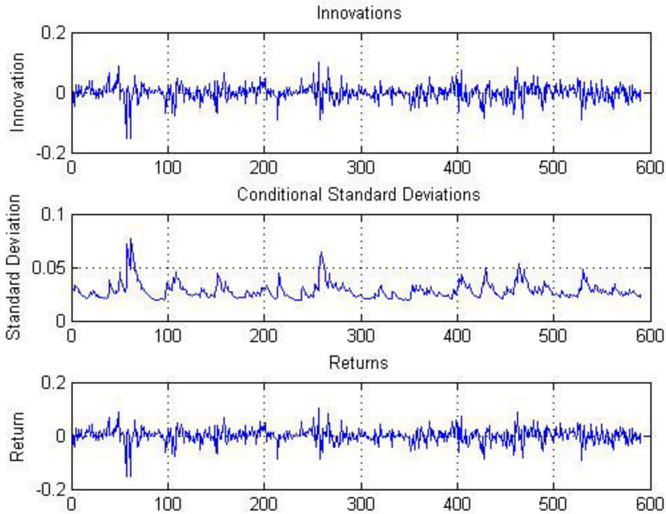


Figure 4 – MRJD Plots

The figure displays the innovations of the mean-reverting jump diffusion model in the upper panel. The middle panel shows the conditional standard deviations while the lower panel gives the comparison to the raw return data.

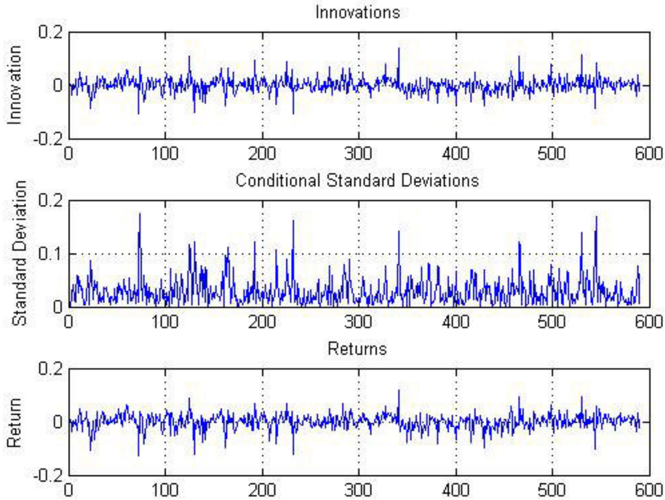


Figure 5 – Kernel Density Estimation

This figure shows the empirical distribution of the EUA December 2008 futures and one-day ahead simulated log returns of the GARCH, t-GARCH and mean-reverting jump diffusion models obtained by a Kernel density estimator. We employed a normal kernel smoothing procedure proposed by Bowman and Azzalini (1997). The estimates are based on a normal Kernel function, where the density is evaluated at 100 equally spaced points that cover the range of the data. For comparison, a Gaussian density with matched moments for the December 2008 futures ($\mu = 8.5860e-004$, $\sigma = 0.0278$) is plotted as a blue dashed line.

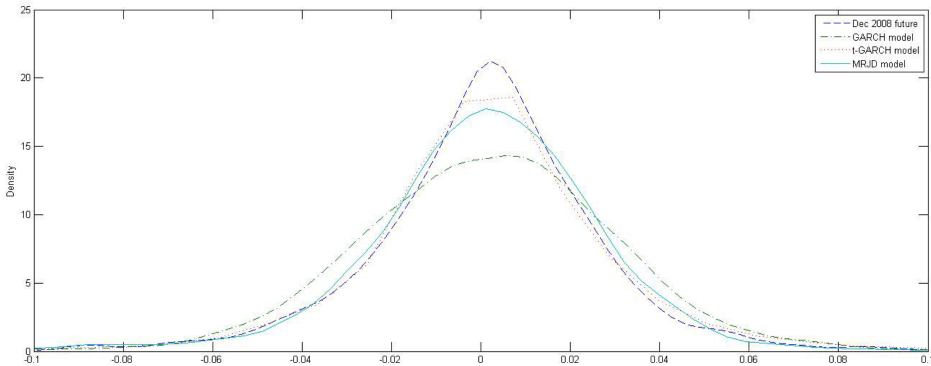


Figure 6 – QQ-Plots

This figure shows the QQ-plots of the EUA December 2008 futures and simulated log returns of the GARCH, t-GARCH and mean-reverting jump diffusion models based on one-day-ahead forecasts.

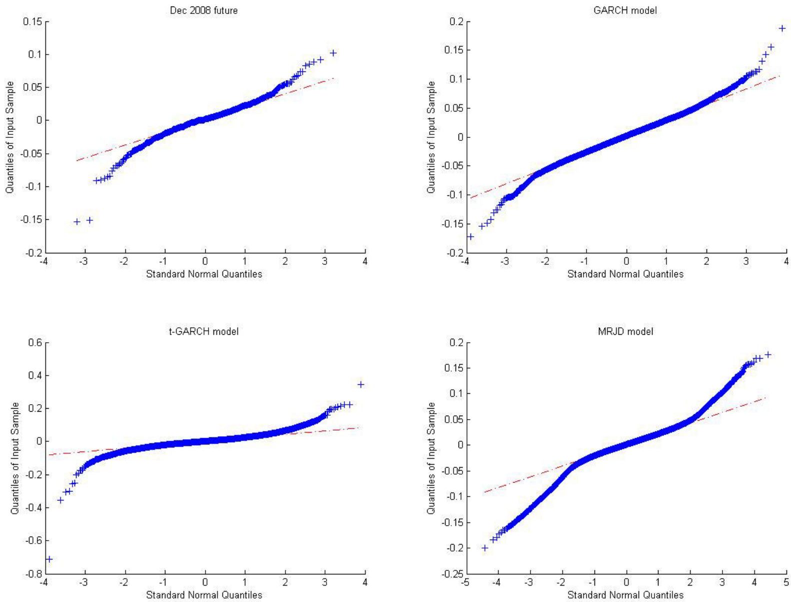
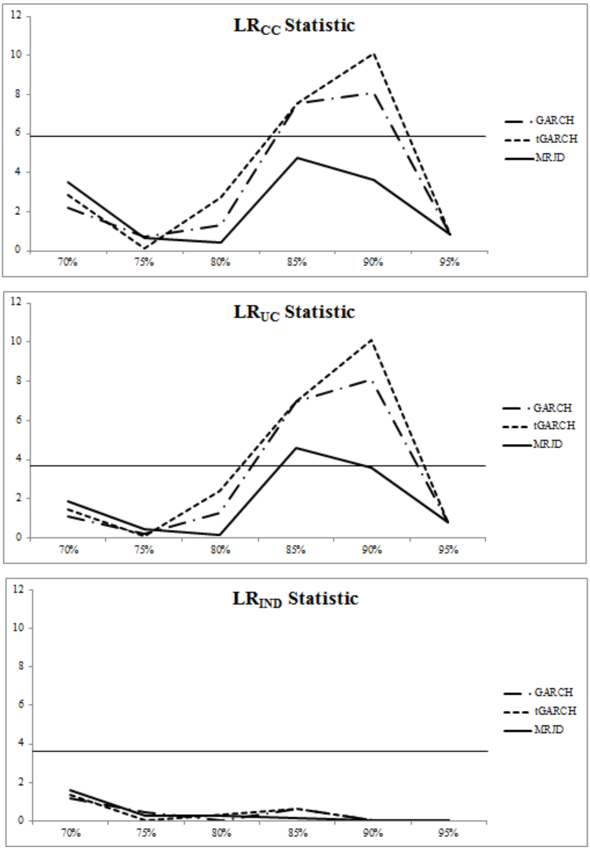


Figure 7 – Likelihood Ratios of Conditional Coverage, Unconditional Coverage, and Independence

The three panels show the results of the interval forecasts for the three different models based on one-day-ahead forecasts. The top panel shows the LR statistics of conditional coverage for three interval forecasts. The middle and bottom panels show the corresponding values of the LR tests of unconditional coverage and independence, respectively. The dashed-dotted line shows the GARCH(1,1) forecasts, the short dashed line are the t-GARCH(1,1) forecasts and the solid line are the mean-reverting jump diffusion forecasts. The solid horizontal line represents the 5% significance level of the appropriate χ^2 distribution. The test values are plotted for coverage rates ranging between 70% and 95%.



Part II.
Selling Winners, Holding Losers: The Relation between the Disposition Effect and Investment Characteristics

This paper is accepted for publication and is forthcoming in the Journal of Behavioral Finance.

Abstract

Documenting the disposition effect for a large sample of mutual fund managers in the U.S., we find that stock-level characteristics may be a possible explanation for the cross-sectional variation of the effect. Previous papers discover that the disposition effect - which is the tendency to sell winner stocks too early and hold on to loser stocks for too long - is linked to fund characteristics (e.g. Cici (2012)), fund manager characteristics (e.g. Scherbina and Jin (2011)), and fund flows (e.g. Singal and Xu (2011)). We add to the literature by analyzing the unexplored relationship between the disposition effect and stock characteristics. Using different measures of stock and market uncertainty, we show that mutual fund managers display a stronger disposition driven behavior when stocks are more difficult to value. We also find that the level of the disposition effect is increasing with the level of systematic risk and decreasing with the profitability of stocks. In addition, we uncover that the behavior of mutual fund managers is partly driven by trading of attention-grabbing stocks (dividend-paying stocks). Overall, our results suggest that stock-level uncertainty and trading of attention-grabbing and less profitable stocks amplify the disposition effect.

1. Introduction

More than $26.8 trillion are invested worldwide in equity mutual funds in 2012[1], and despite the growing number of index funds and exchange traded funds (ETFs), the vast majority of funds remains actively invested. However, research has consistently shown that on average actively-managed portfolios do not outperform their benchmarks[2]. Lately, the presence of the disposition effect among mutual fund managers has been put forward as a major behavioral based reason for underperformance (e.g. Scherbina and Jin (2011), Singal and Xu (2011)). The disposition effect - which has been termed by Shefrin and Statman (1985) - refers to the tendency of investors to prefer holding on to their loser stocks and selling their winner stocks. Although the disposition effect is one of the most robust findings in behavioral finance, and is documented for different settings, time periods, and assets (e.g. Frazzini (2006), Grinblatt and Keloharju (2001), Hartzmark and Solomon (2012), Odean (1998), Wermers (2003)), its underlying drivers remain rather unclear. Previous papers attribute the presence of the disposition effect to fund characteristics, fund managers' characteristics as well as fund in- and outflows. We add to this literature by analyzing the unexplored relationship between the disposition effect and stock characteristics.

The goals of this paper are threefold: first, we analyze to what extent the disposition effect is present among a sample of U.S. equity mutual fund managers. Specifically, we examine under which circumstances the disposition effect is

[1] Source: 2013 Investment Company Fact Book, Investment Company Institute.
[2] E.g. Daniel et al. (1997), Jensen (1986), Malkiel (1995).

more pronounced among a sample of actively-managed, U.S. equity mutual fund managers between 1980 and 2010. While extensive research exists on the behavior of individual investors, there is rather little and mixed evidence on the effect of biased behavior among mutual fund managers (e.g. Ammann et al. (2012), Cici (2012), Frazzini (2006), Ringov (2012), Scherbina and Jin (2011), Singal and Xu (2011)). It is questionable why the disposition effect persists since merely pointing out any sort of bias should lead investors to adjust their behavior and to make them disappear.

Second, we test the hypothesis whether the cross-sectional variation in the magnitude of the disposition effect can be explained by differences in mutual fund stock holdings. Only little research has been conducted on the relationship between the magnitude of the disposition effect and stock characteristics (e.g. Kumar (2009) for a sample of individual investors). Previous studies focus on the stock-picking abilities of top-performing mutual fund managers: positive alphas suggest that the respective fund manager has skills (e.g. Kacperczyk et al. (2008), Wermers (2000)). However, specific characteristics of the stock holdings of fund managers, and why some managers hold top-performing while others hold under-performing stocks have not been fully explored yet. We analyze the relationship between the magnitude of the stock-level disposition effect and valuation uncertainty. Stocks with higher idiosyncratic volatility levels might be perceived as more difficult to value, and therefore could be a driver of the disposition effect. Experimental evidence indicates that people are more likely to use heuristics and display a higher level of behavioral biases when they are faced with more difficult situations (e.g. Kahneman and Tversky (1979)). Theoretical financial models (Daniel et al. (1998), Hirshleifer (2001)) formalize the experimental results of decision-making in an investment environment, and state that investors' biases will be stronger when stocks are harder to value. In addition, we anaylze whether more disposition prone fund managers are more likely to trade attention-grabbing stocks. This so called attention hypothesis was first formulated by Odean (1999) stating that attention will affect the buying and selling decisions of investors asymmetrically. Since individuals have limited abilities to evaluate a large number of stocks available in the market, they only consider purchasing stocks which their attention is drawn to. Graham and Kumar (2006)) find that dividends may serve as a proxy for attention-grabbing net buying behavior of individual investors. We test whether mutual fund managers with higher disposition levels are more prone to trade dividend-paying stocks.

Third, we analyze whether more disposition prone funds prefer to invest in underperforming stocks. Scherbina and Jin (2011) and Singal and Xu (2011) discover that funds that show disposition driven behavior underperform compared to their less biased counterparts. One reason for the underperformance of biased funds might be the investment in less profitable as well as higher risk stocks.

Our analysis delivers three main results. First, we provide evidence that mutual fund managers are prone to the disposition effect. Using Odean's (1998) methodology of calculating the disposition effect, we find that mutual fund managers show on average an annual disposition effect of 3.96%. Using the standard approach, our results are directly comparable to previous results (e.g. Ammann et al. (2012), Cici (2012)).

Our second result is that we identify stock characteristics that explain the cross-sectional variation of the disposition effect. Using different measures for stock valuation (idiosyncratic volatility, stock return volatility), we find a positive relationship between the stock-level disposition effect and valuation uncertainty. Our results show that fund managers display a higher level of the disposition effect when the respective stock is more difficult to value. We also analyze whether attention-grabbing events can partly explain disposition driven behavior of mutual fund managers. Using dividends as a proxy for attention-grabbing stocks, we find that more biased managers tend to trade stocks which draw their attention.

Third, it might be argued that stocks associated with higher risk are also more profitable since higher risk stocks simply could provide higher returns. We counter this argument by showing that disposition prone investors indeed trade stocks with higher risk. We find that the level of the disposition effect is increasing with the level of systematic risk (i.e. beta). But, counter-intuitively, the traded stocks are also less profitable which might explain the underperformance of disposition prone funds detected in previous papers (e.g. Scherbina and Jin (2011), Singal and Xu (2011)). Biased fund managers hold on loser stocks too long and sell winner stocks too early which is more prominent among stocks with lower returns on assets (ROA), lower profit margins, and higher costs (as measured by capital expenditures (CAPEX)).

Our focus is on fund managers' holdings, and is motivated by several reasons.

First, mutual funds offer a particularly suitable setting for studying the drivers and implications of organizational decision-making processes. Since mutual funds are subject of regulated disclosure, reliable data is available. Second, as professional investors, mutual funds constantly trade securities in financial markets, and thereby continuously acquire experience. Hence, mutual fund managers should on average be more skilled than retail investors, and therefore are more likely to avoid behavioral biases (Cici (2012), Seru et al. (2010)). Finally, the mutual fund industry is of great economic relevance. Given the predominance of institutional investors in the markets, evidence of the existence of the disposition effect would have far reaching consequences in confirming or denying the extent of rationality reflected in asset pricing models.

Previous literature has widely documented the presence of the disposition effect. After Odean (1998)'s influential study finding the disposition effect for a sample of U.S. retail investors, subsequent papers analyzed the effect in greater detail using data for international markets. Grinblatt and Keloharju (2001) and Shapira and Venezia (2001) show evidence of the disposition effect affecting both inexperienced and sophisticated individual investors in Finland and Israel, respectively. The tendency to hold on to losing investments and selling winner investments is also detected in other settings. Genesove and Mayer (2001) find home owners to be averse selling their houses below the purchase price. Kaustia et al. (2008) show that investors are reluctant to sell shares of an IPO trading below the offer price. Heath et al. (1999) discover the same behavior with regards to executive stock options, and Hartzmark and Solomon (2012) find evidence of holding on losing investments and selling winning investments in prediction markets.

Among different explanations suggested for the observed behavior, the disposition effect is attributed to key characteristics of mental accounting (Thaler (1985)) and prospect theory (Kahneman and Tversky (1979)). People tend to value gains and losses relative to a reference point (e.g. purchase price in Odean (1998)'s paper). Prospect theory refers to a risk averse preference in the domain of gains and risk seeking preference in the domain of losses (both measured relative to a reference point). The main idea of mental accounting is that investors set different reference points for different accounts which determine gains and losses. They divide different types of gambles into separate accounts, and use prospect theory for each account separately, thereby ignoring possible interactions. The combination of mental accounting and prospect theory creates the disposition effect. Recent papers challenge previous findings and make contrary predictions regarding prospect theory as a driver of the disposition effect. Barberis and Xiong (2012) show that prospect theory predicts a reverse disposition effect. Kaustia (2010) finds that prospect theory is inconsistent with empirical patterns of the probability of selling stocks.

Another explanation that has been put forward in recent research for the existence of the disposition effect is that investors rather focus on realization utility than utility from the value function as stated by the prospect theory (e.g. Barberis and Xiong (2012), Frydman et al. (2014), Ingersoll and Jin (2013)). The underlying assumption is that investors not only derive utility from consumption but also derive direct utility from realizing gains and losses of an asset previously owned. Results are supported by an experimental study using neural data by Frydman et al. (2014). The authors confirm that realization utility is indeed leading to the disposition effect. In summary, there is no consensus of the underlying theories, and this paper does not take position on which psychological bias is underlying the disposition effect.

We contribute to the empirical literature on the presence of behavioral biases among mutual fund managers. Perhaps unsurprisingly, given the perceived opinion that professional investors are the "smart money" (Frazzini and Lamont (2008)), empirical research on biases among professionals has so far reported mixed results. Coval and Shumway (2005), Locke and Mann (2000), and Shapira and Venezia (2001) find evidence of the disposition effect among future traders at the Chicago Board of Trade, and professional investors, respectively. The disposition effect is also detected among U.S. equity mutual fund managers (Cici (2012), Frazzini (2006), Scherbina and Jin (2011), Wermers (2003)). For example, Wermers (2003)'s findings suggest a reluctance of selling loser stocks among mutual fund managers in the U.S. from 1975 to 1994, and that loser funds tend to be more disposition prone. Frazzini (2006) confirms previous results showing that the disposition effect is related to the post-announcement price drift, and that it drives stock price underreaction to news. He also finds that the extent of the disposition effect adversely affects returns. In their study about newly hired fund managers, Scherbina and Jin (2011) conclude that previous managers are reluctant to sell loser stocks in their portfolios. Other recent studies confirm previous results and show that U.S. equity mutual fund managers are disposition prone (e.g. Ammann et al.

(2012), Chiang and Huang (2010), Ringov (2012)).

Previous literature also documents contrary evidence on the presence of the disposition effect among U.S. mutual fund managers. Cici (2012) documents that the average mutual fund manager is not disposition prone. Singal and Xu (2011) show that only 30% of the mutual funds in their sample display a disposition tendency, and that this fraction of funds significantly underperforms compared to non-biased funds.

Therefore, the existence of the disposition effect at an institutional level is less clear. A recent paper by Cici (2012) summarizes the current state of research: *"I observe a great deal of heterogeneity among my sample funds, as 22 - 55% of them exhibit a propensity to realize gains more readily than losses. While this pattern is consistent with the disposition effect for this subset of funds, it could also be caused by random variation in the empirical distribution"* (Cici (2012), p. 796). This statement combined with the mixed evidence of previous papers calls for a more in-depth analysis of the disposition effect among mutual fund managers and its underlying drivers. We contribute to this literature by providing a detailed analysis of the disposition effect among a large and comprehensive sample of actively-managed U.S. funds.

Although the disposition effect is uncovered for a variety of settings, time periods and assets, its underlying drivers remain rather unclear. Some papers argue that fund characteristics (e.g. fund costs, turnover, fund volatility, fund size, fund's age) determine the level of the disposition effect (Ammann et al. (2012), Gil-Bazo and Ruiz-Verdu (2009)). Other papers find fund managers' characteristics (e.g. manager's age, manager's experience, team- or single managed fund) to infer with the level of disposition prone behavior (Ringov (2012), Scherbina and Jin (2011), Solomon et al. (2012)). Recently, the disposition effect has also been attributed to fund in- and outflows (Chiang and Huang (2010), Cici (2012), Singal and Xu (2011)). As another possible driver of the disposition effect, stock characteristics are identified. Graham and Kumar (2006) find that purchases and sales of attention-grabbing stocks influences the disposition effect. Cici (2012) shows that disposition driven behavior is related to lower market betas and value-oriented characteristics of portfolio holdings, but does not have any effect on performance. So far, there is only little evidence on the direction and magnitude of the relationship between the disposition effect and stock characteristics.

To the best of our knowledge, our paper is the first to focus exclusively on identifying stock-related factors to explain the cross-sectional variation in the level of the disposition effect among U.S. mutual fund managers. However, a number of papers in the broader literature on mutual fund manager behavioral biases contain related results. We add to previous literature by analyzing what factors amplify the presence of behavioral biases. In order to understand which factors support or depress the level of the disposition effect, we study stock characteristics as one possible explanation for cross-sectional differences. Our study uses the variation of the disposition bias between funds at a given point in time to analyze whether differences in stock related characteristics explain variations in the level of the disposition effect. We provide new insights in possible drivers of the disposition effect by investigating the link between the disposition effect and various stock characteristics.

The rest of the paper is structured as follows. In Section 2, we explain the methodology of the disposition effect. In Section 3, we provide details on the data and sample characteristics. We present the main empirical results in Section 4. In Section 5, we give a brief summary and conclude.

2. Methodology

We calculate the disposition effect following the method of Odean (1998) in order to determine how quickly fund managers realize capital gains and capital losses. To determine the disposition effect, we use stock holdings' information of mutual funds as well as the weighted average purchase price. For any given investor, the proportion of all potential realized gains and realized losses are calculated and compared to paper gains and losses, respectively.

Our research design is implemented as follows: each quarter a sale takes place the selling price is compared to a reference price in order to determine whether the sale is a realized gain or loss. In order to determine the reference price, one has to be clear about which cost basis to use. In our paper, the reference price is the historical weighted average purchase price ($WAPP$) which is updated each time a buy transaction takes place[3]. Using the weighted average purchase price as reference price is based on the assumption that fund managers regularly update their reference points after each (net) purchase. The weighted average purchase price for stock i hold by fund x on a day t is

[3] The weighted average purchase price is calculated as the purchase price of the stock on the reporting day divided by the amount of shares bought (e.g. Cici (2012), Grinblatt and Keloharju (2001), Huddart and Narayanan (2002), Odean (1998), Da Silva Rosa et al. (2005)).

calculated as follows:

$$WAPP_{i,x,t} = \frac{[(ShrPrc)_{i,t} \times (ShrBuy)_{i,x,t}] + [WAPP_{i,x,t-1} \times (ShrHeld)_{i,x,t-1}]}{(ShrHeld)_{i,x,t}} \tag{2.1}$$

where *ShrPrc* is the respective share price, *ShrBuy* indicates the number of shares bought, and *ShrHeld* is defined by the number of shares held in the portfolio. We have to distinguish two different cases: whether the fund decreases or maintains the level of its holdings of stock i, then the weighted average purchase price of stock i on day t equals the weighted average purchase price of stock i on day $(t-1)$. In the second case, the fund increases its level of holdings of stock i, then the weighted average purchase price of stock i on day t held by fund x is calculated as in equation (1). The calculation of the weighted average purchase price based on the above equation is done for each fund-stock-date combination.

Due to limitations of the data and to be consistent with other studies (e.g. Cici (2012), Huang et al. (2007), Frazzini (2006)), we assume that all changes in holdings occur at the end of each quarter[4]. By a comparison of holdings at the end of one quarter with holdings at the end of the previous quarter, we are able to determine whether a sell or buy transaction has taken place during the respective quarter. On each day a sale takes place, the selling price for each stock is compared with the weighted average purchase price in order

[4]Previous papers (e.g. Cici (2012)) analyzed differences in the assumptions about when a trade takes place (at the beginning, during or at the end of a quarter). The results indicate that variations in assumptions about the timing of a trade do not change the results with respect to the presence of the disposition effect.

to determine whether the sale transaction is a realized gain or realized loss. For all other stocks in the portfolio of a specific fund which are held but not sold on the same day as a given stock is sold, the market price is compared with the weighted average purchase price in order to determine whether it is a paper gain or paper loss.

Having calculated the realized gains, realized losses, paper gains and paper losses, we are now able to calculate the proportion of realized gains (PGR) and the proportion of realized losses (PLR) on each day that a fund is a net seller of a certain stock. The following equations show the calculation of the proportion of realized gains and proportion of realized losses:

$$PGR_{i,t} = \frac{(realized\ gains)_{i,t}}{(realized\ gains)_{i,t} + (paper\ gains)_{i,t}} \tag{2.2}$$

$$PLR_{i,t} = \frac{(realized\ losses)_{i,t}}{(realized\ losses)_{i,t} + (paper\ losses)_{i,t}} \tag{2.3}$$

We further calculate the disposition effect as the difference between the proportion of gains realized and the proportion of losses realized by a mutual fund in a given period (e.g. Dhar and Zhu (2006), Frazzini (2006), Goetzmann and Massa (2008), Kumar (2009), Odean (1998), Ringov (2012)). The disposition effect is calculated as the following:

$$DE_{i,t} = PGR_{i,t} - PLR_{i,t} \tag{2.4}$$

If the disposition effect is positive, then the respective fund realizes disproportionally more gains than losses (disposition prone fund). Therefore, the larger the disposition effect gets, the stronger is the level of the disposition effect exhibited by the respective fund manager. We measure the average quarterly disposition effect for each fund by aggregating the number of gains and losses by each fund and taking the average (e.g. Chiang and Huang (2010)). The annual disposition effect (which is used in the regression settings) is calculated as the average of the four quarters of each year.

3. Data

3.1. Mutual Fund Data

The data used in this study comes from various sources: quarterly fund holdings data from Thomson Financial (previously known as CDA/Spectrum), monthly and annual mutual fund characteristics from Center for Research in Security Prices at the University of Chicago (CRSP), daily and monthly stock return files from CRSP, and monthly and annual accounting data from COMPUSTAT. We obtain our main fund sample by merging the CRSP Survivorship Bias Free Mutual Fund Database (CRSP MF, henceforth), and the Thomson Reuters Mutual Fund Holdings database (TR MF, henceforth) using MFLinks from Wharton Research Data Services (WRDS). For each single fund, information about the fund characteristics (sector, style, starting date, manager, etc.), and performance information (returns, asset under management, fees, etc.) is extracted from the CRSP MF database. In addition to the fund characteristics from CRSP MF, we extract holdings' information from the TR MF database. The TR MF database reports all changes in holdings as well as holdings characteristics, i.e. ticker symbol, *permno* (CRSPs permanent stock issue identifier), *cusip* (CRSP's stock identifier), and the price of each asset on a quarterly basis. The *cusips* are used to extract different accounting information and trading statistics for each stock from COMPUSTAT. The price for each stock is taken at the date of reporting as well as at the end of each month as in previous literature (e.g. Barber and Odean (2008), Frazzini (2006)). Furthermore, we get daily data from CRSP to calculate stock related variables, e.g. stock volatilities, betas, book to market ratio, and returns. Data on the annual book value of common equity, market capitalization, intangible assets, earnings, dividend payments, property, plant, and equipment, total assets, operational income, sales, capital expenditures, leverage, etc. are retrieved from COMPUSTAT.

To arrive at the final sample used in the empirical analysis, we start with the entire universe of U.S. mutual funds for the period between 1980 and 2010. Next, following previous literature (e.g. Kacperczyk et al. (2008) Pool et al. (2012)), we limit our sample to actively-managed, diversified equity mutual funds which are based in the U.S.[5]. We match the TR MF and CRSP MF datasets for the period between 1980 and 2010 using MFLinks.

In our sample, there are funds with multiple asset classes holding the same portfolio of stocks since they are listed as separate entities in the CRSP MF

[5]Details on the sample selection procedure can be found in Appendix A.

database. They usually vary with respect to their fee structure or minimum purchase limits but are based on exactly the same portfolio of assets. To avoid multiple counting, we aggregate all share classes of the same fund using the unique *wficn* (Wharton Financial Institution Center) fund number to aggregate fund data across different share classes into one observation per fund-year. For variables that vary across share classes (e.g. returns, turnover ratio, expense ratio, etc.), we take weighted averages using total net assets as weights.

For benchmarking our results, we use the return on S&P 500 index as the market portfolio and the 3-month Treasury bill rate as the risk-free rate which are provided by Datastream.

3.2. Stock Data

In our empirical setting, we focus on several stock related variables. We obtain monthly balance sheet data items from COMPUSTAT. First, we include the annual book to market ratio (*BM ratio*) which is measured as the book value divided by the current market price. The book to market ratio is included as a proxy for the expected growth opportunities of a firm's operations. Since the book to market ratio is highly volatile, we use the annual median instead of the annual mean in our regression settings. Second, we include earnings per share (*EPS*) as ratio to account for the financial health of a firm. Earnings per share is based on the ratio of net income and common shares outstanding. To gain insights on whether more disposition prone investors prefer stocks with higher uncertainty, we include different measures of stock valuation uncertainty. The ratio of intangible assets to total assets (*intan. assets*) gives an indication whether investors prefer firms which are easier (lower percentage intangible assets) or more difficult (higher percentage of intangible assets) to value. Contrary, more disposition prone investors might prefer firms which are easy to value as defined by a higher percentage of property, plant, and equipment to total assets (PPE). We also include the *leverage ratio* to account for differences in financing between firms. Leverage might positively affect the value of a firm as a signal of the management to show its willingness to distribute cash flows. The leverage ratio is defined as total debt divided by total assets where total debt is calculated as the sum of long-term debt and debt in current liabilities. As measures of profitability of a firm, we include *profit margin* and return on assets (ROA) in our analysis. Profit margin is defined as operating income after depreciation divided by total sales. Return on assets is the ratio of operational income after depreciation divided by total assets. In addition, we include the *dividend yield* which is calculated as annualized dividend rate divided by the stock price. To account for differences in cost structures between different firms, we include capital expenditures ($CAPEX$). Capital expenditures is the product of common shares outstanding and an adjustment factor divided by total assets. To control for differences in growth opportunities we also include sales growth. *Sales growth* is calculated as the average annual growth of sales over the past three years.

All stock related variables are winzorized at the 1^{st} and 99^{th} percentiles in order to make sure that our results are not driven by outliers. We further exclude observations with negative values for the following variables: intangible assets, book to market ratio, earnings per share, sales, leverage ratio, and capital expenditures.

Further, we include *idiosyncratic volatility* in our regressions to capture stock-level uncertainty. We calculate the idiosyncratic volatility of a stock as the standard deviation of the residuals obtained by fitting a one-factor model to the daily stock price time series. The idiosyncratic volatility for each stock is estimated each year by using daily returns. We also analyze the relationship between a stock's *beta* and the disposition effect. We include beta in order to analyze whether differences in risk taking can explain the variation in the level of the disposition effect. Betas are estimated from a one-factor model fitted to the daily stock return series using the S&P 500 as market index. In addition, we include *stock return volatility* to account for differences in risk between different stocks as well *market return volatility.*

3.3. Control Variables

In order to avoid spurious correlations, we control for the effect that variables might influence the level of a fund's disposition effect while being correlated with the independent variables of interest in this paper. We control for different fund related characteristics like fund size, fund age, expense ratio, turnover ratio, fund strategy, fund capacity, institutional, retail ownership, front loads, rear loads, 12b-1 fees, and fund performance. *Fund size* is measured as the logarithm of the annual fund's assets under management in million U.S. $. In addition, we control for the possibility that learning experiences might influence the level of the disposition effect as measured by *fund age*. Previous papers indicate that the level of the disposition effect increases with the lifetime of a fund (Ammann et al. (2012)). We construct the variable fund age as the as the number of years when the fund was first offered. We further include the *expense ratio* of a fund which is the percentage of a fund's operating expenses and a fund's assets. We also include the *turnover ratio* of a fund which is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month total net assets of the fund. In addition, we control for differences in *funds' strategies* including different fund strategy variables. Fund strategy 1 is based on a fund's investment objective code (ioc) including the following ioc codes: AGG, GMC, GRI, GRO, ING, SCG, SEC. Fund strategy 2 is based on a fund's Wiesenberger Fund Type including the following funds: G, G-I, G-I-S, I, I-G, I-S, IEQ, LTG, MCG, SCG. Fund strategy 3 is based on a fund's Lipper Classification including the following codes: LCCE, LCGE, LCVE, MCCE, MCGE, MLCE, MLVE, SCCE, SCGE, SCVE. We include fund strategy 3 in our regressions since we have the most observations compared to the other two fund strategy variables[6]. The level of the disposition effect may also be affected by the fact whether a fund is open or closed for investors. Therefore, we include a *fund's capacity* as a dummy variable taking a value one when the fund is open to investments and zero

[6]Fund strategy 1 and 2 are included in the regressions for robustness checks. Results are available upon request from the authors.

when it is closed for investors (*fund closed*). We also include dummy variables for ownership of institutional or retail investors (*institutional dummy* and *retail dummy*) as defined by CRSP MF (items *inst_fund* and *retail_fund*). Since fees play an important role for mutual funds, we also control for differences in *front loads* and *rear loads*, where front loads are fees charged to investors when investing into a mutual fund and rear loads are charged when selling the fund. We also include *12b-1 fees* which are costs attributed to marketing and distribution relative to total assets. *Fund performance* is measured as the monthly market adjusted average returns of a fund's total monthly return, i.e. the return of a fund's portfolio, including reinvested dividends.

We also control for fund manager characteristics since they may also influence the level of the disposition effect. We control for a fund managers' experience, a new manager dummy variable and whether a fund is team- or single-managed. Fund *managers' experience* is defined as the number of years of a specific manager at the respective fund and is included to control for differences in fund manager's experience at a certain fund. Seru et al. (2010) find that investors are more likely to avoid behavioral biases as they gain experience through trading, and hence experience plays an important role in the level of the disposition effect. We also add a dummy variable (*new manager*) to account for the fact if the manager has been with the fund for a long time or recently got replaced. The dummy variable is equal to one when the fund manager is three years or less at the respective fund and zero otherwise. Scherbina and Jin (2011) discover that newly hired fund managers tend to sell off the losing positions of their predecessors, and hence do not display the disposition bias. We also include a dummy variable accounting for the number of fund managers. The variable *team-managed* is equal to one when a fund is managed by more than one fund manager and zero if it is single-managed. Previous papers detect that team-managed funds and single-managed funds behave differently (e.g. Baer et al. (2011), Cici (2012)). One possibility is that in a team-managed fund the presumed objectivity of other members might help to avoid holding on to certain stocks. Contrary, team members of a portfolio team may show signs of "herding" which could intensify any behavioral bias as critical evaluation is not performed but rather a trend toward groupthink is observable. Cici (2012) finds that team-managed funds show a stronger tendency to disproportionately realize more winner stocks than loser stocks compared to their single-managed counterparts.

All fund related control variables are winzorized at the 1^{st} and 99^{th} percentiles to exclude extreme observations which could drive our results. For fund age, fund size, front loads, rear loads, expense ratio, and turnover ratio we exclude values below zero.

In our regression settings, we also include several stock related control variables. We include *firm size* and *firm age* to control for experience and size related effects in our regressions. Firm size is calculated as the logarithm of market capitalization and is included to account for the possibility that observed differences are due to differences between small and large firms. Firm age is defined as the number of years since the stock first appeared in the CRSP database. *Stock turnover* is included to account for possible liquidity-based effects and is calculated as the number of shares traded divided by the number of shares outstanding. We control for monthly *past returns* since the overall tendency to realize capital losses more readily than capital gains could also be due to following a momentum strategy by mutual fund managers. For instance, the trading activities of mutual fund managers might be influenced by following a contrarian strategy or trend-following behavior. Past returns may additionally capture other kinds of behavior such as rebalancing. Furthermore, Odean (1998) mentions that past returns could also reflect transaction costs consideration. For example, funds which have to sell due to liquidity reasons might prefer to sell a stock that has recently increased in value since stocks which decreased are lower priced, and hence are less liquid (Odean (1998)). All variables are winzorized at the 1^{st} and 99^{th} percentiles. We further include *market return* which is the return on the S&P 500.

We also control for stable unobservable effects influencing the level of the disposition effect by including *year and fund fixed effects*. For a detailed description and definition of all variables please refer to Appendix B.

3.4. Summary Statistics

We look at the summary statistics for the number of shares and the value of trades for the 2,605 funds in our sample between 1980 and 2010. Table 1 shows the trading statistics for the 2,605 mutual funds in our final sample. Panel A shows that fund managers purchased about 180,000 stocks and sold 195,000 stocks during the sample period from first quarter of 1980 to the last quarter of 2010. Overall, our sample consists of 373,610 changes in assets.

On average, there were 6,000 purchases and 6,500 sales per year which means that each fund has roughly 5 trades per year which are reported to the SEC on a quarterly basis. Panel B of Table 1 displays the value of the trades of all mutual funds during the sample period between 1980 and 2010. The average market value of all purchase is \$ 3 million and \$ 10 million for sales.

Table 1 about here

Table 2 presents the summary statistics for the 2,605 funds and 75,545 fund-year observations. Our sample starts in 1980 with 8 funds and consists of 1185 funds in 2010. The average fund in our sample is around 17 years (log fund age is 2.33 years) in business with an average fund size of around \$ 4 billion. Monthly total net assets (TNA) increase from an average of \$ 227 million in 1980 to \$ 720 million in 2010 which reflects the rising interest in mutual funds as an asset class. Monthly net asset value (NAV) is around \$ 15 million. Over the last 30 years, the average mutual fund delivered a monthly return of -0.98%. Fees attributed to marketing and distribution costs (12b-1 fees) are on average 0.5% in our sample. Our results indicate that the average fund charges a front load of 0.6% which is paid upfront by the fund investors. The average rear load is 0.2% which is charged to investors when withdrawing the money from the respective fund. The expense ratio is 1.26% in 1980 and increases over time to 1.3% in 2010. The average expense ratio is 1.33%. The turnover ratio at the beginning of the sample period is 77% which is equal to a holding period of 1.5 years. The mean turnover for the whole sample period is 86% implying a holding period of 1.2 years. The turnover figures are comparable to those reported in prior research which are between 85% and 100% (e.g. Cici (2012), Kacperczyk et al. (2008), Singal and Xu (2011)). We also look at a fund's capacity (fund closed) which is a dummy variable equal to one if the fund is open to new investors and zero otherwise. We find that mutual funds are on average open to investors (89%) and that only around 10% of the funds are closed. The institutional dummy indicates that 70% of the funds are institutional while 30% are retail funds.

Table 2 about here

We also look at fund manager characteristics. Most of the funds in our sample are managed by teams with an average experience of a fund manager of around 10 years. We also report whether a fund is taken over by a new fund manager (e.g. Scherbina and Jin (2011)), and we find that only 3% of the funds are managed by new fund managers.

Table 3 about here

In Table 3, we report the summary statistics for the stock holdings of the 2,605 mutual funds in our sample between 1980 and 2010. The 2,605 funds hold 15,110 different stock positions (identified by their individual *cusips*) during the sample period between 1980 and 2010. We include several financial ratios in the empirical analysis to account for differences in stock characteristics. The book to market ratio is included to proxy for valuation uncertainty regarding the fundamentals of a firm. Since the mean book to market ratio (0.52) is varying significantly (standard deviation of almost 100%), we use the median book to market ratio (0.64) in our regression settings. Earnings per share are on average 1.21. Dividend yield is equal to 1.15% for all stocks held by mutual fund managers in our sample. To measure company-specific differences, we analyze the mean ratio of intangible assets to total assets which is roughly 8%, and the ratio of property, plant, and equipment to total assets is 54%. The profitability of firms is assessed by including return on assets which is on average 8% and profit margin which is on average equal to 12%. Sales growth which is calculated as the average over three years is on average 88% and accounts for the growth potential of a firm. The leverage ratio is 0.22 and capital expenditures are on average around 18%.

4. Empirical Analysis

4.1. Disposition Effect

4.1.1. Baseline Results

In this section, we look at the disposition effect calculated as the proportion of realized gains minus the proportion of realized losses. The disposition effect of all funds in our sample for the entire sample period between 1980 and 2010 is shown in Panel A of Table 4. The proportion of realized gains, the proportion of realized losses and the disposition effect are first calculated for each single fund separately. Second, we take the time-series averages of the fund-level measures to calculate the overall disposition effect. In doing so, we assume independence of the disposition effect across mutual funds.

The results for the whole sample show that there is a significantly positive disposition effect (3.96%), and that the average mutual fund in our sample is prone to the disposition bias. A large fraction of funds shows a positive disposition effect which means that the majority of funds in our sample display the analyzed behavioral bias. Figure 1 (a) shows the disposition effect based on a fund- and stock-level averages. The results indicate a strong and positive disposition effect for all used measures. The standard deviation of the disposition effect measure is rather low which might be due to the sample selection process. Further, a decline of the disposition effect over time is observable.

Panel A of Table 4 and Figure 1 (a) about here

Our results are in line with previous research. Da Silva Rosa et al. (2005) find an average disposition effect of 0.12% ($-value basis: 0.0559) for a sample of U.K. managed funds. Other papers also find a positive disposition effect (e.g. Ammann et al. (2012), Cici (2012), Frazzini (2006), Goetzmann and Massa (2008), Ringov (2012), Scherbina and Jin (2011), Wermers (2003)). A recent paper by Ammann et al. (2012) shows that the disposition effect is 3.2% calculated on a share basis for the time period 1993 to 2005, and how it is related to fund characteristics and changes in the macroeconomic environment. Cici (2012) studies mutual fund managers' behavior between 1980 and 2009, and documents the disposition effect for a large fraction of his sample. His analysis indicates that learning effects and spill-over effects from academics to practitioners have taken place reducing the disposition effect over time. Frazzini (2006) finds a positive disposition effect (3.1%) for U.S.

professional investors. Goetzmann and Massa (2008) as well as Ringov (2012) also discover the disposition effect among U.S. mutual fund managers. Our results are also conform with Scherbina and Jin's (2011) paper who report that old managers are reluctant to realize capital losses compared to their newly-hired counterparts, and thereby support the disposition effect.

New explanations and models based on private information are introduced in recent papers by Ben-David and Hirshleifer (2012) and Dorn and Strobl (2011). A leading explanation for the presence of the disposition bias is that investors are reluctant to realize losses because of a direct disutility from doing so. For a sample of individual U.S. investors, Ben-David and Hirshleifer (2012) uncover the opposite finding that the disposition effect is not driven by a simple direct preference for selling a stock by virtue of having a gain versus a loss but is rather driven by beliefs. In line, Dorn and Strobl (2011)'s theoretical model which is based on the information asymmetry between informed and uninformed investors, attributes the disposition effect to investors' preferences rather than beliefs.

In sum, we show that the average mutual fund has a stronger preference to lock in gains compared to realize losses. Although the average disposition effect is positive, we observe some cross-sectional variation in the range of the effect. Table 4 indicates that the disposition effect has a standard deviation of 8.6%. Therefore, this paper is devoted to shed new light on evaluating which stocks mutual fund managers trade, and whether there is systematic variation between disposition prone and less disposition prone mutual funds.

4.1.2. Results Stratified by Subperiods

In this section, we focus on the question whether the behavior of mutual funds with respect to the realization of gains and losses changes over time. We are especially interested whether certain learning effects take place when looking at the level of the disposition effect over time. Panel B of Table 4 reports the results for the whole period and for subperiods, namely between 1980 and 1989, between 1990 and 1999, and between 2000 and 2010. On average, mutual funds show the disposition effect in any of the subperiods. In the periods between 1980 and 1989 and between 1990 and 1999 funds show an increased tendency to realize disproportionally more gains than losses. Especially since the beginning of 1990's, the level of the disposition effect sharply declines. This pattern might be due to the increased awareness of behavioral finance since the 1990s among mutual fund managers, and thereby the level of the disposition effect steadily declines since then. Panel B of Table 4 and Figure 1 (a) show a decline of the level of the disposition effect over time. While between 1980 and 1989 the bias has a value of around 4.6%, it is around 4.4% for the period between 1990 and 1999, and falls to 3.4% in the last decade of our sample period. This pattern might be due to the increased awareness of behavioral finance among mutual fund managers. Some of the first research on the disposition effect was published during our second subperiod (e.g. Grinblatt and Keloharju (2001), Odean (1998), Weber and Camerer (1998)). Thus, consistent with practitioners first being introduced to behavioral biases in the 1990s, we observe that the level of the disposition effect steadily declines thereafter. In addition, advances in technology affecting quantitative investment strategies could have introduced more discipline and less reliance on biased human decision making.

Panel B of Table 4 about here

A second explanation for the observed behavior is that possible learning effects of mutual fund managers affect our results. A reduction in the level of the disposition effect through time is consistent with the theory that investors learn from trading. Informed investors update their price targets more often, and hence are less prone to display behavioral biases.

In line with previous literature our results suggest that more active fund managers have persistent stock-picking skills and learn to avoid biases over time (Wermers (2000)). Empirical evidence by Kumar and Lim (2008) is in line with our results indicating that investors who tend to execute several trades during the same day suffer less from the disposition effect. Our results are an indication that mutual fund managers update their price targets regularly and learn to avoid behavioral biases through time.

Figure 1 (b) about here

For robustness checks, we also investigate the disposition effect across different market states. We analyze whether mutual fund managers are forced to sell off their losing positions during crisis times, and hence the level of the disposition effect is reduced. Figure 1 (b) graphically shows a decline of the average level of the disposition effect during crisis times. However, when analyzing the disposition effect during "normal" times, the relationship is less clear. During the 1980s the level of the disposition effect in our sample stays roughly the same, while the S&P 500 is monotonically increasing. The S&P 500 keeps rising during the 1990s and reaches its first peak around 2000. During this time, the disposition bias is increasing as well as decreasing, and no clear pattern is observable. Between 2000 and 2010, the tendency to realize disproportionately more winner stocks than loser stocks is decreasing most of the time due to learning effects. Overall, Figure 1 (b) indicates that there is no clear relationship between the level of the disposition effect and crisis times observable.

4.1.3. Sorting Results

We report the summary statistics of fund characteristics for the ten mutual fund subsamples based on the level of the disposition effect in Table 5. Disposition deciles are based on the average annual disposition effect of each fund during the whole sample period. Decile one contains the funds with the lowest disposition effect, whereas decile ten includes funds with the highest disposition effect. In this statistics, a fund can only be counted once; if the database contains more than one report for the respective mutual fund, we calculate the average disposition effect and the average fund characteristics across time. Results in Table 5 show that funds with a lower disposition effect are on average younger and smaller. Our results are in line with previous research that an increase in the lifetime of a mutual fund also results in an increase of the magnitude of the disposition effect (e.g. Ammann et al. (2012)). With respect to the fee structure, we observe that the average front load charged by mutual funds is lower for funds with a higher level of the disposition effect. The rear load is distributed between 0.18% and 0.40% for all ten deciles, and there are no large differences observable between the highest and lowest disposition deciles. The expense ratio is 1.28% for the highest disposition decile which is lower than the expense ratio of 1.37% for the lowest disposition decile. Thus, mutual fund managers with a higher level of the disposition effect tend to charge their customers lower fees. This is contrary to the results of Gil-Bazo and Ruiz-Verdu (2009) who find a positive relationship between the expense ratio and the disposition effect arguing that a higher disposition effect may be interpreted as a sign of lower abilities. Funds in the lowest disposition decile are more often traded as measured by the turnover ratio compared to funds with higher disposition levels. The turnover ratio for the lowest disposition decile is 94% and for the highest decile it is 86%. Therefore, an increase in trading activity often involves winner stocks to be less readily sold compared to loser stocks, thereby contributing to an increase of the level of the disposition effect. The negative relationship between the turnover ratio of a fund and the disposition effect is in line with previous findings (Ammann et al. (2012), Carhart (1997)).

Table 5 about here

Analyzing a managers' experience at a certain fund, we find that the more experience a manager has, the higher the likelihood for displaying the disposition effect. One explanation might be that tenure could proxy for effort rather than for experience. This means that more junior managers need to invest more effort in order to signal their type (Chevalier and Ellison (1997)). On average, managers in disposition decile one have nine years of experience, whereas managers in decile ten have more then ten years experience. Fund managers with longer tenure might have a different standing within their firm leading to contractual agreements and agency issues that might influence their investment behavior. For example, more experienced fund managers might be afraid of being fired due to underperformance (e.g. Dangl et al. (2008)) and are overly conservative (e.g. Prendergast and Stole (1996)). When we look at the new manager dummy variable, we observe that more disposition prone funds hire on average more new managers compared to their less disposition prone counterparts. Comparing our results to previous findings, we cannot confirm the result by Scherbina and Jin (2011) who find that new managers show lower levels of the disposition effect. In their paper, new managers inherit momentum loser from their predecessors and tend to sell these loosing positions as soon as they take over a new fund. Differences between our results and the findings by Scherbina and Jin (2011) might be due to differences in the data used. We also analyze whether team- or single-managed funds show any differences. We find that less disposition prone funds tend to be managed rather by teams than by single fund managers. This result is in line previous results in the experimental and behavioral economics literature finding that decision making in teams is less likely to show biases than individual decision making (Baer et al. (2011), Ringov (2012)).

For robustness checks, we also test different subdivisions of our sample[7]. We divide our sample in two and five groups. We find that our results are robust. In Table 6, we report the summary statistics for the stock characteristics for the ten disposition deciles. Decile one contains the funds with the lowest stock-level disposition effect, whereas decile ten includes funds with the highest stock-level disposition effect. The differences in the level of the disposition effect can be interpreted as an indication of the stock picking ability of a mutual fund managers.

Table 6 about here

In Table 6, we show that mutual fund managers with a lower disposition level invest in different assets compared to managers with a higher disposition level. We find that fund managers with higher disposition levels invest in stocks of smaller and younger firms. In the lowest disposition decile, the average firm age as measured the number of years when the stock first appeared in CRSP is roughly 14 years, compared to 13 years in the highest disposition decile. Firm size which is defined as the natural logarithm of the end-of-quarter market capitalization (shares outstanding times prices) is higher for the lowest disposition decile and lower for the highest disposition decile. This means that mutual fund managers with a higher disposition effect try to achieve superior performance by investing in smaller stocks. The differences between the highest and lowest decile for firm age and firm size are highly significant (t-values of -44.99 and -42.44, respectively). Kumar (2009) also finds a

[7]Results are unreported. They are available on request from the authors.

negative coefficient for the relationship between firm age and the disposition effect for stock holdings of individual investors in the U.S. from 1991 to 1996. Comparing stock turnover across the different disposition deciles, our results indicate that less disposition prone fund managers tend to invest in stocks with a higher turnover. The relationship between turnover and the disposition effect is almost monotonically decreasing. A possible explanation is that less biased fund managers tend to trade more often, and especially sell their losing positions at a higher rate compared to their more disposition prone counterparts. By trading more often, less disposition prone fund managers show more discipline in realizing their losing position, and thereby reducing their level of the disposition effect. When analyzing the book to market ratio, we find that it is almost the same for disposition decile one (value of 0.4594) compared to decile ten (value of 0.4567). However, the difference between the book to market ratio in the tenth and first decile is not significantly different from zero (t-value of 1.54). Our sorting results for earnings per share indicate that less biased fund managers trade stocks with higher earnings per share. We find that fund managers in the lowest disposition decile invest in stocks with significantly (t-value of -17.73) lower earnings per share compared to their more biased counterparts. In order to capture the level of uncertainty in fundamental values of a stock, we include the level of property, plant, and equipment to total assets as well as the ratio of intangible assets to total assets. The property, plant, and equipment variable is around 47% for the lowest disposition decile while it is 52% for the highest decile (t-value for the significance between the highest and lowest disposition deciles is -18.94).

This indicates that more biased fund manager prefer firms with a higher percentage invested in tangible assets. Concerning the level of intangible assets to total assets, we do not find large variations between the different disposition deciles. We also include the dividend yield of a stock in our analysis to capture any attention-driven trading behavior of mutual fund managers. Graham and Kumar (2006)) illustrate that dividends may serve as a proxy for attention-grabbing net buying behavior of individual investors. The authors present evidence that confirms the importance of attention in selecting stock. When analyzing the dividend yield across the different disposition deciles in our sample, we can confirm the attention hypothesis: more biased fund managers prefer on average stocks with a higher dividend yield. This result is also significant as supported by the t-value of -24.92 between the lowest and highest disposition decile. Since previous research discovers that funds displaying the disposition bias perform worse than their unbiased counterparts (e.g. Scherbina and Jin (2011), Singal and Xu (2011)), we also include profitability related stock characteristics. When analyzing the return on assets, we do not observe any obvious differences between the highest and lowest disposition deciles. However, when we compare profit margins across different disposition decile, we find that biased fund managers tend to invest in less profitable stocks. Fund managers in decile one prefer stocks with higher profit margins while in decile ten fund managers on average pick stocks with lower profit margins. Sales growth which is included to capture potential growth opportunities of a firm, is similar for fund managers in the lowest and highest disposition group (t-value of -6.10 for the difference between the highest and lowest disposition group). Furthermore, our finding that fund managers with a lower level of the disposition bias trade more profitable stocks is supported by the results regarding leverage ratios and capital expenditures. Leverage ratios and capital expenditures are higher for stock holdings of more disposition prone fund managers. Our findings indicate that disposition prone fund managers not only trade less profitable stocks but also engage in riskier stocks. Our results taken together provide a possible explanation why disposition prone funds underperform compared to their less biased counterparts (Scherbina and Jin (2011), Singal and Xu (2011)).

For robustness checks[8], we also test different subdivisions of our sample. First, we divide our sample in two groups and second, we use quintiles to separate our sample. For both settings, we find that our results are robust.

4.2. Disposition Effect and Stock Characteristics

In the previous section, we show the existence of the disposition effect among our sample of U.S. mutual fund managers between 1980 and 2010. The presence of the disposition effect raises the questions of possible explanations for the existence and the persistence of the effect. In this section, we study the how different stock holdings' characteristics are related to the likelihood of a fund to show a positive disposition effect.

[8]Results are unreported. They are available upon request from the authors.

4.2.1. Baseline Results

To gain more insights into the relationship between the level of the disposition effect and stock characteristics, we estimate different OLS regressions. We employ the following regression specification:

$$DS = \alpha + \beta_k^{DS} * Stock\ Characteristics_k + \epsilon^{DS} \tag{4.1}$$

where *Stock Characteristics* are the book to market ratio, earnings per share, property, plant, and equipment in percentage of total assets, intangibles assets as percentage of total assets, return on assets, profit margin, dividend yield, sales growth, leverage, and capital expenditures (for the definition of these variables please refer to Table B3 in Appendix B). We obtain the stock characteristics for each mutual fund by taking value-weighted averages of the single stock figures.

In Panel A and Panel B of Table 7, we present the results of the baseline regressions using different OLS regression models with year and fund fixed effects. In the different models in Panel A and Panel B of Table 7, we use the annual stock-level disposition effect as the dependent variable and different stock characteristics as independent variables. In Panel B of Table 7, we show the regression results including different fund related control variables. In specific, in Model 1 of Panel B of Table 7, we include fund age, fund size, expense ratio, turnover ratio, and a fund's return. All variables are lagged one year. In Model 2 of Panel B, we additionally include unlagged control variables, namely a dummy variable to account for differences in fund strate-

gies (fund strategy 3[9]), a dummy variable whether a fund is open or close to investors, a dummy variable for institutional funds, and a dummy variable for retail funds. In Model 3 of Panel B, we include control variables based on fund managers' characteristics, namely manager experience, team-managed, and a new manager dummy variable. In Model 4 of Panel B, we include all previously mentioned control variable plus controls for differences in fee structures. We include front loads, rear loads, and marketing fees (12b-1 fees).
In all models of Panel A and Panel B of Table 7, the results suggest a highly significant positive relationship between the level of the disposition effect and stock characteristics. Only in Model 2 and 3 of Panel B of Table 7 the coefficients of the disposition effect become insignificant. Nevertheless, the coefficients in Model 2 and 3 remain positive. Overall, the results show that part of the differences in the disposition effect can be explained by differences in stock holdings (R^2 between 7.70% and 28.20%).

Panel A and Panel B of Table 7 about here

In the regression specification of Model 1 in Panel A of Table 7, we include several financial ratios which are commonly used for stock valuation. The book to market ratio indicates whether investors think that the stock is under- or overvalued (low book to market ratio, high book to market ratio, respectively). We find that the book to market ratio is negatively linked to the level of the disposition effect (coefficient of -0.0003 with a t-value of -10.54). This means that stocks with a lower book to market ratio are preferably traded

[9] We include fund strategy 3 as we have the most observation for this variable. As robustness checks, we also include fund strategy 1 and 2. The results remain the same.

by less disposition prone mutual fund managers implying that they expect a firm's management to create additional value from given assets. This part of the regression results confirms our previous sorting results (see Table 6) documenting that less disposition prone mutual fund managers tend to invest in more expensive assets as measured by the book to market ratio. Since the book to market ratio does not directly provide any indication on the ability of a firm to generate profits or cash flows for shareholders, we also include earnings per share. We find that more disposition prone fund managers tend to invest in stocks with higher earnings per share. Our result indicates that less biased fund managers seem to invest in more expensive stocks as measure by earnings per share which is in line with our previous findings. Besides the different financial ratios we also analyze what kind of firms are preferably traded by more disposition affected mutual fund managers. Variables related to the percentage of total assets invested in plant, property, and equipment as well as in intangible assets give an indication whether fund managers prefer companies with rather tangible or intangible products. We find a zero coefficient for the property, plant, and equipment variable and a negative relationship between the disposition effect and intangible assets (coefficient of -0.0002 with a t-value of 6.09). Less disposition prone fund managers prefer to invest in companies with a higher level of tangible assets rather than intangible assets. In Model 2 of Panel A of Table 7, we include different profitability related stock characteristics. We analyze whether more disposition prone fund managers invest in less profitable stocks explaining the previously revealed underperformance of biased funds (Scherbina and Jin (2011), Singal and Xu (2011)).

Results for return on assets, profit margins and sales growth support this hypothesis. We find that more disposition prone fund investors trade stocks which are less profitable as proxied by return on assets and profit margins (coefficients of -0.0003 and -0.0001 with t-values of -3.08 and -4.72, respectively). The return on assets variable indicates how efficient the management of a firm is at using its assets to generate earnings or to generate sales as measured by the profit margin, respectively. The results also reveal that more biased fund managers invest in stocks with less sales growth. These results hold even when including various control variables (see Panel B of Table 7).

In Model 2 of Panel A, we also include dividends as a proxy for trading behavior which is based on buying and selling attention-grabbing stocks. Our result reveals that mutual fund managers with a higher disposition level invest in dividend-paying stocks (coefficient of 0.0008 with a t-value of 7.63), thereby confirming the attention-grabbing hypothesis formulated by Odean (1999), and empirically tested by Graham and Kumar (2006). Thus, mutual fund managers who are more prone to behavioral biases seem to focus their trading activities on dividend-paying stocks. In this case, dividend payments are interpreted by fund managers as a sign that the management of a company is feeling confident about their firms long-term perspectives, and hence the stock appeals as a good investment opportunity. Disposition prone mutual fund managers prefer buying dividend-paying stocks and selling winner stock too early while holding on loser stocks for too long (compared to the future performance of the respective stock).

In the third regression specification of Panel A of Table 7, we analyze the financial situations of firms. We find that more disposition prone fund managers invest in stocks with lower leverage ratios. The interpretation of this result is that less biased fund managers rather engage in highly leveraged stocks to increase returns. Leverage can be used to increase return while keeping risk low. Using this strategy, fund managers who are less willing to sell winner stocks and holding on to their losers stocks try to achieve outperformance by investing in highly leveraged stocks. We also include capital expenditures and find a zero coefficient for the variable in the baseline regression. In Panel B, we include various fund related control variables, and we find a positive relationship (coefficient of 0.0002 with a t-value of -2.94 significant at the 5% level including fund characteristics, manager characteristics, and fees) between capital expenditures and the disposition effect.

In Model 4 of Panel A of Table 7, we include all stock variables. We confirm that the level of the disposition effect is significantly influenced by stock related variables. We find that the book to market ratio, the level of intangible assets to total assets, return on assets, profit margin, sales growth, and leverage ratios have a significant negative influence on the level of the disposition effect. We detect that earnings per share, property, plant, and equipment, dividend yield, and capital expenditures are positively related to the level of the disposition effect. Our results hold when we include different control variables to account for differences in fund characteristics, manager characteristics, and fee structure as reported in Panel B of Table 7. To this end, we conclude that parts of the disposition effect can indeed be explained by the stock characteristics of mutual funds' holdings.

To gain more insights in the relationship between the disposition effect and different investment styles, we include further stock related variables. Results are displayed in Table 8. We include firm size, stock turnover, stock return, market return, stock return volatility, and market return volatility in various regression specifications. In the different models in Table 8, we use the annual stock-level disposition effect as the dependent variable and include year and fund fixed effects. Various fund characteristics and fund manager related control variables are included in the different regression specifications. In Model 1, Model 3, and Model 5, we include fund age, fund size, expense ratio, turnover ratio, and a fund's return as control variables. All variables are lagged one year. We additionally include unlagged control variables: a dummy variable to account for differences in fund strategies (fund strategy 3[10]), a dummy variable whether a fund is open or close to investors, a dummy variable for institutional funds, and a dummy variable for retail funds. In Model 2, Model 4, and Model 6, we additionally include control variables based on fund managers' characteristics, namely manager experience, a dummy variable whether a fund is team- or single-managed, and a new manager dummy variable. In all model specifications, the results suggest a highly significant positive relationship (coefficients of the disposition effect between 0.0303 and 0.0337) between the level of the disposition effect and the employed stock characteristics.

Table 8 about here

[10]We include fund strategy 3 as we have the most observation for this variable. As robustness checks, we also include fund strategy 1 and 2. The results remain the same.

In the first and second regression specification in Table 8, we use firm size, stock turnover, stock return, and stock return volatility as explanatory variables to analyze whether size effects or volatility play a role in explaining the level of the disposition effect. We find that firm size, turnover, and stock return volatility are significant at the 1% significance level. Firm size is positively, however with a zero coefficient, related to the disposition effect (t-values of 27.09 and 13.13 for Model 1 and Model 2, respectively) which means that more biased fund managers invest in larger companies. This indicates that mutual fund managers with a lower disposition effect try to achieve outperformance by investing in smaller firms confirming previous results (e.g. Ammann et al. (2012)). One reason may be that less biased fund managers believe that finding undervalued stocks is easier for firms in the small cap sector. Our results further indicate that stock turnover has a negative effect on the level of the disposition effect (coefficients of -0.0000 and -0.0000 with t-values of -19.12 and -22.81 for Model 1 and Model 2, respectively). However, the coefficient of the turnover variable is zero in Model 1 and Model 2 (where we additionally control for fund manager differences) and results have to be interpreted with care. Hence, fund managers with higher disposition levels prefer stocks which are less often traded. High turnover may be interpreted as a proxy for attention-grabbing stocks which is uncovered for a sample of individual investors of a large broker from 1991 to 1996 in the U.S. by Odean (1998). Our results indicate that mutual fund managers are not incline to use trading volume as a heuristic to determine which stocks to buy or sell. Including stock return in our models, we find a negative coefficient of -0.0005 (with a t-value of -0.58). This indicates that fund managers with a higher disposition levels invest in stocks with lower returns confirming our previous findings related to profitability in Table 7. We also include stock return volatility as a measure of stock-level uncertainty. Our results exhibit a positive and significant effect for stock return volatility on the level of the disposition effect (coefficient of 0.0037 with a t-value of 4.37). This shows that mutual fund managers have a stronger tendency to sell winners too early and hold on losers for too long when valuation uncertainty as proxied by a stock's volatility is higher. Previous papers suggest that based on a private investor sample, individuals show an increased disposition effect when valuation uncertainty as proxied by stock volatility is higher (Kumar (2009)). Our results in Model 1 and 2 are robust to including different control variables and confirm that not only individual investors but also professional investors are incline to show higher levels of the disposition effect when stock valuation uncertainty is higher.

In Model 3 and Model 4, we include the market return (S&P 500), market return volatility, firm size, and stock turnover as explanatory variables. We find that the S&P 500 return is negative and not significant. The negative coefficient indicates that fund managers with a higher disposition level invest in stocks with lower S&P 500 returns. Since the coefficient is not significant, result have to be interpreted with care. As one possible interpretation of the result, one can note that mutual fund managers are usually benchmarked against a large index (like the S&P 500) and evaluated by the information ratio (ratio of benchmark-return to benchmark-relative risk; benchmark-return is the expected difference between the return earned by the fund manager and the return of an index). A typical mutual fund manager contract is based on a mandate to maximize the performance relative to a specific cap-weighted benchmark. Hence, mutual fund managers are incentivized to closely follow the respective index in order to minimize the potential tracking error compared to a cap-weighted index. Our results are robust when controlling for different fund and manager characteristics. Analyzing the effect of market uncertainty as proxied by market return volatility, we document a positive and significant effect on the level of the disposition effect (coefficient of 0.0205 with a t-value of 6.47). The main result from Model 3 and Model 4 is that the disposition effect is higher when valuation uncertainty is higher.

In Model 5 and Model 6 of Table 8, we include all previously mentioned stock characteristics. Confirming that stock characteristics are positively related to the level of the disposition effect, we infer that part of the observed behavioral bias among mutual fund managers may be explained by their stock holdings. In summary, our results indicate that stock variables partly explain the level of the disposition effect. Combining the results from Model 1 and Model 2 with results from Model 3 and Model 4, we find that that the disposition effect is higher when market- and stock-level volatility is higher. Including different control variables in order to capture unobservable effects on the fund or manager levels, we can confirm that our results are not due to differences between funds or differences between fund managers. We find that firm size is positively related to the level of the disposition effect, while stock turnover is negatively linked. It further appears that the disposition effect is related to stock-level uncertainty (stock return volatility) and market-level uncertainty

(S&P 500 volatility) which explain parts of the disposition effect. We also discover that the trading behavior of mutual fund managers is partly related to benchmark-oriented behavior (market return).

4.2.2. Disposition Effect and Uncertainty

Having identified that volatility measures are positively linked to the level of the disposition effect, we further examine whether mutual fund managers are less prone to realize losses and more prone to realize winners when stocks are more difficult to value as proxied by idiosyncratic volatility. Idiosyncratic volatility is based on the variance of the residuals obtained by fitting a one-factor model to the stock return time series. The idiosyncratic volatility measure for each stock is estimated each year by using daily stock data.

When valuation uncertainty is high, then various mechanisms can introduce a higher level of the disposition effect. First, a prospect theory based explanation (Shefrin and Statman (1985)) explains why differences in holdings drive differences in the level of the disposition effect. If valuation uncertainty is high, higher price levels are more likely to be observed, and hence a higher reference point for the respective stock position is established. From a higher level references point, the disposition effect is more likely to be amplified.

Second, the disposition effect can be based on the explanation of mean reversion (Odean (1998)). The experimental empirical evidence indicates that people show a stronger "tracking" behavior when valuation uncertainty is higher (e.g. when volatility is high) since they believe that mean reversion is more likely.

Third, the reluctance to realize losses can also be attributed to gambling tendencies motivating investors to hold on to their losers when valuation uncertainty is high. Gambling-minded people are more likely to hold on to their positions until their stocks yield the desired extreme payoff. Therefore, when valuation uncertainty is higher, the level of the disposition effect should also be higher (Kumar (2009)).

To analyze whether the cross-sectional variation of the disposition effect is related to the stock-level valuation uncertainty, we sort all stock holdings based on their idiosyncratic volatility. First, we sort all stocks based on their average annual idiosyncratic volatility measure during our sample period. Then, we calculate the mean disposition effect in each of the ten idiosyncratic volatility decile portfolios. As a first indication, Figure 2 (a) indicates that mutual fund managers display a higher disposition effect when valuation uncertainty - as measured by idiosyncratic volatility - is higher, e.g. when stocks are more difficult to value.

Figure 2 (a) about here

We find that the disposition effect is the lowest for the first volatility decile (lowest volatility decile) and the highest for the tenth idiosyncratic volatility decile (highest volatility decile). The relationship between volatility and the disposition effect is almost monotonically increasing. This result is in line with previous findings for individual investors (Kumar (2009)), and shows that the disposition effect is driven by how difficult stocks are to value. Kumar (2009) finds an increase in the level of the disposition effect when valuation uncertainty is higher for a sample of U.S. individual investors from 1991 to 1996. Furthermore, a previous paper by Ammann et al. (2012) points towards the idea that less biased find managers tend to invest in less risky equities. The interpretation of our result is that less disposition prone fund managers prefer to invest in less risky equities, i.e. lower idiosyncratic volatility. This indicates that mutual fund managers even though they are professionals also rely on idiosyncratic volatility as a parameter for their valuation of stocks.

We further report sorting results for the annual disposition effect estimates for the top three (harder-to-value stocks) and bottom three (easier-to-value stocks) idiosyncratic volatility deciles. Figure 2 (b) presents the average disposition effect per year.

Figure 2 (b) about here

One can observe that the level of the disposition bias is higher for harder-to-value stocks. We find that only in two (year 1987 and year 1990) out of thirty years, the easier-to-value stocks show a higher level of the disposition effect. This means that mutual fund managers have a stronger tendency to display the analyzed behavioral bias when valuation uncertainty is higher. Moreover, we illustrate that the disposition effect declines over time for both the harder- and easier-to-value stocks which confirms results reported in Table 4.

To further test our hypothesis that the level of the disposition effect is higher for harder-to-value stocks, we estimate different OLS regressions with various control variables and year and fund fixed effects. We employ the following regression specification:

$$DS = \alpha + \beta^{DS} * Valuation\ Uncertainty + \beta_k^{DS} * Stock\ Characteristics_k + \epsilon^{DS} \tag{4.2}$$

where *Valuation Uncertainty* is the annual idiosyncratic volatility. We include the following *Stock Characteristics*: book to market ratio, earnings per share, property, plant, and equipment in percentage of total assets, intangibles assets as percentage of total assets, return on assets, profit margins, dividend yield, sales growth, leverage, and capital expenditures (for the definition of these variables please refer to Table B3 in Appendix B).

Table 9 about here

In all models, we use the annual stock-level disposition effect as the dependent variable and idiosyncratic volatility as the independent variable. Regression results are reported in Table 9. For all specifications we find a significant and positive relationship between the disposition effect and idiosyncratic volatility (with coefficients between 0.0400 and 0.0423 which are significant at the 1% significance level). In Models 1, 3, 5, 7, and 9, we include fund characteristics as additional control variables (all control variables are lagged one year), whereas in Models 2, 4, 6, 8, and 10, we also control for differences in fund manager characteristics. In addition, we include fund controls for fund strategy (fund strategy 3[11]), a dummy variable whether a fund is open or close to investors, a dummy variable for institutional funds, and a dummy variable

[11] We include fund strategy 3 as we have the most observation for this variable. As robustness checks, we also include fund strategy 1 and 2. The results remain the same.

for retail funds. Manager controls include the following variables: manager experience, team-managed, and a new manager dummy variable.

In the baseline specification in Model 1 and 2 of Table 9, we show that idiosyncratic volatility positively influences the level of the disposition effect. Adding fund based controls in Model 1, idiosyncratic volatility has a coefficient of 0.0014 (with a t-value of 41.15). In Model 2, we test whether idiosyncratic volatility has an incremental effect on the level of the disposition effect over and above fund and manager controls. The baseline effect of the idiosyncratic volatility variable remains almost the same with a coefficient of 0.0016 (with a t-value of 29.59). We detect a positive, highly significant relationship between idiosyncratic volatility and the disposition bias indicating that mutual fund managers have difficulties to value stocks when the level of stock-related uncertainty is higher.

In Model 3 and 4 of Table 9, we include different financial ratios of stocks (book to market ratio, earnings per share, property, plant, and equipment as well as the ratio of intangible assets to total assets) to capture the attractiveness of a stock. Adding these stock characteristics does not change the baseline effect of idiosyncratic volatility on the level of the disposition effect. Idiosyncratic volatility has a coefficient of 0.0015 (with a t-value of 42.40) when controlling for fund characteristics and 0.0017 (with a t-value of 31.31) when controlling for fund and manager characteristics. Thus, mutual fund managers who are less disposition prone tend to invest in equities with lower idiosyncratic risk even when accounting for differences between stocks by including financial ratios in the regression specifications.

In Model 5 and Model 6, we include several stock characteristics related to the profitability of a firm. The coefficient of 0.0011 of the idiosyncratic volatility variable in Model 5 is smaller compared to our previous models. However, the effect of idiosyncratic volatility on the level of the disposition effect remains positive and significant despite adding controls for differences in the profitability of stocks. Analyzing how the dividend yield of a stock is related to the level of the disposition effect, we can confirm our previous findings that mutual fund managers tend to trade attention-grabbing stocks. In other words, more disposition prone investors do not only tend to trade attention-grabbing stocks and invest in less profitable stocks, but also prefer stocks with a higher risk as proxied by idiosyncratic volatility. The magnitude of this effect is substantial and might explain why disposition prone funds tend to underperform their less biased counterparts (Scherbina and Jin (2011), Singal and Xu (2011)).

To provide a comparison whether our results may be explained by differences in the financial soundness of firms, we include leverage ratios and capital expenditures in Model 7 and 8 of Table 9. We explore how the effect of idiosyncratic volatility varies with the disposition effect when including the leverage ratio of stocks. We find that the coefficient of 0.0014 of idiosyncratic volatility remains unchanged compared to our previous settings (with a t-value of 41.12). To this end, we conclude that differences in the level of the disposition effect are rather explained by differences in risk taking than by financing decisions of a firm.

In Model 9 and 10 of Table 9, we explore how the effect of idiosyncratic volatility changes when we include all stock related characteristics in our regression settings. We find that our result remains stable and that our conclusion that differences in the level of the disposition effect can be explained by differences in the riskiness of traded stocks, is confirmed.

In summary, we find that the higher the level of valuation uncertainty as measured by idiosyncratic volatility, the higher the level of the disposition bias. Our results hold even when controlling for differences in stock characteristics based on financial ratios, profitability, and financial soundness. Stocks with a higher level of idiosyncratic volatility might be perceived as more difficult to value and may be related to the disposition effect. Given that mutual funds are not completely diversified, the higher idiosyncratic volatility level of stock holdings of mutual fund managers with a higher magnitude of the disposition effect indicates that they take more risk in their portfolios.

4.2.3. Disposition Effect and Beta

In the previous section, we find that the disposition bias increases when unsystematic risk raises. In this section, we analyze whether the disposition effect is stronger when systematic risk is higher. We investigate the relationship between fund factor loadings on the market factor from a one-factor model and the level of the disposition bias.

Traditional finance is based upon the idea that higher risk is rewarded with higher average returns. Contrary, recent empirical evidence (Baker et al. (2011)) indicates that over the past 40 years U.S. portfolios comprising of high-risk stocks have substantially underperformed their low-risk counterparts. This so-called "high risk, low return puzzle" offers potential investment opportunities for mutual fund investors. Recent empirical and theoretical evidence shows that low-beta stocks may offer higher returns than the capital asset pricing model (CAPM) would predict. A basic assumption of the CAPM is that all agents invest in the asset with the highest expected excess return per unit of risk (Sharpe ratio). Risk preferences are adjusted by leveraging or de-leveraging this portfolio. However, investors like mutual funds are constrained in their leverage possibilities, and therefore they have to overweight risky assets instead of using leverage. Hence, investments in low-beta stocks may be rational and may explain why less biased mutual fund managers would invest in low beta equities.

The persistent outperformance of low-beta stocks is not compatible with much of financial theory including the efficient market hypothesis and the CAPM. As shown in previous papers (Baker et al. (2011), Hong and Sraer (2012)), key principles of behavioral finance as well as structural issues including benchmarking may explain the persistence of this anomaly across markets and across time. Theoretical behavioral models of security prices are based on the assumption that some market participants behave irrational. In this context, the "high risk, low return" anomaly can be explained by a combination of well established biases of representativeness and overconfidence leading to a demand for high-beta stocks. Overconfidence is induced by the underlying assumption that investors "agree to disagree" (Hong and Sraer (2012)). In times of high uncertainty, overconfidence amplifies the level of disagreement regarding future expectations. However, the question remains why sophisticated institutional investors like mutual fund managers do not profit from the mistakes of the "irrational crowd". One explanation why the "smart money" does not offset the induced pricing behavior introduced by the irrational investor group may be limits of arbitrage. One interpretation of the limits of arbitrage is benchmarking (Baker et al. (2011)). The performance of the asset management industry heavily depends on benchmarks which induces a strong structural impediment. Mutual fund managers usually have a fixed-benchmark mandate (capitalization-weighted benchmarks) which may discourage investments in low-beta stocks. Hence, when a manager moves away from investments in low-beta stocks, there is potential of a higher tracking error compared to a cap-weighted index. The trading behavior influences the information ratio which is often the primary measure used to quantify the skills of a manager. A typical mutual fund manager contract contains an implicit or explicit mandate to maximize the performance relative to a specific cap-weighted benchmark without using any leverage. Therefore, fund managers evaluated relatively to an index are incentivized to invest in low-beta stocks.

To examine whether differences in risk taking can explain the cross-sectional variation of the disposition effect, we relate the beta of a stock to the level of the disposition effect and other potential stock and fund related characteristics. Betas are estimated from a one-factor model fitted to the daily stock return series using the S&P 500 as market index. First, we sort all stocks based on their average annual beta during the sample period between 1980 and 2010 and divide them into deciles. Second, we calculate the mean disposition effect in each of the ten beta deciles.

As a first indication, Figure 3 (a) shows that mutual funds display a higher disposition effect when beta is higher. We find that the relationship between beta and the level of the disposition effect is positive and increasing from beta decile one (lowest beta) to beta decile ten (highest beta). The disposition effect is on average 3.87% in the lowest beta decile and 3.96% in the highest beta decile.

We further report sorting results for the annual disposition effect for the top three and bottom three beta deciles. Figure 3 (b) shows the average disposition effect per year for high- and low-beta stocks across time.

Figure 3 (a) and Figure 3 (b) about here

Our results indicate that fund managers with a higher level of the disposition effect tend to invest in high-beta stocks. Only in the years 2006 and 2007, less biased fund managers traded stocks with a higher average beta value compared to their more biased counterparts. This result might be due to the financial crisis where more biased fund managers were also forced to sell off their losing positions.

To further test our hypothesis that fund managers who are more prone to the disposition effect preferably trade high-beta stocks, we estimate different regressions with various stock level control variables. We employ the following regression specification:

$$DS = \alpha + \beta^{DS} * Beta + \beta_k^{DS} * Stock\ Characteristics_k + \epsilon^{DS} \tag{4.3}$$

where *Beta* is estimated from a one-factor model using the S&P 500 as market index. *Stock Characteristics* include idiosyncratic volatility, book to market ratio, earnings per share, property, plant, and equipment in percentage of total assets, intangibles assets as percentage of total assets, return on assets, profit margin, dividend yield, sales growth, leverage, and capital expenditures (for the definition of these variables please refer to Table B3 in Appendix B). Regression results including year and fund fixed effects are reported in Table 10. In all models we use the annual stock-level disposition effect as the dependent variable and beta as independent variable. We control for possible unobservable differences in fund characteristics and fund managers by including fund and manager related control variables. In Models 1, 3, 5, 7, and 9, we include fund age, fund size, expense ratio, turnover ratio and a fund's return. All variables are lagged one year. In addition, we also include unlagged fund control variables for fund strategy (fund strategy 3[12]),, a dummy variable whether a fund is open or close to investors, a dummy variable for institutional funds, and a dummy variable for retail funds. In Models 2, 4, 6, 8, and 10, we also control for differences in fund manager characteristics, namely manager experience, team-managed, and a new manager dummy variable. In all regression specifications, we find that beta has a significant positive effect on the level of the disposition effect (coefficients between 0.0012 and 0.0027 which are significant at the 1% significance level for Model 1, 3, 5, 7, and 9). We discover a positive relationship between the systematic risk of a stock and

[12]We include fund strategy 3 as we have the most observation for this variable. As robustness checks, we also include fund strategy 1 and 2. The results remain the same.

the disposition bias indicating that more biased mutual fund managers tend to invest in stocks with higher betas. The beta estimates of the regression analysis confirm our graphical results of an increasing relationship between the disposition effect and the systematic risk of mutual fund managers' stock holdings.

Table 10 about here

In the baseline specifications of Model 1 and Model 2 in Table 10, we include beta as the main independent variable. We find a positive, significant relationship (coefficients of 0.0014 and 0.0013 with t-values of 41.92 and 32.08, respectively) between the systematic risk of a stock and the disposition bias while controlling for fund characteristics as well as manager characteristics. To account for differences in fundamentals between stocks, we include different financial ratios (book to market ratio, earnings per share, property, plant, and equipment, and the ratio of intangible assets to total assets). Results are reported in Model 3 and 4 of Table 10. Adding these stock characteristics does not change the baseline effect of the systematic risk of a stock on the level of the disposition effect.

In the regression specifications of Model 5 and Model 6, we control for differences in the profitability between different firms. The relationship between beta and the level of the disposition effect remains stable when controlling for profitability. Return on assets and profit margins are significantly negative (coefficients of -0.0029 and -0.0019 with t-values of -30.36 and -42.04, respectively) confirming previous findings that more biased fund managers tend to trade less profitable stocks.

To provide information whether our results are based on differences in the financial structure of firms, we include leverage and capital expenditures in Model 7 and 8 of Table 10. The positive link between beta and the level of the disposition effect remains unchanged.

In Model 9 and 10 of Table 10, we include all stock characteristics and analyze how beta changes. We find that the main result remains stable and that our conclusion that differences in the level of the disposition effect can be explained by differences in the beta factor of stocks, is confirmed.

In summary, our results show that less disposition prone investors tend to invest in less risky equities. Using graphical and regression-based approaches, we find an increasing relationship between the level of the disposition effect and a stock's beta. To that end, our results indicate that mutual fund managers who are more prone to behavioral biases tend to hold high-beta stocks in their portfolios. Investing in high-beta stocks which do not yield as high returns as predicted by the CAPM, may be one reason why more biased fund managers underperform compared to their less biased counterparts (Scherbina and Jin (2011), Singal and Xu (2011)).

5. Summary and Conclusion

As professional investors, mutual fund managers are assumed to show rational behavior and by searching for mispriced securities and market anomalies are supposed to profit from mispricings and make financial markets more efficient.

In this paper, we show that the average fund is disposition prone, a behavioral bias which is usually attributed to individual investors.

On a large sample of actively-managed U.S. equity mutual funds' trading decisions between 1980 and 2010, this paper finds robust empirical evidence for the existence of the disposition effect. First, we show that on average, mutual fund managers in our sample are more likely to realize capital gains than losses. Second, we uncover that stock characteristics of mutual funds' holdings may partially explain the magnitude of the disposition effect. In particular, trading stocks with a high level of valuation uncertainty significantly increases the likelihood and the extent of the disposition bias of mutual fund managers' investment decisions. Third, we show that the level of systematic risk (i.e. beta) is increasing with the level of the disposition effect while the profitability of stocks is decreasing with the level of the disposition effect. We find that fund managers with a high-level disposition effect tend to invest in stocks with low return on assets and low profit margins. In addition, those stocks are associated with a higher leverage ratio indicating higher capital costs. Investments in high-beta stocks which empirically do not outperform low-beta stocks (Baker et al. (2011)) combined with the lower profitability of those stocks contribute to explain the underperformance of biased mutual funds (Scherbina and Jin (2011), Singal and Xu (2011)). Fourth, our results indicate that the disposition effect is partly explained by trading of attention-grabbing stocks. We find that mutual fund managers tend to invest in dividend-paying stocks where the dividend payment serves as a signalling feature of the respective firm.

Our results suggest that a significant de-biasing of mutual funds' outcomes can be achieved through taking not only fund related characteristics, but also stock related characteristics into account when making trading decisions. These findings call for more research on the relationship between trading decisions and behavioral biases.

Our results shed new light on the interaction of stock holdings' characteristics and behavioral biases. The behavior of mutual fund managers is consistent with recent evidence of the disposition effect in a professional setting (e.g. Scherbina and Jin (2011)). Moreover, we contribute to the ongoing discussions of the underlying factors of behavioral biases. Our findings suggest that fund managers display difficulties in evaluating stocks, and are also prone to employ heuristics when making their trading decisions.

Future research may further analyze the circumstances and organizational settings enhancing or decreasing behavioral biases like the disposition bias.

A. Appendix: Mutual Fund Sample Selection

This appendix provides additional details of how we constructed our data. The data in this paper is collected from several sources. We start with a sample of all mutual funds in the CRSP MF database covering the period between 1980 to 2010. Both databases are provided by Wharton Research Data Services (WRDS). The focus of our analysis is on domestic equity mutual funds for which the holdings data is most complete and reliable.

We start constructing our sample with the universe of all open-end funds listed by the Survivor-Bias-Free U.S. Mutual Fund Database maintained between January 1980 and December 2010, inclusive. The database covers all (live and dead) equity, bond, and money market mutual funds since December 1961. CRSP MF database provides a complete historical record for each fund, including fund name, identifying information (e.g. fund number, fund name), start and end dates, net asset values, loads, various classification system for investment category, assets under management, returns, fund families, and further items. The initial sample is downloaded from CRSP MF database and the sample constitutes of 1,193,818 observations and 49,004 funds.

Since the estimation of mutual funds' decision-making process (here: disposition effect) also requires holding-level data on fund portfolio decisions, we use a second data source, namely the Thomson Reuters Mutual Fund Holdings database (TR, henceforce). The database contains survivor-bias-free data on quarter-end holdings which are reported by U.S.-based mutual funds in the mandatory Securities and Exchange Commission (SEC) filings. Mutual funds in the U.S. are required by the SEC to report their portfolio holdings semi-annually prior to June 2005 and since then changed to a quarterly reporting mode[13].

The main dataset is created by merging the CRSP MF with the TR MF database by using the MFLinks document, also provided by WRDS. We obtain fund stock holdings from Thomson's SP12 database since 1980, which in turn determines the starting date of our analysis. Thomson sometimes backfills gaps with information from previous quarters which is identified by the variable *rdate* (reporting date). Besides the quarterly frequency of holding reports, a further limitation is that short positions are unobserved. Also, assumptions about holding returns and trade timing have to be made. In addition, *fdate* is reported referring to the actual date for which the holdings are valid. We follow standard practice and limit our sample of holdings to those observations where the *fdate* is equal or larger than the *rdate* to avoid the use of stale data in our analysis (Pool et al. (2012)).

Since we are interested in the domestic portion of funds' portfolios, we remove holdings in firms head-quartered outside the U.S.. We further limit our analysis to actively-managed equity funds and thereby exclude index funds, international funds, and funds focused on bonds, governments, REITs, convertible debt, precious metals, and other asset classes as these types of funds generally hold and trade in very small quantities of domestic equity. In detail, during each quarter, we include only mutual funds having a self-declared investment

[13] Nevertheless, the majority of mutual funds reported their holdings on a quarterly basis to Thomson prior to June 2005.

objective of *aggressive growth, growth,* and *growth and income, income,* at the beginning of each quarter. As CRSP MF provides one observation per period for each share class of each mutual fund we use the unique *wficn* (Wharton Financial Institution Center Number) fund number for aggregation of fund data across share classes into one observation per fund-year. We calculate weighted-averages using the total net assets of each class as weight for characteristics that vary across fund share classes such as returns and expense ratios. For the total net assets of a fund, we measure the sum of the total net assets of all the classes of that fund.

We merge the TR MF databse with the CRSP MF database using WRDS's MFLinks, a table which links Thomson's fund identifier with those of the CRSP MF database. Approximately 92% of the target universe is matched. The unlinked U.S. equity funds are mainly small, defunct funds where accurate information for a proper linking procedure is not available. In addition, fairly new funds are also less likely to be linked since they are not yet documented in the TR MF database.

We base the selection of our sample on varies filtering methods which are also applied in previous similar studies (e.g. Kacperczyk et al. (2008), Pool et al. (2012)). We eliminate all balanced, bond, money market, sector, and international funds, as well as funds which are not primarily invested in equities. In detail, we use the classification information from Lipper, Strategic Insight, Wiesenberger Objective and the variable policy. The following Lipper classification codes are used to determine the funds as equity: LCCE, LCGE, LCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, MCCE, MCGE, or

MCVE. Further, funds are also defined as equity if they have AGG, GMC, GRI, GRO, ING, or SCG as Strategic Insight classification code, or GRO, LTG, MCG, or SCG as Wiesenberger Objective code. Finally, if the fund has a CS policy (common stocks are the securities mainly held by the fund), we also classify the fund as equity fund. We eliminate all funds which do not meet the above mentioned criteria.

In order to address the problem of the incubation bias (e.g. Evans (2010), Pool et al. (2012)), we drop all observations where the month for the observation is prior to the reported fund starting month in CRSP MF database. In addition, we also exclude observations in CRSP MF where the fund had less than \$5 million under management or where fewer than 11 stock holdings are identified (Pool et al. (2012), Scherbina and Jin (2011)) in the previous month since incubated funds tend to be smaller. The rationale behind is to keep our analysis away from errors in the database and underreporting issues. The resulting sample is merged with the TR MF data using MFLinks. The MFLinks table provides information in order to combine the CRSP MF database that covers mutual fund returns, loads/fees/expenses and related information to equity holdings data in the TR MF datasets. In a first step, we obtain the Wharton Financial Institution Center Number (*wficn*) for each share class in CRSP MF database and investment objective codes (*ioc*) from the TR MF database. In a second step, the *wficn* is used to find the associated *fundno* and date range in the TR MF data bank. Funds without a record in MFLinks are dropped from the sample.

Even after the previous mentioned filtering, our sample still contains a number of non-equity as well as international funds. Therefore, we apply further filtering mechanisms (based on Kacperczyk et al. (2008)) in order to ensure a sample consisting only of U.S. based equity funds. We first look at the percentage invested in common shares (*per_com*) from the CRSP MF annual summary file and exclude all funds that on average hold less than 80% or more than 105% in common stocks. In order to check the robustness of the MFLinks merger, we compare total fund assets (*tna*) in CRSP MF to *tna* in the TR MF database which is given in the following equation:

$$Abs_{diff} = \frac{|TNA_{CRSP} - TNA_{TR}|}{TNA_{CRSP}} \tag{A.1}$$

If the median absolute difference for a particular fund over all overlapping data observations is larger than 1.3 or smaller than 1/1.3, we also drop the fund from our sample.

In order to focus on actively-managed funds, we further exclude index funds and ETF. In a first step, we eliminate all funds which are marked as index funds, ETF or ETN in the CRSP MF database. We also apply a second filter procedure which is based on the works of Pool et al. (2012). To do so, we use fund names and drop any fund name including any of the following strings: "Index", "Idx", "Ix", "Indx", "Nasdaq", "Dow", "Mkt", "DJ", "S&P 500", "S&P, 500", "Barra", "DFA", "Vanguard", "ETF", "SPDR", "ETN", "Powershares", "Wisdomtree", "Tracker", and "Profunds".

B. Appendix: Variable Definition

The following tables briefly outline how our main variables used in the empirical analysis are constructed. Data comes from three different data sources used in this paper: (i) quarterly fund holdings data from Thomson Financial, (ii) quarterly mutual fund characteristics from CRSP, (iii) daily (monthly) stock return files from CRSP.

Table B1 – **Fund Data**

Variable Name	**Description and Definition**
Disposition effect	Disposition effect calculated according to Odean's (1998) method in a particular quarter. It is calculated as PGR (proportion gains realized) minus PLR (proportion loses realized).
Expense ratio	Ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. It may include waivers and reimbursements, causing it to appear to be less than the fund management fees.
Fund return	Monthly market-adjusted average returns of funds total monthly return, i.e. the return on the fund's portfolio, including reinvested dividends.
NAV	Net asset value in a particular quarter. Reported in $ millions.
TNA	Total net assets in a particular quarter. Reported in $ millions.
Trades	Number of all executed transactions in a particular quarter.
Turnover ratio	It is the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month Total Net Assets of the fund. The ratio is expressed as a percentage of the fund.
Volume	Sum of the absolute values of all purchases and sales in a particular quarter.

Table B2 – Fund Characteristics

Variable Name	Description and Definition
12b-1 fee	12b-1 fees are reported as the ratio of the costs attributed to marketing and distribution costs to total assets. Represents the actual fee paid in the most recently completed fiscal year as reported in the Annual Report Statement of Operations.
Front load	Front loads for investments represent maximum sales charges at breakpoint.
Fund age	Log of age in years, relative to the date when the fund was first offered.
Fund closed	Dummy variable equal to 1 if the fund is open to new investors; 0 otherwise.
Fund size	Log of annual assets under management (AUM) in millions of $ dollar for each fund.
Fund strategy 1	Is based on a fund's investment objective code (ioc) based on Thomson Financial database. We include the following ioc codes: AGG, GMC, GRI, GRO, ING, SCG, SEC.
Fund strategy 2	Is based on a fund's Wiesenberger Fund Type based on Thomson Financial database. We include the following codes: G, G-I, G-I-S, I, I-G, I-S, IEQ, LTG, MCG, SCG.
Fund strategy 3	Is based on a fund's Lipper Classification based on Thomson Financial database. We include the following ioc codes: LCCE, LCGE, LCVE, MCCE, MCGE, MLCE, MLVE, SCCE, SCGE, SCVE.
Institutional dummy	Is equal to one if the fund is an institutional fund and zero otherwise.
Manager's experience	Years of manager at specific fund.
Max 12b-1 fee	Is the maximum contractual 12b-1 fee. Represented in decimal format.
New manager	Dummy variable that equals one if the fund manager has been at the fund for less than three years.
Rear load	Fees which are charged when withdrawing funds.
Retail dummy	Is equal to one if the fund is a retail fund and zero otherwise.
Team-managed	Dummy variable that equals one if the fund is managed by a team and zero otherwise.

Table B3 – Stock Characteristics

Variable Name	Description and Definition	Data source	Time period
BM ratio	Book to market ratio is defined as book value divided by the current market price.	COMPUSTAT	Monthly
CAPEX	Capital expenditures is the product of common shares outstanding and an adjustment factor divided total assets.	COMPUSTAT	Monthly
Dividend yield	Is calculated as annualized dividend rate divided by monthly closing price. Reported in percentage.	COMPUSTAT	Monthly
EPS	Earnings per share is net income divided by common shares outstanding.	COMPUSTAT	Monthly
Firm age	Is the number of years since the stock first appears in the CRSP database.	CRSP	Daily
Firm size	Is defined as the natural log of market capitalization (in $ million), which is calculated as the number of shares outstanding (shrout) times price.	CRSP	Daily
Idiosyncratic volatility	Is the volatility of the residuals obtained by fitting a one-factor model to the daily stock price time series. The idiosyncratic volatility for each stock is estimated each year by using daily returns.	CRSP	Daily
Intangible assets	Ratio of intangible assets to total assets.	COMPUSTAT	Monthly
Leverage ratio	Is total debt divided by total assets. Total debt is calculated as the sum of long-term debt and debt in current liabilities.	COMPUSTAT	Monthly
Market capitalization	Shares outstanding times price. The market value of shares traded is calculated as daily closing price minus daily trading volume.	COMPUSTAT	Monthly
Market return	Return on the S&P 500.	CRSP	Daily
Market return volatility	Is the standard deviation of daily returns of the S&P 500.	CRSP	Daily
Past 12-month stock return	Past stock returns of the last year.	CRSP	Daily
PPE	Ratio of property, plant, and equipment to total assets.	COMPUSTAT	Monthly
Profit margin	Is operating income after depreciation divided by total sales.	COMPUSTAT	Monthly
ROA	Return on assets is the ratio of operation income after depreciation divided by total assets.	COMPUSTAT	Monthly
Sales growth	Is calculated as the average annual growth of sales over the past three years.	COMPUSTAT	Monthly
Stock beta	Is the beta coefficient obtained from fitting a one-factor model to the daily stock price time series.	CRSP	Daily
Stock price	Is the daily stock price.	CRSP	Daily
Stock return volatility	Is the standard deviation of daily stock returns.	CRSP	Daily
Stock turnover	Is the ratio of the number of shares traded and shares outstanding.	CRSP	Daily

6. Tables and Figures

Table 1 – Summary Statistics of Trading Activities
The table shows the number of shares and value of trades for all mutual funds in our sample during the sample period between 1980 and 2010 traded per quarter. *Panel A* of the table reports the summary statistics for the number of shares The table shows the number of purchases and the number of sales as well as total trades. *Panel B* shows the summary statistics for the value of purchases and sales in $ traded during the sample period between 1980 and 2010. Purchases are defined as changes in holdings which are larger than zero. A sale is defined as a change in stock holdings being equal or smaller than zero.

Panel A

Variable	Obs.	Mean	Std. Dev.	Min	Max
Buy	178,987	108,095	529,138	1	269,000,000
Sell	194,623	-101,170	547,238	-535,000,000	-1
Total	373,610	-917,000	548,693	-535,000,000	269,000,000

Panel B

Variable	Obs.	Mean	Std. Dev.	Min	Max
Buy	178,987	2,969,600	13,000,000	1	576,000,000
Sell	194,623	-101,170	547,238	-53,000,000	-1
Total	373,610	-158,336	19,600,000	-53,000,000	576,000,000

Table 2 – Summary Statistics of Fund Characteristics

The table reports the summary statistics of fund characteristics of all mutual funds in the sample over the period from January 1980 through December 2010. The table displays the number of observations (Obs.), mean, standard deviation (St.Dev.), minimum (Min.) and maximum (Max.) of the different fund related variables. Fund age is measured as the logarithm of years between the first offer date and the last reporting date. Fund size is measured as quarterly total net asset value in million $. Monthly TNA is the monthly total net asset value calculated in million $. Monthly NAV is the monthly net asset value measured in million $. Return is the monthly market-adjusted average returns of funds total monthly return, i.e. the return on the fund's portfolio, including reinvested dividends. 12b-1 fees are reported as the ratio of total assets attributed to marketing and distribution costs. Front loads for investments represent maximum sales charge at breakpoint. Rear loads are fees which are charged when withdrawing funds. Expense ratio is the ratio of total investment that shareholders pay for the fund's operating expenses, which includes 12b-1 fees. Turnover ratio is the average of the absolute values of all purchases and sales in a particular quarter divided by the average of the portfolio values at the beginning and end of a particular quarter. Fund closed is a dummy variable which is equal to one if the fund is open to investments and zero otherwise. The variable institutional dummy is equal to one if the fund is an institutional fund and zero otherwise. The retail dummy variable is equal to one if the fund is a retail fund and zero otherwise. Team-managed is a dummy variable which is equal to one if the fund is managed by a team and zero for single-managed funds. Manager's experience is measured in years that the manager has worked at a specific fund. The dummy variable new manager is equal to one if the manager is less than three years at the specific fund or zero otherwise.

Variable	Obs.	Mean	St.Dev.	Min.	Max.
Fund age	206,068	2.33	0.69	0	4.11
Fund size	349,249	4.22	2.00	0.26	9.73
Monthly TNA	179,512	475.64	1307.06	1.20	8933.10
Monthly NAV	180,915	15.18	8.77	3.19	54.47
Monthly return	180,885	-0.0098	0.0604	-0.1334	0.1105
12b-1 fee	136,097	0.0054	0.0036	0	0.0100
Front load	180,718	0.0058	0.0143	0	0.0575
Rear load	205,095	0.0024	0.0080	0	0.0500
Expense ratio	245,688	0.0133	0.0053	0.0017	0.0265
Turnover ratio	243,611	0.8662	0.7232	0.0400	4.2700
Fund closed	264,633	0.89	0.31	0	1
Institutional dummy	264,633	0.31	0.46	0	1
Retail dummy	264,633	0.68	0.47	0	1
Team-managed	349,249	0.30	0.46	0.00	1.00
Manager experience	136,179	10.42	5.71	2.00	54.03
New manager	349,249	0.03	0.17	0	1
Funds	2,605				
Fund*year	75,545				

Table 3 – Summary Statistics of Stock Characteristics

The table presents the characteristics for the 15,110 different stock holdings of the mutual funds in our sample between 1980 and 2010. Accounting and stock related information are retrieved from Compustat and CRSP, respectively. The table displays the number of observations (Obs.), mean, standard deviation (St.Dev.), minimum (Min.) and maximum (Max.). The table reports annual estimates based on monthly data for balance sheet variables, namely intangible assets as percentage of total assets, book to market ratio (BM ratio), earnings per share (EPS), dividend yield,intangible assets (intan. assets), property, plant, equipment as percentage of total assets (PPE), return on assets (ROA), profit margin, sales growth, leverage and capital expenditures (CAPEX). All other variables are based on daily time series. For the definition of variables please refer to Appendix B Table B3. Market capitalization is reported in million $; shares outstanding and volume are reported in millions.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
BM ratio	103,270	0.64	0.33	0	1.86
EPS	95,158	1.21	1.15	-2.43	5.20
Dividend yield	103,265	0.0115	0.0321	0	0.2175
Intan. assets (in%)	88,457	0.0797	0.1369	0	0.6649
PPE (in %)	88,550	0.5403	0.3749	0	1.6851
ROA	97,846	0.0794	0.0688	-0.3080	0.2912
Profit margin	97,795	0.1164	0.2704	-2.7971	0.7229
Sales growth	62,817	0.8844	3.0035	-0.2423	21.6238
Leverage	97,826	0.2199	0.1594	0.0000	0.7425
CAPEX	97,949	0.1774	0.3232	0.0027	2.3795
Market capitalization	162,145	1.40	6.60	0	172.00
Firm size	162,145	12.24	1.80	0	18.96
Firm age	103,451	17.15	8.99	0	43
Mean stock return	163,628	0.2072	0.2125	-3.5945	10.6995
Stock turnover	162,026	6.31	22.77	0	1,834.38
Volume	163,628	0.3699	2.6017	0	300
Market return	163,628	0.0874	0.0474	-0.3282	0.3560

Table 4 – Summary Statistics of the Disposition Effect

Panel A of the table reports the disposition effect. It reports the number of observations (Obs.), mean, standard deviation (St. Dev.), 25^{th} percentile (P25), median (P50), the 75^{th} percentile (P75) of the disposition effect for the whole period and for different subperiods 1980 to 1989, 1990 to 1999 and 2000 to 2010. The disposition effect is calculated as the proportion of gains realized (PGR) minus the proportion of losses realized (PLR). PGR is defined as the ratio of realized gains to the sum of realized and unrealized gains. Accordingly, PLR is measured as the ratio of realized losses to the sum of realized and unrealized losses. The table displays the absolute share numbers for all funds in our sample. The disposition effect is calculated in a two-step process: first, the mean PGR, PLR and disposition effect for each fund is calculated for all quarters in which the fund has valid data, and second, the mean PGR, PLR and disposition effect across all funds are averaged. We show results for all four quarters measured in number of trades. *Panel B* reports the disposition results for crisis and non-crisis periods. We define the following crisis times: the U.S. recessions between 1980 and 1982 and between 1990 and 1992, the Asian crisis of 1997, the Russian crisis 1998 and the collapse of Long-Term Capital Management (LTCM) in 1998, the Dot-com bubble from 2000 to 2001 and the recent financial crisis from 2007 to 2009.

Panel A

Period	Obs.	% of funds	Mean	Sd	p25	p50	p75
1980-1989	81,186	4.39	0.0464	0.0053	0.0441	0.0454	0.0474
1990-1999	509,541	27.58	0.0448	0.0064	0.0414	0.0444	0.0469
2000-2010	1,256,718	68.02	0.0370	0.0084	0.0324	0.0371	0.0422
Total	1,847,445	100	0.0396	0.0086	0.0348	0.0399	0.0449

Panel B

Period	Obs.	% of funds	mean	sd	p25	p50	p75
Non-crisis	1,050,130	56.84	0.0396	0.0084	0.0353	0.0400	0.0450
Crisis	797,315	43.16	0.0395	0.0088	0.0342	0.0397	0.0448
Total	1,847,445	100	0.0396	0.0086	0.0348	0.0399	0.0449

Table 5 – Sorting Results: Fund Characteristics

The table presents different fund related measures for different disposition effect deciles. Decile one contains the funds with the lowest disposition effect, whereas decile ten includes funds with the highest disposition effect. In the table, a fund can only be counted once; if the database contains more than one report for the respective mutual fund, we calculate the average disposition effect and the average fund characteristics across time. Fund age is defined as logarithm of the years relative to the date the fund was first offered. Fund size is measured as the log of annual assets under management (AUM) in millions of $ for each fund. Front load for investments represents maximum sales charge. Rear load is defined as the fees charged when funds are withdrawn. Expense ratio is the total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. It may include waivers and reimbursements, causing it to appear to be less than the fund management fees. Turnover ratio is the average of the absolute values of all purchases and sales in a particular quarter divided by the average of the portfolio values at the beginning and end of a particular quarter. Manager experience is defined as the years of manager at specific fund. New manager is a dummy variable which equals one if the fund manager has been at the fund for less than three years. Team-managed is a dummy variable that equals one if the fund is managed by a team and zero otherwise. The reported t-values show the significance of the difference between the first and tenth deciles for the respective variable.

Disposition deciles	Fund age	Fund size	Front load	Rear load	Expense ratio	Turnover ratio	Manager experience	New manager	Team-managed
1 (low)	1.98	3.70	0.0086	0.0031	0.0137	0.94	9.11	0.02	0.34
2	2.20	3.87	0.0085	0.0020	0.0137	0.85	8.70	0.03	0.39
3	2.14	3.80	0.0069	0.0031	0.0135	0.98	8.83	0.03	0.28
4	2.19	3.73	0.0045	0.0029	0.0148	0.85	10.27	0.04	0.23
5	2.43	4.42	0.0040	0.0019	0.0133	0.87	10.20	0.02	0.24
6	2.66	5.14	0.0033	0.0018	0.0111	0.67	11.84	0.02	0.27
7	2.26	4.24	0.0057	0.0022	0.0125	0.89	11.74	0.03	0.27
8	2.51	4.41	0.0047	0.0040	0.0130	1.03	10.61	0.02	0.38
9	2.39	4.41	0.0056	0.0025	0.0130	0.79	11.29	0.01	0.31
10 (high)	2.30	4.29	0.0075	0.0027	0.0128	0.86	10.18	0.07	0.33
t-statistics	-44.99	-42.44	5.62	4.64	20.07	12.08	-15.64	-37.42	4.43

Table 6 – Sorting Results: Stock Characteristics

The table contains the averages of different characteristics of the mutual fund stock holdings by disposition effect deciles. Decile one contains the funds with the lowest disposition effect, whereas decile ten included funds with the largest disposition effect. *Panel A* reports firm age as the number of years since the stock first appears in the CRSP database. Firm age is the number of years since the stock first appears in the CRSP database. Firm size is defined as the natural log of market capitalization (in $ million), which is calculated as the number of shares outstanding (shrout) times price. Stock turnover is the ratio of the number of shares traded and shares outstanding. Book to market ratio (BM ratio) is calculated as the book value divided by the current market price. Earnings per share (EPS) is net income divided by common shares outstanding. PPE is defined as the ratio of property, plant, and equipment to total assets. The variable intangible assets is the ratio of intangible assets to total assets (intan assets). Dividend yield is calculated as annualized dividend rate divided by monthly closing price. Reported in percentage. The reported t-statistics show the significance of the difference between the first and tenth deciles for the respective variable. *Panel B* includes the return on assets (ROA) defined as operational income after depreciation divided by total assets. Profit margin is the operating income after depreciation divided by total sales. Sales growth is calculated as the average annual growth of sales over the past three years. Leverage ratio is total debt divided by total assets. Capital expenditures (CAPEX) is the product of common shares outstanding and an adjustment factor divided total assets. The reported t-statistics show the significance of the difference between the first and tenth deciles for the respective variable.

Panel A

Disposition deciles	Firm size	Firm age	Stock turnover	BM ratio	EPS	PPE	Intan. Assets	Dividend yield
1 (low)	14.11	13.14	10.69	0.4594	1.5539	0.4668	0.2049	0.0173
2	14.27	16.77	10.03	0.4415	1.6705	0.4815	0.2071	0.0210
3	14.33	18.98	9.29	0.4400	1.6941	0.4743	0.2031	0.0222
4	14.15	21.47	8.40	0.4321	1.7402	0.4835	0.2058	0.0256
5	14.29	23.19	8.43	0.4257	1.8054	0.4945	0.2016	0.0283
6	14.61	25.34	7.42	0.4103	1.9158	0.4842	0.2044	0.0323
7	15.25	26.12	7.01	0.4235	1.8743	0.4845	0.2005	0.0301
8	15.14	25.82	6.31	0.4131	1.8828	0.4824	0.2002	0.0305
9	13.67	18.34	5.93	0.4223	1.8494	0.4842	0.2079	0.0280
10 (high)	13.15	11.66	5.90	0.4567	1.7097	0.5199	0.1561	0.0266
t-statistics	196.00	48.52	223.67	1.54	-17.73	-18.94	32.80	-24.92

Panel B

Disposition deciles	ROA	Profit margin	Sales growth	Leverage	CAPEX
1 (low)	0.1074	0.1212	1.7914	0.2156	0.2283
2	0.1089	0.1296	1.9960	0.2170	0.2386
3	0.1101	0.1336	2.0747	0.2142	0.2405
4	0.1110	0.1241	2.0856	0.2158	0.2600
5	0.1109	0.1326	2.1563	0.2162	0.2483
6	0.1145	0.1318	2.0863	0.2231	0.2777
7	0.1096	0.1421	1.9855	0.2241	0.2518
8	0.1144	0.1406	1.9702	0.2147	0.2695
9	0.1127	0.1317	1.8934	0.2193	0.2653
10 (high)	0.1085	0.1199	1.8703	0.2223	0.2335
t-statistics	-2.18	0.81	-6.10	-5.55	-1.68

Table 7 – Regression Estimates: Disposition Effect and Accounting Related Stock Characteristics

The table reports the regression estimates where the disposition effect in a given stock in a year is employed as dependent variable. The disposition effect is first calculated on a quarterly basis for each fund, secondly, aggregated to annual measures and thirdly, summarized for each stock in the holdings of mutual funds during our sample period between 1980 and 2010. We include the following accounting related stock variables in our regressions: book to market ratio (BM ratio), earnings per share (EPS), property plant, and equipment (PPE) in percentage of total assets, intangibles assets as percentage of total assets (intan. assets), return on assets (ROA), profit margin, dividend yield, sales growth, leverage and capital expenditures (CAPEX). *Panel A* shows the baseline regressions with year and fund fixed effects. *Panel B* shows the baseline analysis including several fund related control variables. In Model 1 we include fund age, fund size, expense ratio, turnover ratio and fund return which are all lagged one year. In Model 2 we include unlagged fund characteristics: fund closed, fund strategy 3, institutional dummy, and retail dummy. In Model 3 we include mutual fund manager control variables: team-managed, manager's experience, new manager dummy. In Model 5 we also include fees: front loads, rear loads and marketing fees (12b1 fee). All specifications include year and fund fixed effects. Along with the coefficient estimates, R-squared values and the number of observations are reported. t-statistics are shown in parenthesis. *** denotes 1%, ** denotes 5% and * denotes 10% significance level, respectively.

Panel A

	Model 1	Model 2	Model 3	Model 4
Constant	0.0485***	0.0486***	0.0486***	0.0488***
	(229.27)	(230.16)	(230.13)	(229.40)
BM ratio	-0.0003***			-0.0004***
	(-10.54)			(-11.41)
EPS	0.0001***			0.0001***
	(13.56)			(16.06)
PPE	0.0000*			0.0001***
	(2.48)			(4.28)
Intan. assets	-0.0002***			-0.0002***
	(-6.09)			(-7.09)
ROA		-0.0003**		-0.0009***
		(-3.08)		(-7.45)
Profit margin		-0.0001***		-0.0001***
		(-4.72)		(-3.47)
Dividend yield		0.0008***		0.0003**
		(7.63)		(2.59)
Sales growth		-0.0001***		-0.0001***
		(-20.08)		(-21.10)
Leverage			-0.0001***	-0.0002***
			(-3.43)	(-5.57)
CAPEX			0.0000*	0.0001***
			(-2.41)	(-4.43)
Obs.	335,076	335,074	335,076	335,074
R-squared	0.2038	0.2041	0.2031	0.2051

Panel B

	Model 1	Model 2	Model 3	Model 4
Constant	0.0436***	0.0354	0.0351	0.0358***
	(100.66)	(0.01)	(0.01)	(17.44)
BM ratio	-0.0004***	-0.0003***	-0.0002*	-0.0002
	(-8.76)	(-5.81)	(-2.49)	(-1.22)
EPS	0.0001***	0.0001***	0.0000	0.0001**
	(13.00)	(6.91)	(1.79)	(2.84)
PPE	0.0001*	0.0000	0.0000	0.0002*
	(2.48)	(0.30)	(0.30)	(2.01)
Intan. assets	0.0001	0.0001*	0.0002*	0.0001
	(1.45)	(2.22)	(2.05)	(0.37)
ROA	-0.0008***	-0.0005**	-0.0001	-0.0007
	(-4.63)	(-2.81)	(-0.29)	(-1.28)
Profit margin	-0.0001*	-0.0001	-0.0004***	-0.0004*
	(-2.16)	(-1.84)	(-3.81)	(-2.19)
Dividend yield	0.0005**	0.0003	0.0007*	0.0004
	(3.08)	(1.22)	(2.00)	(0.54)
Sales growth	-0.0001***	-0.0001***	-0.0002***	-0.0001**
	(-11.63)	(-14.59)	(-14.08)	(-2.72)
Leverage	-0.0001	-0.000	-0.0002***	-0.0001
	(-1.58)	(-0.65)	(-2.94)	(-0.34)
CAPEX	0.0001*	0.0000	0.0000	0.0002**
	(2.49)	(0.05)	(0.52)	(2.94)
Fund age	0.0000	0.0001***	0.0002***	0.0000
	(1.01)	(6.08)	(7.22)	(0.66)
Fund size	0.0001***	0.0000***	0.0000***	0.0000
	(12.19)	(6.72)	(3.80)	(0.01)
Expense ratio	0.0069***	0.0043*	0.0178***	0.0458***
	(4.08)	(2.15)	(5.62)	(4.37)
Turnover ratio	-0.0000**	-0.0001***	-0.0001***	-0.0001
	(-3.02)	(-5.78)	(-5.47)	(-1.81)
Return	-0.0007***	-0.0006***	-0.0007***	-0.0005*
	(-10.54)	(-7.86)	(-5.84)	(-2.05)
Fund closed		-0.0002***	-0.0004***	-0.0004***
		(-8.17)	(-9.47)	(-4.58)
Fund strategy		0.0004**	0.0009***	0.0008
		(3.12)	(4.58)	(1.90)
Inst. dummy		0.0003**	0.0008***	0.0009*
		(2.88)	(4.16)	(2.04)
Retail dummy		-0.0001***	-0.0001***	-0.0001***
		(-16.16)	(-9.40)	(-4.86)
Team-managed			0.0001***	0.0004***
			(4.63)	(6.93)
Manager experience			0.0000***	0.0000***
			(3.52)	(3.99)
New manager			0.0001	0.0001
			(1.51)	(0.82)
Front load				0.0061**
				(2.71)
Rear load				0.0684***
				(25.51)
12b-1 fee				0.0483***
				(3.84)
Obs.	143,551	96,711	40,725	10,424
R-squared	0.1033	0.077	0.0910	0.2820

Table 8 – Regression Estimates: Disposition Effect and Stock Characteristics

The table reports the regression estimates where the disposition effect in a given stock in a year is employed as dependent variable. We include firm size, turnover, stock return, stock return volatility, market return (S&P 500) and market return volatility as stock characteristics. All specifications include fund-level control variables. All models include fund age, fund size, expense ratio, turnover ratio and fund return which are all lagged one year. In addition, we include unlagged fund related control variables: fund closed, fund strategy 3, institutional dummy, and retail dummy. In Model 2, Model 4, and Model 6 we also include mutual fund manager control variables: team-managed, manager's experience, new manager dummy. All specifications include year and fund fixed effects. Along with the coefficient estimates, R-squared values and the number of observations are reported. t-statistics are shown in parenthesis. *** denotes 1%, ** denotes 5% and * denotes 10% significance level, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.0337***	0.0312***	0.0329***	0.0303***	0.0328***	0.0299***
	(9.27)	(10.67)	(9.09)	(10.41)	(9.10)	(10.37)
Firm size	0.0003***	0.0002***	0.0003***	0.0001***	0.0003***	0.0001***
	(27.09)	(13.13)	(21.32)	(6.73)	(22.33)	(8.24)
Turnover	-0.0000***	-0.0000***	-0.0000*	-0.0000	-0.0000***	-0.0000***
	(-19.12)	(-22.81)	(-2.48)	(-1.67)	(-7.50)	(-9.83)
Stock return	-0.0005	-0.0036***			-0.0001	-0.0025
	(-0.58)	(-3.42)			(-0.08)	(-1.83)
Stock vola	0.0037***	0.0101***			0.0018	0.0074***
	(4.37)	(9.41)			(1.66)	(5.34)
Market return			-0.0004	-0.0091*	-0.0005	-0.0041
			(-0.12)	(-2.38)	(-0.13)	(-0.84)
Market vola			0.0205***	0.0354***	0.0180***	0.0250***
			(6.47)	(9.18)	(4.32)	(5.01)
Fund age	0.0006***	0.0013***	0.0006***	0.0014***	0.0006***	0.0014***
	(18.86)	(32.61)	(19.43)	(33.36)	(19.56)	(33.65)
Fund size	0.0001***	0.0000	0.0001***	0.0000	0.0001***	0.0000
	(6.63)	(0.01)	(7.40)	(0.72)	(6.86)	(0.18)
Expense ratio	-0.0761***	-0.0784***	-0.0714***	-0.0756***	-0.0715***	-0.0724***
	(-20.59)	(-17.44)	(-19.45)	(-16.87)	(-19.49)	(-16.30)
Turnover ratio	-0.0005***	-0.0004***	-0.0004***	-0.0003***	-0.0004***	-0.0003***
	(-18.96)	(-12.50)	(-17.53)	(-9.79)	(-17.82)	(-10.61)
Return	-0.0010***	-0.0001	-0.0010***	-0.0001	-0.0011***	-0.0003
	(-6.99)	(-0.31)	(-7.49)	(-0.63)	(-7.77)	(-1.70)
Fund closed	0.0007***	0.0007***	0.0008***	0.0008***	0.0007***	0.0007***
	(14.72)	(11.78)	(16.08)	(14.86)	(15.54)	(12.91)
Fund strategy 3	0.0002***	0.0002***	0.0002***	0.0003***	0.0002***	0.0002***
	(26.90)	(28.81)	(28.99)	(30.42)	(27.87)	(27.83)
Inst. dummy	0.0006*	0.0001	0.0006*	0.0001	0.0006*	0.0002
	(2.33)	(0.18)	(2.44)	(0.40)	(2.35)	(0.57)
Retail dummy	0.0008***	0.0002	0.0008***	0.0003	0.0008**	0.0001
	(3.39)	(0.78)	(3.39)	(0.84)	(3.24)	(0.38)
Team-managed		0.0006***		0.0007***		0.0006***
		(15.27)		(17.41)		(15.39)
Manager experience		-0.0001***		-0.0001***		-0.0001***
		(-12.29)		(-14.75)		(-12.80)
New manager		0.0022***		0.0024***		0.0020***
		(29.30)		(32.02)		(26.50)
Obs.	102,855	63,323	102,855	63,323	102,855	63,323
R-squared	0.0749	0.1554	0.0862	0.1592	0.0888	0.1747

Table 9 – Regression Estimates: Disposition Effect and Valuation Uncertainty

The table reports the results of the regression analysis of the annual stock-level disposition effect (stock-level DE) and valuation uncertainty. We measure valuation uncertainty as the idiosyncratic volatility which is calculated as the variance of the residuals obtained by fitting a one-factor model to the stock return time series. The idiosyncratic volatility (idio. vola) measure for each stock is estimated each year by using daily stock data. In addition, we control for the following stock characteristics: book to market ratio (BM ratio), earnings per share (EPS), property plant, and equipment (PPE) in percentage of total assets, intangibles assets as percentage of total assets (in. assets), return on assets (ROA), profit margin (P. margin), dividend yield (div. yield), sales growth (S. growth), leverage and capital expenditures (CAPEX). We also include various control variables related to fund characteristics and fund manager characteristics. All specifications include fund-level control variables lagged one period (fund age, fund size, expense ratio, turnover ratio, fund closed, returns), unlagged fund-level control variables (fund closed, fund strategy 3 (based on Lipper Classification Code), institutional dummy (inst. dummy), retail dummy) and fund manager characteristics (team-managed, manager experience and new manager). All models include year and fund fixed effects. Along with the coefficient estimates, R-squared values and the number of observations are reported. t-statistics are shown in parenthesis. *** denotes 1%, ** denotes 5% and * denotes 10% significance level, respectively.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Constant	0.0422***	0.0404***	0.0425***	0.0403***	0.0422***	0.0406***	0.0421***	0.0403***	0.0423***	0.0400***
	(90.14)	(37.18)	(91.57)	(37.58)	(91.87)	(38.82)	(89.94)	(37.08)	(93.41)	(38.75)
Idio. vola	0.0014***	0.0016***	0.0015***	0.0017***	0.0011***	0.0012***	0.0014***	0.0016***	0.0013***	0.0014***
	(41.15)	(29.59)	(42.40)	(31.31)	(33.48)	(22.51)	(41.12)	(29.28)	(39.29)	(25.58)
BM ratio			-0.0012***	-0.0013***					-0.0010***	-0.0008***
			(-39.92)	(-26.51)					(-27.90)	(-13.17)
EPS			0.0001***	0.0001***					0.0001***	0.0001***
			(15.33)	(6.23)					(19.20)	(12.90)
PPE			0.0001***	0.0000					0.0003***	0.0003***
			(3.64)	(1.02)					(14.18)	(9.99)
In. assets			-0.0009***	-0.0011***					-0.0011***	-0.0012***
			(-26.07)	(-20.57)					(-31.88)	(-22.48)
ROA					-0.0028***	-0.0037***			-0.0031***	-0.0043***
					(-26.84)	(-22.79)			(-21.91)	(-19.58)
P. margin					-0.0016***	-0.0019***			-0.0024***	-0.0027***
					(-32.35)	(-26.60)			(-45.46)	(-34.60)
Div. yield					0.0043***	0.0040***			0.0025***	0.0024***
					(34.53)	(21.94)			(18.87)	(12.72)
S. growth					-0.0001***	-0.0001***			-0.0001***	-0.0001***
					(-43.17)	(-37.46)			(-41.88)	(-35.56)
Leverage							-0.0004***	-0.0002***	-0.0012***	-0.0012***
							(-10.47)	(-3.57)	(-26.80)	(-16.61)
CAPEX							0.0000**	0.0001***	0.0003***	0.0001***
							(3.17)	(3.50)	(16.88)	(5.86)
Obs.	91,650	37,720	91,650	37,720	91,650	37,720	91,650	37,720	91,650	37,720
R-squared	0.2506	0.3140	0.2683	0.3319	0.2815	0.3629	0.2518	0.3143	0.3046	0.3816
Fund controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Manager controls	no	yes	no	yes	no	yes	no	yes	no	yes

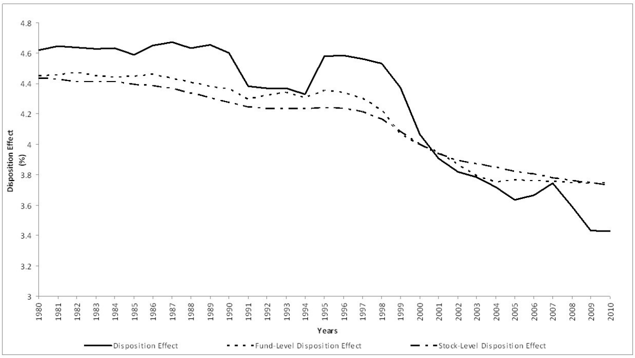
Table 10 – Regression Estimates: Disposition Effect and Beta

The table reports the results of the regression analysis of the annual stock-level disposition effect (stock-level DE) and betas estimated from a one-factor model fitted to the daily stock return series using the S&P 500 as market index. In addition, we control for the following stock characteristics: idiosyncratic volatility (idio. vola), book to market ratio (BM ratio), earnings per share (EPS), property plant, and equipment (PPE) in percentage of total assets, intangibles assets as percentage of total assets (in. assets), return on assets (ROA), profit margin (P. margin), dividend yield(div. yield) , sales growth (S. growth) leverage and capital expenditures (CAPEX). We also include various control variables related to fund characteristics and fund manager characteristics. All specifications include fund-level control variables lagged one period (fund age, fund size, expense ratio, turnover ratio, fund closed, returns), unlagged fund-level control variables (fund closed, fund strategy 3 (based on Lipper Classification Code), institutional dummy (inst. dummy), retail dummy) and fund manager characteristics (team-managed, manager experience and new manager). All models include year and fund fixed effects. Along with the coefficient estimates, R-squared values and the number of observations are reported. t-statistics are shown in parenthesis. *** denotes 1%, ** denotes 5% and * denotes 10% significance level, respectively.

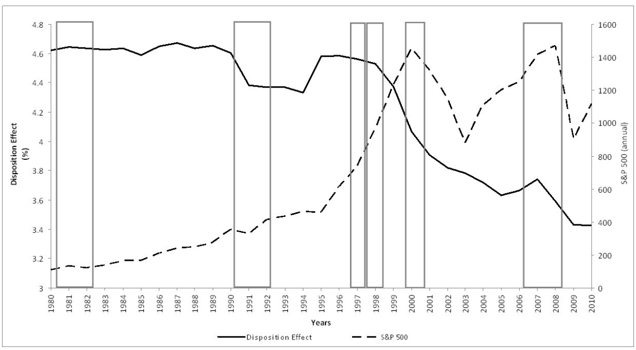
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Constant	0.0403***	0.038	0.0405***	0.0382	0.0403***	0.0382	0.0403***	0.038	0.0403***	0.0383
	(30.84)	(0.01)	(31.29)	(0.01)	(31.51)	(0.01)	(30.83)	(0.01)	(31.95)	(0.01)
Beta	0.0017***	0.0013***	0.0027***	0.0022***	0.0018***	0.0016***	0.0016***	0.0012***	0.0023***	0.0019***
	(12.85)	(7.52)	(20.34)	(12.44)	(13.49)	(9.22)	(11.79)	(6.86)	(17.75)	(11.27)
Idio. vola	0.0014***	0.0013***	0.0013***	0.0013***	0.0011***	0.0011***	0.0014***	0.0014***	0.0013***	0.0012***
	(41.91)	(32.08)	(41.06)	(32.24)	(34.46)	(26.65)	(42.40)	(32.19)	(39.07)	(29.51)
BM ratio			-0.0012***	-0.0011***					-0.0010***	-0.0007***
			(-42.54)	(-29.42)					(-28.75)	(-15.64)
EPS			0.0001***	0.0000***					0.0001***	0.0001***
			(12.74)	(7.20)					(17.54)	(11.31)
PPE			0.0001***	0.0000					0.0002***	0.0002***
			(6.96)	(1.95)					(11.44)	(10.39)
In. assets			-0.0008***	-0.0007***					-0.0011***	-0.0010***
			(-25.71)	(-16.77)					(-33.76)	(-23.93)
ROA					-0.0029***	-0.0034***			-0.0035***	-0.0045***
					(-30.36)	(-26.51)			(-26.66)	(-25.75)
P. margin					-0.0019***	-0.0018***			-0.0026***	-0.0024***
					(-42.04)	(-31.53)			(-51.32)	(-38.87)
Div. yield					0.0036***	0.0024***			0.0017***	0.0008***
					(29.93)	(16.58)			(13.63)	(5.28)
S. growth					-0.0001***	-0.0001***			-0.0001***	-0.0001***
					(-45.33)	(-34.82)			(-44.25)	(-33.54)
Leverage							-0.0002***	-0.0000	-0.0011***	-0.0011***
							(-4.17)	(-0.91)	(-23.89)	(-18.40)
CAPEX							0.0001***	0.0001***	0.0003***	0.0003***
							(9.71)	(6.28)	(22.57)	(17.36)
Obs.	106,917	63,550	106,917	63,550	106,917	63,550	106,917	63,550	106,917	63,550
R-squared	0.2761	0.3292	0.2913	0.3398	0.3063	0.3576	0.2772	0.3297	0.3267	0.3728
Fund controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Manager controls	no	yes	no	yes	no	yes	no	yes	no	yes

Figure 1 – Disposition Effect over Time

Figures (a) and (b) show the disposition effect over time. Subfigure (a) shows the annual disposition effect over time. The disposition effect is computed first for each single fund and second, its time-series mean is taken. All disposition effect measures are calculated based on the number of shares. In addition, we report the fund-level disposition effect which is the time-series mean across all funds. Further, we display the stock-level disposition effect which is the annual average of the effect across all stocks in our sample. Subfigure (b) displays the disposition effect over time and the development of the S&P 500 during the sample period between 1980 and 2010. Crisis times are shaded in grey and are defined as follows: U.S. recessions between 1980 and 1982 and between 1990 and 1992, the Asian crisis of 1997, Russian crisis and the collapse of Long-Term Capital Management (LTCM) in 1998, Dot-com bubble between 2000 and 2001 and the recent financial crisis between 2007 and 2009.



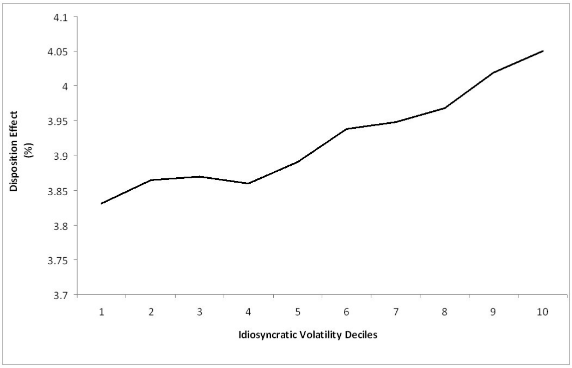
(a) Disposition Effect over Time



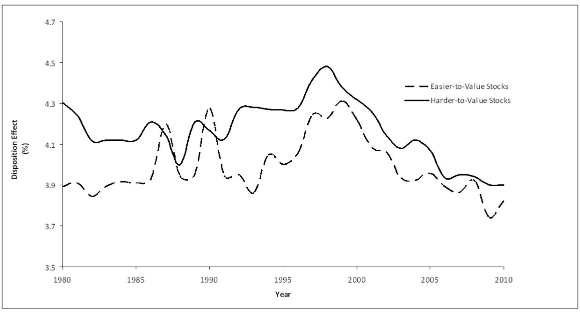
(b) Disposition Effect over Time, S&P 500 and Crisis Times

Figure 2 – Disposition Effect and Valuation Uncertainty

Figures (a) and (b) show the mean stock-level disposition effect (PGR − PLR) for the different idiosyncratic volatility deciles. PGR is the proportion of gains realized, and it is defined as the ratio of the number of realized winner positions and the total number of winners (realized and paper gains). PLR is the proportion of losses realized and is defined analogously. The idiosyncratic volatility for each stock is estimated each year using daily return time series. Figure (a) displays the average annual stock-level disposition effect for each of the ten idiosyncratic volatility deciles. Figure (b) shows the sorting results for the annual stock-level disposition effect estimates for the top three (harder-to-value stocks) and bottom three (easier-to-value stocks) idiosyncratic volatility deciles.



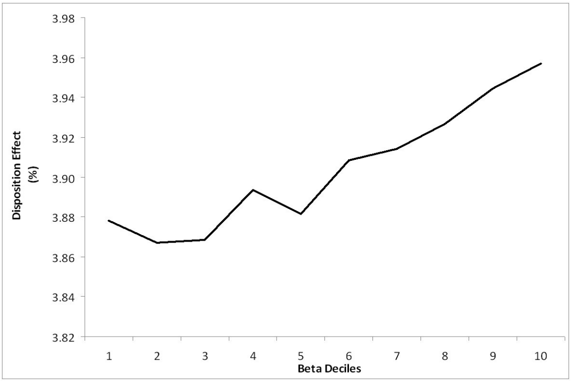
(a) Sorting Results



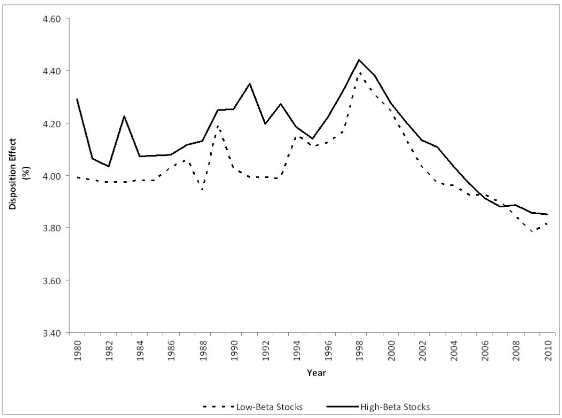
(b) Harder- and Easier-to-Value Stocks

Figure 3 – Disposition Effect and Beta

Figures (a) and (b) show the mean stock-level disposition effect (PGR − PLR) for the different beta deciles. PGR is the proportion of gains realized, and it is defined as the ratio of the number of realized winner positions and the total number of winners (realized and paper gains). PLR is the proportion of losses realized and is defined analogously. Betas are estimated from a one-factor model fitted to the daily stock return series using the S&P 500 as market index. Subfigure (a) displays the average annual stock-level disposition effect for each of the ten beta deciles. Subfigure (b) shows the sorting results for the annual stock-level disposition effect estimates for the top three (high-beta stocks) and bottom three (low-beta stocks) beta deciles.



(a) Sorting Results



(b) High- and Low-Beta Stocks

Part III.
Momentum, Reversal and the Disposition Effect: An Empirical Investigation of Mutual Fund Manager Behavior

Abstract

Finding the disposition effect on a stock-level basis and documenting that momentum is pre-sent in our sample, we focus on the link between the behavioral bias and the stock anomaly. Based on the theoretical model of Grinblatt and Han (2005), we test whether the disposition effect is a possible explanation for the presence and persistence of the momentum effect. For a sample of actively managed U.S. equity mutual funds, we find that stocks predominate-ly held by less disposition prone mutual fund managers experience greater momentum profits than stocks held by more disposition prone fund managers. We also test whether the cross-sectional differences in momentum profits are a compensation for risk, or whether they are attributable to stock characteristics related to momentum, namely firm size, book to market ratio, and stock turnover. The negative relationship between the disposition effect and mo-mentum holds even when controlling for risk and stock characteristics as well as for different time periods and subsamples. Our results suggest that it is likely that there is more to the story of momentum than just the disposition effect.

1. Introduction

The consistent profitability of momentum strategies remains one of the most puzzling anomalies in finance. Since the seminal work of Jegadeesh and Titman (1993), the momentum effect is for almost two decades among the most popular and pervasive return anomalies. Jegadeesh and Titman (1993) show that past winners continue to outperform past losers over three to twelve months holding periods which they define as momentum. Empirical evidence indicates that the positive autocorrelation at time horizons of three to twelve months cannot be explained by the Fama and French (1993) three-factor model, industry effects, or cross-sectional differences in expected returns (e.g. Fama and French (1996), Grundy and Martin (2001), Jegadeesh and Titman (2001), Moskowitz and Grinblatt (1999)). Hence, the underlying factors driving the momentum effect remain rather unclear.

The disposition effect has lately gained importance in explaining various market anomalies including the momentum effect. For example, Grinblatt and Han (2005) as well as Weber and Zuchel (2002) develop models in which the disposition effect creates return predictability. Various empirical papers study the relationship between disposition prone investors and momentum in stock prices (e.g. Birru (2011), Goetzmann and Massa (2008), Grinblatt and Han (2005)). However, results are mixed and it is unclear to what extent the disposition effect is related to the momentum effect.

The goal of this paper is to understand the potential role that the disposition effect plays in explaining the momentum effect. Our focus is on the direction and magnitude of the relationship between the disposition effect and momentum returns in the U.S. equity market and how it is related to known drivers of momentum profits (firm size, book to market ratio, stock turnover). In addition, we control for stock characteristics which are known to correlate with momentum, namely firm size, book to market ratio, and turnover. In order to test the prediction that the disposition effect is an important factor influencing stock return momentum, we first calculate the disposition effect using Odean's (1998) methodology. Second, we sort stocks independently into portfolios based on previous returns and the stock-level disposition effect measure. Concerning the momentum strategy, we apply the standard 6-month formation and 6-month holding period[1] of Jegadeesh and Titman (1993). In our empirical section, we compare portfolios containing the tercile of stocks with the highest disposition level measures with portfolios containing the tercile of stocks with the lowest stock-level disposition measures. We also analyze whether the observed differences are a compensation for risk and estimate alphas by Fama and French (1993)'s three-factor model.

Our second goal is that we test the hypothesis that reversal is stronger for stocks held by less disposition prone investors which is also derived from the Grinblatt and Han (2005) model. The overreaction theory (Daniel et al. (1998)) predicts that there is an initial underreaction to information in the short run resulting in momentum, but that momentum profits will reverse in the long run as more information becomes publicly available. Therefore, we expect a weaker reversal for stocks held by more disposition prone investors

[1] In the robustness section, we also apply different formation and holding periods.

since they tend to misinterpret new information.

Our first main result is that less disposition prone mutual fund managers earn higher momentum profits. On average, funds in the lowest disposition tercile earn monthly raw returns of 1.05% while fund managers in the highest disposition tercile earn only 0.63% of momentum profits. The relationship between the level of the disposition effect and momentum is monotonically decreasing. Therefore, we do not confirm our hypothesis and the prediction of Grinblatt and Han (2005) that the disposition effect positively correlates with the momentum effect. We also show that our results are not due to a risk compensation: when including Fama and French (1993) factors our result remains unchanged. Our finding is robust even when controlling for stock characteristics which are documented to be related to the momentum effect, namely firm size, book to market ratio, and turnover.

Second, we provide evidence that the reversal of stock returns is stronger for less disposition prone mutual fund managers. Employing a 24-month momentum strategy, we find that mutual fund managers in the lowest disposition tercile pick stocks with stronger return reversal. We show that less disposition prone mutual fund managers earn 0.37% monthly raw returns employing a 24-month strategy. More disposition prone fund managers yield 0.41% of momentum returns. Overall, the reversal is strongest for stocks held by less disposition prone fund managers.

We primarily contribute to two strands of literature. First, we add to the literature on possible factors which support the presence of the momentum effect. While its existence is documented for a variety of countries, time periods, indices, asset classes, and industries[2], its underlying mechanisms remain rather unclear. Although several theoretical and empirical papers offer rational explanations (e.g. Holden and Subrahmanyam (2002), Johnson (2002), Vayanos and Woolley (2010)), the literature mainly focuses on behavioral based explanations. So far, there is no widely accepted explanation for the existence of momentum profits. Several previous empirical studies (e.g. Frazzini (2006), Grinblatt and Han (2005), Scherbina and Jin (2011)) provide evidence in favor of a link between the disposition effect and momentum. However, from previous literature it is not clear to what extent the disposition effect might be a valid explanation for the existence of the momentum effect.

Second, our paper contributes to prior literature by showing that momentum is related to various stock characteristics. Empirical studies find that momentum profits are stronger for smaller stocks (Jegadeesh and Titman (1993)). We also analyze the relationship between momentum and turnover showing that momentum profits are weaker for stocks with higher turnover ratios (Lee and Swaminathan (2000)). In addition, we investigate whether value or growth stocks (as measured by the book to market ratio) are more incline to momentum. Daniel and Titman (1999) show that the momentum

[2]The momentum effect was first described in Jegadeesh and Titman (1993). U.S. stock momentum in earlier and later time periods is shown in e.g. Fama and French (2008), or Jegadeesh and Titman (2001). Asness et al. (2013), Fama and French (2012), Griffin et al. (2003), Rouwenhorst (1998) find international evidence of the momentum effect. Previous research uncovers the profitability of momentum at the stock index level (e.g. Bhojraj and Swaminathan (2006)). Momentum effects in other asset classes such as bonds, commodities, or currencies are identified in e.g. Asness et al. (2013). Momentum based on industries is revealed in e.g. Menzly and Ozbas (2010) or Moskowitz and Grinblatt (1999). Tests for momentum in out-of-sample periods is shown in e.g. Carhart (1997), Grundy and Martin (2001), Jegadeesh and Titman (2001).

effect is stronger for growth stocks (low book to market ratio). In order to analyze whether the disposition effect has incremental explanatory power over these stock characteristics, we apply a triple-sorting procedure based on different disposition effect measures, past returns, and stock characteristics.

In summary, previous findings are consistent with behavioral based theories. However, direct evidence on the impact of behavioral biases on momentum is rather scarce. The controversial results on the underlying causes of the momentum effect call for a re-examination of this issue. As (Hong et al. (2000), p. 266) state: "*while the existence of momentum in stock returns does not seem to be too controversial, it is much less clear what might be driving it.*".

The rest of this paper is structured as follows: in Section 2, we review related literature and develop hypotheses for the empirical analysis. In Section 3, we introduce our methodology and report descriptive statistics. Section 4 presents the data. Section 5 contains the empirical results. In Section 6, we report robustness checks and in Section 7, we give a brief summary and conclude.

2. Hypothesis Development and Related Literature

In this section, we develop the hypotheses that we test in the empirical section of this paper. We also review related literature which puts our paper in perspective.

2.1. Disposition Effect

The disposition effect describes the tendency of investors to realize gains by selling assets that gained in value and to avoid realizing losses by holding on to assets that lost in value. The effect was first discovered and labelled by Shefrin and Statman (1985). For the last two decades, researcher argue that the disposition effect is based on prospect theory (Kahneman and Tversky (1979)) and the idea of mental accounting (Thaler (1985)). Prospect theory states that an individuals' utility function is convex for losses and concave in the area of gains. Mental accounting refers to the idea that an individual's utility is only affected when gains and losses are realized not for unrealized, open positions. Individuals behaving according to both theories are more likely to hold on to their losing positions and to sell their winning positions causing the disposition effect.

The disposition effect is documented in a variety of data sets, time periods, and asset classes. Empirical investigations of individual stock trading activity (e.g. Feng and Seasholes (2005), Grinblatt and Keloharju (2001), Odean (1998), Shapira and Venezia (2001)) show that both inexperienced and sophisticated individual equity investors in the U.S., Finland, Israel, and China, respectively, are affected. The effect is also present in other markets: residential housing (Genesove and Mayer (2001)), executive stock options (Heath et al. (1999)), and prediction markets (Hartzmark and Solomon (2012)).

At an institutional level the existence of behavioral biases is less clear. Previous papers find mixed results regarding the presence and the magnitude of the disposition effect among U.S. equity mutual fund managers (e.g. Ammann et al. (2012), Cici (2012), Frazzini (2006), Goetzmann and Massa (2008), Ringov (2012), Scherbina and Jin (2011), Wermers (2003)). Ammann et al. (2012) discover the disposition effect for a sample of U.S. equity mutual fund managers from 1993 to 2005 and show how it is related to fund characteristics and changes in the macroeconomic environment. Cici (2012) studies mutual fund managers' behavior between 1980 and 2009 and provides evidence in favor of the disposition effect. In addition, he detects underperformance of disposition prone funds: the higher the level of the disposition effect, the weaker a funds' performance. Frazzini (2006) analyzes the cross-section of stock returns and how stock prices underreact to corporate news. He also studies how event-driven return predictability is generated by trading limitations of disposition prone investors. In addition, he uncovers that the extent of the disposition effect adversely affects returns. Looking at under- and outperforming funds separately, the author highlights that loser funds tend to be more disposition prone. This is in line with previous findings of Wermers (2003) suggesting a reluctance of selling loser stocks among mutual fund managers. He also shows that winning managers continue to post better returns by investing new inflows in momentum stocks, and not by underweighting the loser stocks in their portfolio.

Goetzmann and Massa (2008) as well as Ringov (2012) find the disposition effect among U.S. mutual fund managers. In line, Scherbina and Jin (2011) find that the existence of the disposition effect depends on the duration a manager is associated with a certain fund. While existing managers continue to hold on to their losing investments, newly-hired managers do not display the disposition effect since they do not feel responsible for the "inherited" mistakes of their predecessors.

Recently, the disposition effect gained attention as a possible factor supporting momentum (e.g. Ben-David and Hirshleifer (2012), Grinblatt and Han (2005), Goetzmann and Massa (2008), Shumway and Wu (2007)) which will be further discussed in Section 2.3.

2.2. Momentum

Momentum or relative strength strategies are based on buying past winner stocks and selling past loser stocks. The key fact of the profitability of the momentum strategy is that past winners continue to outperform past losers. Since the seminal work of Jegadeesh and Titman (1993), the momentum effect, i.e. positive autocorrelations at time horizons of three to twelve months, gained importance. Momentum profits are positive and significant in the first six to twelve months, but exhibit reversal afterwards (Jegadeesh and Titman (1993), Jegadeesh and Titman (2001)). While its existence is analyzed for a variety of countries, time periods, indices, asset classes, and industries, its underlying mechanisms remain unclear. Recent evidence indicates that momentum, especially when looking at intermediate time horizons, cannot be explained by any previously known results (Novy-Marx (2012)). It cannot be explained by the 12-month effect identified by Jegadeesh (1990) and studied in detail by Sadka and Heston (2008), and it is essentially unrelated to the consistency of performance results of Grinblatt and Moskowitz (2004). However, Bulkley and Nawosah (2009), and Conrad and Kaul (1998) argue that momentum can be mainly explained by risk. Grinblatt and Moskowitz (2004) find that tax-loss selling strongly drives the negative December returns for losing firms and that this explains a large part of the profitability of momentum strategies.

Due to the lack of convincing rational explanation for the existence of momentum, behavioral based explanations of momentum are put forward (e.g. Bhootra (2011), Jegadeesh and Titman (2002)). Some papers argue for overreaction and herding of investors as drivers of momentum (e.g. Hoitash and Krishnan (2008)). Daniel et al. (1998) find that overconfident investors initially underreact to new information, and thereby contribute to the profitability of momentum strategies. Recently, Chui et al. (2010) show how cultural differences affect the profitability of momentum. They find that the degree of individualism is positively associated with the magnitude of momentum profits. Barberis et al. (1998) report that momentum arises as a combination of representativeness and investor sentiment. However, from studying previous literature, it remains rather unclear which factors support the momentum effect.

Several recent studies discover that momentum profits are stronger for stocks with certain characteristics. Momentum returns are stronger for stocks that are smaller (Hong et al. (2000), Jegadeesh and Titman (2001)). (Daniel and Titman (1999))show that the momentum effect is much stronger for growth stocks (low BM ratio). The relationship between trading volume and price momentum is rather complex but points towards weaker momentum returns for high turnover stocks (Lee and Swaminathan (2000)). Further, Hong et al. (2000) show that momentum is stronger among stocks with lower analyst coverage, higher analyst forecast dispersion (Zhang (2006), Verardo (2009)), and lower return R^2 (Hou et al. (2006)). Since these characteristics are commonly used to proxy for information uncertainty and limits to arbitrage, these findings are often interpreted as evidence in support of behavioral based explanations of momentum.

In addition to the previously mentioned behavioral biases, the disposition effect lately gained importance as a possible explanation for momentum. While theoretical models find that the disposition effect has indeed a major impact on the magnitude of momentum (e.g. Grinblatt and Han (2005), Strobl (2003), Weber and Zuchel (2002)), empirical evidence is mixed regarding the sources of momentum.

2.3. Disposition Effect and Momentum

The disposition effect received support for inducing underreaction to news and driving return predictability. Several recent theoretical and empirical papers offer evidence consistent with the hypothesis that the disposition effect may be one possible explanation for the existence and magnitude of the momentum effect (e.g. Daniel et al. (1998), Grinblatt and Han (2005) Hong et al. (2000), Hong and Stein (1999)). In this paper, we test the predictions of the Grinblatt and Han (2005) model that momentum is partly explained by the presence of the disposition effect.

Grinblatt and Han (2005) develop a theoretical model and argue that investors initially underreact to new information causing the disposition effect. This behavior leads to momentum in stock returns. The authors argue that in turn this explains the profitability of momentum strategies. Underreaction challenges the efficient market hypotheses (Fama (1970)) that prices are believed in reflecting all information about individual stocks and about the market as a whole. Daniel et al. (1998) find that stock prices initially underreact to information and mean-revert in the medium- to long-term horizon. Empirical and theoretical evidence by Grinblatt and Han (2005) as well as by Frazzini (2006) show that the underreaction to information and earnings news results in equilibrium stock prices being lower than fundamental values. As an explanation for this behavior the disposition effect is identified in these papers[3]. Based on underreaction theory, other theoretical models also detect that disposition prone behavior predicts momentum returns (e.g. Strobl (2003), Weber and Zuchel (2002), Xiong and Peng (2006)).

In the setting of Grinblatt and Han (2005), the authors hypotheses that there are a large number of disposition prone investors. Their demand functions are biased and therefore, equilibrium prices are distorted relative to those predicted by rational models. The magnitude of the price distortion depends on the degree to which the marginal investor experiences the stock as a winner

[3]Investors tend to sell stocks that increased in value since purchasing, and therefore depress its price. From this lower basis, subsequent returns tend to be higher. Hence, higher past returns lead to subsequent higher future returns. Similarly, investors require a premium to sell stocks that went down in value since purchasing. From this higher base, subsequent returns tend to be lower.

or a loser. As the share price increases, the disposition prone investor has an increased likelihood for selling the asset too early. Thereby, the disposition prone investor creates a gap between the market value and fundamental value (i.e. its equilibrium price in absence of disposition-prone investors) of the respective stock. Since the upward pressure on the market is decreased, the price adjustment process slows down. Combining with the distorted demand, the respective price will take relatively long to adjust to equilibrium levels thereby generating price underreaction (to public information). From this lower basis (created by the presence of a large enough number of disposition-prone investors), subsequent returns tend to be higher. Similarly, disposition prone investors require a premium to sell stocks which have decreased in value since purchasing; from the higher base subsequent returns tend to be lower. This means that the presence of disposition prone investors results in past winner stocks to be undervalued and past loser stocks to be overvalued.

Another implication of the underreaction theory is that momentum profitability will reverse in the long-run. Therefore, we also expect to find stronger return reversal among stocks with a higher stock-level disposition effect.

Empirical support for the relationship between the disposition effect and momentum includes Grinblatt and Han (2005) in the U.S., and Shumway and Wu (2007) in international markets. Grinblatt and Han (2005) test their implications empirically by constructing a proxy for unrealized gains or losses by comparing the current price of a particular stock to a volume-weighted past price. Shumway and Wu (2007) use data from the Shanghai Stock Exchange and sort stocks based on their unrealized gains and losses, and find a statistically and economic significant ”momentum-like” effect with a winner/loser spread of 7% per year. Using a non-price level related reference point, Zhang (2006) reveals that the degree of underreaction and the level of uncertainty about the news impact stock prices. Using this proxy in return forecasting regressions, any momentum variables are driven out.

Subsequent research finds consistent evidence for the relationship between the disposition effect and momentum: Goetzmann and Massa (2008) provide an empirical test of Grinblatt and Han's (2005) model, and document evidence in favor of their hypothesis that disposition prone behavior drives return predictability. Frazzini (2006) constructs variables for unrealized gains and losses for mutual funds, and finds that the unrealized gains variable has significant predictive power for future returns. Scherbina and Jin (2011) shows the existence of the disposition effect following instances of managerial change. While existing managers continue to hold on to their losing investments, newly-hired managers do not display the disposition effect since they sell the ”inherited” mistakes of their predecessors. They conclude that the disposition effect among mutual fund managers as a large investor group may lead to the existence of the momentum effect. Barber et al. (2007) find evidence against the hypothesis by analyzing trades of different investor groups on the Taiwan Stock Exchange from 1995 to 1999. The authors confirm the existence of the disposition effect, but conclude that the effect is too weak to create momentum. For a sample of U.S. mutual fund managers, Da et al. (2013) discover underreaction to information that arrives continuously in small amounts rather than discrete and large amounts predicts since investors are inattentive to small changes. Their results provide evidence that the disposition effect contributes to price momentum.

Contrary to the previous mentioned results, recent theoretical and empirical evidence makes opposite predictions. This research stream indicates that the disposition effect may slow the incorporation of news into stock prices, but not to the extent that it can be the main and only explanation of return momentum. Theoretical models suggest that contrarian investors are more likely to display disposition prone behavior than momentum traders (e.g. Birru (2011), Dacey and Zielonka (2008)). Cici (2012) notes that selling winners and holding on to losers may lead to portfolios dominated by stocks with negative returns in the past. According to Jegadeesh and Titman (1993) losers will continue to underperform in the short term. Thus, disposition prone fund managers hold portfolios which are heavily tilted towards poor performing momentum stocks, which might be interpreted as short term contrarian orientation.

Empirical evidence supports the theoretical predictions that contrarian and not momentum traders are more likely to display disposition prone behavior (e.g. Birru (2011), Cici (2012) Kubinska et al. (2012), Novy-Marx (2012)). Birru (2011) argues that the disposition effect may reduce the speed of how news are processed in stock prices, but not to the extent that it alone can explain momentum. Cici (2012) shows that that disposition prone funds overweight stocks with negative momentum creating the appearance of following a short-term contrarian strategy. Novy-Marx (2012) discovers that the momentum effect cannot be explained by capital gains overhang or the disposition effect, but rather by a firm's performance twelve to seven months prior to the portfolio formation.

Overall, theoretical models focusing on the link between the disposition effect and momentum yield mixed predictions. In addition, differences in empirical evidence do not allow a clear conclusion to what extent the disposition effect may be a possible explanation for return momentum. This calls for a more detailed analysis of the question whether the disposition effect can be ruled out as an explanation for the momentum effect, and whether alternative explanations need to be developed to explain momentum.

3. Methodology

In this section, we give insights on how the disposition effect is calculated based on the standard approach suggested by Odean (1998). We also show details on the calculation of the momentum effect which is based on the methodology of Jegadeesh and Titman (1993).

3.1. Disposition Effect

To analyze the relationship between the disposition effect and momentum, we first need to calculate the disposition effect. We follow Odean's (1998) approach in determining the level of the disposition effect. We use stock holdings' information of mutual funds as well as the weighted average purchase price[4] to identify the disposition effect. For any given investor, the proportion

[4] The weighted average of shares of all reported purchases is taken as the weighted average purchase price of the stock. The weighted average purchase price is calculated as the purchase price of the stock on the reporting day divided by the amount of shares bought

of all potential realized gains (PGR) and realized losses (PLR) is calculated and compared to paper gains and losses, respectively.

Our research design is implemented as follows: each quarter a sale takes place, the selling price is compared to a reference price in order to determine whether the sale is a realized gain or loss. Results are based on the assumption that trades happen sometime during the quarter, and hence averages of daily stock prices during the respective quarter are used. The reference price in our paper is the historical weighted average purchase price which is updated each time a buy transaction takes place. Using the weighted average purchase price as reference price is based on the assumption that fund managers regularly update their reference points after each purchase.

The proportion of gains realized (PGR) and the proportion of losses realized (PLR) are calculated as follows:

$$PGR_{i,t} = \frac{(realized\ gains)_{i,t}}{(realized\ gains)_{i,t} + (paper\ gains)_{i,t}} \tag{3.1}$$

$$PLR_{i,t} = \frac{(realized\ losses)_{i,t}}{(realized\ losses)_{i,t} + (paper\ losses)_{i,t}} \tag{3.2}$$

We further calculate the disposition effect as difference between the proportion of gains realized and the proportion of losses realized by a mutual fund in

(e.g. Cici (2012), Da Silva Rosa et al. (2005), Grinblatt and Keloharju (2001), Huddart and Narayanan (2002), Odean (1998)).

a given period (e.g. Frazzini (2006), Goetzmann and Massa (2008), Odean (1998), Ringov (2012)). The disposition effect (DE) is defined by the following equation:

$$DE_{i,t} = PGR_{i,t} - PLR_{i,t} \tag{3.3}$$

A fund realizes disproportionally more gains than losses (disposition prone fund) when the difference between proportion of gains realized and the proportion of losses realized is positive. Therefore, the larger the disposition effect gets, the stronger is the level of the disposition effect exhibited by the respective mutual fund manager.

If the disposition effect is an factor explaining stock return momentum, we expect stocks with a higher stock-level disposition effect to exhibit stronger momentum profits than stocks with a low stock-level disposition effect. To test this prediction, we sort our dataset independently into portfolios based on prior returns and on the stock-level disposition effect. While the disposition effect is a fund manager-level characteristic, momentum is a stock-level anomaly. To examine how the disposition effect is related to the momentum effect, we construct stock-level disposition measures. For converting the disposition effect into a stock-level measure, each quarter we calculate for each stock the difference in holdings of the top tercile of managers with the highest and bottom tercile with the lowest disposition measure. In addition, we calculate the weighted average of the disposition measure for each stock (manager's disposition effect weighted by the respective stock holdings). We construct our measure for the disposition effect by comparing the average purchase price with the selling price. We adjust our return calculations for stock splits and dividend payments. Once, we calculated the total loss or gain on each position in the dataset, we calculate average unrealized gains or losses at the stock level by multiplying the unrealized gains or losses of each fund in our dataset by the number of shares the fund purchased or sold.

3.2. Momentum

We follow Jegadeesh and Titman (1993) in constructing the portfolios and using equally-weighted returns. When we sort stocks based on prior performance, we use ten portfolios for calculating the momentum returns. In order to make our results comparable to previous papers, we use the standard momentum methodology proposed by Jegadeesh and Titman (1993) based on deciles rankings and different formation and ranking periods.

To get the monthly raw momentum returns, we follow the methodology proposed by Jegadeesh and Titman (1993). We use different time periods and base our momentum strategy on J-month lagged returns and held for K-month. First, we rank the stocks in our sample in ascending order based on the J-month lagged returns. Second, stocks with the lowest J-month return are placed in the bottom decile and a loser-portfolio is formed as an equally-weighted portfolio of those stocks. Stocks with the highest J-month return are based in the top decile and a winner-portfolio is formed as an equally-weighted portfolio of those stocks (J-month lagged returns and held for K-month where J and K are equal to three, six, nine and twelve months).

Third, we calculate the average monthly raw returns for each portfolio and also for the difference between the winner-minus-loser portfolio (WML). All stocks with available stock return data in the J months before the portfolio formation date are included in our analysis.

To analyze how the disposition effect is related to the momentum effect, we use a 6-month formation period and 6-month holding period for our momentum strategy. We construct several momentum-related variables by sorting stocks by the variable of interest (past returns, disposition effect, stock characteristics) into terciles when we include the disposition effect and stock characteristics in our empirical analysis. Unlike Jegadeesh and Titman (1993), we apply a sorting procedure based on three rather than ten portfolios formed on prior performance since we are comparing momentum profits across different subsamples of stocks. The double- and sometimes triple-sorting procedure (see Section 5.4) could result in less diversified portfolios (and create large standard errors in test statistics), and hence only terciles are considered. We list stocks in the top decile/tercile as "winners" and the stocks in the bottom decile/tercile as "losers". During the holding period, we take a long position in the best and contemporaneously, a short position in the worst performing tercile portfolio. We calculate monthly momentum returns for each disposition level and investigate the returns for a zero investment winner-minus-loser portfolio. To test a possible relationship between disposition prone mutual funds and momentum, we sort all stocks into independent portfolios by one of our disposition measures and prior returns.

We also test test whether return reversal is present in our sample. To determine the return reversal, we use a 6-month formation period and a 24-month holding period starting in month t+13 to month t+36[5].

We implement the momentum strategies with and without a one month lag between the formation period and the holding period. We include a one month lag between the formation and holding period in order to neglect the impact of bid-ask bounce or short-term reversal (Jegadeesh (1990), Lehmann (1990)). In Section 5.2 and in Section 6, we include a one month lag in our analyses.

Prior literature established a significant relationship between momentum and certain stock characteristics; e.g. Hong and Stein (1999) and Jegadeesh and Titman (2001) find that return momentum is stronger for smaller stocks; Hong and Stein (1999) link momentum to analyst coverage; Daniel and Titman (1999) show that momentum is stronger for low book to market stocks; Lee and Swaminathan (2000) shed light on the relationship between momentum and stock turnover finding that stocks with higher turnover ratios exhibit weaker momentum returns. If the stock-level disposition effect is correlated with one or more of these stock characteristics, then our results may be due to stock characteristics and not due to the disposition effect. We include size, book to market ratio, and turnover to account for differences in stock characteristics. To examine whether the disposition effect has incremental explanatory power over these stock characteristics, we apply a triple-sorting procedure based on the stock-level disposition measure, prior returns, and stock characteristics.

[5] In the robustness section, we further analyze different momentum strategies based on different time horizons and subsamples.

4. Data

4.1. Mutual Fund Data

To analyze the previously stated hypotheses, we need holdings data, return information, and fund characteristics of the respective U.S. mutual funds. The data used in this study comes from various sources: quarterly fund holdings data from Thomson Financial, monthly and annual mutual fund characteristics from CRSP, daily and monthly stock return files from CRSP and monthly and annual accounting data from COMPUSTAT.

We obtain our main fund sample by merging the CRSP Survivorship Bias Free Mutual Fund Database (CRSP MF, henceforth) and the Thomson Reuters Mutual Fund Holdings database (TR MF, henceforth) using MFLinks from Wharton Research Data Services (WRDS). For each single fund, information about the fund characteristics (sector, style, starting date, manager, etc.), and performance information (returns, asset under management, fees, etc.) is extracted from the CRSP MF database. In addition to the fund characteristics from CRSP MF, we extract holdings' information from the TR MF database. The TR MF database reports all changes in holdings as well as holdings characteristics, i.e. ticker symbol, *permno* (CRSPs permanent stock issue identifier), *cusip* (CRSP's stock identifier), and the price of each asset on a quarterly basis. The *cusips* are used to extract different accounting information and trading statistics for each stock from COMPUSTAT. Furthermore, we get daily data from CRSP to calculate stock-related variables, e.g. stock volatilities, betas, book to market ratio, and returns. Additional accounting data is retrieved from COMPUSTAT: the annual book value of common equity, market capitalization, intangible assets, earnings, dividend payments, PPE (property, plant, and equipment), and total assets.

To arrive at the final sample used in the empirical analysis, we start with the entire universe of U.S. mutual funds for the period between 1980 and 2010. Next, following previous literature, we limit our sample to U.S., actively managed, diversified equity mutual funds. We match the TR MF and CRSP MF datasets for the period between 1980 and 2010[6].

In our sample, there are funds with multiple asset classes holding the same portfolio of stocks since they are listed as separate entities in the CRSP MF database. They usually vary with respect to their fee structure or minimum purchase limits, but are based on exactly the same portfolio of assets. To avoid multiple counting, we aggregate all share classes of the same fund using the unique *wficn* (Wharton Financial Institution Center fund number) to aggregate fund data across different share classes into one observation per fund-year. For variables which vary across share classes (e.g. returns, turnover ratio, expense ratio, etc.), we take weighted averages using total net assets as weights.

4.2. Stock Data

In the empirical section, we use a triple-sorting procedure based on past returns, the disposition effect, and stock characteristics. We include known factors which are correlated with momentum, namely firm size, book to mar-

[6]For further details on the sample selection process, please refer to Appendix A.

ket ratio, and turnover (e.g. Daniel and Titman (1999), Hong et al. (2000), Lee and Swaminathan (2000)). *Firm size* is calculated as the natural logarithm of the market capitalization in a month prior to the pre-ranking period. Hong et al. (2000) as well as Jegadeesh and Titman (2001) find that return momentum is stronger for smaller stocks. To examine the possibility that our results are related to differences between small and large stocks, we include firm size in the triple-sorting procedure. We also control whether our results are related to differences in the expected growth opportunities of a firm's operations as captured by the book to market ratio (*BM ratio*). Daniel and Titman (1999) find that momentum profits are stronger for stocks with lower book to market ratios as for stocks with higher book to market ratios. The annual book to market ratio is calculated as the book value divided by the current market price. We include the one year lagged book to market ratio in the triple-sorting procedure. We further base our triple-sorting procedure on a stock's *turnover*. Previous papers (e.g. Lee and Swaminathan (2000)) find a negative relationship between return momentum and stock turnover. The authors show that past trading volume provides a link between "momentum" and "value" strategies. In detail, this paper find that firms with high past turnover exhibit lower future returns while stocks with lower past turnover ratios exhibit "value" characteristis. Monthly stock turnover is defined as the number of shares divided by the number of shares outstanding in the month prior to the return pre-ranking period. We use six the months lagged turnover in our sorting procedure.

Stock variables are winzorized at the 1% and 99% level in order to avoid that our results are driven by outliers. In addition, we delete all negative values for observations of firm size, book to market ratio, and stock turnover.

For benchmarking our results, we use the return on S&P 500 index as the market portfolio and the 3-month Treasury bill rate as the risk-free rate which are provided by Datastream.

In order to calculate momentum profits, we use monthly stock return data from CRSP for the time period between 1980 and 2010. We use the data to construct monthly momentum decile/tercile portfolios. Our sample includes all firms listed by CRSP and we only keep stocks with exchange code 1 and 2 (NYSE and AMEX securities, only). Following previous papers (e.g. Brav et al. (2010), Hong et al. (2000), Jegadeesh and Titman (2001)), we only use stocks with share codes equal to 10 and 11 (only common stocks) dropping from our analysis American Depositary Receipts (ADRs), closed-end funds, and Real Estate Investment Trusts (REITs). In addition, we require that firms have valid share prices, a valid number of shares on the formation date, and a valid number of returns over the formation period. We also exclude stocks which are priced below 5$. All prices are closing prices and all returns are calculated close-to-close in line with the general convention and CRSP availability.

4.3. Summary Statistics

Table 1 presents the summary statistics for the 2,536 funds in our sample for the time period between 1980 and 2010. For the analysis of the relationship between the momentum effect and the disposition effect, we analyze 4,511 different stock positions (*cusips*). The sample consists of 2,536 funds and 76,080 fund-year-observations. Our sample includes 201 funds in 1980 and increases over time to 1,236 funds in 2010 showing that mutual funds became a popular investment vehicle especially in the last ten years of our sample period. The average fund in our sample is roughly 16 years in business and has an average fund size of $ 4.31 billion. Over the last 30 years, the average mutual fund yields a return of -0.89%. The net asset value (NAV) of the last trading day of each month is on average $ 16.5 billion. The monthly net asset value value is equal to the fund's underlying assets (including cash) minus its liabilities (fees, expenses, etc.) divided by the number of shares outstanding. Concerning the fee structure of the funds in our sample, we find that marketing and sales fees (12b-1 fees) are 0.5% per year. Our results indicate that the average fund charges a front load of 0.6% paid upfront by the fund investors. The average rear load is 0.3% which the investor has to pay when withdrawing the money from the respective fund. The mean turnover for the whole sample period is 86% implying a holding period of 1.2 years. The turnover figures are comparable to those reported in prior research which are between 85% and 100% (e.g. Cici (2012), Kacperczyk et al. (2008), Singal and Xu (2011)). The expense ratio is on average 1.32%.

Table 1 about here

In addition to fund related variables, we also analyze fund manager characteristics. We include a dummy variable which is equal to one when the respective fund is managed by a team and zero if the fund is managed by a single fund managers. Most of the funds in our sample are managed by single managers (team-managed dummy is equal to 0.3) with an average experience of a fund manager of 11 years. We also report whether a fund is taken over by a new fund manager (dummy variable which is one if the fund manager is three years or less at a specific fund and zero otherwise; see Scherbina and Jin (2011)) and we find that only 3% of the funds are managed by new fund managers. We also look at a fund's capacity which is a dummy variable equal to one if the fund is open to new investors and zero otherwise. We find that mutual funds are on average open to investors (88%). Around 30% of the funds in our sample are institutional funds, the remainder are retail funds.

Table 2 about here

In Table 2, we report the summary statistics for the stock holdings of the 2,536 mutual funds in our sample between 1980 and 2010. We include firm size, book to market ratio, and turnover in our empirical analysis. The average firm size is 13.65 $ million. The mean book to market ratio is 0.72 and the mean turnover rate is 0.97.

5. Empirical Analysis

5.1. Disposition Effect

In this section, we look at the disposition effect calculated as the proportion of realized gains minus the proportion of realized losses. The disposition effect for all funds in our sample for the entire sample period and for different subperiods (1980 to 1989, 1990 to 1999, and 2000 to 2010) is shown in Table 3. The proportion of realized gains, proportion of realized losses and the disposition effect measures are first calculated for each single fund separately. Second, we take the annual averages for each fund. Since we want to calculated stock-related momentum returns, we need to transform the fund-level disposition effect into a stock-related measure. Therefore, in a third step we take the time series averages of the disposition measures for each stock in our sample to calculate the disposition effect on the stock level. In doing so, we assume independence of the disposition effect across mutual funds and stocks.

For the results of the whole sample, there is a significantly positive disposition effect (4.13%) indicating that on average mutual funds in our sample are prone to the disposition bias. Looking at the 25^{th} and 75^{th} percentiles, we see only little variation in our sample. One explanation for the low standard deviation of our sample is rooted in the sample selection process. We only consider actively-managed, domestic equity mutual funds[7]. Additionally, we limit our sample by only including certain stock holdings of the respective mutual funds where enough data is available[8]. Since our sample only shows little variation of the level of the disposition effect, our results in the empirical section need to be treated with caution. The negative scew of the distribution of the disposition effect in our sample needs to be kept in mind for the cross-sectional analysis.

[7]Details on the fund selection process can be found in the Appendix.
[8]Details on the stock selection process can be found in Section 4.2.

Table 3 also shows a decline of the level of the disposition effect over time. While between 1980 and 1989 the bias has a value of 4.42%, it falls to 4.21% in the time between 1990 and 1999, and further declines to 3.86% in the last decade of our sample period. The reduction of the disposition effect might be due to the increased awareness of behavioral finance among practitioners. Some of the first research on the disposition effect was published during the second decade of our sample period (e.g. Grinblatt and Keloharju (2001), Odean (1998), Weber and Camerer (1998)).

Table 3 about here

Our results are in line with previous papers finding a positive disposition effect for mutual fund managers in the U.S. (e.g. Ammann et al. (2012), Frazzini (2006), Scherbina and Jin (2011)). In line, a recent paper by Ammann et al. (2012) shows that the disposition effect is 3.2% calculated on a share basis for the time period 1993 to 2005 for a sample of U.S. equity mutual funds. Frazzini (2006) also finds a positive disposition effect (3.1%) for mutual funds in the U.S. between 1980 and 2002. Scherbina and Jin (2011) report that old managers are reluctant to realize capital losses compared to their newly-hired counterparts, and thereby supports the presence of the disposition effect among established mutual fund managers.

In sum, we discover that the average mutual fund has a stronger preference to lock in gains than to realize losses. In the following, this paper is devoted to shed new light on the relationship between momentum and the disposition effect. First, we report sorting results for different fund and stock characteristics based on different disposition deciles. Second, we analyze whether momentum is present in our sample. Third, we investigate momentum returns in different disposition terciles as well as how reversal in stock returns and the disposition effect are related. Fourth, we further analyze the relationship between the disposition effect and momentum controlling for stock characteristics correlating with momentum like firm size, book to market ratio, and turnover.

5.2. Momentum Effect

In this section, we examine whether momentum exists in our sample and whether different momentum strategies are profitable.

If momentum explains future returns, then winning portfolios should outperform losing portfolios over the relevant holding period. To analyze the performance of winning and losing portfolios, we calculate the average monthly returns of these stocks. We report results with and without a skip of one month between the formation and holding period in Table 4. Some papers argue that a one month skip should be included in the momentum analysis to avoid short-term reversal due to micro structure issues and bid-ask bounce (Jegadeesh (1990), Lehmann (1990), Lo and MacKinlay (1990)).

Table 4 about here

Table 4 reports the results for the different momentum strategies for our sample between 1980 and 2010. Table 4 reports the average monthly raw returns of the different winner and loser portfolios as well as of the zero-cost portfolio (winner-minus-loser portfolio). We find that all reported returns for the winner-minus-loser portfolios are positive indicating that momentum is present in the stocks held by mutual fund managers in our sample. Most returns of the winner-minus-loser portfolio are statistically significant indicating that momentum strategies in the time period between 1980 and 2010 were profitable. The most profitable strategy which yields 1.89% for the winner-minus-loser portfolio is based on a 12-month formation and holding period with no lag between the two periods. When we include a one month skip in our analysis, this reduces the monthly raw return of this strategy to 1.77%. The lowest momentum return of 1.19% is still positive and quite high for a strategy based on a 3-month formation and holding period with one month skip in between.

Having established that momentum is present in our sample, we proceed with analyzing one specific strategy in more detail and how it is related to the disposition effect. We look at the strategy based on a 6-month formation period and a 6-month holding period which does not skip one month in between. We use this specific strategy as it is most commonly used in previous papers and makes our results comparable (e.g. Jegadeesh and Titman (1993)). The results of this strategy are representative for the results of other strategies. Robustness checks with different time periods are performed in the robustness section 6.

5.3. Disposition Effect and Momentum

5.3.1. Baseline Analysis

To test whether the disposition effect may be related to the momentum effect, we apply a double-sorting procedure based on past returns and the disposition effect. In total, we have nine different past-return-disposition portfolios. Portfolio one contains the momentum returns for the stocks with the lowest past returns and lowest disposition effect, while portfolio nine includes stocks with the highest past return and the highest stock-level disposition measure. Like Jegadeesh and Titman (1993), we focus on a momentum strategy with 6-month formation and holding periods[9] using equally-weighted returns.

Panel A of Table 5 reports the average monthly raw returns for the nine different past-return-disposition portfolios. In addition, the table shows the differences between the past winner- and loser-portfolios for each disposition group (PR3-PR1) and the monthly returns for the differences between the highest and lowest disposition terciles (DE3-DE1). The average annual return of the momentum strategy with a 6-month holding and a 6-month formation period without one month skip in between is 0.97% for the full sample (significant with a t-value of 3.34). Analyzing the difference between the past loser (PR1) and past winner portfolios (PR3), we find that the loser portfolios shows weaker momentum returns than the winner portfolio which is in line

[9]In Section 6, we report baseline robustness results using alternative periods for the momentum strategy. We also report results for different subsamples and momentum returns in different market states as well as comparing results for December versus non-December returns. In general, results are robust to different choices of the momentum strategy and different subsamples.

with previous findings (Jegadeesh and Titman (1993)). Momentum profits are significant for some of the disposition effect portfolios and are monotonically decreasing with the level of the disposition effect: the momentum profit for the lowest disposition group is 1.05% while the momentum return for the highest disposition group is 0.63%. The difference in momentum returns between low- and high-disposition portfolios is -0.42% per month which amounts to -5.02% annually. Analyzing the differences between the highest and lowest disposition group (DE3-DE1), we detect a positive difference for the past return loser portfolio (PR1), while the difference is slightly negative (-0.05%) for the past return winner portfolio (PR3). Our results are contrary to the predictions of the Grinblatt and Han (2005) model, but are in line with recent empirical findings by Birru (2011). His results are consistent with models that attribute the ability of the disposition effect to explain momentum, but they cannot determine the extent to which the disposition effect drives momentum. Birru (2011) finds that the disposition effect is absent following stock splits since investors fail to properly update their reference price. However, he discovers the presence of momentum following stock splits which is inconsistent with a model relaying on the disposition effect as the main explanation of return momentum (e.g. Grinblatt and Han (2005)).

Table 5 about here

Panel B of Table 5 reports the average monthly portfolio returns for the mutual fund managers who are in the top tercile of the disposition effect. The results are strikingly similar to those reported in Panel A. Momentum profits decrease over the three different disposition portfolios from 1.33% for the lowest disposition group to 0.73% for the highest disposition group. The results for the top tercile of the disposition effect shows that the magnitude of the disposition effect is based on holding on too long to loser stocks and not selling the winner stocks too early. Monthly raw returns for the past loser portfolio (PR1) are significantly weaker than comparable returns in Panel A. The average momentum profit for all stocks in our sample is 1.16% which is stronger than the reported momentum profit in Panel A.

Panel C of Table 5 shows the average monthly returns for the tercile of fund managers with the lowest disposition effect. The pattern of monthly raw returns is different compared to our previous results. We observe almost the same momentum profits for the highest and lowest disposition terciles. Interestingly, the difference for the winner-minus-loser (PR3-PR1) portfolios between the different disposition tercile groups is fairly small (the difference for the winner-minus-loser portfolio between DE3 and DE1 is -0.02%). The monthly raw momentum profit for the lowest disposition group is 0.77%, while it is 0.76% for the highest disposition group.

In summary, we do not support the hypothesis that more disposition prone investors are a possible explanation for the existence of the momentum effect as developed in the model by Grinblatt and Han (2005). However, our results are in line with recent empirical papers who also detect that on average mutual funds in the highest disposition decile earn lower momentum profits compared to the lowest tercile. In our sample, fund managers earn 1.05% in the lowest disposition decile while fund managers in the highest disposition decile earn monthly momentum profits of 0.63%.

5.3.2. Risk Adjusted Returns

To analyze whether the differences in momentum profits between high- and low-disposition portfolios are a compensation for risk, we calculate risk adjusted returns. As Jegadeesh and Titman (1993) point out, the magnitude of higher past returns may be partly due to higher expected returns. The winner portfolio of the momentum strategy could potentially contain stocks associated with higher risk that would continue to earn higher expected future returns. Contrary to the previously mentioned results, Grundy and Martin (2001) find that momentum profits are not due to a compensation of risk.

To account for the possibility of a risk based explanation of momentum profits, we analyze the Fama and French (1993) three-factor model for the monthly time series of past-return-disposition portfolios in excess of the risk-free rate. As the market index, we use the S&P 500 and as the risk-free rate, we use the 3-month Treasury bill rate. The dependent variables are the momentum profits in each of the past return and past disposition groups. Results are reported in Table 6.

Analyzing the monthly risk adjusted momentum returns, we find that alphas decrease from 0.94% per month for the tercile containing the least disposition prone fund managers. For fund managers with the highest level of the disposition effect, the risk adjusted alpha (0.66%) is almost the same as the reported raw return (0.63%). The monthly difference between the lowest and highest disposition tercile is -0.28% (which is equal to -3.36% on an annual basis).

Table 6 about here

Comparing Table 6 to Table 5, we find that the estimates of alphas are similar to the average raw return results. The relation between disposition tercile one and three is confirmed in the risk adjusted setting: less disposition prone mutual fund managers earn on average higher raw and risk adjusted momentum returns. Overall, our results suggest that the observed momentum differences between stocks held by high- and low-disposition prone fund managers are not a compensation for risk. Our results are in line with previous results by Grundy and Martin (2001) who find that momentum profits cannot be explained by the exposure to the Fama and French (1993) factors. Our results are also comparable to a recent paper by Birru (2011) who shows that the disposition effect is absent following stock splits but momentum is still present. The strong presence of momentum in the low disposition subsample indicates that it is likely that there is more to the story of momentum than just the disposition effect.

5.3.3. Return Reversal

In this section, we analyze the empirical results of Jegadeesh and Titman (1993) and the prediction of the Daniel et al. (1998) model that momentum profits will reverse (e.g. negatively correlated returns) in the long-run as more information becomes available. Bondt and Thaler (1985) also discover long-term-reversal effects for a formation period of six months and a holding period of 36 months. If reversal is present, the market should correct any mispricings in the medium- to long-term horizon. Therefore, if the disposition effect partially induces stock prices to deviate from fundamentals because of the release of news, then prices should fully revert to their fundamental value when the level of the disposition effect is low. Hence, we expect stocks with a lower disposition measure to show stronger reversal than stocks primarily held by more disposition prone fund managers.

To test our prediction, we sort all stocks in independent portfolios based on their prior 6-month return and their prior stock-level disposition effect. We analyze the returns for a 24-month holding period starting in month t+13 to month t+36. We report the results of monthly raw returns in Table 7.

Table 7 about here

We find that return reversal is present for all disposition terciles and that the monthly raw return for a 24-month momentum strategy is on average 0.36% for all stocks in our sample. The 24-month momentum return is 0.36%. This return is lower compared to the mean monthly raw return of the strategy with a 6-month formation period and holding period. The 24-month raw return for the lowest disposition tercile is 0.37% per month, whereas fund managers in the highest disposition tercile earn on average of 0.41% monthly raw returns. Interestingly, we do see a return reversal for all disposition terciles. The reversal is strongest for the lowest disposition tercile. The difference between the strategy of 6-month holding period and 6-month formation period compared to the 24-month strategy for the lowest disposition tercile (DE1) is 0.67%

which is equal to a reversal rate of 65%. The highest disposition group (DE3) does not show as strong reversal rate as their less biased counterparts. Mutual fund managers in the highest disposition decile (DE3) display a reversal rate of 36% (difference of 0.22% per month between the 6-month and 24-month momentum strategy). Overall, the return reversal is strongest for the lowest disposition tercile which is in line with the predication of Grinblatt and Han (2005)'s model.

Figures 1 and 2 about here

Figure 1 and Figure 2 support findings from Table 7. Figure 1 shows the monthly raw returns for the differences between the highest and lowest disposition terciles based on momentum strategies with 3-, 6-, 9-, 24-, and 36-month formation and holding periods, respectively. Analyzing the differences between the highest and lowest past returns for the different disposition groups reveal an interesting pattern. We find that for the lowest disposition tercile monthly returns are decreasing for the momentum strategies with a 3- to 9-month formation and holding periods. The slope is also decreasing for momentum strategies based on 12- to 36-month periods. The figure supports the finding that the return reversal is strongest for stocks held by fund managers in the lowest disposition tercile which is in line with previous results (Daniel et al. (1998), Jegadeesh and Titman (1993)). For the highest disposition group, we find a decrease in monthly raw returns for the formation and holding periods from 3- to 9-month. In contrast, from 9- to 36-month formation and holding periods, we observe an increase in the slope of monthly raw returns. In addition, the figure reveals that the 36-month momentum return is even stronger than the 3-month return which is contrary to the predictions of the Daniel et al. (1998) model.

Figure 2 shows the average monthly raw returns for different portfolios sorted on past returns and the level of the disposition effect. For portfolio one which contains the stocks with the lowest past returns and the lowest level of the disposition effect, we can clearly observe the reversal in returns. In contrast, for portfolio nine which is based on stocks with the highest past returns and the highest level of the disposition effect, the reversal over time is not obvious. For portfolio nine, there is a slight decrease from the 3- to the 9-month based momentum strategy. For time periods longer then nine months, there is no clear relationship observable. In summary, this means that loser portfolios contribute more to return reversal than winner portfolios.

For robustness checks, we analyze risk adjusted returns based on the Fama and French (1993) three-factor model. The results in Table 8 show the same pattern as the results for the raw returns in Table 7. The risk adjusted return for the 24-month momentum strategy is 0.71% for the lowest disposition group and is 0.57% for the highest disposition group.

Table 8 about here

On average, the 24-month momentum return is 0.20% lower compared to the return for the 6-month formation and holding period momentum strategy. The difference between the 6-month formation and holding period return and the 24-month return is 0.23% for disposition tercile one (DE1) and 0.09%

for the highest disposition group (DE3). The results suggest that the return reversal is stronger for the lowest disposition tercile. The analysis for the risk adjusted returns confirms our findings for the raw returns suggesting that the observed differences between high and low disposition prone fund managers are not a compensation for risk. Our results are in line with the reversal patterns documented in Bondt and Thaler (1987). The authors show that momentum profits are not driven by market risk (as measured by CAPM betas).

Overall, our findings suggest that the lowest disposition group trades stocks with a stronger reversal during the analyzed 24-month period while more biased fund managers tend to trade stocks with weaker return reversal rates. The result shows that in the absence or when low level of the disposition effect occur, momentum returns revert to their fundamental values as suggest by the underreaction theory (Daniel et al. (1998)). Our findings also hold for risk adjusted momentum returns and confirm that the observed differences in momentum profits between high- and low-disposition stocks are not a compensation for risk.

5.4. Disposition Effect, Momentum and Stock Characteristics

Prior literature reveals a significant relationship between stock return momentum and certain stock characteristics (e.g. Hong and Stein (1999), Jegadeesh and Titman (2001), Lee and Swaminathan (2000)). In the following section, we consider both stock characteristics and the disposition effect as explanations for high and significant momentum profits. If the discovered stock-level disposition effect is correlated with one or more of these stock characteristics, then our previous results may be rather due to stock characteristics than due to the disposition effect. To rule out this possibility, we apply a triple-sorting procedure based on momentum (6-month formation period and 6-month holding period), the disposition effect and certain stock characteristics.

Previous papers discover that momentum profits are related to certain stock characteristics. For example, Hong and Stein (1999) and Jegadeesh and Titman (2001) find that return momentum is stronger for smaller stocks. Other papers report that momentum returns are stronger for stocks that have low analyst coverage Hong and Stein (1999), and high analyst forecast dispersion (Verardo (2009), Zhang (2006)). Daniel and Titman (1999) show that momentum profits are stronger for low book to market stocks and low return R^2 stocks (Hou et al. (2006)). In addition, in the paper by Lee and Swaminathan (2000) a negative relationship between momentum and stock turnover is documented.

Previous findings are often interpreted as evidence in favor of behavioral based explanations of momentum profits since these stock characteristics are commonly used to proxy for limits to arbitrage and information uncertainty. A recent paper by Bandarchuk and Hilscher (2013) challenges previous findings related to stock characteristics as factors explaining the presence of the momentum effect. The authors find that previously observed patterns are not due to certain stock characteristics but rather because of the fact that stocks with extreme characteristics tend to have more extreme past returns and that in turn results in stronger momentum profits (e.g. Fama and French (1996), Jegadeesh and Titman (1993)). Bandarchuk and Hilscher (2013) show that more volatile stocks and stocks with more extreme past movements tend to be small stocks, have low return R^2, are young and illiquid, have low analyst coverage, high analyst forecast dispersion, high market-to-book ratios, low share prices, and recent turnover was high. Therefore, existing explanations on enhanced momentum profits based on stock characteristics should be reconsidered. Our paper does not take a certain position on what the underlying forces are, but rather wants to test whether the observed relationship between the disposition effect and momentum can be explained by stock characteristics.

To analyze the relationship between momentum, the disposition effect and certain stock characteristics, we employ a triple-sorting procedure. We sort stocks based on the following stock characteristics: firm size, book to market ratio, and stock turnover. We report raw returns and intercepts from Fama and French (1993) regressions of the differences in momentum profits between high- and low disposition portfolios to account that these profits are not a compensation for risk.

5.4.1. Firm Size

Table 9 reports the results for the momentum-disposition portfolios while controlling for firm size. We include firm size as previous papers reveal that momentum profits are related to firm size: smaller stocks which are primarily held by individual investors show stronger momentum than larger stocks (e.g. Hong et al. (2000), Jegadeesh and Titman (2001)). Consistent with our previously reported results, we find that momentum profits decrease with size (for raw returns and risk adjusted returns) for higher disposition levels. Our results only hold for the top tercile of disposition prone fund investors. Contrary to previous findings, we discover an increasing relationship between firm size and momentum profits for the lowest and the middle disposition terciles. While these fund managers earn on average 1.00% monthly raw returns in the smallest firm size tercile, they earn 1.11% in the large cap sector. These results indicate that more biased fund managers try to achieve outperformance by investing in smaller stocks. However, comparing the momentum strategy results for low and high disposition groups, we find that the low disposition group always outperforms the more biased fund manager group despite firm size. The difference between the high- and low-disposition groups is that in the higher disposition group momentum returns are weaker. The effect becomes even stronger in the highest firm size tercile: mutual fund managers in the highest disposition tercile earn raw momentum returns of only 0.07% per month, while their less biased counterparts earn momentum profits of 1.11% per month.

Table 9 about here

In Table 9, we also show the results for risk adjusted return momentum strategies. We confirm our previous results and find that the discovered relationship between the disposition effect and momentum is neither due to firm size nor due to risk related factors. The direction of the difference in momentum profits does not change when comparing raw and risk adjusted returns. Nevertheless, the difference between the momentum profits becomes smaller for the smallest size tercile and larger for the largest firm size tercile. While for the smallest firm size the difference between disposition tercile one (DE1) and three (DE3) in raw returns is 0.23%, the difference in risk adjusted returns is only 0.08%. For the large cap tercile, the difference in raw returns is 1.04% and the difference in risk adjusted returns is 0.85%. Overall, the results for raw and risk adjusted momentum strategies indicate that the previously detected relationship between the disposition effect and momentum is not based on any size- or risk related factors.

5.4.2. Book To Market Ratio

Table 10 reports the raw and risk adjusted returns for the momentum-disposition portfolios controlling for the book to market ratio. We include the book to market ratio since previous papers find that momentum profits are smaller for value stocks than for growth stocks (e.g. Daniel and Titman (1999)). In line with previously reported results, we find that momentum returns are decreasing with the book to market ratio. Table 10 indicates that momentum returns are strongest for stocks which are held by less disposition prone fund managers. More disposition prone fund manager earn weaker momentum returns for all three book to market terciles. The difference between the lowest and highest disposition group is 0.56% for the growth stocks category (book to market ratio tercile one) and 0.47% for the value category (book to market ratio tercile three). The momentum effect is likely to be strongest for those stocks whose valuation requires the interpretation of ambiguous information (growth stock). Our results show that more disposition prone fund mangers have difficulties in valuing information related to stocks with lower book to market ratios. Therefore, one possible explanation is that more disposition prone investors sell their winner stocks too early and hold on to their loser stocks for too long since they misinterpret stock information.

Table 10 about here

In Table 10, we also check whether the observed momentum profits are a compensation for risk. Returns are based on the Fama and French (1993) three-factor model. The results in Table 10 support our findings for the raw returns and confirm that the observed relationship is not attributable to risk. Our results are also in line with findings by Daniel and Titman (1999) illustrating that the momentum effect is stronger for growth stocks than for value stocks. In summary, the negative relationship between the disposition effect and momentum returns is confirmed even when controlling for growth opportunities as proxied by the book to market ratio.

5.4.3. Stock Turnover

Table 11 shows the momentum effect for different disposition terciles while controlling for stock turnover. We find a negative relationship between momentum profits and stock turnover. Table 11 indicates that the momentum effect is strongest for stocks with low turnover. This means that stocks that are less frequently traded are more likely to be momentum stocks. The result may be an indication that less disposition prone fund manager engage in less traded stocks as they may provide better performance as highly traded stocks. Comparing more and less biased fund managers, we can confirm that more biased fund managers systematically underperform regarding the momentum profits compared to less biased fund managers. In the lowest turnover decile, less biased fund managers earn 1.05% raw momentum returns, while more biased fund manager earn only 0.92%. The difference becomes even more pronounced for the highest turnover tercile: less disposition fund managers (DE1) earn 0.85% momentum returns, while more biased fund managers (DE3) earn more than half of these momentum profits (0.34%). Our results are in line with previous findings by Lee and Swaminathan (2000) who show that high (low) volume stocks earn lower (higher) average returns.

Table 11 about here

Table 11 also reports results for risk adjusted returns. We find that our results are robust to risk adjustment. Overall, our results suggest that the disposition effect may be one possible explanation for the momentum effect which holds across different stock turnover levels.

6. Robustness Checks

In this section, we report different robustness checks to show that our results are not due to a particular setting or sample period[10]. We use different formation and holdings periods to construct momentum returns. In addition, we employ different sample periods to account for possible seasonality in momentum profits and analyze momentum-disposition profits in different market states. Results are reported in Table 12.

Table 12 about here

A. Alternative Momentum Strategies

Panel A of Table 12 shows momentum profits for all stocks across different disposition groups, as well as the difference between the highest and lowest disposition terciles. The first row displays the results for a momentum strategy based on a 6-month formation and holding period including a one month skip between. We include a one month gap between the formation and holding period to avoid liquidity or micro structure effects documented in e.g. Jegadeesh (1990), Lehmann (1990), and Lo and MacKinlay (1990). Since stock returns are normally measured close-to-close and traded at the bid or at the ask price, a momentum strategy may spuriously appear to earn abnormal returns because of the bid-ask-bounce. We find similar results as reported in Table 5: momentum profits are positive for all disposition groups. Further, monthly raw returns are higher for the lowest disposition group compared to

[10] We only report results for raw returns. The results for risk adjusted returns are qualitatively similar and available from the author upon request.

the highest disposition group. The difference between the highest and lowest disposition groups (-0.38% with a t-value of -1.43) is comparable to the difference reported in Table 5 (-0.42% with a t-value of -1.30).

In row three and row four of Panel A of Table 12, we examine strategies with the same formation period (six months) and varying holding periods of nine and twelve months, respectively and no gap between the formation and holding period. We show that the relationship between the disposition effect and momentum is not related to the formation or holding period.

Overall, results are robust to different time periods and we can conclude that our main results are not based on the choice of a specific momentum strategy.

B. Seasonality in Momentum Profits

Panel B of Table 12 highlights robustness results regarding seasonality. We divide our sample in subsamples based on December only and non-December months to account for differences in momentum profits. Since the rational grounds for which the disposition effect can occur could also be tax effects, we analyze whether the level of the disposition effect as well as momentum profits decrease in December. Consistent with Odean (1998), we find that tax-motivated selling is most evident in December. In general, our results indicate that momentum profits calculated for all stocks are weaker in December (0.71% with a t-value of 3.76) compared to the average of all months excluding December (0.99% with a t-value of 3.32). On the on hand, supporting the argument that the selling decision in December is driven by tax reasons, we find even negative momentum profits for the highest disposition group in

December (-0.20% with a t-value of -0.39). On the other hand, the lowest disposition group earns higher momentum profits in December (1.18% with a t-value of 6.53) compared to momentum profits in non-December months (1.04% with a t-value of 1.91). These results support that the level of the disposition effect is related to tax incentives as illustrated in previous papers (e.g. Huddart and Narayanan (2002), Da Silva Rosa et al. (2005), Sialm and Stark (2012)). Selling winners too soon and holding on to losers for too long is particularly costly for higher-income fund managers because they face higher marginal tax rates. In contrast, realizing losses in December instead of other months could represent a sophisticated tax minimization strategy (e.g. Lakonishok and Smidt (1986), Poterba and Weissbrenner (2001)). Under the seasonal tax-loss selling hypothesis, investors are more likely to realize past loser stocks in December in order to realize capital losses and defer the realization of capital gains to January.

C. Momentum-Disposition Profits in Different Subsamples

In Panel C of Table 12, we explore results for different subsamples based on different time periods, namely 1980 to 1989, 1990 to 1999, and 2000 to 2010. Momentum profits are stronger in the first subsample and decline over time for all three disposition groups. The same is true for the disposition effect: the effect declines over time and is smallest in the last decade of our sample period. The difference in momentum profits between the highest and lowest disposition groups is largest in the first decade of our sample period. Comparing momentum returns between the lowest and highest disposition tercile, we find that the difference in the first decade is 0.88% and 0.56%.

Previous papers have also shown that momentum returns are decreasing over time, especially after 2000 (e.g. Chuang and Ho (2013), Daniel and Moskowitz (2013), Hwang and Rubesam (2014)). The decline can be attributed to the learning abilities of investors. They learn to value new information more accurately, specifically the information during the formation period, thereby reducing possible mispricing in this period. A second explanation is that fund managers learn to exploit momentum profits and arbitrage them away. Both explanations predict an increased reaction to both winner and loser stocks in the formation period itself, which would result in a substantial decrease in return continuation in the holding period.

In sum, we find that the disposition effect as well as the momentum effect decline over time. We conclude that the relationship between the disposition effect and the momentum effect are not due to a specific time period.

D. Momentum-Disposition Profits in Different Market States

In Panel D of Table 12, we report results across different market states which we define as crisis and non-crisis periods. We include the following years in the results related to the crisis periods: U.S. recessions between 1980 and 1982 and between 1990 and 1992, the Asian crisis of 1997, Russian crisis and the collapse of Long-Term Capital Management (LTCM) in 1998, Dot-com bubble between 2000 and 2001, and the recent financial crisis between 2007 and 2009. We find strong and significant momentum profits for crisis and non-crisis periods, and pronounced differences in momentum profits between the highest and lowest disposition groups. Momentum returns in crisis times are 0.7% smaller compared to the non-crisis returns (0.99% with a t-value of 2.77 in the non-crisis period).

Our results are supported by previous findings (e.g. Cooper et al. (2004), Grundy and Martin (2001)). Cooper et al. (2004) demonstrate that momentum profits are smaller in periods following negative market returns. They define "UP" and "DOWN" market states based on the lagged three-year return of the market. They find that in the "UP" states, the mean monthly returns of an equally-weighted momentum strategy are 0.93%. In the "DOWN" states, the mean monthly returns of an equally-weighted momentum strategy are 0.37%. Their results are robust even when controlling for market as well as size and value.

Interestingly, the difference in momentum returns between the lowest and highest disposition group is large and significant in crisis times indicating that less biased fund managers sell their losing positions at a higher rate than their less biased counterparts. The difference is smaller and becomes insignificant (-0.28% with a t-value of -0.39) during non-crisis times. An explanation may be provided by the results of Kelsey et al. (2011) who examine the asymmetric profitability of momentum trading strategies. The authors conclude that the different reactions of past winner stocks and past loser stocks to market uncertainty drive asymmetric patterns in price continuations. Hence, in times of high volatility which is likely to be during crisis times, more disposition prone fund managers have difficulties identifying the right point in time to sell their losing stock positions.

7. Summary and Conclusion

In this paper, we confirm that past winners outperform past loser. However, there is no generally accepted explanation for high and significant momentum profits. We add to the growing strand of literature showing how behavioral frameworks are helpful in explaining asset pricing anomalies. Motivated by the presence of the disposition effect in our sample, our paper provides empirical evidence on the link between the disposition prone behavior of mutual fund managers and momentum in the cross-section of stock returns. We examine the extent to which the disposition effect among mutual fund managers is responsible for momentum and reversal in stock returns, and how it is related to known stock-related drivers of momentum.

Our main result is that stocks predominately held by less disposition prone fund managers show stronger momentum profits than stocks held by more disposition prone fund managers. Our results do not confirm the predictions of the Grinblatt and Han (2005) model, but are in line with recent empirical findings (e.g. Birru (2011), Kubinska et al. (2012)). Using Fama and French's (1993) three-factor model, we confirm that our findings are not due to a compensation for risk. Including firm size, book to market ratio, and stock turnover as known stock-related characteristics related to momentum does not change our main results. Moreover, stocks held by managers displaying a weaker disposition effect show a stronger reversal compared to stocks predominately held by more disposition prone fund managers. This evidence partly supports the underreaction theory: the disposition effect slows the incorporation of news and induces momentum (Frazzini (2006), Goetzmann and Massa (2008), Grinblatt and Han (2005), Shumway and Wu (2007)). Consistent with these findings, we confirm that a lower level of the disposition effect results in stock prices reverting to their fundamental values.

Our results contribute to recent findings that funds with common strategies - like the momentum strategy - are less prone to behavioral biases (Wei et al. (2013)). While our paper does not disclaim that the disposition effect plays a role in return predictability, our evidence suggests that it is not the only explanation.

A. Appendix: Mutual Fund Sample Selection

This appendix provides additional details of how we constructed our data. The data in this paper is collected from several sources. We start with a sample of all mutual funds in the CRSP MF database covering the period between 1980 to 2010. Both databases are provided by Wharton Research Data Services (WRDS). The focus of our analysis is on domestic equity mutual funds for which the holdings data is most complete and reliable.

We start constructing our sample with the universe of all open-end funds listed by the Survivor-Bias-Free U.S. Mutual Fund Database maintained between January 1980 and December 2010, inclusive. The database covers all (live and dead) equity, bond, and money market mutual funds since December 1961. CRSP MF database provides a complete historical record for each fund, including fund name, identifying information (e.g. fund number, fund name), start and end dates, net asset values, loads, various classification system for investment category, assets under management, returns, fund families, and further items. The initial sample is downloaded from CRSP MF database and the sample constitutes of 1,193,818 observations and 49,004 funds.

Since the estimation of mutual funds' decision-making process (here: disposition effect) also requires holding-level data on fund portfolio decisions, we use a second data source, namely the Thomson Reuters Mutual Fund Holdings database (TR, henceforce). The database contains survivor-bias-free data on quarter-end holdings which are reported by U.S.-based mutual funds in the mandatory Securities and Exchange Commission (SEC) filings. Mutual funds in the U.S. are required by the SEC to report their portfolio holdings semi-annually prior to June 2005 and since then changed to a quarterly reporting mode[11].

The main dataset is created by merging the CRSP MF with the TR MF database by using the MFLinks document, also provided by WRDS. We obtain fund stock holdings from Thomson's SP12 database since 1980, which in turn determines the starting date of our analysis. Thomson sometimes backfills gaps with information from previous quarters which is identified by the variable *rdate* (reporting date). Besides the quarterly frequency of holding reports, a further limitation is that short positions are unobserved. Also, assumptions about holding returns and trade timing have to be made. In addition, *fdate* is reported referring to the actual date for which the holdings are valid. We follow standard practice and limit our sample of holdings to those observations where the *fdate* is equal or larger than the *rdate* to avoid the use of stale data in our analysis (Pool et al. (2012)).

Since we are interested in the domestic portion of funds' portfolios, we remove holdings in firms head-quartered outside the U.S.. We further limit our analysis to actively-managed equity funds and thereby exclude index funds, international funds and funds focused on bonds, governments, REITs, convertible debt, precious metals and other asset classes as these types of funds generally hold and trade in very small quantities of domestic equity. In detail, during each quarter, we include only mutual funds having a self-declared investment

[11] Nevertheless, the majority of mutual funds reported their holdings on a quarterly basis to Thomson prior to June 2005.

objective of *aggressive growth, growth,* and *growth and income, income,* at the beginning of each quarter. As CRSP MF provides one observation per period for each share class of each mutual fund we use the unique *wficn* (Wharton Financial Institution Center Number) fund number for aggregation of fund data across share classes into one observation per fund-year. We calculate weighted-averages using the total net assets of each class as weight for characteristics that vary across fund share classes such as returns and expense ratios. For the total net assets of a fund, we measure the sum of the total net assets of all the classes of that fund.

We merge the TR MF databse with the CRSP MF database using WRDS's MFLinks, a table which links Thomson's fund identifier with those of the CRSP MF database. Approximately 92% of the target universe is matched. The unlinked U.S. equity funds are mainly small, defunct funds where accurate information for a proper linking procedure is not available. In addition, fairly new funds are also less likely to be linked since they are not yet documented in the TR MF database.

We base the selection of our sample on varies filtering methods which are also applied in previous similar studies (e.g. Kacperczyk et al. (2008), Pool et al. (2012)). We eliminate all balanced, bond, money market, sector and international funds, as well as funds which are not primarily invested in equities. In detail, we use the classification information from Lipper, Strategic Insight, Wiesenberger Objective and the variable policy. The following Lipper classification codes are used to determine the funds as equity: LCCE, LCGE, LCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE, MCCE, MCGE, or

MCVE. Further, funds are also defined as equity if they have AGG, GMC, GRI, GRO, ING, or SCG as Strategic Insight classification code, or GRO, LTG, MCG, or SCG as Wiesenberger Objective code. Finally, if the fund has a CS policy (common stocks are the securities mainly held by the fund), we also classify the fund as equity fund. We eliminate all funds which do not meet the above mentioned criteria.

In order to address the problem of the incubation bias (e.g. Evans (2010), Pool et al. (2012)), we drop all observations where the month for the observation is prior to the reported fund starting month in CRSP MF database. In addition, we also exclude observations in CRSP MF where the fund had less than $5 million under management or where fewer than 11 stock holdings are identified (Pool et al. (2012), Scherbina and Jin (2011)) in the previous month since incubated funds tend to be smaller. The rationale behind is to keep our analysis away from errors in the database and underreporting issues. The resulting sample is merged with the TR MF data using MFLinks. The MFLinks table provides information in order to combine the CRSP MF database that covers mutual fund returns, loads/fees/expenses and related information to equity holdings data in the TR MF datasets. In a first step, we obtain the Wharton Financial Institution Center Number (*wficn*) for each share class in CRSP MF database and investment objective codes (*ioc*) from the TR MF database. In a second step, the *wficn* is used to find the associated *fundno* and date range in the TR MF data bank. Funds without a record in MFLinks are dropped from the sample.

Even after the previous mentioned filtering, our sample still contains a number of non-equity as well as international funds. Therefore, we apply further filtering mechanisms (based on Kacperczyk et al. (2008)) in order to ensure a sample consisting only of U.S. based equity funds. We first look at the percentage invested in common shares (*per_com*) from the CRSP MF annual summary file and exclude all funds that on average hold less than 80% or more than 105% in common stocks. In order to check the robustness of the MFLinks merger, we compare total fund assets (*tna*) in CRSP MF to *tna* in the TR MF database which is given in the following equation:

$$Abs_{diff} = \frac{|TNA_{CRSP} - TNA_{TR}|}{TNA_{CRSP}} \tag{A.1}$$

If the median absolute difference for a particular fund over all overlapping data observations is larger than 1.3 or smaller than 1/1.3, we also drop the fund from our sample.

In order to focus on actively-managed funds, we further exclude index funds and ETF. In a first step, we eliminate all funds which are marked as index funds, ETF or ETN in the CRSP MF database. We also apply a second filter procedure which is based on the works of Pool et al. (2012). To do so, we use fund names and drop any fund name including any of the following strings: "Index", "Idx", "Ix", "Indx", "Nasdaq", "Dow", "Mkt", "DJ", "S&P 500", "S&P, 500", "Barra", "DFA", "Vanguard", "ETF", "SPDR", "ETN", "Powershares", "Wisdomtree", "Tracker", and "Profunds".

B. Appendix: Variable Definition

In the following, we outline how our main variables are constructed.

Table B1 – Fund Characteristics

Variable Name	**Description and Definition**
12b-1 fee	12b-1 fees are reported as the ratio of the total assets attributed to marketing and distribution costs.
Expense ratio	Ratio of total investments that shareholders pay for the fund's operating expenses, which include 12b-1 fees. It may include waivers and reimbursements, causing it to appear to be less than the fund management fees.
Front load	Front loads for investments represent maximum sales charges at breakpoint.
Fund age	Fund age in years, relative to the date when the fund was first offered.
Fund return	Quarterly market-adjusted average returns of funds total quarterly return, i.e. the return on the fund's portfolio, including reinvested dividends.
Fund size	Log of annual assets under management (AUM) in millions of $ dollar for each fund.
Manager's experience	Years of manager at specific fund.
NAV	Net asset value in a particular quarter. Reported in $ millions.
New manager	Dummy variable that equals one if the fund manager has been at the fund for less than three years and zero otherwise.
Rear load	Fees which are charged when withdrawing funds.

Variable Name	Description and Definition
Team-managed	Dummy variable that equals one if the fund is managed by a team and zero otherwise.
TNA	Total net assets in a particular quarter. Reported in $ millions.
Turnover ratio	Average of the absolute values of all purchases and sales in a particular quarter divided by the average of the portfolio values at the beginning and end of a particular quarter.

Table B2 – Stock Characteristics

Variable Name	Description and Definition
Book to market ratio	Ratio of book equity to market equity as of December of year t-1. Data is annual and comes from COMPUSTAT.
Firm size	Is the natural logarithm of the market capitalization of a firm in a month prior to the return ranking period. Market capitalization (in $ million) is calculated as shares outstanding times price. The market value of shares traded is based on daily closing price minus daily trading volume. Data is in monthly format and comes from CRSP.
Turnover	Average monthly share volume divided by shares outstanding in the month prior to the portfolio formation period. Data is monthly and comes from CRSP.

8. Tables and Figures

Table 1 – Summary Statistics of Fund Characteristics

The table reports the summary statistics of fund characteristics. The table displays the number of observations (Obs.), mean, standard deviation (Std. Dev.), minimum (Min.) and maximum (Max.). Fund age is the years since the first offer date. Fund size isthe log of annual assets under management (AUM) in millions of \$. Monthly TNA is the monthly total net asset value calculated in million \$. Monthly return is the fund return per month. Monthly NAV is the monthly net asset value in million \$. Expense ratio is the ratio of total investment that shareholders pay for a fund's operating expenses. Turnover ratio is the average of all purchases and sales in a particular quarter divided by the average of the portfolio values at the beginning and end of a particular quarter. 12b-1 fees are fees attributed to marketing and distribution. Front loads are sales charges at breakpoint. Rear loads are fees charged when withdrawing funds. Team-managed is a dummy variable and is equal to one if a fund is team-managed and zero for single fund managers. Manager's experience is measured in years that a manager has worked at a specific fund. New manager is equal to one if the manager is less than three years at the specific fund and zero otherwise.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Fund age	336,226	16.40	13.27	0	86
Fund size	547,888	4.31	2.28	-6.91	11.60
Monthly TNA	294,084	937.75	3'811.44	0.10	58'394.60
Monthly return	296,958	-0.0089	0.0607	-0.3112	0.5097
Monthly NAV	296,991	16.48	16.55	0.16	411.66
Expense ratio	397,910	0.0132	0.0091	0	0.4845
Turnover ratio	395,433	0.8569	0.8224	0	17.1300
12b-1 fees	213,641	0.0055	0.0037	0	0.0133
Front load	322,378	0.0065	0.0158	0	0.1360
Rear load	341,849	0.0029	0.0093	0	0.0600
Team-managed	547,888	0.30	0.46	0	1
Manager experience	221,999	10.86	6.61	2.00	54.03
New manager	547,888	0.03	0.17	0	1

Table 2 – **Summary Statistics of Stock Characteristics**
The table presents the stock characteristics for the 4,511 different stock holdings of the mutual funds in our sample between 1980 and 2010. The table displays the number of observations (Obs.), mean, standard deviation (Std. Dev.), minimum (Min.) and maximum (Max.) of the different stock related variables. Firm size is the natural logarithm of the monthly market capitalization ($ million) of a firm in a month prior to return pre-ranking period. Market capitalization is calculated as shares outstanding times price. Book to market ratio (BM ratio) is the book value divided by market equity as of December in year t-1. Turnover is the average monthly share volume divided by shares outstanding in a month prior to the portfolio formation period.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Firm size	383,574	13.65	1.65	10.08	17.86
BM ratio	131,640	0.7226	0.4635	0.0654	2.8876
Turnover	383,574	0.9706	0.7066	0.1048	3.8151

Table 3 – **Summary Statistics of the Disposition Effect**
The table reports the disposition effect for the whole sample period and different subperiods. It reports the number of observations (Obs.), mean, standard deviation (St. Dev.), 25th percentile (P25), median (P50), the 75th percentile (P75) of the disposition effect for the whole period and for different subperiods (1980 to 1989, 1990 to 1999, 2000 to 2010). The disposition effect is calculated as the proportion of gains realized (PGR) minus the proportion of losses realized (PLR). PGR is defined as the ratio of realized gains to the sum of realized and unrealized gains. Accordingly, PLR is measured as the ratio of realized losses to the sum of realized and unrealized losses. The underlying assumption for the calculation of (capital) gains and losses is that mutual fund managers first sell those stocks with the highest cost basis (HIFO method). The proportion of gains realized, the proportion of losses realized and the disposition effect are calculated on a annual and on a fund level basis. The numbers are calculated in a two-step process: first, the mean proportion of gains realized, the proportion of losses realized and the disposition effect for each fund is calculated separately for all years in which the fund has valid data. Second, we take the time-series average of the disposition measures for each stock in our sample to calculate the disposition effect on a stock-level basis.

Period	Obs.	Mean	St. Dev.	P25	P50	P75
1980-1989	102,061	0.0442	0.0034	0.0411	0.0448	0.0461
1990-1999	136,603	0.0422	0.0028	0.0396	0.0423	0.0446
2000-2010	144,910	0.0386	0.0021	0.0372	0.0386	0.0398
Total	383,574	0.0413	0.0036	0.0388	0.0404	0.0445

Table 4 – Raw Returns of Different Momentum Strategies

The table presents monthly raw returns for different momentum strategies. We base our momentum returns on J-month lagged returns (formation period) and held for K-month (holding period). The different time periods for K and J are displayed in the first column. To get the monthly raw momentum returns, we follow the methodology proposed by Jegadeesh and Titman (1993). First, we rank the stocks in our sample in ascending order based on the J-month lagged returns. Second, stocks with the lowest J-month return are placed in the bottom decile and a loser-portfolio is formed as an equally-weighted portfolio of those stocks. Stocks with the highest J-month return are based in the top decile and a winner-portfolio is formed as an equally-weighted portfolio of those stocks. Third, we calculate the average monthly raw returns for each portfolio and the difference between the winner-minus-loser portfolio (WML). In *Panel A* portfolios are formed immediately after the J-month returns are measured. In *Panel B* portfolios are formed one month after the formation period to account for micro-structure effects. t-statistics are reported in parentheses.

		Panel A	*Panel B*
J=/K=		no lag	1m lag
3m3m	Loser	0.63%	0.84%
		(0.42)	(0.57)
	Winner	2.09%	2.03%
		(1.41)	(1.30)
	WML	1.46%	1.19%
		(2.33)	(4.00)
6m6m	Loser	0.65%	0.78%
		(1.29)	(1.55)
	Winner	2.23%	2.06%
		(3.44)	(3.20)
	WML	1.58%	1.28%
		(1.80)	(1.53)
9m9m	Loser	0.51%	0.55%
		(1.97)	(2.11)
	Winner	2.18%	2.09%
		(6.33)	(6.20)
	WML	1.67%	1.54%
		(2.15)	(2.27)
12m12m	Loser	0.31%	0.33%
		(1.93)	(2.07)
	Winner	2.19%	2.10%
		(10.08)	(9.66)
	WML	1.89%	1.77%
		(2.69)	(2.50)

Table 5 – Momentum Profits Across Stock-Level Disposition Portfolios: Raw Returns

The table presents monthly raw returns of the double-sorting procedure based on past returns and the stock-level disposition effect. Our sample is based on all stocks of mutual fund managers' holdings for our sample period from January 1980 to December 2010. Each year, we allocate all CRSP firms into independent terciles based on their past 6-month return and their stock-level disposition measure. The stock-level disposition measure is calculated as the mean disposition effect for each stock across all mutual fund managers' holdings. DE1 (DE3) is the tercile containing stocks with the lowest (highest) value of the stock-level disposition measure. PR1 (PR3) is the tercile containing past loser (winner) stocks based on a 6-month formation and 6-month holding period. *Panel A* shows the average monthly raw returns over the subsequent six months. It also shows the average momentum returns for the three disposition portfolios, and the average differences in momentum returns between high and low disposition portfolios (DE3-DE1). *Panel B (Panel C)* shows the mean monthly raw returns for a 6-month formation and 6-month holding period for the shares held by the tercile of managers with highest (the tercile of managers with lowest) disposition level. We also report the t-statistics in parentheses and the number of stocks in each past-return-disposition portfolio.

Panel A - All Mutual Funds

Prior return	All stocks	DE1	DE2	DE3	DE3-DE1
PR1	0.44%	0.33%	0.62%	0.70%	0.37%
	(0.44)	(1.22)	(1.36)	(0.92)	(1.56)
# Stocks		1,656	2,207	2,300	
PR2	0.52%	0.38%	0.65%	0.64%	0.26%
	(0.56)	(0.92)	(1.54)	(1.46)	(0.47)
# Stocks		1,645	2,230	2,273	
PR3	1.41%	1.38%	1.63%	1.33%	-0.05%
	(1.10)	(2.30)	(3.18)	(2.76)	(0.08)
# Stocks		1,648	2,215	2,321	
PR3-PR1	0.97%	1.05%	1.01%	0.63%	-0.42%
	(3.34)	(2.00)	(2.01)	(3.10)	(-1.30)

Panel B - Top Tercile Disposition Effect Mutual Funds

Prior return	All stocks	DE1	DE2	DE3	DE3-DE1
PR1	0.15%	-0.17%	0.29%	0.34%	0.51%
	(0.17)	(-0.32)	(0.54)	(0.55)	(0.94)
# Stocks		791	1,308	1,394	
PR2	0.34%	0.07%	0.55%	0.43%	0.35%
	(0.39)	(0.19)	(1.06)	(0.84)	(0.54)
# Stocks		795	1,327	1,408	
PR3	1.31%	1.16%	1.58%	1.07%	-0.08%
	(1.19)	(1.62)	(2.62)	(1.80)	(-0.12)
# Stocks		800	1,324	1,458	
PR3-PR1	1.16%	1.33%	1.30%	0.73%	-0.59%
	(5.12)	(1.18)	(2.79)	(5.06)	(-0.47)

Panel C - Bottom Tercile Disposition Effect Mutual Funds

Prior return	All stocks	DE1	DE2	DE3	DE3-DE1
PR1	0.46%	0.56%	0.56%	0.52%	-0.04%
	(0.44)	(0.87)	(0.90)	(1.33)	(-0.91)
# Stocks		528	465	306	
PR2	0.56%	0.52%	0.58%	0.75%	0.23%
	(0.59)	(0.89)	(1.21)	(1.41)	(0.76)
# Stocks		519	474	314	
PR3	1.30%	1.33%	1.48%	1.28%	-0.05%
	(0.94)	(1.53)	(2.01)	(2.19)	(-0.03)
# Stocks		526	465	304	
PR3-PR1	0.84%	0.77%	0.91%	0.76%	-0.02%
	(2.44)	(3.36)	(1.42)	(1.16)	(-0.20)

Table 6 – Momentum Profits Across Stock-Level Disposition Portfolios: Risk Adjusted Returns

The table presents risk adjusted returns of the double-sorting procedure based on past returns and the stock-level disposition effect. As the market index, we use the S&P 500 and as the risk-free rate, we use the 3-month Treasury bill rate. The stock-level disposition effect is defined as the mean disposition effect for each stock across all mutual fund managers' stock holdings. DE1 (DE3) is the tercile containing stocks with the lowest (highest) value of the stock-level disposition measure. PR1 (PR3) is the tercile containing past loser (winner) stocks based on a 6-month formation and 6-month holding period. We report the Fama and French (1993) three-factor model coefficients (*mktrf* is the market factor, *smb* is the small-minus-big factor, and *hml* is the high-minus low factor) for each of the nine portfolios based on past returns and the disposition effect. In addition, we show the coefficients for the winner-minus-loser portfolios (PR3-PR1). We also report the t-statistics in parentheses based on Newey and West (1987) standard errors robust to heteroscedasticity and serial-correlation for up to three lags.

		Intercept	mktrf	smb	hml
DE1	PR1	0.24%	-0.01%	-0.12%	-0.02%
		(4.19)	(-0.49)	(-5.73)	(-0.87)
	PR2	0.31%	0.03%	-0.07%	-0.02%
		(6.48)	(2.14)	(-4.01)	(-0.93)
	PR3	1.18%	0.08%	-0.14%	-0.02%
		(15.64)	(3.67)	(-4.71)	(-0.60)
	PR3 - PR1	0.94%	0.09%	-0.02%	0.00%
		(52.51)	(15.55)	(-2.18)	(0.07)
DE2	PR1	0.45%	0.04%	-0.05%	0.05%
		(8.13)	(2.21)	(-2.26)	(1.79)
	PR2	0.46%	0.08%	-0.06%	0.07%
		(9.98)	(5.26)	(-2.82)	(2.61)
	PR3	1.46%	0.06%	-0.07%	0.11%
		(19.26)	(2.58)	(-1.78)	(2.28)
	PR3 - PR1	1.01%	0.02%	-0.01%	0.06%
		(50.02)	(3.74)	(-0.92)	(3.01)
DE3	PR1	0.45%	0.04%	-0.10%	0.02%
		(8.52)	(2.61)	(-4.22)	(0.66)
	PR2	0.46%	0.05%	-0.10%	0.04%
		(9.46)	(3.58)	(-5.10)	(1.53)
	PR3	1.12%	0.09%	-0.11%	0.01%
		(15.74)	(4.12)	(-4.34)	(0.19)
	PR3 - PR1	0.66%	0.05%	-0.02%	-0.01%
		(37.41)	(8.70)	(-5.08)	(-0.98)

Table 7 – Return Reversal Across Stock-Level Disposition Portfolios: Raw Returns

The table presents monthly raw returns of the double-sorting procedure based on past returns and the stock-level disposition effect. The table shows the monthly raw momentum returns over a 24-month holding period which is from t+13 to t+36. Each year, we allocate all CRSP firms into independent terciles based on their past 6-month return and their stock-level disposition measure. The stock-level disposition measure is calculated as the mean disposition effect for each stock across all mutual fund managers' holdings. DE1 (DE3) is the tercile containing stocks with the lowest (highest) value of the stock-level disposition measure. PR1 (PR3) is the tercile containing past loser (winner) stocks based on a 6-month formation and 24-month holding period. Results are displayed for all stocks, for different disposition terciles, for different past return terciles as well as for the winner-minus-loser portfolios (PR3-PR1). We also report the t-statistics in parentheses.

Prior return	All stocks	DE1	DE2	DE3	DE1-DE3
PR1	0.39%	0.26%	0.57%	0.54%	0.28%
	(3.57)	(5.89)	(13.47)	(11.88)	(9.39)
PR2	0.44%	0.34%	0.61%	0.61%	0.27%
	(3.99)	(7.73)	(14.13)	(12.46)	(2.08)
PR3	0.75%	0.64%	0.95%	0.95%	0.31%
	(5.43)	(12.28)	(18.07)	(16.07)	(1.73)
PR3-PR1	0.36%	0.37%	0.38%	0.41%	0.03%
	(12.46)	(12.38)	(1.48)	(1.22)	(0.21)

Table 8 – Return Reversal Across Stock-Level Disposition Portfolios: Risk Adjusted Returns

The table presents the coefficients of the Fama and French (1993) three-factor model (*mktrf* is the market factor, *smb* is the small-minus-big factor, and *hml* is the high-minus low factor). As the market index, we use the S&P 500 and as the risk-free rate, we use the 3-month Treasury bill rate. The monthly reported returns are calculated based on the double-sorting procedure relying on past returns and the stock-level disposition effect. The table shows the risk adjusted monthly momentum returns over 24-month from t+13 to t+36 for the nine different portfolios. Results are based on the double-sorting method across the three different disposition terciles and for the different momentum strategies between high and low disposition portfolios. We also report the t-statistics in parentheses based on Newey and West (1987) standard errors robust to heteroscedasticity and serial-correlation for up to three lags.

		Intercept	mktrf	smb	hml
DE1	PR1	0.07%	0.05%	-0.11%	-0.10%
		(2.73)	(6.52)	(-10.47)	(-8.55)
	PR2	0.20%	0.07%	-0.09%	-0.07%
		(8.08)	(10.33)	(-9.86)	(-6.44)
	PR3	0.78%	0.05%	-0.07%	-0.04%
		(14.70)	(2.67)	(-5.10)	(-2.53)
	PR3 - PR1	0.71%	0.00%	0.04%	0.06%
		(2.65)	(-0.36)	(10.19)	(13.64)
DE2	PR1	0.31%	0.08%	-0.06%	-0.05%
		(11.05)	(9.63)	(-4.90)	(-3.42)
	PR2	0.40%	0.10%	-0.08%	-0.03%
		(1.69)	(14.31)	(-6.92)	(-2.37)
	PR3	1.04%	0.05%	-0.03%	0.03%
		(25.84)	(4.64)	(-1.70)	(1.59)
	PR3 - PR1	0.72%	-0.02%	0.04%	0.08%
		(6.21)	(-6.81)	(12.59)	(13.06)
DE3	PR1	0.25%	0.10%	-0.16%	-0.13%
		(8.79)	(12.08)	(-12.37)	(-8.63)
	PR2	0.35%	0.12%	-0.19%	-0.14%
		(13.22)	(15.21)	(-14.91)	(-9.76)
	PR3	0.82%	0.13%	-0.18%	-0.14%
		(19.86)	(10.96)	(-10.44)	(-6.27)
	PR3 - PR1	0.57%	0.03%	-0.02%	-0.01%
		(4.36)	(8.32)	(-5.15)	(-1.72)

Table 9 – Momentum-Disposition Profits Controlling for Firm Size

The table presents monthly raw returns and the alphas of the Fama and French (1993) three-factor model for momentum profits in each momentum-disposition group for different firm size terciles. The reported returns are calculated on the triple-sorting procedure based on momentum, the stock-level disposition effect and firm size. Firm size is measured as the natural logarithm of the market capitalization in a month prior to the return formation period. Momentum is calculated based on a 6-month formation period and 6-month holding period. The table shows the raw and risk adjusted monthly momentum returns over 6-month based on the triple-sorting method across the three different disposition terciles and the three firm size terciles. Size tercile one includes the smallest stocks while tercile three includes stocks with the highest market capitalization. We also report the t-statistics in parentheses for raw returns. For risk adjusted returns, t-statistics are also displayed in parentheses based on Newey and West (1987) standard errors robust to heteroscedasticity and serial-correlation for up to three lags.

		DE1		DE2		DE3	
Size	Prior return	ret	alpha	ret	alpha	ret	alpha
1	PR1	0.80%	0.52%	0.83%	0.73%	0.68%	0.48%
		(1.50)	(4.40)	(1.83)	(8.08)	(1.41)	(5.78)
	PR2	0.62%	0.39%	0.89%	0.59%	0.65%	0.42%
		(1.30)	(3.39)	(1.90)	(6.45)	(1.48)	(5.52)
	PR3	1.80%	1.35%	1.65%	1.30%	1.45%	1.22%
		(2.51)	(8.16)	(3.11)	(10.93)	(2.97)	(10.37)
	PR3-PR1	1.00%	0.83%	0.82%	0.57%	0.77%	0.75%
		(5.43)	(1.78)	(1.78)	(1.97)	(2.50)	(2.09)
2	PR1	0.30%	0.33%	0.55%	0.39%	0.54%	0.40%
		(0.55)	(2.71)	(0.96)	(3.88)	(1.00)	(4.26)
	PR2	0.33%	0.28%	0.61%	0.37%	0.52%	0.45%
		(0.75)	(3.33)	(1.32)	(4.86)	(1.32)	(5.13)
	PR3	1.36%	1.26%	1.56%	1.37%	1.40%	1.32%
		(1.95)	(7.26)	(2.52)	(10.72)	(2.45)	(10.44)
	PR3-PR1	1.06%	0.94%	1.01%	0.98%	0.86%	0.92%
		(6.91)	(1.74)	(3.72)	(0.00)	(4.82)	(2.79)
3	PR1	0.12%	0.09%	0.36%	0.25%	0.90%	0.48%
		(0.24)	(1.12)	(0.66)	(2.45)	(1.40)	(4.05)
	PR2	0.36%	0.35%	0.50%	0.50%	0.72%	0.52%
		(0.85)	(4.81)	(1.22)	(6.14)	(1.44)	(4.72)
	PR3	1.23%	1.09%	1.75%	1.79%	0.97%	0.63%
		(2.51)	(1.21)	(3.32)	(11.34)	(2.06)	(4.78)
	PR3-PR1	1.11%	1.00%	1.39%	1.53%	0.07%	0.15%
		(4.83)	(1.09)	(1.08)	(2.85)	(4.82)	(1.18)

Table 10 – Momentum-Disposition Profits Controlling for Book to Market Ratio

The table presents monthly raw returns and the alphas of the Fama and French (1993) three-factor model for momentum profits in each momentum-disposition group for stocks with different book to market ratios (BM ratios). The reported returns are calculated on the triple-sorting procedure based on momentum, the stock-level disposition effect and the BM ratio. The BM ratio is the ratio of book equity to market equity as of December of year t-1. The table shows the raw and risk adjusted monthly momentum returns over six months based on the triple-sorting across the three different disposition terciles and differences in value- and growth stocks. BM tercile one includes stocks with the lowest tercile BM ratios (growth stocks) while BM tercile three includes stocks with the highest BM ratios (value stocks). We report the t-statistics in parentheses for raw returns and for risk adjusted returns t-statistics are based on Newey and West (1987) standard errors robust to heteroscedasticity and serial-correlation for up to three lags.

		DE1		DE2		DE3	
BM	Prior return	ret	alpha	ret	alpha	ret	alpha
1	PR1	0.12%	-0.06%	0.27%	0.16%	0.68%	0.74%
		(0.27)	(1.05)	(0.60)	(4.32)	(1.41)	(9.41)
	PR2	0.36%	0.29%	0.49%	0.43%	0.65%	0.79%
		(0.89)	(5.04)	(1.17)	(6.76)	(1.48)	(8.89)
	PR3	1.48%	1.39%	1.78%	1.70%	1.45%	1.62%
		(2.62)	(1.24)	(2.86)	(9.59)	(2.97)	(11.65)
	PR3-PR1	1.35%	1.45%	1.51%	1.54%	0.79%	0.88%
		(1.26)	(6.84)	(1.44)	(2.24)	(4.34)	(2.87)
2	PR1	0.15%	0.00%	0.48%	0.39%	0.54%	0.31%
		(0.28)	(2.86)	(0.89)	(6.01)	(1.00)	(6.40)
	PR2	0.32%	0.26%	0.64%	0.58%	0.52%	0.67%
		(0.74)	(5.70)	(1.37)	(8.52)	(1.32)	(9.81)
	PR3	1.16%	1.09%	1.43%	1.35%	1.40%	1.48%
		(1.73)	(1.22)	(2.71)	(13.26)	(2.45)	(1.32)
	PR3-PR1	1.01%	1.09%	0.95%	0.96%	1.07%	1.16%
		(8.14)	(4.22)	(10.03)	(6.83)	(3.71)	(4.55)
3	PR1	0.63%	0.49%	0.85%	0.73%	0.90%	0.62%
		(1.05)	(5.64)	(1.41)	(7.74)	(1.40)	(7.34)
	PR2	0.66%	0.56%	0.65%	0.65%	0.72%	0.53%
		(1.25)	(5.80)	(1.46)	(8.42)	(1.44)	(7.21)
	PR3	1.50%	1.38%	1.35%	1.26%	0.97%	1.17%
		(2.11)	(8.86)	(2.37)	(1.21)	(2.06)	(1.33)
	PR3-PR1	0.88%	0.89%	0.50%	0.53%	0.41%	0.55%
		(7.45)	(2.13)	(2.29)	(8.31)	(0.89)	(5.39)

Table 11 – Momentum-Disposition Profits Controlling for Stock Turnover

The table shows monthly raw returns and alphas of the Fama and French (1993) three-factor model for momentum profits in each momentum-disposition group controlling for stock turnover. The reported returns are calculated on the triple-sorting procedure based on momentum, the stock-level disposition effect and turnover. Turnover is calculated as the number of shares divided by the number of shares outstanding in the month previous to the formation period. The table presents the raw and risk adjusted monthly momentum returns over 6-month formation and 6-month holding period based on the triple-sorting method across the three different disposition and turnover terciles. Turnover tercile one includes stocks with the lowest turnover while tercile three displays results for stocks with the highest turnover. We also show the t-statistics in parentheses for raw returns and for risk adjusted returns, t-statistics are based on Newey and West (1987) standard errors robust to heteroscedasticity and serial-correlation for up to three lags.

		DE1		DE2		DE3	
Turnover	Prior return	ret	alpha	ret	alpha	ret	alpha
1	PR1	0.16%	0.11%	0.37%	0.29%	0.20%	0.11%
		(0.40)	(1.09)	(0.92)	(4.13)	(0.47)	(1.77)
	PR2	0.19%	0.16%	0.63%	0.64%	0.33%	0.28%
		(0.59)	(2.09)	(1.54)	(8.39)	(0.88)	(5.09)
	PR3	1.22%	1.16%	1.61%	1.54%	1.12%	1.08%
		(2.57)	(9.60)	(2.99)	(1.04)	(2.44)	(13.48)
	PR3-PR1	1.05%	1.06%	1.24%	1.25%	0.92%	0.96%
		(1.51)	(4.49)	(1.52)	(1.62)	(5.28)	(6.12)
2	PR1	-0.01%	-0.12%	0.34%	0.27%	0.75%	0.56%
		(-0.02)	(-1.62)	(0.74)	(3.14)	(1.37)	(6.71)
	PR2	0.47%	0.41%	0.59%	0.55%	0.71%	0.65%
		(1.12)	(5.68)	(1.44)	(8.01)	(1.44)	(8.62)
	PR3	1.37%	1.30%	1.54%	1.49%	1.27%	1.19%
		(2.57)	(1.24)	(2.99)	(1.53)	(2.49)	(1.19)
	PR3-PR1	1.38%	1.42%	1.21%	1.22%	0.52%	0.63%
		(2.04)	(4.76)	(3.47)	(0.01)	(2.41)	(3.92)
3	PR1	0.56%	0.36%	1.18%	0.96%	1.54%	1.19%
		(0.94)	(4.86)	(1.68)	(8.57)	(2.18)	(8.92)
	PR2	0.42%	0.34%	0.83%	0.73%	1.42%	1.28%
		(0.85)	(5.30)	(1.50)	(7.73)	(1.92)	(8.51)
	PR3	1.41%	1.32%	1.82%	1.69%	1.88%	1.78%
		(2.12)	(1.45)	(2.85)	(1.39)	(3.02)	(1.15)
	PR3-PR1	0.85%	0.96%	0.63%	0.73%	0.34%	0.59%
		(1.28)	(5.68)	(1.57)	(7.38)	(2.41)	(2.78)

Table 12 – Robustness Checks

The table presents raw returns of the double-sorting procedure based on past returns and the disposition effect. *Panel A* shows momentum results using alternative momentum strategies for the formation and holding period as well as including a one month skip in between. *Panel B* reports results for subsamples based on December only, and non-December months. *Panel C* presents the raw returns for different subsamples (1980 to 1989, 1990 to 1999, 2000 to 2010). *Panel D* shows momentum returns in crisis and non-crisis times. Crisis times are defined as follows: U.S. recessions between 1980 and 1982 and between 1990 and 1992, the Asian crisis of 1997, Russian crisis and the collapse of Long-Term Capital Management (LTCM) in 1998, Dot-com bubble between 2000 and 2001 and the recent financial crisis between 2007 and 2009. We report the t-statistics in parentheses.

Panel A - Raw Returns of Alternative Momentum Strategies

		All stocks	DE1	DE2	DE3	DE3-DE1
6m-1m-6m	PR3-PR1	0.78%	0.85%	0.80%	0.47%	-0.38%
		(2.89)	(1.62)	(1.59)	(1.81)	(-1.43)
6m-0m-3m	PR3-PR1	0.58%	0.66%	0.60%	0.38%	-0.28%
		(1.32)	(4.87)	(1.18)	(3.63)	(-8.89)
6m-0m-9m	PR3-PR1	1.18%	1.29%	1.22%	0.74%	-0.55%
		(7.20)	(2.55)	(2.41)	(3.07)	(-2.08)
6m-0m-12m	PR3-PR1	1.56%	1.61%	1.59%	1.12%	-0.49%
		(1.06)	(3.32)	(3.14)	(3.72)	(-2.66)

Panel B - Raw Returns in December and Non-December Months

		All stocks	DE1	DE2	DE3	DE3-DE1
December	PR3-PR1	0.71%	1.18%	0.66%	-0.20%	-1.38%
		(3.76)	(6.53)	(1.31)	(-0.39)	(-4.09)
Non-December	PR3-PR1	0.99%	1.04%	1.04%	0.70%	-0.34%
		(3.32)	(1.91)	(2.05)	(4.29)	(-0.89)

Panel C - Raw Returns in Subsamples

		All stocks	DE1	DE2	DE3	DE3-DE1
1980-1989	PR3-PR1	1.35%	1.43%	1.55%	0.98%	-0.45%
		(2.46)	(2.07)	(3.07)	(1.43)	(-0.33)
1990-1999	PR3-PR1	1.01%	1.29%	1.05%	0.58%	-0.70%
		(4.06)	(4.87)	(2.08)	(1.50)	(-1.08)
2000-2010	PR3-PR1	0.65%	0.55%	0.60%	0.42%	-0.13%
		(4.21)	(0.60)	(1.20)	(0.65)	(-0.49)

Panel D - Raw Returns in Crisis and Non-Crisis Times

		All stocks	DE1	DE2	DE3	DE3-DE1
Crisis	PR3-PR1	0.92%	1.07%	0.84%	0.51%	-0.55%
		(4.15)	(1.75)	(1.66)	(0.75)	(-7.21)
Non-crisis	PR3-PR1	0.99%	1.00%	1.15%	0.72%	-0.28%
		(2.77)	(2.76)	(2.28)	(1.99)	(-0.39)

Figure 1 – Monthly Raw Returns for Different Disposition Terciles and Different Momentum Strategies

The figure shows the average monthly raw returns for different disposition terciles. DE1 is equal to the disposition tercile with the lowest disposition effect, whereas DE3 is equal to the top disposition tercile. The figure displays monthly raw returns for the winner minus loser portfolio for different momentum strategies ranging from a 3-month formation period and 3-month holding period to a 36-month formation period and 36-month holding period.

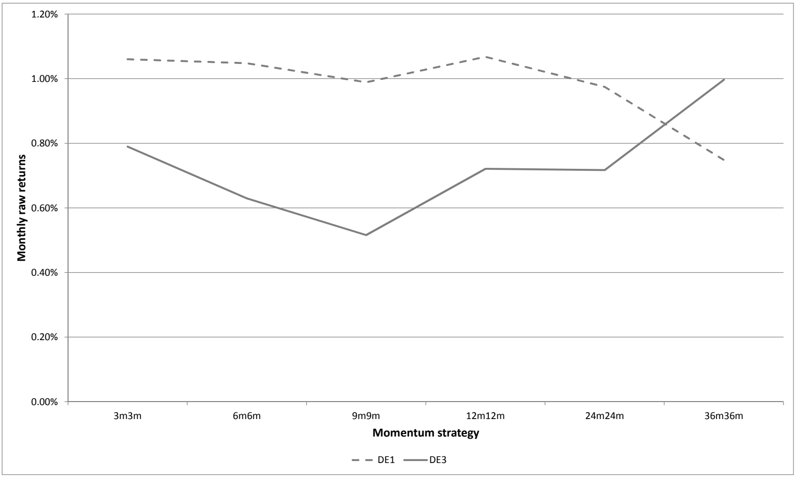
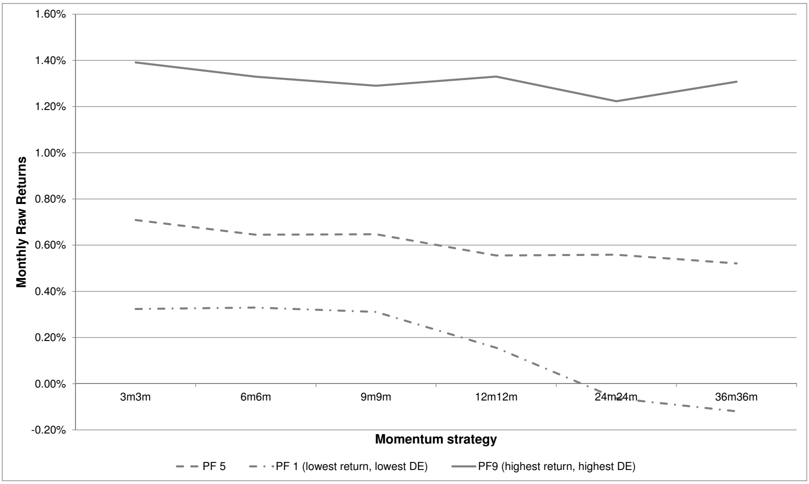


Figure 2 – Monthly Raw Returns For Different Past-Return-Disposition Portfolios

The figure shows the average monthly raw returns for different portfolios sorted on past returns and the level of the disposition effect. Portfolio one contains the stocks with the lowest past returns and the lowest level of the disposition effect. Portfolio nine is based on stocks with the highest past returns and the highest level of the disposition effect.



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Professional Experience

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