Essays on Investor Behavior in Mutual Fund Investments

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Inhalt

Teil I

Einleitung

1 Problemstellung und Stand der gegenwärtigen Forschung

Die private Geldanlage hat in den letzten Jahren stark an Bedeutung gewonnen. So hat sich das Geldvermögen privater Haushalte seit 1993 von 2,3 Billionen Euro auf 4,4 Billionen Euro im Jahr 2008 beinahe verdoppelt (vgl. Bundesbank (2009)). Dieses Thema wird auch in den nächsten Jahren immer wichtiger werden, da die gesetzliche Rente zukünftig vermehrt durch private Rücklagen ergänzt werden muss, um den im Alter benötigten Geldbedarf zu decken.

Von den verschiedenen Möglichkeiten der Geldanlage hat insbesondere die Anlageklasse der Investmentfonds an Bedeutung gewonnen: Wurden 1993 nur 5,9% des gesamten privaten Geldvermögens in Investmentfonds angelegt, so waren es im Jahr 2008 bereits 11,3%. Dies entspricht einem Wachstum um 9,0% p.a., von 136 Milliarden Euro (1993) auf 497 Milliarden Euro (2008). Damit sind Investmentfonds die mit Abstand am stärksten wachsende Anlageklasse im Vergleich zu Anlagen in Versicherungen (6,7% p.a.), Anlagen aus Pensionsrückstellungen (3,9% p.a.), Anlagen bei Banken (3,2% p.a.) und direkte Anlagen in Wertpapieren (2,7% p.a.)[1].

Bereits seit den 50er Jahren des letzten Jahrhunderts beschäftigt sich wissenschaftliche Literatur mit der Fragestellung, wie Investoren optimal Ihr Geld anlegen sollten. Ausgehend von Markowitz (1952) gibt die moderne Portfoliotheorie Leitsätze vor, wie private Investoren ihr Portfolio strukturieren sollten, um ein optimales Verhältnis von erwarteter Rendite und Risiko zu erhalten. Allerdings verhalten sich private Investoren in der Realität nicht rational und legen ihr Geld nicht gemäß der Portfoliotheorie an. Hieraus hat sich in den letzten Jahren ein eigener Forschungsstrang entwickelt, der auch als *Behavioral Finance* bezeichnet wird. Wissenschaftler stellen hierbei eine Grundannahme der Portfoliotheorie in Frage: Das rationale Handeln der Investoren.

So gibt es eine ganze Reihe von wissenschaftlichen Beiträgen, die irrationale Verhaltensmuster bei Investoren aufdecken. Zum Beispiel untersuchen Shefrin und Statman (1985) den Dispositionseffekt, d.h., die Tatsache, dass Investoren gewinnbringende Wertpapiere zu früh verkaufen und verlustbringende Wertpapiere zu lange halten. Ein weiteres Beispiel ist der sogenannte „Home-Bias“ (vgl. u.a. Lewis (1999)): Investoren übergewichten in ihren Portfolios einheimische Wertpapiere und versäumen somit, das

[1] Alle Zahlen aus: Bundesbank, Deutsche, 2009, "Geldvermögen und Verbindlichkeiten der Privaten Haushalte 1991 - 2008".

Risiko international zu diversifizieren. Coval und Moskowitz (1999) zeigen sogar, dass Investoren auch innerhalb der einheimischen Wertpapiere Papiere von Unternehmen, die in der Nähe ihres Wohnortes ihren Firmensitz haben, übergewichten. Barber und Odean (2000) belegen, dass übermäßig häufiges Handeln zu einer unterdurchschnittlichen Portfoliorendite führt. Sie erklären diesen Zusammenhang damit, dass Investoren, die übermäßig viel handeln, in der Regel ihre eigenen Fähigkeiten überschätzen. In einer weiteren Arbeit finden Barber und Odean (2001) heraus, dass insbesondere Männer zu übermäßigem Trading und somit zu Selbstüberschätzung neigen. Mit allgemeinen Aspekten fehlender bzw. mangelhafter Portfolio Diversifikation beschäftigen sich Bernatzi und Thaler (2001). Sie finden heraus, dass viele Investoren Wertpapiere in ihren Pensionsrücklagen einfach mit der Heuristik 1/n gewichten - ungeachtet von Überlegungen hinsichtlich einer optimalen Asset Allocation. Bezüglich der Anlagen in Investmentfonds stellt Gruber (1996) die Frage, warum Investoren in aktiv gemanagte Fonds investieren, obwohl diese sich im Durchschnitt schlechter als der Markt entwickeln.

Vor dem Hintergrund von massiven Investmentfehlern privater Investoren hat vor kurzem Campbell (2006) ein neues Forschungsgebiet abgegrenzt, das er mit *Household Finance* bezeichnet. Dabei fordert er Wissenschaftler dazu auf, ein besseres Verständnis dieser Investmentfehler zu gewinnen, um somit die daraus resultierenden Verluste zu begrenzen. Als weit verbreitete Investmentfehler identifiziert er insbesondere die Unterlassung, in riskante Anlageklassen zu investieren, mangelhafte Diversifikation riskanter Portfolios sowie das Versäumnis Optionen zum Refinanzieren von Hypotheken auszuüben.

Die vorliegende Dissertation greift diesen Punkt auf und hat zum Ziel, Investmentfehler privater Investoren im Bereich von Investmentfonds aufzudecken, ihre Implikationen zu untersuchen sowie die Frage zu beantworten, ob Finanzberater privaten Investoren dabei helfen, diese Fehler zu vermeiden.

Parallel zu der starken Verbreitung von Investmentfonds hat sich auch eine große Anzahl an Literatur entwickelt, die sich mit Investmentfonds beschäftigt. Im Folgenden wird, ausgehend von Anderson und Schnusenberg (2005), ein Überblick über diese Literatur gegeben. Dabei wird sich auf diejenigen Arbeiten fokussiert, die Bezug zu der vorliegenden Dissertation haben. Für einen breiteren Überblick über Literatur zum Thema Investmentfonds sei der Leser auf Anderson und Schnusenberg (2005) verwiesen. Diesen beiden Autoren folgend wird die existierende Literatur in drei Teilgebiete unterteilt, nämlich (i) Performance von Investmentfonds, (ii) Market-Timing, d.h. die Fähigkeit des Fonds, Marktphasen zu antizipieren, und (iii) Persistenz von Investmentfonds.

Wissenschaftliche Arbeiten zum Teilgebiet Performance von Investmentfonds gibt es seit den 60er-Jahren des letzten Jahrhunderts. Zuvor wurde die Wertentwicklung von Investmentfonds durch Vergleich der jeweiligen einfachen Rendite mit den Renditen anderer Fonds bewertet. Dabei wurde das Risiko, das der Fond eingeht, um die Rendite zu erwirtschaften, nicht in Betracht gezogen. Dies hat sich erst durch den Einzug der modernen Portfoliotheorie geändert (vgl. z.B. Treynor (1965) oder Sharpe (1966)). Das auch heute noch gebräuchlichste risiko-adjustierte Performance-Maß ist Jensens Alpha (Jensen (1968)). Hierbei wird die Performance eines Investmentfonds, das sogenannte Alpha, relativ zu seinem Benchmark-Index gemessen. Ist das Alpha positiv, so ist dies ein Zeichen für eine überdurchschnittliche Wertpapierauswahl des Fonds. Ein negatives Alpha hingegen bedeutet entweder eine unterdurchschnittliche Wertpapierauswahl oder hohe Kosten.

In den darauf folgenden Jahren beschäftigt sich die Literatur hauptsächlich mit Fragestellungen, wie sich die Wertentwicklung unterschiedlicher Fondstypen und Anlageschwerpunkte unterscheidet (z.B. Carlson (1970) und McDonald (1974)) bzw., inwieweit sich die konkrete Auswahl des Benchmark-Index auf die Wertentwicklung auswirkt (z.B. Lehmann und Modest (1987)). Seit Ende der 80er Jahre hält dann die Berücksichtigung der Fondskosten vermehrt Einzug in die Literatur: So identifizieren zum Beispiel Grinblatt und Titman (1989) eine überdurchschnittliche Performance bei Wachstumsfonds und bei kleineren Fonds. Sobald sie jedoch die Kosten in ihre Betrachtung mit einbeziehen, verschwinden diese abnormalen Renditen. In einer weiteren Arbeit analysiert Malkiel (1995) Aktienfonds im Zeitraum 1971 bis 1991. Er erhält im Durchschnitt positive Alphas vor der Betrachtung von Kosten und negative Alphas nach der Betrachtung von Kosten. Allerdings sind alle Alphas nicht statistisch signifikant verschieden von Null. Eine zentrale Forschungsarbeit hinsichtlich der Performance von Investmentfonds ist die Arbeit von Gruber (1996). Der Autor zeigt, dass aktiv gemanagte Investmentfonds sich im Durchschnitt um 1,94% p.a. schlechter entwickeln als der Markt. Diese negative Wertentwicklung hat Bestand, auch wenn andere Performancemaße verwendet werden. Wermers und Moskowitz (2000) zerlegen die Rendite von Investmentfonds in drei Faktoren, nämlich in die gehaltenen Aktien, die anteiligen Kosten sowie die Transaktionskosten. Die Autoren zeigen, dass die Aktien, welche der durchschnittliche Fond hält, zwar überdurchschnittliche Renditen erwirtschaften, die Nettorendite des gesamten Fonds hingegen 1% niedriger als der entsprechende Benchmark-Index ist. Dieser Renditeunterschied lässt sich zum einen durch die Kosten und zum anderen durch den Anteil des Fondsvermögens, der nicht in Aktien investiert ist, erklären.

Neuere Literatur beschäftigt sich hauptsächlich mit alternativen Ansätzen, um die Performance von Investmentfonds zu messen (z.B. schlagen Baks, Metrick und Wachter (2001) ein Bayes'sches Maß vor), sowie mit dem optimalen Incentive-Modell für Fondsmanager (z.B. Elton, Gruber und Blake (2003)).

Zusammenfassend lässt sich also sagen, dass die Forschung in den letzten 50 Jahren umfassende Modelle erarbeitet hat, Fondsrenditen unter Berücksichtung des eingegangenen Risikos zu messen. Allerdings entwickeln sich die meisten Fonds schlechter als der jeweilige Vergleichs-Index.

Frühe Arbeiten zum Teilbereich Market-Timing präsentieren statistische Modelle, mit denen die Fähigkeit von Fonds bzw. der Fondsmanager gemessen werden soll, Marktbewegungen zu antizipieren (z.B. Treynor und Mazuy (1966) und Hendrickson und Merton (1981)). In den folgenden Jahren untersuchen Wissenschaftler hauptsächlich die Fragestellung, ob Fondsmanager besser darin sind, die richtigen Wertpapiere zu identifizieren oder Marktphasen richtig zu antizipieren. Als Beispiel hierfür sei die Arbeit von Kon (1983) genannt, welcher zeigt, dass in seinem Datensatz Investmentfonds bessere Ergebnisse hinsichtlich der Auswahl der Wertpapiere als hinsichtlich des Market-Timings erzielen.

Jagannathan und Korajczyk (1986) zeigen, dass Investmentfonds, die signifikante Timing-Charakteristika aufweisen, sich häufiger unter- als überdurchschnittlich entwickeln. Eine wichtige Arbeit haben Ferson und Schadt (1996) zur Diskussion beigesteuert. Sie modifizieren das Alpha-Maß von Jensen (1968) sowie die Market-Timing-Modelle von Treynor und Mazuy (1966) und Hendrickson und Merton (1981) dergestalt, dass sie „bedingte Informationen“ berücksichtigen, d.h., sie betrachten zeit-abhängige Betas. Mit diesem Modell finden sie heraus, dass Investmentfonds in der Tat bedingte Informationen über Marktbewegungen nutzen. Weitere zeitbedingte Modelle entwickeln anschließend Ferson und Warther (1996) und Becker, Ferson, Myers und Schill (1999). Schließlich schlägt Jiang (2003) ein neues, nicht-parametrisches Maß für die Fähigkeit vor, Marktphasen zu antizipieren. Mit diesem Maß zeigt der Autor, dass die Wahrscheinlichkeit, dass ein Fondsmanager die Marktphase falsch antizipiert, höher ist als die Wahrscheinlichkeit, dass er die Marktphase richtig antizipiert.

Insgesamt hat die Literatur zum Teilgebiet Market-Timing also Modelle entwickelt, die die Fähigkeit messen, Marktphasen zu antizipieren. Mit diesen Modellen lassen sich zwar Anzeichen finden, dass Fonds diese Antizipations-Fähigkeiten besitzen; allerdings ist die Wertentwicklung dieser Fonds trotzdem unterdurchschnittlich.

Der dritte Teilbereich der Literatur bezüglich Investmentfonds beschäftigt sich mit der Frage, ob Investmentfonds persistent sind, d.h. ob Fonds, welche sich in der Vergangenheit überdurchschnittlich entwickelt haben, sich auch in Zukunft überdurchschnittlich entwickeln werden. Erste empirische Studien von Sharpe (1966) sowie Grinblatt und Titman (1992) zeigen, dass Unterschiede in der Wertentwicklung von Investmentfonds im Laufe der Zeit bestehen bleiben. Elton, Gruber und Blake (1996) bekräftigen diese Ergebnisse, indem sie risiko-adjustierte Performance-Maße anwenden. Auch, wenn es zwischenzeitlich kontroverse Diskussionen gab (z.B. zwischen Hendricks, Patel und Zeckhauser (1993) und Carhart (1997)), zeigen darauffolgende Studien wiederum die Existenz der Performance Persistenz bei Investmentfonds (z.B. Hsiu-Lang, Jegadeesh und Wermers (2000) sowie Wermers und Moskowitz (2000)). Chevalier und Ellison (1999) können belegen, dass hauptsächlich die Fondsmanager und nicht die Fonds selbst für herausragende Fonds-Performance verantwortlich sind. In einer aktuelleren Arbeit nutzen Kosowski, Timmermann, Wermers und White (2006) eine spezielle Bootstrap-Analyse und finden heraus, dass die Fondsmanager, die überdurchschnittliche Alpha-Performance mit ihren Fonds erzeugen, in der Tat besondere Fähigkeiten besitzen und nicht einfach nur Glück haben.

Zusammenfassend kann man also sagen, dass, obwohl das Thema in den letzten Jahren kontrovers diskutiert worden ist, Persistenz in der Wertentwicklung von Investmentfonds zu existieren scheint.

2 Vorgehensweise und Einordnung in die bestehende Literatur

Diese Dissertation besteht insgesamt aus drei Forschungsarbeiten. Die erste Arbeit beschäftigt sich mit der Fragestellung, welche Kriterien Privatinvestoren nutzen, wenn sie Investmentfonds kaufen. Neben der Analyse einzelner möglicher Kaufkriterien wird außerdem untersucht, welches dieser Kriterien bei der Kaufentscheidung das dominierende ist. Der zweite Forschungsbeitrag untersucht insbesondere, welche Auswirkungen die Fähigkeit, Investmentfonds mit Hilfe historischer Wertentwicklungen auszuwählen, auf den gesamten Anlageerfolg hat. Die dritte Forschungsarbeit untersucht schließlich die

Fragestellung, inwieweit Finanzberater ihren Kunden helfen, bessere Investmentfonds auszuwählen und somit ihre „Investmentsophistikation“[2] zu verbessern. Dabei werden auch potentielle Endogenitätsprobleme adressiert.

Alle drei Fragestellungen bauen auf derselben Datengrundlage auf, die von einem deutschen Online-Broker zur Verfügung gestellt wurde. Dieser Datensatz umfasst soziodemographische, Portfolio- und Transaktionsdaten. Soziodemographische Daten beinhalten investorspezifische Informationen wie z.B. Alter, Geschlecht, Familienstand, Risikoeinschätzung sowie die Information, ob der Kunde beraten wird. Monatliche Portfoliodaten liegen von Januar 2000 bis Juli 2007 vor, während Transaktionsdaten den Zeitraum von Januar 1999 bis Juli 2007 umfassen. Insgesamt beinhalten die Transaktionsdaten mehr als 19 Millionen Transaktionen von ca. 71.000 Investoren. Dieser detaillierte Datensatz ermöglicht es, mit Analysen auf Investoren- bzw. Transaktionsebene einen Beitrag zur bestehenden Literatur bezüglich Investmentfonds, smarten Investmententscheidungen, Household Finance sowie Finanzberatung zu leisten.

Die Tatsache, dass die Daten auf Transaktionsebene vorliegen, hat im Vergleich zu vielen bestehenden Studien, die mit monatlichen Mittelzuflüssen arbeiten, mehrere Vorteile: Erstens kann so zwischen Käufen und Verkäufen unterschieden werden. Mittelzuflüsse hingegen sind immer die Differenz von aggregierten Kaufstransaktionen und aggregierten Verkaufstransaktionen. Da für Kaufentscheidungen zum einen nur eine eingeschränkte Menge an Investmentfonds zur Verfügung steht (nämlich diejenigen Fonds, die der Anleger zum Verkaufszeitpunkt im Portfolio hält) und zum anderen die Verkaufsentscheidung von anderen Motiven als der smarten Entscheidungsfindung beeinflusst werden kann (z.B. Liquiditätsengpässe, Steueroptimierung), fokussiert die vorliegende Arbeit sich auf Kaufentscheidungen. Studien, die auf Mittelzuflüssen beruhen, sind hingegen immer verzerrt durch die Fonds-Verkäufe. Zweitens ist es ein Vorteil des vorliegenden Datensatzes, dass sich auf Kaufentscheidungen von privaten Investoren beschränkt werden kann. Lediglich aus Mittelzuflüssen hingegen lässt sich nicht erkennen, ob es sich um private oder institutionelle Anleger handelt. Drittens besteht die Möglichkeit, die Daten auf einer wöchentlichen Basis zu analysieren, wohingegen Zuflüsse im Allgemeinen nur monatlich oder per Quartal berichtet werden.

[2] Unter einem „sophistizierten“ Investor verstehe ich Anleger, die zum einen hinreichend informiert und zum anderen hinreichend erfahren sind, und somit für sich passgenaue Investmententscheidungen treffen.

Um das Kaufverhalten bei Investmentfonds von Privatinvestoren zu studieren, muss der Datensatz natürlich noch mit weiteren Informationen über die Investmentfonds angereichert werden. Hierfür werden die Datenbanken von Morningstar sowie dem deutschen Anbieter VWD genutzt. Wöchentliche Performancedaten der Investmentfonds stammen von Thomson Financial Datastream. Letztendlich wird für die Analysen ein Datensatz konstruiert, der mehr als 2,8 Millionen Fonds-Transaktionen von ungefähr 49.000 unterschiedlichen Investoren beinhaltet.

Im verbleibenden Teil der Einleitung soll dargestellt werden, wie jede der drei Forschungsarbeiten in die aktuelle Literatur eingebettet ist. Außerdem werden die Kernergebnisse und Implikationen der Arbeiten zusammengefasst.

Wie im ersten Kapitel dieser Einleitung beschrieben, scheint Persistenz bezüglich der Wertentwicklung von Investmentfonds zu existieren. Auch wenn dies ein kontrovers diskutiertes Thema ist, so lässt sich auf jeden Fall sagen, dass Investoren, die aktiv gemanagte Fonds kaufen, daran glauben müssen, dass diese Fonds überdurchschnittliche Renditen abwerfen. Im anderen Fall wäre es für sie eine dominante Strategie, einfach den Marktindex zu kaufen. Da es aber auch keine anderen Messgrößen für zukünftige überdurchschnittliche Fondsrenditen gibt, müssen diese Investoren schlussendlich an die Persistenz glauben. Investoren, die Investmentfonds nicht anhand historischer Performance auswählen, machen also kostspielige Investmentfehler.

Allerdings hat die bestehende Literatur, die den Zusammenhang von historischer Wertentwicklung und Mittelzuflüssen in Investmentfonds untersucht (z.B. Gruber (1996), Sirri und Tufano (1998) oder Ber, Kempf und Ruenzi (2008) für den deutschen Markt), gezeigt, dass Fonds, die sich unterdurchschnittlich entwickeln, nach wie vor Zuflüsse verzeichnen. Gruber (1996) gibt für dieses „Puzzle" zwei mögliche Erklärungen: Zum einen vermutet er, dass institutionelle Schranken[3] Investoren davon abhalten könnten, bessere Fonds zu kaufen. Die andere Erklärung ist, dass Investoren schlicht „unsophistiziert" sind. In der ersten Forschungsarbeit mit dem Titel ***„The Determinants of Mutual Fund Inflows – Evidence from Private Investor Transactions"*** wird auf diese Fragestellung eingegangen. Es wird gezeigt, dass die Investoren in diesem Datensatz, die aus dem vollständigen Investmentfonds-Universum auswählen können und daher institutionell unbeschränkt sind,

[3] Institutionelle Schranken bedeuten, dass Investoren nicht Fonds aus dem gesamten Investmentfond-Universum auswählen können, sondern beim Fondskauf nur auf eine beschränkte Menge von Fonds, die von Ihrer Bank angeboten werden, zurückgreifen können.

nach wie vor den Fehler machen, Investmentfonds nicht aufgrund ihrer historischen Wertentwicklung auszuwählen.

Wenn der Großteil der Anleger Investmentfonds nicht aufgrund ihrer historischen Performance kauft, muss es offensichtlich andere Kaufkriterien geben, welche diese Investoren nutzen. Es gibt zwar einige Veröffentlichungen, die sich mit einzelnen möglichen Kaufkriterien beschäftigen. Zum Beispiel analysieren Barber, Odean und Zheng (2005) den Zusammenhang von Kostenquoten und Mittelzuflüssen, und Sirri und Tufano (1998) finden heraus, dass die Berichterstattung in den Medien einen Einfluss auf das Fondsvolumen hat. Nach meiner Kenntnis gibt es aber keine Arbeit, die vollständig das Thema „Kriterien bei Kaufentscheidungen von Investmentfonds" behandelt. In der ersten Forschungsarbeit wird gezeigt, dass die Fondsgröße (gemessen in Nettovermögen) das dominierende Kaufkriterium ist. Außerdem kaufen Privatinvestoren vermehrt Fonds, die zu einer der Top-Marken-Fondsfamilien gehören, wohingegen geringe Ausgabeaufschläge kein Kaufkriterium sind.

Die zweite Forschungsarbeit dieser Dissertation trägt den Titel ***„Whose Money is Smart? Smart Decision Making Measured by Investors' Ability to Select Mutual Funds".*** In ihr wird zunächst noch einmal der Punkt Performance Persistenz von Investmentfonds aufgegriffen. Innerhalb des genutzten Datensatzes kann die Persistenz sowohl innerhalb aller erhältlichen Fonds als auch innerhalb der Fonds, die die privaten Investoren gekauft haben, nachgewiesen werden. Des Weiteren baut diese Arbeit direkt auf einer aktuellen Veröffentlichung von Keswani und Stolin (2008) auf. Die Autoren finden dort einen robusten „Smart-Money" Effekt sowohl für private als auch für institutionelle Investoren. Der „Smart-Money" Effekt besagt, dass die Mehrheit des Geldes, das Anleger investieren, in Investmentfonds fließt, die sich zukünftig überdurchschnittlich entwickeln werden. Auf der anderen Seite zeigen viele Studien – wie schon oben beschrieben -, dass auch sich unterdurchschnittlich entwickelnde Fonds nach wie vor Mittelzuflüsse erhalten. Ausgehend von diesem Punkt erlaubt der vorliegende Investor-spezifischer Datensatz, die Frage zu stellen „Whose Money is Smart?", d.h., es wird untersucht, welche einzelnen Investoren Fonds mit Hilfe historischer Wertentwicklung kaufen und somit smarte Kaufentscheidungen treffen und welche Investoren dies nicht tun. Die Ergebnisse zeigen, dass Investoren, die smarte Fondsauswahlentscheidungen treffen, älter, erfahrener und wohlhabender sind sowie weniger stark zur Selbstüberschätzung neigen.

Schließlich diskutiert diese Arbeit im zweiten Teil die ökonomischen Auswirkungen der smarten Fondsauswahlentscheidungen. Konkret zeigt sich, dass Investoren, die sich smart verhalten und Investmentfonds aufgrund ihrer historischen Performance auswählen, insgesamt mehr Investmenterfolg haben. Investmenterfolg wird sowohl mit einfachen Portfolio-Renditen als auch mit der Sharpe Ratio des Portfolios gemessen, um so auch dem Portfoliorisiko Rechnung zu tragen. Dies ist das zentrale und wichtigste Ergebnis der zweiten Forschungsarbeit. Dadurch, dass nachgewiesen wird, dass die Fähigkeit, smarte Entscheidungen bezüglich der Auswahl von Investmentfonds zu fällen, einen direkten Einfluss auf die Portfolioperformance hat, ist ein Ex-Ante Maß für Investmenterfolg gefunden. Im Gegensatz zur Portfoliorendite selbst hat dieses Ex-Ante Maß den großen Vorteil, dass es nicht potentiell zufälligen Schwankungen des Aktienmarktes unterliegt. Dieses Ex-ante Maß lässt sich vielfältig bei unterschiedlichsten Fragestellungen einsetzen, bei denen Investmenterfolg privater Investoren gemessen werden muss.

Die dritte Forschungsarbeit in dieser Dissertation hat den Titel ***„Do Advisors Help Investors to Make Better Investments? Evidence from Investors' Mutual Fund Purchase Decisions"*** und beschäftigt sich mit der Fragestellung, inwieweit Finanzberater Privatkunden helfen, bessere Investmententscheidungen zu treffen. Die Arbeit baut direkt auf einer aktuellen Veröffentlichung von Bergstresser, Chalmers und Tufano (2009) auf. Hierin zeigen die Autoren, dass Investmentfonds, welche durch einen Broker verkauft werden, sich schlechter entwickeln als Fonds, die durch einen direkten Vertriebskanal (also ohne Finanzberatung) verkauft werden.

Hier tritt ein weiterer Vorteil des genutzten Datensatzes in Erscheinung. Im Gegensatz zur existierenden Literatur (wie z.B. Bergstresser, Chalmers und Tufano (2009)) können genau diejenigen Einzelinvestoren identifizieren werden, die Finanzberatung in Anspruch nehmen. Somit kann das Investmentverhalten dieser Anleger mit dem Investmentverhalten derjenigen Anleger, die keine Beratung in Anspruch nehmen und damit Ihre Investitionsentscheidung eigenständig fällen, verglichen werden. Der Onlinebroker, von dem der Datensatz stammt, hat das Beratungsmodell erst im Laufe des Jahres 2004 eingeführt. Daher kann sogar zusätzlich das Verhalten identischer Anleger zu dem Zeitpunkt vor der Beratung und zu dem Zeitpunkt nach der Beratung verglichen werden.

Um die Qualität der Finanzberatung zu bewerten, muss in irgendeiner Weise deren Auswirkung auf den Investmenterfolg der Privatanleger bewertet werden. Für die Messung des Investmenterfolges nutzt die dritte Forschungsarbeit das Ex-Ante Maß, welches in dem zweiten Forschungsbeitrag entwickelt worden ist (s.o.). Dies ist ein weiterer Vorteil gegenüber existierender Literatur zum Thema Finanzberatung (z.B. Bergstresser, Chalmers und Tufano (2009), aber auch Hackethal, Haliassos und Jappelli (2008)), die jeweils Ex-Post Portfoliorenditen nutzen, die zufälligen Schwankungen unterliegen.

Mit dieser Methodik wird zunächst gezeigt, dass vermehrt „unsophistizierte" Investoren Finanzberatung in Anspruch nehmen. Danach wird die eigentliche Fragestellung diskutiert, nämlich ob Finanzberater diesen Investoren helfen, bessere Investmententscheidungen zu fällen und somit ihren Grad an „Sophistikation" zu erhöhen. Die Ergebnisse zeigen, dass Finanzberater ihren Kunden nicht helfen, vermehrt Investmentfonds auf Basis der historischen Wertentwicklung zu kaufen. Folgerichtig erhöhen Berater nicht den Grad der „Investmentsophistikation" ihrer Kunden. Das Gegenteil ist der Fall: Kunden, die beraten wurden, weisen ein geringeres Niveau an „Investmentsophistikation" auf.

Studien, die Unterschiede im Anlageverhalten von beratenen und nicht-beratenen Investoren untersuchen, haben immer das Problem, dass potentiell andere Faktoren als die Beratung selbst die Ergebnisse beeinflussen können. Um diese möglichen Endogenitätseinflüsse zu adressieren, werden zwei weitere Analysen als Robustheitstests durchgeführt. Dabei handelt es sich zum einen um den sogenannten „Propensity-Score" Ansatz, bei dem zu jedem beratenden Investor ein statistischer Zwilling gesucht und Unterschiede im Anlageverhalten dieser beiden Investoren untersucht werden. Zum anderen handelt es sich um eine „Ereignisstudie", in der Unterschiede im Anlageverhalten identischer Investoren, bevor und nachdem sie beraten wurden, untersucht werden. Beide Analysen führen zu keinen veränderten Ergebnissen und bestärken die Erkenntnis, dass Finanzberater nicht den Grad der „Investmentsophistikation" ihrer Kunden erhöhen.

Offensichtlich nutzen Finanzberater also nicht die historische Fondsrendite als Verkaufsargument. Um besser zu verstehen, welche Verkaufsargumente die Berater stattdessen benutzen, um ihre Kunden zu überzeugen, analysiert die dritte Forschungsarbeit noch weitere mögliche Kaufkriterien für Investmentfonds, die bereits im ersten Forschungsbeitrag dieser Dissertation untersucht worden sind. Es zeigt sich, dass Finanzberater insbesondere Fonds mit einem hohen Fondsvolumen und solche, die zu einer der Top-Marken gehören, verkaufen. Immerhin helfen die Berater ihren Kunden Geld zu sparen, da sie reduzierte Ausgabeaufschläge als weiteres Verkaufsargument nutzen. Folgerichtig machen Finanzberater offenbar dieselben Investmentfehler wie ihre Kunden: Sie empfehlen große Fonds von bekannten Marken, anstatt sich die historische

Wertentwicklung anzuschauen. Folglich sind Finanzberater daher eher Verkäufer als Berater.

Die Arbeit an dieser Dissertation – sowohl die Durchsicht existierender Literatur als auch meine eigenen empirischen Analysen - hat mich zu der Erkenntnis gebracht, dass der Grad der Aufklärung hinsichtlich Fragestellungen der Geldanlage in der Bevölkerung nach wie vor stark verbesserungswürdig ist. Auch auf dem Gebiet der Investmentfonds machen private Anleger Investmentfehler, wenn sie einen Fonds zum Kauf auswählen, und diese Fehler wirken sich auch auf die gesamte Portfoliorendite aus.

In Zeiten, in denen aufgrund sinkender gesetzlicher Renten die private Geldanlage für die Altersvorsorge immer mehr an Bedeutung gewinnt und dies von der Politik ja auch gefordert wird, ist es aus meiner Sicht dringend notwendig, das Bewusstsein für dieses Thema in der Bevölkerung zu schärfen. Viele Anleger erkennen ihren Informationsbedarf und verlassen sich in Fragen der Geldanlage auf externe Berater. Allerdings scheinen auch Finanzberater ihren Kunden nicht zu helfen, bessere Anlageentscheidungen zu fällen. Folglich ist hier die Politik gefordert, Rahmenbedingungen zu setzten, die dazu führen, dass die Qualität der Finanzberatung verbessert wird.

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Teil II

Fachartikel

The Determinants of Mutual Fund Inflows –

Evidence from Private Investor Transactions

Fabian Niebling[1]

Abstract:

This paper contributes to literature on mutual fund purchasing decisions. In contrast to existing studies which use aggregated net fund flow data (e.g. Gruber (1996), Sirri and Tufano (1998)), I use an administrative data set allowing for an empirical analysis on transaction- and fund-specific level. I show that lacking investor sophistication and not institutional boundaries is the dominant driver preventing self-directed investors from chasing historical performance. Additionally, I find that investors primarily purchase mutual funds with high fund volume which predominantly belong to a top-brand fund family and that reduced (smaller than 5%) initial charges are no purchase criterion. Moreover, I rank all considered purchase criteria and provide evidence, that indeed the volume is the dominating decision criterion for private investors when choosing among mutual funds, whereas historical performance is only of minor importance. As there exists empirical evidence pointing out that chasing historical performance is beneficial when investing in actively managed mutual funds, I conclude that the majority of investors makes serious and costly investment mistakes.

Keywords: Mutual funds, Fund selection criterion, Fund performance, Household finance

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1 Introduction

In the light of the increasing participation of households in equity markets (e.g. Guiso, Haliassos and Jappelli (2008)), researchers are urged to form scientific opinions on the investment behavior of households (Metrick (1999)). Moreover, the decreasing generosity of public pension schemes increases the importance of private investor decision making (OECD (2005)). However, in contrast to recommended actions derived from normative theory, extensive research has documented that households do not seem to be well prepared to meet these challenges as they make serious investment mistakes (see e.g. Campbell (2006)).

With respect to mutual fund investments, research so far has shown that a large number of investors invest their money through actively managed mutual funds that do not outperform their respective benchmark indices (see Malkiel (2003)). Although heavily discussed whether there exists persistence among mutual funds (e.g., Gruber (1996), Carhart (1997), Zheng (1999) and Keswani and Stolin (2008)), those investors investing into mutual funds need to believe in skilled fund managers. Fund managers' skill is revealed by past performance if at all (according to Jensen (1968)). Therefore, for investors a smart strategy is to use historical performance as purchasing criterion. However, research analyzing the relationship between mutual fund performance and net cash inflows (e.g. Gruber (1996), Sirri and Tufano (1998)) finds that funds with an inferior historical performance still receive net cash inflows. As potential explanations Gruber (1996) points out that investors might suffer from institutional boundaries or are simply unsophisticated.

Apparently, private investors use other decision criteria than historical performance when selecting mutual funds. Some academic work using net monthly mutual fund flow data has been conducted concerning single purchase criteria, e.g. Barber, Odean and Zheng (2005) who analyze the relationship between the mutual fund fee structure and the funds cash inflow and Sirri and Tufano (1998) who find that increased media coverage has a positive influence on the fund volume growth. However, to the best of my knowledge, there is no paper that aims at comprehensively analyzing which particular purchase criteria apart from historical performance investors use when choosing among mutual funds.

In contrast to existing studies working with monthly mutual fund flows, I use a comprehensive data set that allows me to analyze single mutual fund purchase transactions of private investors. This methodology has three major advantages compared to analyses based on fund flows. First, it enables me to focus on purchase decisions of private investors, whereas someone using fund flow data can hardly distinguish between private and institutional investors. Second, I am thus able to work on a weekly basis whereas fund flows are obtained only monthly. Third and most importantly, I can distinguish clearly between purchases and sells, whereas fund flow analyses are usually based on net inflows which are the difference of aggregated purchases and aggregated sells. Hence, when using net fund flows in order to analyze investors' purchase decisions, results are always biased by sell transactions. In contrast, I exclusively focus on purchase transactions as for sell transactions, the choice set of an individual investor is limited to the funds he previously purchased and the actual transactions date might be determined by other factors such as liquidity needs or tax optimization.

Besides the methodological advantage my paper has two major contributions separating it from existing literature on mutual fund purchase decisions. First, the investor-specific level of my data set allows me to single out investors and transactions that are not subject to any institutional boundary like saving (pension) plans for example. Thus, these investors can choose from the entire available fund universe, which permits analyzing whether institutional boundaries are preventing investors from chasing performance. As I obtain qualitatively comparable results to Gruber (1996), I can reject the hypothesis that institutional boundaries are the reason why investors do not chase historical performance and hence I find additional evidence that investors are indeed unsophisticated. Second, if investors are not found to use historical performance, then the question, which has not yet been directly addressed, arises which purchase criterion investors are actually using. In this paper I comprehensively address this question, by analyzing which particular purchase criteria investors predominantly seem to use when making their mutual fund purchasing decisions.

Of course, results can only be obtained, if I enrich my dataset of mutual fund transactions with information on the mutual fund universe from Morningstar and a German provider, VWD, as well as with weekly mutual fund performance data from Thomson Financial Datastream. Finally, I am thus able to construct a data set that contains more than 1.5m mutual fund transactions. The data set includes portfolio compositions, respective trading history as well as socio-demographics for all investors. On a fund level the database also contains total net assets as well as initial and annual charges.

In order to make funds comparable across time and peer-groups I use a special approach ranking the mutual funds into deciles according to their historical performance and other fund characteristics, respectively. Thus, I am able to compare the relative performance of purchased mutual funds with the average performance of the funds' peer group. This methodology allows me to draw conclusions on the purchasing behavior of the mutual funds investors.

Using my methodological approach I find that the majority of private investors do not use historical performance as their decision criterion when purchasing mutual funds. I find that investors mainly purchase high volume mutual funds: More than 80% of all purchased mutual funds are in the top 20% of mutual fund volume measured in total net assets. Moreover, I show that investors prefer mutual funds belonging to a top-brand fund family and that initial charges are apparently no crucial purchase criterion, as purchased mutual funds have above-average initial charges. Finally, by conducting a regression analysis I find that the fund volume indeed is the purchase criterion dominating all other criteria; historical performance is only of minor importance. Hence, the majority of investors make serious investment mistakes when investing in mutual funds.

The rest of the paper is organized as follows. In section 2 I give an overview over existing literature in the field of mutual fund purchasing criteria and derive my research questions. Section 3 describes the construction of the data set this paper employs to address my research questions. Section 4 deals with methodological issues. The empirical results on mutual fund purchasing decisions are reported and discussed in section 5. In section 6 I describe results of some additional robustness tests and section 7 draws conclusions.

2 Literature Review and Research Questions

Existing literature on the purchase behavior of private mutual fund investors mainly focuses on the relationship between historical performance and mutual fund cash inflow.

In order to analyze whether investors who purchase mutual funds without chasing historical performance are making investment mistakes, it is an imperative that persistence of mutual fund performance exists. Based on the existing evidence, performance persistence in the mutual fund industry seems to be present. First empirical evidence goes back to Grinblatt and Titman (1992) who find that performance differences between funds persist over time. Elton, Gruber and Blake (1996) confirm these results by applying risk-adjusted measures. Despite interim controversial discussions (e.g. Carhart (1997) in response to Hendricks, Patel and Zeckhauser (1993)), subsequent studies again underline the notion of performance persistence among mutual funds (e.g. Hsiu-Lang, Jegadeesh and Wermers (2000) and Wermers and Moskowitz (2000)). Furthermore, Chevalier and Ellison (1999) show that the fund managers and not so much the funds themselves are the cause for outstanding fund performances. Recently, Kosowski, Timmermann, Wermers and White (2006), by using a bootstrap analysis, provided evidence that those fund managers who generate superior Alphas are not simply lucky but, in fact, skilled. For an extensive review on mutual fund performance persistence the interested reader is referred to Anderson and Schnusenberg (2005).

By analyzing US mutual funds cash flow data Gruber (1996) finds that there are indeed investors who invest in past winning mutual funds, but he also observes money remaining in the underperforming funds. This result is confirmed by Zheng (1999) expanding the data set to a larger time period, Keswani and Stolin (2008) using UK mutual fund data and Ber, Kempf and Ruenzi (2008) who focus on the German mutual fund market. Sirri and Tufano (1998) again show that mutual fund investors fail to stop investing in poor performing funds.

In order to explain this investment behavior, the most intuitive explanation is the existence of sophisticated and unsophisticated investors (see Gruber (1996)). However, apart from lacking financial sophistication, Gruber (1996) provides a second plausible explanation: He argues that institutional boundaries might hinder investors from actually chasing past performance. However, Fischer, Hackethal and Meyer (2008) find evidence that institutional boundaries are only of economic relevance for sophisticated investors. Following this line of arguments leads to my first research question:

<u>Question 1:</u> ***Do investors who are institutionally unbounded use historical performance as a decision criterion when choosing among mutual funds?***

Apart from historical performance, someone can imagine other crucial purchase criteria for private mutual funds investors. For example, it could be possible that private investors purchase mutual funds with high fund volume, reduced initial charges or less annual charges. For this reason I want to expand the question on mutual fund purchase criteria to criteria other than historical performance in this paper.

In contrast to historical performance, these other criteria are not covered comprehensively in the existing literature. Only a few articles discuss the influence of other criteria than historical performance on the purchase behavior. Sirri and Tufano (1998) find by analyzing again fund inflows that funds with higher fees have a stronger performance-inflow relationship than their rivals with lower fees. They explain their findings with the fact that high-fee funds usually spend more money for marketing activities. Moreover, Sirri and Tufano (1998) study the media coverage of mutual funds and find evidence that a high share of media attention is positively related to faster fund volume growth. Another work concerning mutual fund fees is conducted by Barber, Odean and Zheng (2005). They find that investors are more sensitive to front-end fees than operating expenses and, counter intuitive, investors even purchase mutual funds with higher operating expenses. They again explain this fact with the increased marketing efforts which are usually paid from operating expenses, and conclude that mutual fund marketing works. Finally, Ber, Kempf and Ruenzi (2008) state in their analysis of the flows in the German mutual fund market that the inflows are positively influenced by the funds family volume.

Therefore, I formulate my second research question as follows:

<u>Question 2:</u> ***Do investors purchase mutual funds by looking at other criteria than historical performance?***

Elaborating several purchase criteria by answering question 1 and question 2 directly yield to my third and central research question. So far I (and existing literature as well) studied all possible purchase criteria separately. However, if I can observe more than one purchase criterion, which one of these criteria will be the dominating one and which criteria will be only of minor importance? As - to the best of my knowledge - there is no research conducted so far concerning this issue, this is a central contribution of this paper. Summarizing, my third research question is as follows:

<u>Question 3:</u> ***Which mutual fund purchase criterion is dominating the other criteria?***

3 Data

In contrast to most of the existing studies on the purchasing behavior of mutual fund investors which use funds flow data (e.g. Gruber (1996), Sirri and Tufano (1998) or Ber, Kempf and Ruenzi (2008)), I build my analyses on a data set that enables me to work on a transaction-specific level. This data set has been supplied by a German discount brokerage house and contains in total more than 19m transactions of all types of securities. These transactions have been placed by roughly 71k individual investors between January 1999 and July 2007. Note that the customers of this bank can choose from the whole available fund universe and are thus institutionally unbounded. This comprehensive data set enables me to investigate the mutual fund purchasing behavior on investor- and transaction-level respectively. However a few amendments to the data have to be made, when constructing the final data set to answer the research questions (compare table 1).

Table 1: Construction of the data set

The table presents the necessary steps of data restriction.

	Number of Transactions						
	Alpha	**APR**	**Appraisal**	**Weekly Returns**	**One-year Returns**	**Volume (TNA)**	**Initial Charges**
Original data base restricted to mutual funds	2,816,030	2,816,030	2,816,030	2,816,030	2,816,030	2,816,030	2,816,030
Saving plan transactions	- *841,222*	- *841,222*	- *841,222*	- *841,222*	- *841,222*	- *841,222*	- *841,222*
Without saving plans	1,974,808	1,974,808	1,974,808	1,974,808	1,974,808	1,974,808	1,974,808
Sell Transactions	- *392,180*	- *392,180*	- *392,180*	- *392,180*	- *392,180*	- *392,180*	- *392,180*
Buy-Transactions Only	1,582,628	1,582,628	1,582,628	1,582,628	1,582,628	1,582,628	1,582,628
No mutual fund performance data/ charactetristics available	- *54,841*	- *107,257*	- *54,841*	- *8,210*	- *53,343*	- *369,265*	- *735,613*
Final data base for analyses	**1,527,787**	**1,475,371**	**1,527,787**	**1,574,418**	**1,529,285**	**1,213,363**	**847,015**

For this paper's analyses I restrict the data set to mutual fund transactions resulting in more than 2.81m mutual fund transactions of more than 48k distinct individual investors. Approximately 30% of these transactions (841k) are part of mutual fund saving plans. However, when setting up a saving plan investors make the purchase decision only once in advance and then the mutual funds are purchased repeatedly and automatically by the bank. Also, saving plan investors usually cannot choose their mutual funds from the whole mutual funds universe, but can select only from a restricted set of mutual funds which are provided from the bank for saving plans. For these two reasons I exclude the ~841k saving plan transactions from my data set that then maintains approximately 1.97 transactions[2].

My study focuses exclusively on purchase transactions for mainly two reasons. First, in contrast to a purchase decision where the individual investor can choose among mutual funds of the whole available mutual fund universe, the choice set for sell transactions is

[2] I also conduct all analyses including saving plan transactions for robustness reasons. Results mainly remain qualitative unchanged (compare section 6)

limited to the funds the investor previously purchased. Second, when selling mutual funds there are further decision criteria imaginable which are investor-specific. For example, the concrete transaction date might be based on liquidity needs or considerations regarding tax optimization. Only analyzing purchase transactions reduces the number of transactions to approx. 1.58m transactions.

In order to address research question 1, I need to determine the relative performance of a fund purchased by an individual investor within its particular peer group of all available mutual funds. Therefore, it is highly important to create a survivorship bias free sample of the German mutual fund market. I use the Morningstar database that has been proven to be of high quality in studies on the American mutual fund market (see Elton, Gruber and Blake (2001)). Since Morningstar data is only available from 2002 to 2006, I supplement my database with data that has been provided by two German suppliers, namely Hoppenstedt and VWD. Finally, the private investors purchase 254 funds that are not covered in one of my databases. In case no peer group was provided by any of the data providers, the mapping of funds into peer groups relies on regression techniques as they are also used in Koijen (2008). Essentially, this means that this paper relies in self-reported peer groups on which private investors have to rely when selecting mutual funds.

The weekly mutual fund return data was obtained from Thomson Financial DataStream and is dividend adjusted and net of fees, but does not include initial charges. Unfortunately, (sufficient) performance data is not available for all funds purchased, which reduces the number of transactions. In case of the one-factor Alpha measure and the Appraisal measure I result in approx. 1.53m transactions, in case of the Alpha Persistence Ratio (APR) measure in approx. 1.48m transactions, in case of the Weekly Return measure in approx. 1.57m transactions and in case of the One-year Return measure in approx. 1.53m transactions (compare table 1).

In order to answer research question 2 I am in need of some additional information on the purchased mutual funds (e.g. fund volume (monthly), initial charges (end of 2008)) which I obtain from Lipper/Reuters. Unfortunately, these data are only available for the years 2002 – 2008, which leaves me with a database still consisting of 1.21m transactions in the case of the fund volume and of 847k transactions in the case of initial charge (see table 1).

Table 2: Descriptive statistics

The table displays some descriptive statistics of the investor data I use for my studies. Dummy variables indicate if an investor is classified as male, as married or as heavy trader by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Number of Portfolio Positions and Share of International Equity are proxies for diversification.

	Obs	Mean	Median	Std. Dev.
Gender (Dummy; 1 = male)	43,880	84.31%		
Age	43,881	46.12	44.00	12.16
Marital Status (Dummy; 1 = married)	23,595	60.91%		
Riskclass	43,679	4.56	5.00	1.28
Heavy Trader (Dummy)	44,029	27.56%		
Deposit Value	44,028	55,802	36,296	131,441
Cash Value	44,029	34,637	15,139	86,061
Mutual Funds Trade Volume	44,029	4,206	2,557	14,273
Number of Trades	44,029	97	22	502
Number of Portfolio Positions	33,589	12.13	9.00	11.64
Share of International Equity	32,869	49%		
Length of Customer Rel. (years)	44,029	8.05	7.80	3.01

In order to get a feeling of the approx. 44k investors[3] purchasing mutual funds in my database, I present some descriptive statistics in table 2. Note that the results are very similar if I conduct the same descriptive analysis with the investors before the data restrictions discussed above. Gender, Marital status and Heavy Trader are dummy variables and indicate if an investor is classified as male, married, or heavy trader by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account on a scale from 1 (low) to 6 (high). Number of Portfolio Positions is a simple proxy for diversification following Bernatzi and Thaler (2001). Another measure for diversification is the ratio of international equity in the equity portfolio (compare Bluethgen, Gintschel, Hackethal and Mueller (2007)).

Unfortunately, comprehensive socio-demographic information are not available for all 44k investors which explains the lower amount of observations for particular descriptive numbers. A comparison of the demographics with the ones provided by Deutsches Aktieninstitut (2004)[4] indicates that my sample of 44k investors represents approximately 0.6% of the whole mutual fund investor population in Germany. Investors in my sample are more likely to be male (84% compared to 58% in the population), are almost of the same average age (46 years compared to 47 years in the population) and have a higher average

[3] Investors who only purchased mutual funds via a saving plan are already excluded in this analysis.

[4] Deutsches Aktieninstitut e.V. is a German Research Association of public listed companies and institutions.

deposit value (€56k compared to €20k in the population). However, please note that the latter difference can be explained by the fact that average deposit value in the population is biased by Germans who rather own an investment portfolio (approximately 41% of the population) but do not invest in equity (only 16% of the population invest in stocks or mutual funds). Therefore, I believe that the gap will be significantly reduced when considering only investors who own equity (like the majority of investors in my data set). Hence, my sample is fairly representative for the mutual fund population in Germany.

4 Model and Methodology

In order to address the first research question outlined in chapter 2, I use five fundamental metrics to evaluate mutual fund performance in order to account for the fact that results may depend on the specific performance measure used. These five measures are (i) Jensen's Alpha, (ii) the Alpha Persistence Ratio (APR), (iii) the Appraisal Ratio, (iv) Weekly Returns and (v) One-year Returns.

The Jensen's Alpha is obtained from a one-factor model (see Jensen (1968)):

$$r_i \quad r_f \qquad {}_i \qquad {}_i \, r_m \quad r_f \qquad {}_i \tag{1}$$

where r_i is the return of fund i, r_f is the return of a three month cash position, r_m is the return of a peer group's benchmark index, ${}_i$ is the sensitivity of fund i to the return on the benchmark index, ${}_i$ is the risk-adjusted return on fund i and ${}_i$ is the error term. The benchmark indices are chosen in accordance with a fund's peer group.

As shown in table 3 for all peer groups focusing on stocks this paper uses the according MSCI indices, Datastream indices are used for bond funds and indices provided by Citigroup are used for money market funds. The main reason for choosing these indices is that for these indices the required time series of returns are available. Several studies have shown that results remain qualitatively unchanged once more sophisticated Alpha estimation techniques are used (see Carhart (1997), Gruber (1996) and Kosowski, Timmermann, Wermers and White (2006)).

As a second performance measure I use the Alpha Persistence Ratio (APR) (compare Fischer, Hackethal and Meyer (2008)), which is a derivation of Jensen's Alpha. It is computed by dividing Jensen's Alpha by the standard deviation of the Alpha-deciles of the fund for the year prior to the investment date:

$$APR_{it} \qquad \frac{{}_{i,t\ 1\ \ t}}{Decile(\ {}_{it})} \qquad (2)$$

where ${}_{i,t\text{-}1\ \ t}$ is the risk-adjusted performance of fund i in the one year prior to the investment date, and ${}_{Decile(\ it)}$ represents the standard deviation of Alpha-deciles which is also calculated based on the prior year. The advantage of this measure is that it takes not only the fund managers' ability to generate a high Alpha (measured by the nominator) into account, but also his ability to repeat superior performance regularly (measured by the denominator).

Table 3: Definition of peer groups and peer group's benchmark indices

In this table the definitions of the 56 peer group are given. The according peer group's benchmark indices are used for calculating the risk-adjusted performances (Jensen's Alpha).

ID	Peer group	Peer group's benchmark index
Stock Market by Geography		
1	Stocks World	MSCI World
2	Stocks Europe	MSCI Europe
3	Stocks Germany	MSCI Germany
4	Stocks Spain	MSCI Spain
5	Stocks France	MSCI France
6	Stocks Switzerland	MSCI Switzerland
7	Stocks Italy	MSCI Italy
8	Stocks Scandinavia	MSCI Nordic Countries
9	Stocks UK	MSCI UK
10	Stocks Denmark	MSCI Denmark
11	Stocks Netherlands	MSCI Netherlands
12	Stocks Austria	MSCI Austria
13	Stocks Sweden	MSCI Sweden
14	Stocks Turkey	MSCI Turkey
15	Stocks Finland	MSCI Finland
16	Stocks Russia	MSCI Russia
17	Stocks North America	MSCI North America
18	Stocks Australia	MSCI Australia
19	Stocks Asia/ Pacific	MSCI AC Asia Pacific ex Japan
20	Stocks Japan	MSCI Japan
21	Stocks Emerging Markets	MSCI EM
22	Stocks Latin America	MSCI EM Latin America
23	Stocks Greater China	MSCI Golden Dragon
24	Stocks Singapore	MSCI Singapore
25	Stocks Thailand	MSCI Thailand
26	Stocks Korea	MSCI Korea
27	Stocks India	MSCI India
28	Stocks Brazil	MSCI Brazil
Stock Markets by Industry		
29	Stocks Information Technology	MSCI Information Technology

ID	Peer group	Peer group's benchmark index
Stock Markets by Industry (cont'd)		
30	Stocks Financial Markets	MSCI Financials
31	Stocks Materials	MSCI Materials
32	Stocks Energy	MSCI Energy
33	Stocks Health Care	MSCI Health Care
34	Stocks Consumer Goods	MSCI Consumer Staples
35	Stocks Industrial	MSCI Industrials
36	Stocks Utilities	MSCI Utilities
37	Stocks Media	MSCI Media
38	Stocks Biotech	MSCI Pharmaceuticals & Biotech
39	Stocks Real Estate	MSCI Real Estate
Money Markets by Geography		
40	Money Market EUR	CGBI WMNI 1MTH Euro debt
41	Money Market GBP	CGBI WMNI UK 1MTH Euro debt
42	Money Market USD	CGBI WMNI US 1MTH Euro debt
43	Money Market CAD	CGBI WMNI CN 1MTH Euro debt
44	Money Market CHF	CGBI WMNI SW 1MTH Euro debt
45	Money market AUD	CGBI WMNI AU 1MTH Euro debt
Bond Markets by Geography		
46	Bonds global (EUR)	CGBI WGBI WORLD 10 MKT ALL MATS
47	Bonds USD	CGBI USBIG Gvt-spons
48	Bonds CHF	SW Total all
49	Bonds GBP	UK Total all
50	Bonds AUD	AU Total all
51	Bonds JPY	JP Total all
52	Bonds DKK	DK Total all
53	Bonds CAD	CN Total all
54	Bonds SEK	SD Total all
55	Bonds NOK	NW Total all
56	Bonds Asia	CGBI ESBI 10 years

The third risk-adjusted performance measure I use is the Appraisal ratio. Besides Jensen's Alpha this measure also takes the non-systematic risk via the denominator into account. This means that a mutual fund is valuated the worse the larger the non-systematic risk is. The Appraisal ratio is computed by dividing the Alpha by the standard deviation of the error term of the one-factor model:

$$Appraisal_{it} = \frac{\alpha_{it}}{\sigma(\varepsilon_{it})} \qquad (3)$$

where α_i is Jensen's Alpha of fund i from the one-factor model and $\sigma(\varepsilon_i)$ is the standard deviation of the error term of fund i in the one-factor model.

Whereas Jensen's Alpha, the APR and the Appraisal measure are risk-adjusted performance measures, I also add two simple performance measures into my consideration, namely Weekly Returns and One-year Returns.

Using a rolling-window approach every performance measure for each fund is calculated based on weekly observations between 1997 and 2008. The underlying assumption is that a performance chasing investor chooses among mutual funds by looking at the performance of one year before. In order to assure the comparability of risk-adjusted performances of mutual funds, I compare several peer groups, which are identical to the peer groups I considered already before when calculating the risk-adjusted performance measures (compare table 3).

In order to address my research questions I need to compare the performance measures of the mutual funds purchased to the ones of all mutual funds available. However, it is not possible to compare the performance measures of the mutual funds of different peer groups and in different times directly with each other (for example, the Alpha measures are always subject to different betas). I address this issue by categorizing the funds by their deciles, using their peer group specific past performance. Hence, in any given week and for every peer group the decile 1 contains the mutual funds with the poorest performance and decile 10 contains the mutual funds with the strongest performance. This means that I create a basis on that I can compare the mutual funds according to their relative performance demonstrated by the deciles they join. This information is combined with the transaction data containing all funds purchased by private investors. Thus, this new constructed data set enables me to analyze question 1, as it provides information about the relative performance of a particular mutual fund at the time it was purchased by a private investor.

In order to answer research question 2, I further enrich this data set by adding other mutual fund characteristics (such as fund volume measured in total net assets, initial charges, annual charges and a dummy variable indicating whether a mutual fund belongs to a top-brand fund family). The methodology for mutual funds' volume is the same as the one for the performance measures: Again I categorize all mutual funds into deciles (according to funds' volume) and combine these data with my transaction data. This leads to a data set with information about the relative fund volume of a particular purchased mutual fund that is compared to all available mutual funds at this time.

As this methodology does not work properly for analyzing initial charges, I use a different approach in order to study this possible purchase criterion: I classify all mutual funds into three different categories regarding initial charges, namely (i) mutual funds with no initial charges, (ii) mutual funds with reduced initial charges (initial charges larger than zero and smaller than 5%) and (iii) mutual funds with full initial charges (initial charges of 5% and larger). Subsequently, I compare the proportion of theses three categories for all available mutual funds versus the purchased mutual funds. I use a similar approach in order to study whether purchased mutual funds belong to a top-brand fund family by introducing an accordant indicator variable and comparing this variable for all available mutual funds versus purchased mutual funds.

For the third research question, namely to identify which of the analyzed purchase criterion is the dominating one, I switch from the transaction-specific level to a fund-specific level analyzing mutual fund flows. For that reason I construct a new database containing the sum of the purchased volume of all investors in my database for every mutual fund and for every week. If a fund is not traded in a given week, this fund week combination will get the value zero. Note that I take only the traded volume of the investors who are in my database into account. Hence this methodology differs from the one e.g. Gruber (1996), Sirri and Tufano (1998) or Ber, Kempf and Ruenzi (2008) use, as they analyze aggregated net fund flows. The advantages of my methodology are that I can analyze the data on a weekly basis (instead of monthly fund flows), can consider private investors exclusively (instead of the combination of private and institutional investors in fund flows) and can distinguish between purchases and sells (If someone considers net flows, he will observes only changes in the aggregated fund volume which is the result of purchases minus sells).

Adding the mutual fund characteristics and performance measures allows me to conduct a multiple regression with the logarithm of the purchased volume as depending variable and the performance measures and fund characteristics as independent variables:

$$LN(PV)_{it} \quad PM_{it} \quad IC_{it} \quad AC_{it} \quad LN(TNA)_{it} \quad TB_{it} \quad {}_{it} \tag{4}$$

where $LN(PV)_{it}$ is the natural logarithm of the purchased volume of fund i in week t, PM_{it} is the performance measure of fund i in week t, IC_{it} is the initial charge of fund i in week t, AC_{it}

is the annual charge of fund i in week t, $LN(TNA)_{it}$ is the natural logarithm of the fund volume (measured in total net assets) of fund i in week t, TB_{it} is a dummy variable indicating whether the fund i in week t belongs to one of the top-brand mutual fund families and $_{it}$ is the error term.

In order to take into account that my data set contains panel data across time (I have one observation for every mutual fund in every week), I also compute Fama-MacBeth regressions (compare Fama and MacBeth (1973)) for robustness reasons. This regression technique is a two-step approach. First, regressions for each single time period are computed. Afterwards, the final regression coefficients are calculated as the average of the first step coefficient estimates.

5 Results and Discussion

5.1 Chasing historical performance when choosing among mutual funds

In order to determine whether investors choose mutual funds by chasing historical performance, I analyze the approx. 1.5m considered purchase-transactions of mutual funds where performance data is available. Note again that the investors in my database can choose from the whole available mutual fund universe and are thus institutionally unbounded. As described in section 4, I use five different performance measures to evaluate fund performance. I rank all available funds into deciles according to their historical performance and observe the deciles of the purchased funds in my database. Table 4 summarizes the results for Jensen's Alpha for the 20 largest peer groups[5] as well as the total results over all peer groups. The peer groups are presented on the vertical axis, whereas the horizontal axis shows the Alpha deciles. Decile 1 contains the proportion of purchased funds with the weakest historical Alpha performance and decile 10 contains the proportion of purchased funds with the best historical Alpha performance. The mean represents the average Alpha decile. Over all peer groups the mean of 6.40 indicates that on average the investors purchase mutual funds with above-median historical Alpha performance.

However, only ~25% of purchased mutual funds are in decile 9 or 10, i.e. in the top 20% with respect to historical performance. Assuming that investors who actively chase historical

[5] The 20 largest peer groups represent 99% of total observations. However, results for the remaining 36 peer groups are qualitatively identical.

performance purchase only mutual funds belonging to this top 20%, implies that in 75% of transactions investors do not derive their purchase decision by looking at the historical Alpha performance. Obviously, they use a different purchasing criterion. Recalling that mutual fund performance persistence is present (compare section 2), these investors seem to make a serious investment mistake.

The results still hold on when drilled down to a peer group level: On the one hand, in all but three peer groups the mean of the purchased decile is greater than 5.5[6] indicating that investors purchase mutual funds with above average historical performance. On the other hand, within the 20 largest peer groups there is only one peer group, namely Stocks Greater China, in which investors invest in the top 20% in more than 50% of the cases.

While the mean of purchased deciles of 5.45 (Stocks Germany) and 5.21 (Stocks Asia/Pacific) is very close to the average of 5.50 and hence the difference can probably be explained with statistical noise, investors definitely purchase below-average mutual funds in the peer group Money Market EUR (mean of 4.52). In this peer group only 14% of purchased mutual funds belong to the top 20% of historical performance, whereas more than 30% of purchases took place in the 20% of weakest performing funds. One possible explanation could be that these money market funds by majority invest in short-term securities, which perform worse when upward slopping yield curves are present.

Besides Jensen's Alpha, I consider two further risk-adjusted performance measures, namely the Alpha Persistent Ratio (APR) (see Fischer, Hackethal and Meyer (2008)) and the Appraisal ratio and two simple performance measures, namely Weekly Returns and One-year Returns. As the results are very similar to the ones of the Alpha measure, I provide them at this point only on an aggregated level in table 5. The ten deciles are presented on the vertical axis, whereas the horizontal axis shows the different performance measures. For detailed, peer group specific results for the measures APR-, Appraisal, Weekly Returns and One-year Returns (analogous to table 4 for the Alpha-measure), the interested reader is referred to the Appendix. Table 5 shows that the mean of the deciles of the purchased mutual funds are above average for all considered performance measures.

[6] Note that 5.5 will be the mean of decile 1 to 10, if the purchase transactions are equally distributed

Table 4: Distribution of purchased mutual funds within all mutual funds

This table presents results for research question 1. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of historical performance-deciles of the purchased mutual funds within all mutual funds. Moreover the mean and the standard deviation of the historical performance deciles are presented. As performance measure I use Jensen's Alpha. The analyzed time period is January 1999 – July 2007.

		Alpha-Decile											
Peer Group	**Observations**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	**Std. Dev.**
Stocks Europe	403,235	4.79%	4.45%	4.45%	6.44%	13.55%	17.54%	13.70%	9.05%	9.27%	16.77%	6.45	2.55
Stocks World	393,009	4.99%	2.11%	2.54%	6.56%	11.02%	12.62%	15.87%	17.75%	11.67%	14.87%	6.81	2.41
Stocks Germany	125,703	14.85%	4.65%	12.27%	9.57%	10.30%	6.32%	7.45%	14.70%	12.68%	7.21%	5.45	2.95
Bonds World	116,102	3.82%	8.27%	7.87%	5.85%	5.98%	7.86%	17.43%	20.64%	9.93%	12.35%	6.44	2.64
Stocks North America	77,543	3.25%	5.60%	10.98%	8.43%	7.34%	9.37%	15.77%	19.68%	8.88%	10.69%	6.29	2.55
Stocks Asia/Pacific	57,705	13.55%	10.64%	13.30%	7.22%	12.11%	7.43%	6.05%	8.14%	10.45%	11.09%	5.21	3.03
Stocks Biotech	53,254	0.71%	2.30%	5.91%	4.70%	5.86%	13.35%	11.71%	23.81%	19.18%	12.48%	7.21	2.16
Stocks IT	47,372	5.05%	4.63%	6.53%	9.20%	10.81%	9.07%	12.06%	14.22%	7.01%	21.43%	6.55	2.74
Stocks Real Estate	42,916	0.31%	1.54%	0.17%	4.39%	19.79%	37.74%	16.91%	8.47%	6.02%	4.66%	6.34	1.55
Money Market EUR	35,952	2.84%	29.67%	17.92%	7.43%	8.86%	10.36%	4.76%	4.06%	6.44%	7.66%	4.52	2.70
Stocks Emerging Markets	26,596	8.93%	10.16%	7.11%	5.08%	6.34%	10.37%	5.99%	15.05%	8.93%	22.04%	6.28	3.11
Stocks Materials	24,042	1.08%	1.73%	13.06%	4.32%	10.95%	15.31%	7.30%	11.33%	21.67%	13.26%	6.77	2.45
Stocks Japan	20,067	10.09%	5.91%	4.59%	7.55%	5.68%	6.22%	5.66%	7.95%	20.69%	25.67%	6.78	3.16
Stocks Greater China	19,361	0.19%	1.71%	6.39%	6.04%	5.93%	6.92%	8.59%	10.35%	17.57%	36.30%	7.82	2.40
Stocks India	18,777	0.16%	0.43%	3.05%	22.83%	21.39%	15.99%	20.34%	7.41%	6.84%	1.55%	5.83	1.69
Stocks Healthcare	15,419	2.09%	9.00%	7.84%	10.99%	8.13%	13.42%	12.84%	6.34%	15.09%	14.26%	6.28	2.67
Stocks Latin America	15,006	0.57%	2.25%	5.72%	4.75%	13.03%	31.47%	14.57%	8.98%	13.29%	5.36%	6.42	1.93
Stocks Energy	7,070	3.39%	3.51%	4.58%	8.95%	7.92%	13.97%	36.51%	10.93%	5.53%	4.70%	6.23	2.06
Stocks Media	4,388	4.35%	6.11%	8.71%	24.52%	10.48%	11.53%	9.16%	5.24%	9.14%	10.76%	5.58	2.57
Stocks Russia	3,866	0.05%	0.59%	9.70%	17.54%	14.28%	19.87%	25.14%	4.01%	5.43%	3.39%	5.82	1.80
Other	20,404	3.82%	5.28%	6.35%	6.13%	6.31%	9.23%	7.65%	19.27%	16.48%	19.47%	6.96	
All	**1,527,787**	**5.41%**	**4.91%**	**6.13%**	**7.07%**	**10.94%**	**13.30%**	**13.32%**	**13.90%**	**10.94%**	**14.08%**	**6.40**	**2.62**

Interestingly, the means of the purchased deciles of the risk-adjusted measures (6.40 – 6.62) are slightly higher than the means of the purchased deciles of the simple performance measures (5.66 – 5.68).

Hence, I conclude that, if investors use historical performance as their purchase criterion, they will also take the risk component into account and use a risk-adjusted measure. However, for all considered performance measures the partition of purchased mutual funds belonging to the top 20 % of all available mutual funds (deciles 9 and 10) is only between 20% and 30%. This implies that, regardless of the specific performance measure, investors come to the purchase decision by looking at another criterion than historical performance in more than 70% of cases.

However, I conduct all analyses with an one-year observation period for the historical performance. Hence there is a small probability that investors use historical performance as their decision criterion but base their purchase decisions on performance evaluations for a different time period. However, assuming that there is a gap of two weeks between the observation an investor makes and his purchase decision, or assuming an investor only bases his decisions on last week's raw performance leads to qualitatively unaltered results.

Table 5: Distribution of purchased mutual funds within all mutual funds – different performance measures

The table presents results for research question 1. The frequency of historical performance-deciles of the purchased mutual funds within all mutual funds is presented on the vertical axis, whereas on the horizontal axis the table shows 5 different performance measures. Moreover the mean and the standard deviation of the historical performance deciles are presented. The analyzed time period is January 1999 – July 2007.

	Risk-adjusted Performance Measures			Simple Performance Measures	
	Alpha	**APR**	**Appraisal**	**Weekly Returns**	**One-year Returns**
Observations	1,527,787	1,475,371	1,527,787	1,574,418	1,529,285
Decile 1	5.41%	5.16%	3.30%	8.36%	7.50%
Decile 2	4.91%	5.72%	5.15%	9.25%	9.48%
Decile 3	6.13%	7.24%	5.26%	11.14%	11.74%
Decile 4	7.07%	8.00%	7.53%	9.34%	8.69%
Decile 5	10.94%	8.25%	10.39%	9.82%	10.02%
Decile 6	13.30%	9.20%	11.14%	9.86%	10.52%
Decile 7	13.32%	12.26%	14.78%	10.29%	9.47%
Decile 8	13.90%	13.95%	15.00%	9.83%	10.66%
Decile 9	10.94%	13.58%	14.31%	11.19%	12.21%
Decile 10	14.08%	16.64%	13.14%	10.91%	9.71%
Mean	6.40	6.53	6.62	5.66	5.68
Std. Dev.	2.62	2.75	2.51	2.86	2.82

Summarizing the results concerning the first research question, I find that there are indeed transactions where investors purchase mutual funds by chasing historical performance.

However, in the majority of transactions investors apparently use a different purchase criterion. Recalling that persistence in mutual fund performance exists, these investors make serious investment mistakes. As the investors in my data set are institutionally unbounded, I continue the line of arguments of Gruber (1996) and conclude that institutional boundaries can hardly be the reason for investors not chasing historical performance and that investors are rather unsophisticated.

5.2 *Other purchasing criteria than historical performance*

As we learned in section 5.1, it is in only less than 30% of transactions that investors purchase mutual funds belonging to the top 20% funds regarding historical performance. This implies that the majority of mutual fund investment decisions are made by looking at a different decision criterion. In order to approach my second research question, I first study mutual fund characteristics per historical performance deciles.

Table 6 presents average volume, average initial charges and average annual charges for the considered performance deciles. I use Jensen's Alpha as performance measure. Note, that results keep qualitatively unchanged if I use one of the other four performance measures. It becomes obvious that the top performing mutual funds as well as the poor performing mutual funds have a lower average volume than the middle-rate performing funds. These results are in line with the findings of Koijen (2008) and show that investing in high-volume mutual funds results in obtaining only middle-rate performing funds.

Table 6: Mutual fund characteristics per historical performance deciles

The table presents results for research question 2. Average volume (measured in Total Net Assets), average initial charge and average annual charge are displayed per performance deciles. As performance measure I use Jensen's Alpha. The analyzed time period is January 1999 – July 2007.

Alpha-Deciles	Average Volume (in M€ TNA)	Average Initial Charge (in %)	Average Annual Charge (in %)
1	462	3.10	1.41
2	943	2.75	1.20
3	1,100	3.56	1.20
4	2,970	4.03	1.27
5	5,090	3.97	1.31
6	5,760	3.88	1.33
7	5,140	3.94	1.33
8	3,070	4.02	1.37
9	1,860	4.35	1.44
10	732	4.54	1.50
Total	**3,210**	**3.95**	**1.35**

Moreover, table 6 presents average initial charges and average annual charges for the funds purchased by the private investors. The values in table 6 are equally weighted but are in the same range as those reported in Khorana, Servaes and Tufano (2008) for Germany. Recall that Khorana, Servaes and Tufano (2008) use value-weighted averages. Interestingly, top performing funds have a higher average initial charge than funds with average historical performance, which is in line with the findings of Gruber (1996). It seems, as if investors who purchase mutual funds by chasing historical performance are poised to pay more initial charge. When considering average annual charges I come to very similar results: Better performing mutual funds tend to have higher annual charges.

In a second step I repeat the detailed deciles analyses I conducted in section 5.1 but rank the mutual funds by their fund volume (measured in Total Net Assets). Table 7 shows the respective results. It can be stated that over all per groups the mean of the volume deciles of the purchased mutual funds is 9.16 and that more than 80% of all purchased mutual funds are in the top 20% regarding the fund volume. This implies that in the broad majority of all transactions investors purchase high-volume mutual funds.

On the one hand, someone may claim these results are a self-fulfilling prophecy to some extent, as high-volume funds have just a high volume because investors purchase these funds. On the other hand, this heuristic cannot explain the whole extent of the results. The fact that more than 80% of purchased mutual funds belong to the top 20% volume funds, allows the conclusion, that investors in fact purchase mutual funds mainly by concentrating on the top-volume funds.

A possible explanation is the media attention and marketing efforts of the top-brand fund families. Investors seem to prefer mutual funds of the well-known investment companies to the ones of smaller companies with lower media attention. These results are in line with Sirri and Tufano (1998) as well as Barber, Odean and Zheng (2005).

Drilled down on peer group level the results still remain similar. The mean of the volume deciles is larger than 7.5 for all of the 20 largest peer groups[7] displayed in table 7 and larger than 9.0 for even ten of these 20 peer groups. For 14 peer groups the proportion of mutual funds purchased in decile 9 or 10 is higher than 75%. Therefore, volume seems to be an important purchase criterion for all kind of mutual funds.

When studying the results for initial charges (table 8) I observe that investors indeed mainly purchase mutual funds with higher than average initial charge (as already indicated in table 6).

[7] Please note that the 20 largest peer groups represent 99% of total observations.

Table 7: Distribution of purchased mutual funds within all mutual funds regarding fund volume

The table presents results for research question 2. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of mutual fund volume-deciles of the purchased mutual funds within all mutual funds. Moreover the mean and the standard deviation of the mutual fund volume deciles are presented. The volume is measured in Total Net Assets (TNA). The analyzed time period is January 1999 – July 2007.

		Volume-Decile											
Peer Group	**Observations**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	**Std. Dev.**
Stocks Europe	329,868	0.02%	0.12%	0.27%	0.78%	1.83%	5.93%	5.56%	2.53%	9.20%	73.75%	9.28	1.45
Stocks World	326,167	0.05%	0.13%	0.32%	0.79%	0.57%	1.92%	3.21%	5.21%	12.06%	75.73%	9.49	1.17
Bonds World	101,510	0.02%	0.84%	1.25%	2.69%	4.13%	6.82%	9.46%	9.84%	18.05%	46.89%	8.54	1.89
Stocks Germany	73,387	0.07%	0.57%	4.78%	13.85%	1.32%	2.22%	6.05%	12.27%	41.44%	17.44%	7.79	2.23
Stocks Asia/Pacific	53,528	0.03%	0.68%	0.69%	0.64%	1.13%	2.98%	2.93%	4.86%	12.07%	74.00%	9.38	1.41
Stocks North America	49,181	0.00%	0.08%	0.08%	1.20%	0.56%	1.28%	1.19%	1.74%	17.91%	75.95%	9.59	1.03
Stocks Biotech	40,375	0.14%	0.15%	0.44%	0.21%	0.18%	0.69%	0.40%	0.15%	3.52%	94.13%	9.85	0.84
Stocks Real Estate	39,187	0.02%	0.05%	0.13%	0.47%	3.74%	0.98%	2.14%	2.22%	65.37%	24.89%	8.97	1.11
Money Market EUR	29,999	0.01%	1.18%	0.48%	0.37%	0.73%	1.37%	0.57%	4.60%	23.30%	67.38%	9.42	1.29
Stocks IT	27,757	0.00%	0.06%	0.35%	0.23%	0.43%	1.21%	1.40%	0.98%	57.30%	38.04%	9.25	0.88
Stocks Materials	23,657	0.00%	0.03%	0.11%	0.22%	0.16%	0.77%	1.15%	4.40%	8.46%	84.69%	9.73	0.78
Stocks Emerging Markets	20,993	0.07%	0.16%	0.23%	4.99%	6.10%	16.84%	16.57%	16.57%	9.01%	29.46%	7.77	1.88
Stocks India	18,544	0.17%	0.15%	0.22%	0.35%	0.61%	0.97%	1.41%	7.65%	4.55%	83.92%	9.63	1.06
Stocks Greater China	15,793	0.32%	0.32%	0.84%	0.13%	0.72%	0.61%	3.84%	4.74%	8.40%	80.08%	9.52	1.26
Stocks Healthcare	11,514	0.03%	0.06%	0.43%	0.59%	0.32%	0.99%	1.64%	0.47%	92.48%	3.00%	8.89	0.76
Stocks Japan	11,434	0.23%	0.24%	0.52%	1.26%	1.08%	1.24%	3.18%	21.44%	40.48%	30.33%	8.82	1.29
Stocks Latin America	10,548	0.03%	1.98%	0.12%	0.15%	18.00%	6.18%	7.51%	4.17%	2.61%	59.24%	8.34	2.24
Stocks Energy	7,121	0.01%	6.61%	3.74%	0.56%	5.35%	0.53%	1.76%	2.50%	7.67%	71.27%	8.71	2.52
Stocks Russia	3,925	0.28%	0.71%	0.92%	0.61%	0.36%	20.10%	6.01%	11.39%	10.34%	49.27%	8.48	1.86
Stocks Media	2,788	0.04%	0.04%	0.36%	0.07%	0.04%	0.47%	0.47%	21.31%	64.49%	12.73%	8.86	0.76
Other	16,087	0.60%	1.63%	2.83%	6.92%	9.01%	9.46%	12.85%	18.92%	17.31%	20.46%	7.44	
All	**1,213,363**	**0.05%**	**0.33%**	**0.72%**	**1.81%**	**1.75%**	**3.73%**	**4.53%**	**5.30%**	**17.37%**	**64.39%**	**9.16**	**1.54**

Table 8: Comparison of initial charges of purchased mutual funds versus all mutual funds

The table presents results for research question 2. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of mutual funds with no initial charges, reduced initial charges and full initial charges. These numbers are compared for all available mutual funds versus purchased mutual funds. "No Initial Charges" means initial charge of zero, "Reduced Initial Charges" means initial charge is larger than zero but smaller than 5% and "Full Initial Charge" means a initial charge of 5% or larger.

		All Mutual Funds			Purchased Mutual Funds		
Peer Group	**Observations**	**No Initial Charge**	**Reduced Initial Charge**	**Full Initial Charge**	**No Initial Charge**	**Reduced Initial Charge**	**Full Initial Charge**
Stocks World	317,293	22%	46%	33%	1%	13%	86%
Stocks Europe	158,293	35%	22%	43%	17%	2%	81%
Stocks Germany	82,020	13%	29%	58%	26%	3%	71%
Bonds World	78,452	32%	62%	7%	28%	71%	0%
Stocks Asia/Pacific	34,617	39%	18%	44%	3%	28%	69%
Money Market EUR	30,408	69%	29%	2%	98%	2%	0%
Stocks Materials	22,348	32%	29%	39%	0%	3%	97%
Stocks IT	17,951	28%	30%	42%	79%	0%	21%
Stocks North America	17,742	49%	16%	35%	64%	3%	33%
Stocks Real Estate	14,708	39%	7%	54%	0%	6%	94%
Stocks Emerging Markets	13,581	44%	15%	41%	0%	6%	93%
Stocks Latin America	11,848	31%	16%	53%	3%	43%	54%
Stocks Healthcare	11,148	29%	32%	39%	3%	7%	90%
Stocks Japan	10,646	42%	17%	40%	1%	25%	74%
Stocks Energy	5,864	37%	30%	33%	1%	7%	92%
Stocks Greater China	2,466	44%	9%	47%	5%	0%	95%
Stocks Austria	2,341	5%	60%	35%	0%	22%	78%
Stocks Biotech	2,332	31%	28%	42%	68%	7%	25%
Stocks India	2,269	38%	10%	52%	0%	11%	89%
Stocks Consumer Goods	2,151	10%	57%	33%	0%	1%	99%
Other	8,537	43%	37%	21%	8%	24%	68%
All	**847,015**	**33%**	**38%**	**29%**	**16%**	**15%**	**69%**

Over all peer groups, investors purchase mutual funds with a full initial charge (i.e. initial charges of 5% or larger) in 69% of cases. In only 15% of transactions investors purchase mutual funds with reduced initial charges (i.e. initial charges larger than zero and smaller than 5%) and in 16% of cases mutual funds with no initial charges (i.e. initial charge of zero).

When comparing these numbers to the corresponding ones of all available mutual funds, I state that only 29% of all available mutual funds have full initial charges whereas 38% have reduced initial charges and 33% have no initial charges. This implies that even though mutual funds with high initial charges present only 29% of all available funds, the majority of funds purchased (69%) belongs to this category.

At first view these results seem to be counterintuitive as someone could expect investors to avoid fees and to purchase mutual funds with low initial charges. However, as I discussed earlier (compare table 6) mutual funds with higher historical performance tend to have higher initial charges as well. Therefore, investors who purchase mutual funds by chasing historical performance are poised to pay higher initial charge for the top-performing funds. On the other hand, mutual funds with higher (initial and annual) charges can spend more money for their marketing activities which yield obviously to increased demand.

Drilled down on peer group level, I get a rather heterogeneous picture. For the majority of stock peer groups within the 20 largest peer groups[8] displayed in table 8, the results are close to the total results, namely investors purchase mutual funds with higher than average initial charges. However, I get a different picture when looking at the peer groups Bond World and the Money Market EUR. In these peer groups investors purchase mainly funds with reduced initial charges (Bonds World) and no initial charges (Money Market EUR), respectively.

Finally, I study the proportion of mutual funds belonging to a top-brand fund family. Again, I compare these numbers for the set of purchased mutual funds with the set of all available funds. The results are displayed in table 9. I state that investors prefer mutual funds of the top-brand fund families. Whereas over all peer groups only 18% of all available mutual funds are classified as top-brand funds, the proportion of top-brand mutual funds within the purchased mutual funds is 37%. Considering the results on peer group level[9], I get a very heterogeneous picture. There are peer groups in which the proportion of top-branded

[8] Again, the 20 largest peer groups represent 99% of total observations.

[9] I again display only the 20 largest peer groups which account for 99% of observations

mutual funds within the purchased funds is clearly larger compared to all available funds. On the other hand, there are peer groups where the results are just vice versa. Interestingly, investors seem to prefer top-brand mutual funds especially in the large and important peer groups (such as Stocks World, Bonds World, Money Market EUR, Stocks Germany, etc.) whereas investors purchasing mutual funds in niche markets (e.g. Biotech, Real Estate, Energy, etc.) invest in funds of smaller, non top-branded investment companies.

Table 9: Comparison the variable Top-Brand Indicator of purchased mutual funds versus all mutual funds

The table presents results for research question 2. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of mutual funds with belonging to a Top-Brand fund family. These numbers are compared for all available mutual funds with purchased mutual funds.

		All Mutual Funds		Purchased Mutual Funds	
Peer Group	**Observations**	**No Top-Brand**	**Top-Brand**	**No Top-Brand**	**Top-Brand**
Stocks Europe	372,525	85%	15%	81%	19%
Stocks World	349,731	74%	26%	39%	61%
Bonds World	105,217	80%	20%	39%	61%
Stocks Germany	97,706	64%	36%	41%	59%
Stocks North America	68,383	89%	11%	83%	17%
Stocks Asia/Pacific	55,053	89%	11%	85%	15%
Stocks Biotech	40,677	77%	23%	96%	4%
Stocks Real Estate	39,995	84%	17%	99%	1%
Money Market EUR	30,514	71%	29%	12%	88%
Stocks Emerging Markets	29,796	91%	9%	90%	10%
Stocks IT	28,601	83%	17%	38%	62%
Stocks Materials	23,965	76%	24%	88%	12%
Stocks Greater China	19,029	92%	8%	90%	10%
Stocks India	18,607	98%	2%	97%	3%
Stocks Japan	16,990	92%	8%	90%	10%
Stocks Latin America	15,158	99%	1%	100%	0%
Stocks Healthcare	11,571	86%	14%	9%	91%
Stocks Energy	7,361	83%	17%	98%	2%
Stocks Russia	4,012	85%	15%	17%	83%
Stocks Media	2,992	78%	22%	40%	60%
Other	17,360	90%	10%	61%	39%
All	**1,355,243**	**82%**	**18%**	**63%**	**37%**

Summarizing the results for the second research question, I find that investors indeed purchase mutual funds by looking at other criteria than historical performance. More concrete, they mainly purchase high-volume mutual funds and funds belonging to a top-brand fund family. On the other hand, initial charges do not seem to be a major purchase criterion.

5.3 Dominating purchase criterion

In sections 5.1 and 5.2 I analyzed different criteria private investors may consider when choosing among mutual funds. I find that volume is a major purchase criterion while initial charges seem to have no impact on the purchase decision and that there is a mixed picture concerning historical performance: There is a group of investors who indeed purchase mutual funds by chasing historical performance but there is also a group of investors who apparently do not consider historical performance as their decision criterion.

Table 10: Impact of different purchase criteria on purchase volume

The table presents results for research question 3. Regression coefficients from regression of different purchase criteria on purchased fund volume are displayed. The KAG Top Brand Dummy-Variable indicates whether a fund is classified as belonging to a top-brand fund family. For comparison reasons it is crucial to consider standardized regression coefficients, which are displayed in parentheses. ***, **, * denotes significance at the 1%, 5% and 10% level respectively. The analyzed time period is January 1999 – July 2007.

	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**	**Regression 5**
Depending Variable	Log. Of Purchase Volume	Log. Of Purchase Volume	Log. Of Purchase Volume	Log. Of Purchase Volume	Log. Of Purchase Volume
Alpha Decile	0.0401***				
	(0.0674)				
APR Decile		0.0528***			
		(0.0877)			
Appraisal Decile			0.0496***		
			(0.0836)		
Weekly Returns Decile				0.0109***	
				(0.0192)	
One-year Returns Decile					0.00969***
					(0.0167)
Initial Charge	0.0135***	0.0126***	0.0109***	0.0150***	0.0153***
	(0.0165)	(0.0148)	(0.0133)	(0.0193)	(0.0191)
Annual Charge	0.182***	0.193***	0.181***	0.160***	0.172***
	(0.0585)	(0.0601)	(0.0582)	(0.0535)	(0.0565)
Log. Of Volume (TNA)	0.114***	0.128***	0.114***	0.106***	0.117***
	(0.158)	(0.166)	(0.157)	(0.159)	(0.165)
KAG Top Brand (Dummy)	0.190***	0.217***	0.196***	0.154***	0.166***
	(0.0528)	(0.0587)	(0.0546)	(0.0450)	(0.0475)
Constant	-2.182***	-2.499***	-2.219***	-1.851***	-2.044***
Observations	1,208,046	1,087,075	1,208,046	1,362,631	1,267,501
R-squared	0.039	0.044	0.041	0.032	0.034

However, I cannot make a statement concerning the question which of the considered criteria is the dominating one (compare research question 3) so far. It is a major contribution of this paper to deal with this issue. In order to answer the third research question I use a regression model and study the influence of the analyzed purchase criteria on the purchased fund volume. I conduct a single regression model for every considered performance measure. The results are given in table 10. As I want to figure out which of the purchase criteria has the strongest influence on the fund volume, I need to compare the standardized regression coefficients (displayed in parentheses). With these standardized coefficients it is possible to compare the different criteria with each other. Note that multi-collinearity is not a problem in my model specification: Variance inflation factors (VIF) show values between 1.00 and 1.15 for all independent variables in all computed regression models.[10]

Studying the standardized regression coefficients presented in table 9 I find that the natural logarithm of the mutual fund volume has the highest impact on the natural logarithm of the purchased volume regardless the performance measure used (standardized coefficients vary from 0.157 to 0.166). Hence, volume is the dominating purchase criterion.

The historical performance only has the second largest standardized regression coefficient in the first three regression models (using Jensen’s Alpha, the APR measure and the Appraisal ratio as performance measure) and is thus the second most important purchase criterion. In the other regression models (using simple performance measures) the performance measures are only the least important criterion. In all models the criterion Annual Charges followed by Top Brand are of medium importance to private investors. Finally, in three of five regression models the initial charge shows the lowest standardized regression coefficient. Hence, my presumption in section 5.2 that investors purchase mutual funds without regarding initial charges is confirmed and initial charges are no purchase criterion at all.

These results imply that the majority of investors make serious and costly investment mistakes by purchasing high-volume funds of well-known and top-branded investment companies as these funds usually show only a middle-rate performance.

Summarizing results for research question 3, I state that fund volume is the most important purchase criterion. This criterion is clearly dominating all other purchase criteria including historical performance, which shows only a minor influence in all conducted regression models. Moreover, investors apparently purchase mutual funds without avoiding high initial charges.

6 Robustness

In order to check the validity of the results regarding my three research questions, I perform several robustness tests.

First, I exclude all investors who purchased only one fund in the analyzed time period from my data set. After recalculating the decile analyzes and the regression model, it turns out

[10] Recall that usually multi-collinearity is considered as present if VIF values are larger than 10

that the results remain qualitatively unchanged. The volume is still the dominant purchasing criterion and the majority of investors come to their purchase decision without chasing historical performance. Moreover, initial charges do not play any role for mutual fund purchasing decisions.

After not taking very infrequent traders into account, I investigate whether investors who trade very frequently bias the results. In the data set a variable indicating if an investor is categorized as "heavy trader" by the banks' data warehouse is included. Excluding all these heavy traders from the analyzed data set and repeating all analyzes yields qualitatively unchanged results for all three research questions, since these investors predominantly invest into single stocks and options.

As described in section 3 I excluded all transactions which are part of a mutual fund saving plan when constructing the final data base. However, I repeat all analyzes with the data set including the saving plan transactions for robustness reasons. Again, all results remain qualitatively unchanged (e.g. the mean of the purchased Alpha-decile is 6.20 including saving plan transactions compared to 6.40 excluding safety plan transactions (compare table 4)). This result confirms even more my conclusion that institutional boundaries are not the reason why investors do not chase historical performance, as adding saving plan transactions implies considering investors who are institutionally bounded as well.

Finally, I also conduct Fama-MacBeth regression in order to account for the fact that my data is panel data across time. The methodology of this two-step regression approach is already described in section 4. The group-average regression coefficients are very similar to the coefficients estimated in the regular regressions. Hence, the impression that volume is the strongest purchasing criterion dominating the historical performance and that initial charge is a subordinated purchase criterion is confirmed.

7 Conclusion

This paper contributes to the growing body of literature on mutual fund purchasing decisions. In contrast to earlier studies (e.g. Gruber (1996) or Keswani and Stolin (2008)), I use a data set of a German online brokerage house that allows me to analyze the investment behavior on an transaction- and investor-specific level. Combining this data set with data on the mutual fund universe from Morningstar and a German provider, VWD, and weekly mutual fund performance data from Thomson Financial Datastream, I am able to construct a data set that contains approximately 1.5m mutual fund transactions of roughly 44k distinct individual investors.

By grouping funds into deciles at a peer group level I make the performance measures and fund characteristics of different peer groups comparable and in this way study the purchasing behavior of private mutual fund investors. In detail, I focus on three major research questions.

First, I contribute to the open issue if institutional boundaries prevent investors from chasing historical performance when choosing among mutual funds. By considering institutionally unbounded investors I show that there are indeed investors who use historical performance as purchase criterion, but that there is still a large group of investors who apparently use a different purchase criterion than historical performance. In detail, in only 25% of all transactions investors purchase mutual funds which belong to the top 20% within its according peer group as regards historical Alpha performance. Following Gruber (1996), I conclude that investors are indeed unsophisticated.

Second, I analyze further possible purchase criteria for a mutual fund investment and find out that in more than 80% of transactions investors purchase mutual funds belonging to the top 20% funds with the highest volume. Moreover, I provide evidence that investors prefer mutual funds belonging to top-brand fund families and conclude that the volume and possibly the funds family brand power is an important purchase criterion in the majority of cases. Furthermore, I find that initial charges are not an important purchase criterion, as investors on average purchase mutual funds with above average initial charges. Apparently, investors feel poised to pay higher initial charges for mutual funds they are committed to for other reasons.

Third, I discuss which of the analyzed purchase criteria is the dominating one. This is a key contribution of this paper, as – to the best of my knowledge – nobody considered this issue so far. By performing regression analyses I find that the mutual fund volume is indeed the all-dominant criterion and that historical performance is only of secondary importance. Moreover, I confirm again that low initial charges are no purchase criterion at all. As from a scientific point of view, historical performance is the only reasonable criterion someone should use when investing in actively managed mutual funds (compare e.g. Gruber (1996)), I conclude that the majority of investors make serious and costly investment mistakes when investing in mutual funds.

Research in mutual funds remains an interesting domain. In this paper I have shown that there is a group of investors who purchase mutual funds by chasing historical performance but that the majority of investors do not and that institutional boundaries are not the reason that prevents investors from chasing performance. Hence, the next logical question is why investors do not chase historical performance or - in other words - why investors are unsophisticated. One possible explanation is missing feedback. Therefore, an interesting area for further research is to analyze whether investors learn over time when investing in mutual funds and start chasing historical performance after recognizing their former investment mistakes.

Moreover, potential further research could concentrate on the question which particular investors make correct purchase decisions and which do not, i.e. deal with the issue to divide investors in smart acting and non-smart acting investor groups.

Another interesting field of research is the impact of financial advice. Recent literature (e.g. Bergstresser, Chalmers and Tufano (2009); Hackethal, Haliassos and Jappelli (2008)) have shown that investors who make their investment decisions supported by a professional advisor cannot improve their investment success after cost consideration. It would be interesting to analyze if advised investors use historical performance as purchase criterion more frequently than their unadvised peers.

Finally, potential further research could deal with mutual fund marketing. I show that the majority of individual investors do not use historical performance as their decision criterion. I also find that purchased funds have a clear above average fund volume and assume that advertising works. It would be interesting to study the effects of marketing and advertising activities as well as the effect of news on the individual purchasing behavior in greater detail (compare e.g. Barber, Odean and Zheng (2005) or Sirri and Tufano (1998)).

Table A1: Distribution of purchased mutual funds within all mutual funds – APR-Measure

The table presents results for research question 1. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of historical performance-deciles of the purchased mutual funds within all mutual funds. Moreover the mean and the standard deviation of the historical performance deciles are presented. As performance measure I use the Alpha Persistence Ratio (APR). The analyzed time period is January 1999 – July 2007.

		APR-Decile											
Peer Group	**Observations**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	**Std. Dev.**
Stocks Europe	392,171	4.24%	6.03%	7.81%	9.95%	8.39%	7.45%	12.53%	15.38%	11.20%	17.01%	6.48	2.73
Stocks World	386,220	4.16%	2.77%	5.03%	4.90%	8.88%	12.22%	17.25%	16.84%	15.15%	12.81%	6.82	2.41
Stocks Germany	120,078	13.30%	10.19%	5.53%	6.10%	7.85%	7.76%	8.88%	10.43%	19.42%	10.54%	5.86	3.11
Bonds World	110,120	5.72%	7.24%	7.34%	6.20%	4.66%	7.09%	13.42%	18.44%	14.60%	15.30%	6.59	2.80
Stocks North America	76,864	5.31%	4.83%	11.74%	12.02%	8.28%	4.54%	6.22%	7.53%	15.16%	24.37%	6.51	3.01
Stocks Asia/Pacific	57,065	12.50%	8.63%	9.04%	12.31%	11.28%	9.08%	7.52%	7.94%	11.06%	10.63%	5.39	2.94
Stocks Biotech	48,587	1.95%	5.58%	13.35%	15.17%	13.52%	8.57%	3.48%	10.62%	12.40%	15.35%	6.07	2.71
Stocks IT	42,904	4.27%	11.68%	8.93%	8.77%	7.82%	9.50%	10.94%	13.50%	10.60%	13.99%	6.06	2.83
Stocks Real Estate	40,980	0.07%	0.08%	0.36%	0.54%	2.67%	1.77%	4.56%	3.49%	3.57%	82.90%	9.48	1.32
Money Market EUR	35,034	3.11%	5.30%	7.56%	6.81%	16.32%	15.92%	21.08%	15.09%	2.18%	6.63%	5.95	2.19
Stocks Emerging Markets	23,366	7.78%	11.20%	12.51%	8.15%	5.79%	6.61%	5.12%	10.13%	17.50%	15.22%	5.95	3.12
Stocks Materials	23,185	1.19%	6.97%	12.51%	4.62%	10.13%	24.97%	5.09%	7.16%	17.69%	9.67%	6.20	2.50
Stocks Japan	19,543	7.30%	10.27%	6.57%	6.82%	4.26%	4.48%	6.19%	13.53%	17.41%	23.18%	6.63	3.14
Stocks Greater China	18,674	0.76%	3.33%	8.65%	4.62%	3.41%	2.42%	9.02%	18.82%	18.43%	30.55%	7.68	2.50
Stocks India	18,599	0.42%	2.76%	7.68%	31.25%	10.22%	16.36%	4.02%	3.69%	16.94%	6.66%	5.80	2.31
Stocks Latin America	14,652	1.54%	2.30%	4.48%	11.54%	5.06%	12.71%	16.82%	23.92%	15.90%	5.71%	6.77	2.13
Stocks Healthcare	14,525	3.66%	11.04%	12.61%	7.84%	5.90%	10.91%	12.96%	6.65%	14.01%	14.43%	6.04	2.86
Stocks Energy	6,803	4.57%	3.92%	5.10%	8.92%	2.09%	17.29%	27.43%	17.89%	6.92%	5.87%	6.34	2.25
Stocks Media	4,268	10.59%	8.25%	7.50%	11.93%	14.69%	11.43%	12.00%	5.06%	4.83%	13.73%	5.45	2.81
Stocks Russia	2,697	0.04%	1.93%	1.67%	1.78%	1.59%	4.52%	16.72%	27.62%	43.20%	0.93%	7.87	1.54
Other	19,036	4.52%	8.12%	7.58%	5.22%	5.26%	10.73%	9.09%	10.97%	17.52%	20.99%	6.74	
All	**1,475,371**	**5.16%**	**5.72%**	**7.24%**	**8.00%**	**8.25%**	**9.20%**	**12.26%**	**13.95%**	**13.58%**	**16.64%**	**6.53**	**2.75**

Table A2: Distribution of purchased mutual funds within all mutual funds – Appraisal-Measure

The table presents results for research question 1. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of historical performance-deciles of the purchased mutual funds within all mutual funds. Moreover the mean and the standard deviation of the historical performance deciles are presented. As performance measure I use Appraisal. The analyzed time period is January 1999 – July 2007.

		Appraisal-Decile											
Peer Group	**Observations**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	**Std. Dev.**
Stocks Europe	403,235	3.37%	3.73%	6.15%	10.84%	12.07%	11.75%	10.08%	14.14%	18.36%	9.51%	6.48	2.48
Stocks World	393,009	2.19%	2.87%	2.92%	3.88%	10.49%	12.31%	24.48%	18.34%	10.84%	11.69%	6.91	2.13
Stocks Germany	125,703	7.54%	16.13%	6.97%	9.21%	8.76%	7.09%	6.83%	13.56%	17.27%	6.64%	5.62	2.94
Bonds World	116,102	3.17%	9.27%	7.15%	5.02%	6.60%	10.26%	15.10%	15.05%	13.30%	15.10%	6.54	2.69
Stocks North America	77,543	0.46%	4.17%	7.73%	10.22%	9.88%	10.57%	14.41%	16.34%	15.63%	10.58%	6.64	2.34
Stocks Asia/Pacific	57,705	13.85%	12.70%	7.57%	8.75%	11.27%	9.02%	7.51%	7.72%	9.19%	12.41%	5.29	3.05
Stocks Biotech	53,254	0.52%	2.06%	3.51%	6.28%	5.57%	15.25%	23.55%	13.20%	18.81%	11.25%	7.12	2.02
Stocks IT	47,372	1.78%	3.47%	7.28%	7.38%	11.91%	13.75%	13.27%	14.13%	8.36%	18.67%	6.70	2.45
Stocks Real Estate	42,916	0.14%	0.26%	1.66%	0.51%	2.22%	1.44%	7.54%	6.98%	15.86%	63.40%	9.13	1.55
Money Market EUR	35,952	0.12%	1.55%	5.37%	5.40%	2.69%	14.27%	23.86%	34.77%	3.40%	8.56%	7.01	1.81
Stocks Emerging Markets	26,596	8.08%	10.79%	7.61%	4.62%	6.47%	10.62%	5.59%	10.91%	10.41%	24.89%	6.36	3.16
Stocks Materials	24,042	0.09%	1.20%	2.43%	12.56%	23.98%	8.21%	11.89%	11.51%	13.79%	14.34%	6.72	2.18
Stocks Japan	20,067	9.57%	6.96%	6.34%	6.54%	5.52%	5.15%	7.00%	9.99%	18.18%	24.75%	6.67	3.16
Stocks Greater China	19,361	0.54%	0.89%	2.04%	6.13%	18.38%	8.03%	11.37%	17.75%	21.91%	12.95%	7.21	2.07
Stocks India	18,777	0.29%	0.61%	1.64%	20.78%	23.05%	8.70%	10.20%	10.11%	9.86%	14.75%	6.46	2.22
Stocks Healthcare	15,419	1.01%	3.87%	7.06%	9.13%	12.74%	15.21%	14.67%	6.03%	17.60%	12.68%	6.58	2.38
Stocks Latin America	15,006	0.87%	1.15%	4.24%	8.55%	15.05%	30.43%	11.14%	7.46%	11.04%	10.06%	6.46	2.02
Stocks Energy	7,070	2.08%	5.11%	3.89%	14.09%	37.36%	14.79%	9.80%	4.12%	3.01%	5.76%	5.42	1.93
Stocks Media	4,388	1.53%	5.54%	10.62%	19.58%	15.13%	13.67%	10.96%	5.97%	7.27%	9.73%	5.68	2.37
Stocks Russia	3,866	0.05%	0.31%	0.85%	10.81%	4.63%	12.49%	6.62%	17.23%	24.29%	22.71%	7.74	2.04
Other	20,404	3.95%	5.40%	7.71%	5.60%	6.44%	8.62%	6.79%	14.23%	18.42%	22.84%	7.00	
All	**1,527,787**	**3.30%**	**5.15%**	**5.26%**	**7.53%**	**10.39%**	**11.14%**	**14.78%**	**15.00%**	**14.31%**	**13.14%**	**6.62**	**2.51**

Table A3: Distribution of purchased mutual funds within all mutual funds – Weekly Returns

The table presents results for research question 1. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of historical performance-deciles of the purchased mutual funds within all mutual funds. Moreover the mean and the standard deviation of the historical performance deciles are presented. As performance measure I use Weekly Returns. The analyzed time period is January 1999 – July 2007.

		Weekly Returns - Decile											
Peer Group	**Observations**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	**Std. Dev.**
Stocks Europe	408,013	8.40%	7.88%	9.70%	9.07%	9.55%	10.72%	11.89%	8.63%	12.89%	11.26%	5.83	2.84
Stocks World	400,348	9.88%	9.88%	13.81%	8.21%	7.61%	7.44%	7.21%	10.45%	10.93%	14.59%	5.65	3.06
Stocks Germany	132,999	7.36%	8.36%	12.13%	10.46%	11.68%	10.95%	11.83%	10.46%	9.03%	7.74%	5.51	2.68
Bonds World	117,853	8.04%	9.54%	9.66%	8.03%	10.59%	9.33%	10.71%	12.14%	10.89%	11.07%	5.78	2.85
Stocks North America	77,941	11.02%	14.20%	9.03%	8.53%	10.53%	8.46%	11.34%	9.63%	10.38%	6.88%	5.23	2.87
Stocks Asia/Pacific	58,678	9.33%	8.81%	13.79%	8.25%	10.82%	10.64%	11.87%	8.51%	11.04%	6.95%	5.39	2.76
Stocks Biotech	57,612	5.65%	12.58%	10.67%	11.45%	7.66%	17.99%	11.79%	8.33%	9.16%	4.71%	5.34	2.55
Stocks IT	56,133	9.97%	8.22%	10.58%	10.37%	10.06%	9.82%	8.29%	8.66%	10.65%	13.36%	5.66	2.95
Stocks Real Estate	43,334	3.05%	7.75%	14.31%	15.59%	14.79%	10.67%	9.64%	9.81%	6.16%	8.22%	5.45	2.47
Money Market EUR	36,024	3.25%	1.80%	7.25%	11.89%	14.43%	11.93%	13.00%	16.90%	16.64%	2.91%	6.25	2.25
Stocks Emerging Markets	31,280	9.18%	10.05%	10.00%	9.56%	14.14%	8.56%	7.31%	10.55%	9.26%	11.38%	5.52	2.87
Stocks Materials	24,359	6.47%	10.16%	7.44%	9.67%	8.70%	6.81%	11.85%	11.78%	12.07%	15.05%	6.08	2.91
Stocks Japan	20,688	10.96%	10.01%	10.15%	9.06%	7.99%	9.49%	8.56%	8.54%	11.10%	14.14%	5.64	3.04
Stocks Greater China	19,959	7.71%	8.15%	7.83%	8.84%	11.13%	7.29%	13.11%	8.98%	14.89%	12.07%	6.01	2.86
Stocks India	19,070	1.59%	8.24%	6.99%	14.81%	21.50%	13.00%	15.14%	8.21%	7.83%	2.68%	5.53	2.13
Stocks Healthcare	16,491	8.50%	13.38%	16.94%	8.92%	10.18%	7.78%	10.13%	6.91%	9.79%	7.47%	5.08	2.80
Stocks Latin America	15,093	5.14%	18.45%	6.23%	10.93%	5.93%	17.43%	9.81%	5.25%	13.61%	7.23%	5.44	2.77
Stocks Energy	7,591	6.35%	12.30%	8.19%	8.42%	9.93%	7.85%	11.43%	10.51%	9.84%	15.16%	5.90	2.93
Stocks Media	4,728	12.23%	9.96%	9.90%	7.40%	7.25%	5.77%	12.84%	9.22%	13.58%	11.84%	5.67	3.07
Stocks Russia	3,976	3.02%	2.39%	10.56%	14.99%	11.29%	16.55%	14.03%	9.83%	14.46%	2.87%	5.91	2.26
Other	22,248	5.73%	7.78%	9.83%	9.72%	11.22%	12.44%	12.06%	10.05%	9.88%	11.30%	5.87	
All	**1,574,418**	**8.36%**	**9.25%**	**11.14%**	**9.34%**	**9.82%**	**9.86%**	**10.29%**	**9.83%**	**11.19%**	**10.91%**	**5.66**	**2.86**

Table A4: Distribution of purchased mutual funds within all mutual funds – One-year Returns

The table presents results for research question 1. The twenty largest peer groups of considered mutual funds are presented on the vertical axis, whereas on the horizontal axis the table shows the frequency of historical performance-deciles of the purchased mutual funds within all mutual funds. Moreover the mean and the standard deviation of the historical performance deciles are presented. As performance measure I use One-year Returns. The analyzed time period is January 1999 – July 2007.

		One-year Returns - Decile											
Peer Group	**Observations**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Mean**	**Std. Dev.**
Stocks Europe	403,462	8.02%	9.75%	9.21%	8.39%	10.30%	11.93%	10.44%	9.94%	12.35%	9.68%	5.72	2.81
Stocks World	393,194	8.84%	10.19%	16.24%	8.17%	6.45%	7.74%	6.52%	9.86%	13.48%	12.51%	5.60	3.03
Stocks Germany	125,879	7.98%	8.34%	13.25%	11.60%	11.27%	9.98%	11.41%	10.98%	8.04%	7.14%	5.39	2.67
Bonds World	116,180	8.12%	7.57%	8.67%	9.01%	10.04%	9.93%	10.70%	11.83%	13.42%	10.71%	5.93	2.82
Stocks North America	77,560	6.33%	9.73%	11.41%	7.81%	11.75%	10.56%	9.65%	13.09%	12.06%	7.60%	5.70	2.73
Stocks Asia/Pacific	57,757	6.59%	8.27%	10.50%	8.12%	13.73%	9.97%	11.25%	8.64%	14.59%	8.34%	5.78	2.73
Stocks Biotech	53,378	6.76%	12.10%	12.49%	6.03%	11.33%	18.67%	10.46%	7.69%	7.50%	6.97%	5.33	2.62
Stocks IT	47,505	6.25%	7.68%	11.80%	9.80%	13.52%	10.67%	8.16%	13.19%	9.45%	9.47%	5.70	2.70
Stocks Real Estate	42,931	3.49%	6.75%	10.22%	9.88%	15.67%	15.57%	10.64%	12.61%	9.44%	5.73%	5.77	2.40
Money Market EUR	35,954	2.17%	2.50%	7.57%	8.21%	14.91%	11.93%	13.98%	18.07%	17.86%	2.81%	6.40	2.20
Stocks Emerging Markets	26,881	7.44%	13.49%	9.17%	11.09%	12.43%	7.93%	6.77%	10.51%	11.24%	9.92%	5.48	2.87
Stocks Materials	24,044	4.59%	16.70%	8.46%	6.31%	8.43%	5.93%	10.90%	14.56%	12.74%	11.37%	5.88	2.93
Stocks Japan	20,080	7.42%	10.49%	8.92%	8.89%	8.88%	10.59%	7.39%	9.63%	14.37%	13.43%	5.91	2.94
Stocks Greater China	19,385	6.36%	10.43%	9.56%	8.22%	7.71%	10.91%	10.56%	10.74%	16.32%	9.20%	5.91	2.83
Stocks India	18,781	2.78%	7.12%	13.23%	8.26%	17.40%	15.36%	10.82%	13.73%	7.30%	3.99%	5.60	2.31
Stocks Healthcare	15,442	5.81%	13.55%	10.14%	9.56%	12.61%	9.47%	9.81%	8.68%	14.68%	5.67%	5.49	2.73
Stocks Latin America	15,059	6.85%	13.45%	6.60%	10.66%	11.29%	15.51%	7.34%	7.90%	13.58%	6.82%	5.51	2.73
Stocks Energy	7,072	6.24%	10.41%	7.28%	5.66%	6.32%	9.79%	11.41%	8.03%	13.48%	21.39%	6.41	3.01
Stocks Media	4,388	11.94%	12.33%	9.09%	10.92%	7.54%	5.99%	14.27%	9.14%	9.32%	9.46%	5.33	2.95
Stocks Russia	3,875	1.75%	6.30%	12.75%	14.86%	15.77%	14.06%	16.31%	8.36%	7.15%	2.68%	5.48	2.15
Other	20,478	6.46%	7.71%	11.54%	10.18%	8.61%	12.28%	10.91%	12.96%	10.09%	9.26%	5.77	
All	**1,529,285**	**7.50%**	**9.48%**	**11.74%**	**8.69%**	**10.02%**	**10.52%**	**9.47%**	**10.66%**	**12.21%**	**9.71%**	**5.68**	**2.82**

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Whose money is smart? Smart Decision Making Measured

by Investors' Ability to Select Mutual Funds

Fabian Niebling[1]

Abstract:

This paper contributes to the growing body of literature on mutual fund persistence, smart investment decision making and household finance. I derive three key findings by using administrative data for an empirical analysis on investor-specific level. First, I show that persistence exists in the German mutual fund market resulting in above-average returns for investors who purchase mutual funds by chasing historical performance. Second, I find that smart investment decisions are made by investors who are older, more experienced, wealthier and less overconfident. Third, I provide evidence on the economic impact of smart decision making by pointing out that smart investors realize on average a 179bp higher portfolio return per year. Therefore, I suggest that the quality of mutual fund investment decisions should be used as an ex-ante measure to assess investment decisions of private investors without the problem of potential randomness of stock market returns.

Keywords: Mutual funds, Fund performance, Mutual fund persistence, Smart Decision Making, Household finance

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1 Introduction

Research in mutual fund investments of private investors remains an interesting field. Recently, Keswani and Stolin (2008) documented a robust smart money effect even after controlling for stock momentum for both, individual and institutional investors. The smart money effect reveals that investors by majority purchase mutual funds which outperform their respective benchmarks in the future. Therefore, investors' money is "smart" enough to flow to such funds that will outperform the market. If persistence in the mutual fund market exists, consequently, it will be a winning strategy to purchase mutual funds which have outperformed the market in the past.[2] However, various research find that inferior performing mutual funds still receive net cash inflows (e.g. Gruber (1996), Sirri and Tufano (1998) or Keswani and Stolin (2008)). These results are confirmed for the German mutual fund market by Ber, Kempf and Ruenzi (2008) and Niebling (2010) who works on an investor-specific level. Given these findings Keswani and Stolin (2008) claim: *"Much more needs to be done, however, to understand how different categories of investors arrive at their mutual fund buying and selling decisions"*.

Directly addressing their claim, I am able to identify smart acting investor groups as I work on an investor-specific data level. Moreover, this investor-specific level enables me to show that mutual fund investment decisions are a very good proxy in order to measure overall investment success. In this paper I thereby develop an ex-ante measure for investment success which can be used in order to consider various future research questions for which a measure for investment success is needed.

This paper builds on and contributes to three different strands of literature: First, I add to literature on performance persistence and confirm the existence of performance persistence in the German mutual fund market. I find that investors seem to make smart investment decisions once they decide to purchase mutual funds with respect to historical performance, as they realize above-average returns in the following year. Not chasing past performance is therefore an investment mistake. This result is not surprising considering that performance persistence is proven to be present in the dataset at hand.

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[2] Basically, persistence in the mutual fund market is proven to be existent by many studies (e.g. Gruber, M.J., 1996, "Another puzzle: The growth in actively managed mutual funds", *Journal of Finance* 51, 783-810. or Elton, E.J., M.J. Gruber, and C.R. Blake, 1996, "The persistence of risk-adjusted mutual fund performance", *Journal of Business* 69, 133-157. However, in this paper I confirm the mutual fund persistence once more for the German mutual fund market.

Second, I examine which particular investor groups act smart and chase historical performance. Answering this question contributes to the emerging body of literature on smart decision making (e.g. Elton, Gruber and Busse (2004), Feng and Seasholes (2005) and Keswani and Stolin (2008)). This paper is the first, of which the author is aware, that particularly targets determining which particular investors act smart and purchase mutual funds by chasing historical performance. I find that investors making smart investments are older, more experienced, wealthier and less overconfident. On the other hand, Gender, Marital Status and the Deposit Value do not seem to have influence on the investment behavior. Moreover, I also consider funds' expenses and construct a variable measuring investors' smartness by taking the funds historical Alpha as well as initial charges into account. The impact of the investor characteristics on this new variable is very similar to the one on the historical performance.

Third, I discuss the economic impact of smart decision making and therefore contribute to literature on household finance. I analyze whether investors, who act smart and purchase mutual funds by chasing historical performance, realize higher portfolio returns. In particular, I find that investors who act smart when purchasing mutual funds generate on average a 179bp higher portfolio return per year than investors who do not act smart regarding mutual fund investment decisions. When also taking portfolio risk into account by considering the Sharpe ratio, smart investors even generate on average a 299bp higher Sharpe ratio than non-smart acting investors. Being able to reject the null hypothesis of no relationship between mutual fund selection and investment success makes the previous results even more valuable. The outcomes of my analyses are not subject to any potential random realization of stock markets as in previous studies, e.g. by Campbell (2006), Barber and Odean (2000) and Hackethal, Haliassos and Jappelli (2008). Having empirically confirmed this relationship I suggest using mutual fund investment decisions as an ex-ante measure for investment decision quality, i.e. for financial ability. This measure can be applied to various research questions for which financial ability has to be measured.

In order to derive my findings, I use a high-quality administrative data set of a German online brokerage house and data on the mutual fund universe from Morningstar and a German provider, VWD, as well as weekly mutual fund performance data from Thomson Financial Datastream. Combining these data sources I am able to construct a dataset that contains more than 1.5m mutual fund transactions of roughly 44k distinct individual investors. For all of these investors the dataset includes portfolio compositions, their respective trading history as well as socio-demographics. Moreover, the database also contains total net assets and initial charges on a fund level.

The rest of the paper is organized as follows. In section 2 I give an overview over existing literature in the field of mutual fund persistence, smart decision making as well as over household finance and derive my research questions. Section 3 describes the construction of the dataset this paper employs in order to address the research questions. Section 4 deals with methodological issues. The empirical results on mutual fund persistence, the determination of particular smart acting investor groups and the overall economic impact of smart decision making are reported and discussed in section 5. In section 6 I describe results of some additional robustness tests and section 7 draws conclusions.

2 Literature Review and Research Questions

This paper builds on a wide array of research on mutual funds and behavioral finance adding to three different strands of literature, namely (i) literature on mutual funds performance persistence, (ii) literature on smart investment decisions making and (iii) literature on household finance.

In order to be able to differentiate between smart and non-smart acting investors based on historical performance of mutual funds, it is necessary that persistence exists. This topic has been heavily discussed over the last years. Nevertheless, following the dominating academic opinions, performance persistence in the mutual fund industry can be considered to be present. First empirical evidence goes back to Grinblatt and Titman (1992) who find that performance differences between funds persist over time. These results are confirmed by the work of Elton, Gruber and Blake (1996). They apply risk-adjusted measures and again find performance persistence. Even though there has been interim controversial discussions (e.g. Carhart (1997) in response to Hendricks, Patel and Zeckhauser (1993)), subsequent studies again underline the notion of performance persistence among mutual funds (e.g. Hsiu-Lang, Jegadeesh and Wermers (2000), Wermers and Moskowitz (2000)). Moreover, Chevalier and Ellison (1999) show that not so much the funds themselves but the fund managers are the cause for outstanding fund performances. Recently, Kosowski, Timmermann, Wermers and White (2006) by using a bootstrap analysis provided evidence that those fund managers who generate superior Alphas are not simply lucky but, in fact, are skilled. For an extensive review on mutual fund performance persistence I refer to Anderson and Schnusenberg (2005). However, as the picture is not comprehensively consistent I contribute to this question and recalculate the performance existence for the German mutual fund market. Consequently, my first research question is:

<u>Question 1:</u> ***Does mutual fund performance persistence apply in the German mutual fund market?***

After considering the whole German mutual fund market, I consider the specific transactions in my data set from an investor-specific point of view. I address the question whether investors who have behaved smart in the past and have purchased mutual funds by chasing historical performance benefit by generating above average returns in the future. Affirming this question by showing that smart-acting investors indeed purchase ex-post outperforming mutual funds, finally confirms the hypothesis that chasing historical performance is a valid purchase criterion. Summarizing these issues, my second research question is:

<u>Question 2:</u> ***Do mutual funds purchased by investors who act smart and chase historical performance perform better than mutual funds purchased by investors who do not chase historical performance?***

Gruber (1996) by analyzing US mutual funds cash flow data finds that there are indeed investors who invest in past winning mutual funds, but he also observes money remaining in the losing funds. This result is confirmed by Zheng (1999) expanding the dataset to a longer period of time, Keswani and Stolin (2008) using UK mutual fund data and Ber, Kempf and Ruenzi (2008) focusing on the German mutual fund market. Sirri and Tufano (1998) again show that mutual fund investors fail to stop investing in poor performing funds. All these works have in common that they use aggregated fund flow data. In contrast, Niebling (2010) uses transaction-specific data and finds that there are indeed investors who use historical performance as their decision criterion but that there is also a large investor group who do not chase historical performance and apparently use a different purchase criterion. Moreover, Niebling (2010) shows that mutual fund volume is the dominating purchase criterion for private investors when choosing among mutual funds and he concludes that the majority of investors makes serious investment mistakes.

All these findings lead to the question which particular investors act smart and which do not. Recently, Keswani and Stolin (2008) addressed this question by asking "Which money is smart?". They use a detailed dataset with net inflows instead of Total Net Assets (TNA) flows and are able to differentiate between fund purchases and fund sells in contrast to former studies on aggregated mutual fund flows (e.g. Gruber (1996), Zheng (1999)). They find some indications of educated, smart investors and additionally document a learning effect among investors within the last years. Complementary to these findings, Elton, Gruber and Busse (2004) and more recently Boldin and Cicci (2008) analyze easy predictable index funds and conclude the existence of uninformed investors from their results. They argue that potentially suboptimal financial advice causes net inflows to dominated funds.

All this research suggests the existence of smart acting and non-smart acting investors. However, to the best of my knowledge, there is no comprehensive research dividing mutual fund investors in smart acting and non-smart acting groups regarding their individual investor characteristics. Therefore, I formulate my third research question as follows:

<u>Question 3:</u> ***Which particular investor groups act smart and chase historical performance?***

After answering research question 3 I contribute to the field of household finance by using my results on the purchase decisions of mutual fund investors.

Campbell (2006) initiated a broad discussion on household finance. He finds that households make various investment mistakes, e.g. nonparticipation in risky asset markets, underdiversification of risky portfolios and failure to exercise options to refinance mortgages. He also shows that less wealthy and less educated households are more likely to make these investment mistakes than wealthier and better educated households.

Besides Campbell (2006), there are several studies investigating the influence of certain factors on the overall investment success. For example Barber and Odean (2000) show that investors who are excessive traders generate below average returns and conclude that "trading is hazardous to your wealth". Moreover, Barber and Odean (2001) analyze the influence of gender on investment success and find that men generate less portfolio return than women do, as men are more likely to be overconfident.

All these studies have in common that they use ex-post measures in order to detect investment success and, therefore, are subject to potential random realization of stock markets. As far as I know, nobody has developed an ex-ante measure for evaluating investment success.

In this paper I introduce a measure detecting investors' smartness through their mutual fund investments. If this measure has a positive influence on investors overall investment success (and not only on their success in mutual fund investments), I will indeed find an ex-ante measure for superior investment behavior. Therefore, my fourth research question is as follows:

<u>*Question 4:*</u> ***Do investors who act smart and chase historical performance have more overall investment success?***

3 Data

For this paper's analyses I construct a comprehensive data set from mainly two different sources, namely (i) a database containing transaction and portfolio data and (ii) a database containing mutual fund performance data and other fund characteristics.

The first database has been supplied by a German discount brokerage house and contains in total more than 19m transactions of roughly 71k individual investor transactions placed between January 1999 and July 2007. Therefore, I am able to work on investor- and transaction-level respectively in contrast to most of the existing studies on the purchasing behavior of mutual fund investors which use funds flow data (e.g. Gruber (1996), Sirri and Tufano (1998),Ber, Kempf and Ruenzi (2008)). However, in order to answer the research questions I have to make a few amendments to this dataset.

In a first step, I restrict the data set to mutual fund transactions resulting in more than 2.81m transactions of more than 48k distinct individual investors[3]. In a second step, I exclude transactions which are part of mutual funds saving plans mainly due to two reasons: First, when setting up a saving plan investors make the purchase decision only once in advance and then the mutual funds are purchased repeatedly and automatically by the bank. Second, saving plan investors usually cannot choose from the whole mutual fund universe, but can select only from a restricted set of mutual funds which are provided from the bank for saving plan purposes.

For sell transactions, the choice set of an individual investor is limited to the funds he previously purchased, and the actual transaction date might be determined by factors like

[3] Note that the customers of this bank can choose from the whole available fund universe and are thus institutionally unbounded

liquidity needs or tax reasons instead of smart decision making. For these reasons, I remove all sell transactions in a third step and exclusively focus on mutual fund purchases, where investors choose funds from the entire mutual fund universe at a specific and individual date.

Table 1: Descriptive statistics

The table displays some descriptive statistics of the investor data I use for my studies. Dummy variables indicate if an investor is classified as male, married or as a heavy trader by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Number of Portfolio Positions and Share of International Equity are proxies for diversification.

	Obs	Mean	Median	Std. Dev.
Gender (Dummy; 1 = male)	43,880	84.31%		
Age	43,881	46.12	44.00	12.16
Marital Status (Dummy; 1 = married)	23,595	60.91%		
Riskclass	43,679	4.56	5.00	1.28
Heavy Trader (Dummy)	44,029	27.56%		
Deposit Value	44,028	55,802	36,296	131,441
Cash Value	44,029	34,637	15,139	86,061
Mutual Funds Trade Volume	44,029	4,206	2,557	14,273
Number of Trades	44,029	97	22	502
Number of Portfolio Positions	33,589	12.13	9.00	11.64
Share of International Equity	32,869	49%		
Length of Customer Rel. (years)	44,029	8.05	7.80	3.01

In order to address research questions 3 and 4 I need to work on investor-specific level. This requires not considering the investors with missing observations - socio-demographic information as well as other information (e.g. risk class, deposit value, trading frequency).

In order to get a feeling of the approx. 44k investors[4] purchasing mutual funds in my database, I present some descriptive statistics in table 1. Unfortunately, comprehensive socio-demographic information is not available for all 44k investors, which explains the lower amount of observations for particular descriptive numbers. A comparison of the demographics with the ones provided by Deutsches Aktieninstitut (2004)[5] indicates that my sample of 44k investors represents approximately 0.6% of the whole mutual fund investor population in Germany. Investors in my sample are more likely to be male (84% compared to 58% in the population), are almost of the same average age (46 years compared to 47 years in the population) and have a higher average deposit value (€ 56k compared to € 20k in the population). However, please note that the latter difference can be explained by the fact that

[4] Investors who only purchased mutual funds via a saving plan are already excluded in this analysis.

[5] Deutsches Aktieninstitut e.V. is a German Research Association of public listed companies and institutions.

average deposit value in the population is biased by Germans who rather own an investment portfolio (approximately 41% of the population) but do not invest in equity (only 16% of the population invest in stocks or mutual funds). Therefore, I believe that the gap will be significantly reduced when considering only investors who own equity (like the majority of investors in my data set). All in all, my sample is fairly representative for the mutual fund population in Germany.

The second database I use is a survivorship bias free sample of the German mutual fund market. I use the Morningstar database that has been proven to be of high quality in studies on the American mutual fund market (see Elton, Gruber and Blake (2001)). Since Morningstar data is only available from 2002 to 2006, I supplement my database with information provided by two German suppliers, namely Hoppenstedt and VWD. From these databases I also obtain corresponding peer groups.

Finally, the private investors purchase 254 funds that are not covered in either of my data sets. In case no peer group was provided by any of the data providers, the mapping of funds into peer groups relies on regression techniques as they are also used in Koijen (2008). Essentially, this means that this paper uses self-reported peer groups on which private investors have to rely when selecting mutual funds.

The weekly mutual fund return data was obtained from Thomson Financial Datastream and is dividend adjusted and net of fees, but does not include initial charges. Unfortunately, (sufficient) performance data is not available for all purchased funds, which reduces the number of transactions to approx. 1.5m transactions which are the base for the analyses answering research question 2.

For some of my analyses I need some additional information on the purchased mutual funds (e.g. fund volume, initial charge) which I obtain from Lipper/Reuters. Regrettably, these data are only available for the years 2002 – 2008 which yields to another restriction of the dataset for these analyses.

4 Model and Methodology

The major performance measure I use for my analyses in order to evaluate mutual fund performance is Jensen's Alpha (see Jensen (1968)). Recent studies have shown that results remain qualitatively unchanged once more sophisticated Alpha estimation techniques are used (see Carhart (1997), Gruber (1996), Kosowski, Timmermann, Wermers and White (2006)). The formula for the one-factor model is

$$r_i - r_f = \alpha_i + \beta_i (r_m - r_f) + \varepsilon_i \qquad (1)$$

where r_i is the return of fund i, r_f is the return of a three month cash position, r_m is the return of a peer group's benchmark index, β_i is the sensitivity of fund i to the return on the benchmark index, α_i is the risk-adjusted return on fund i and ε_i is the error term. The benchmark indices are chosen in accordance with a fund's peer group. As shown in table 2, for all peer groups focusing on stocks this paper uses the accordant MSCI indices, for bond funds Datastream indices are used and for money market funds indices provided by Citigroup are used.

In order to control for the fact that results may depend on the specific risk measure used, I consider as a second performance measure the Appraisal ratio[6]. Besides Jensen's Alpha this measure takes also the non-systematic risk via the denominator into account. This means that a mutual fund is valuated the worse the larger the non-systematic risk is.

The Appraisal ratio is computed by dividing the Alpha by the standard deviation of the error term of the one-factor model:

$$Appraisal = \frac{\alpha_i}{\sigma(\varepsilon_i)} \qquad (2)$$

where α_i is Jensen's Alpha of fund i from the one-factor model and $\sigma(\varepsilon_i)$ is the standard deviation of the error term of fund i in the one-factor model.

Using a rolling-window approach, the Alpha for each fund and the Appraisal ratio for each fund are calculated based on weekly observations between 1997 and 2008. The underlying assumption is that that a performance chasing investor chooses among mutual funds by looking at the historical performance of the year before. In order to assure the comparability of risk-adjusted performances of mutual funds, I compare several peer groups (compare table 2).

[6] Note that I performed all analyses with three further performance measures, namely the Alpha Persistence Ratio (APR), Weekly Returns and One-year Returns. As all results and conclusions remain qualitatively unchanged, I abstain from displaying these results. For a definition and results of these measures regarding mutual fund purchasing criteria, the reader is referred to Niebling, F., 2010, "The determinants of mutual funds inflows - evidence from private investor transactions", *Working Paper, Goethe University, Frankfurt a.M.*

Table 2: Definition of peer groups and peer group's benchmark indices

In this table the definitions of the 56 peer group are given. The according peer group's benchmark indices are used for calculating the risk-adjusted performances (Jensen's Alpha) and for ranking the mutual funds into peer group specific deciles.

ID	Peer group	Peer group's benchmark index	ID	Peer group	Peer group's benchmark index
Stock Market by Geography			**Stock Markets by Industry (cont'd)**		
1	Stocks World	MSCI World	30	Stocks Financial Markets	MSCI Financials
2	Stocks Europe	MSCI Europe	31	Stocks Materials	MSCI Materials
3	Stocks Germany	MSCI Germany	32	Stocks Energy	MSCI Energy
4	Stocks Spain	MSCI Spain	33	Stocks Health Care	MSCI Health Care
5	Stocks France	MSCI France	34	Stocks Consumer Goods	MSCI Consumer Staples
6	Stocks Switzerland	MSCI Switzerland	35	Stocks Industrial	MSCI Industrials
7	Stocks Italy	MSCI Italy	36	Stocks Utilities	MSCI Utilities
8	Stocks Scandinavia	MSCI Nordic Countries	37	Stocks Media	MSCI Media
9	Stocks UK	MSCI UK	38	Stocks Biotech	MSCI Pharmaceuticals & Biotech
10	Stocks Denmark	MSCI Denmark	39	Stocks Real Estate	MSCI Real Estate
11	Stocks Netherlands	MSCI Netherlands	**Money Markets by Geography**		
12	Stocks Austria	MSCI Austria			
13	Stocks Sweden	MSCI Sweden	40	Money Market EUR	CGBI WMNI 1MTH Euro debt
14	Stocks Turkey	MSCI Turkey	41	Money Market GBP	CGBI WMNI UK 1MTH Euro debt
15	Stocks Finland	MSCI Finland	42	Money Market USD	CGBI WMNI US 1MTH Euro debt
16	Stocks Russia	MSCI Russia	43	Money Market CAD	CGBI WMNI CN 1MTH Euro debt
17	Stocks North America	MSCI North America	44	Money Market CHF	CGBI WMNI SW 1MTH Euro debt
18	Stocks Australia	MSCI Australia	45	Money market AUD	CGBI WMNI AU 1MTH Euro debt
19	Stocks Asia/ Pacific	MSCI AC Asia Pacific ex Japan	**Bond Markets by Geography**		
20	Stocks Japan	MSCI Japan			
21	Stocks Emerging Markets	MSCI EM	46	Bonds global (EUR)	CGBI WGBI WORLD 10 MKT ALL MATS
22	Stocks Latin America	MSCI EM Latin America	47	Bonds USD	CGBI USBIG Gvt-spons
23	Stocks Greater China	MSCI Golden Dragon	48	Bonds CHF	SW Total all
24	Stocks Singapore	MSCI Singapore	49	Bonds GBP	UK Total all
25	Stocks Thailand	MSCI Thailand	50	Bonds AUD	AU Total all
26	Stocks Korea	MSCI Korea	51	Bonds JPY	JP Total all
27	Stocks India	MSCI India	52	Bonds DKK	DK Total all
28	Stocks Brazil	MSCI Brazil	53	Bonds CAD	CN Total all
Stock Markets by Industry			54	Bonds SEK	SD Total all
			55	Bonds NOK	NW Total all
29	Stocks Information Technolo	MSCI Information Technology	56	Bonds Asia	CGBI ESBI 10 years

In order to address my research questions I need to compare the performance measures of the mutual funds purchased by investors with the ones of all mutual funds available. However, it is not possible to compare the performance measures of the mutual funds of different peer groups and in different times directly with each other (for example the Alpha measures are always subject to different betas). I address this issue by categorizing the funds according to their deciles using their past performance in every specific peer group. Hence, in any given week and for every peer group the decile 1 contains the mutual funds with the poorest performance and decile 10 contains the mutual funds with the strongest performance. This means that I create a basis on that I can compare the mutual funds according to their relative performance indicated by the deciles they belong to. Using this data I am able to analyze research question 1.

In order to address research question 2, this information is combined with the transaction data containing all funds purchased by private investors. Thus, this newly constructed dataset provides information about the relative performance of a particular mutual fund at the time it was purchased by a private investor.

In order to answer questions 3 and 4, I further enrich this dataset by adding additional investor and mutual fund characteristics. As I want to measure the quality of an investors' mutual fund investment decision and not consider single transactions, which could be lucky draws, I calculate investor averages.

Table 3: Definition of Initial Charge Groups

Definitions and proportions of the three initial charge groups are displayed in this table.

Initial Charge Group	Name	Definition	Proportion
1	No Initial Charges	Initial Charges = 0%	33%
2	Reduced Initial Charges	0% < Initial Charges < 5%	38%
3	Full Initial Charges	Initial Charges ≥ 5%	29%

Following this approach, the paper implicitly makes the assumption that it is a smart strategy to purchase mutual funds by chasing Alphas. Whereas the operating expenses are already factored into the Alpha, I do not take any initial charges into account. In order to account for this issue I classify all mutual funds into three different categories with respect to their initial charges, namely (i) mutual funds with no initial charges, (ii) mutual funds with reduced initial charges (initial charges larger than zero and smaller than 5%) and (iii) mutual funds with full initial charges (initial charges of 5% and larger) (compare table 3). Subsequently, I define a new variable "Smartness" assuming that smart investors (i) purchase the mutual funds with the highest historical Alpha performance and (ii) purchase the mutual funds with the lowest initial charge within the group of all funds with the highest historical Alpha performance:

$$Smartness = 3 \text{ x } Alpha\text{-}decile - Initial\text{-}charge\text{-}group + 1 \quad (3)$$

"Smartness" is a natural number between 1 and 30 and it holds that the larger the value of "Smartness", the smarter the investors' investment decisions. Note that the historical Alpha has a stronger influence on the value of "Smartness" than the initial charge.

Table 4: Examples for variable "Smartness"

Table 4 displays some examples for the variable "Smartness". The larger the variable "Smartness" is, the smarter appears the investment decision.

Alpha Deciles	Initial Charge Group	Smartness
10	1	30
10	3	28
9	1	27
1	3	1

Once "locked-in" into an Alpha decile it is not possible to change the decile by purchasing a fund with a low initial charge. In order to illustrate the intuition behind the "Smartness" variable, some examples for the calculation of the variable are given in table 4.

In order to address research question 3, i.e. to identify smart acting investor groups, I conduct a multiple regression model with the investor's average of the purchased Alpha decile and the average Smartness value of an investor, respectively, as depending variable. As both the purchased Alpha decile and the Smartness are censored variables (from 1 to 10 for the Alpha decile and from 1 to 30 for Smartness, respectively), I use a Tobit-Regression model. Depending variables are several investor characteristics. I also control for a couple of fund characteristics which are usually used in other papers[7]. I use the regression model:

$$
\begin{aligned}
&PM_i \quad Gen_i \quad Age_i \quad Mar_i \quad LN(DepVal)_i \quad TradeVol_i \quad TradeFreq_i \\
&\qquad Len_i \quad Risk_i \quad IC_i \quad LN(TNA)_i \quad TB_i \quad {}_i
\end{aligned}
\tag{4}
$$

where PM_i is the investor-average of a given performance measure[8] of investor i, Gen_i is a dummy variable indicating if the investor i is male, Age_i is the age of investor i, Mar_i is a dummy variable indicating if the investor i is married, $LN(DepVal)_i$ is the natural logarithm of the average deposit value of investor i, $TradeVol_i$ is the average fund trade volume of investor i, $TradeFreq_i$ is the trading frequency of investor i[9], Len_i is the length of the relationship to the bank of investor i, $Risk_i$ is the self-reported risk class[10] of investor i, IC_i is the investor-average initial charge of investor i, $LN(TNA)_i$ is the natural logarithm of the investor-average fund volume[11] of investor i, TB_i is the investor-average of a dummy variable indicating whether a fund belongs to one of the top mutual fund families and ${}_i$ is the error term.

Finally, I conduct a second regression analysis in order to answer research question 4, namely if the investors Smartness does have a positive influence on the overall investment success. I use an out-of-sample approach using the time period from October 2006 to September 2007 for measuring the portfolio returns and the time period from January 2003

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[7] For a detailed derivation of these fund characteristics please compare section 5.2

[8] In this regression I use Jensen's Alpha (defined in (1)) and the variable Smartness (defined in (3)) as performance measures.

[9] Measured on a scale from 1 (low trading frequency) to 5 (high trading frequency)

[10] On a scale from 1 (low risk) to 6 (high risk)

[11] Measured in Total Net Assets (TNA)

to September 2006 for calculating the investor average Smartness. This approach with two distinct time periods guarantees that the investment success is not mainly driven by the purchased outperforming mutual funds which are reflected already in the value of the variable Smartness. Additionally, I include several investor characteristics and the portfolio risk as control variables:

$$
\begin{aligned}
&PortPerf_i \quad PM_i \quad Gen_i \quad Age_i \quad Mar_i \quad LN(DepVal)_i \\
&\quad TradeVol_i \quad TradeFreq_i \quad Len_i \quad PortRisk_i \quad {}_i
\end{aligned} \tag{5}
$$

where $PortPerf_i$ is the one-year portfolio performance[12] of investor i, PM_i is the investor-average of a given performance measure[13] of investor i, Gen_i is a dummy variable indicating if an investor is male, Age_i is the age of investor i, Mar_i is a dummy variable indicating if the investor i is married, $LN(DepVal)_i$ is the natural logarithm of the average deposit value of investor i, $TradeVol_i$ is the average fund trade volume of investor i, $TradeFreq_i$ is the trading frequency of investor i[14], Len_i is the length of the relationship of investor i with the bank, $PortRisk_i$ is the portfolio risk[15] of investor i, and $_i$ is the error term.

5 Results and Discussion

5.1 Performance persistence among mutual funds

Although several previous studies have already shown that there is persistence in mutual fund performance (e.g. Gruber (1996) and for the German market Fischer, Hackethal and Meyer (2008)), I replicate these analyses in order to assure the existence of performance persistence within my data set.

In order to determine the performance persistence, I follow the approach outlined by Gruber (1996). I group funds into deciles according to their historical performance and then observe the average performance of funds from a particular decile in the following year. Note that I first calculate averages per given week and peer group respectively and then average over

---

[12] I use the simple portfolio performance as well as the Sharpe ratio of the portfolio

[13] I use the investor average Alpha decile as well as the investor average Smartness variable. Additionally I perform the regressions with so called Top20 dummies indicating whether an investor purchases on average mutual funds in the Alpha deciles 9 and 10 and whether an investor has an average Smartness value of 25 to 30 respectively.

[14] Measured on a scale from 1 (low trading frequency) to 5 (high trading frequency)

[15] Portfolio risk is measured as the portfolios standard deviation.

all weeks and peer groups equally. This approach allows me to display absolute performance measures as I take into account the unequal distribution of the transactions over time and peer groups (Otherwise I could derive only relative statements by considering deciles).

First, I address research question 1 based on the whole German mutual fund market. The results for Jensen's Alpha are summarized in panel A of table 5. The decile 1 includes the 10% of funds with the lowest prior Alpha performance whereas the decile 10 includes the 10% of funds with the highest prior Alpha performance. Column 2-5 present results for the Alpha performance in the following year, whereas column 6-9 display results for average Alpha deciles. Accordingly, the results for the One-year Return measure and for One-year Return deciles respectively are presented in column 10-17.

Looking at the results for the Alpha measure (column 2-5), I observe a positive trend in the mean from the bottom decile to the top one. The average Alpha of the previously poorest performing funds is -1.25% p.a. and the average Alpha of the previously best performing funds is 2.16% p.a.. The results become even more obvious when I compare the average Alpha of deciles 1-8 with the average Alpha of deciles 9 and 10: An investor who purchases mutual funds in the top 20% of historical Alpha performance (deciles 9 and 10) can expect on average an Alpha performance of 1.10% p.a. in the following year. In contrast, an investor who purchases mutual funds in deciles 1 to 8 of historical Alpha performance can expect on average an Alpha performance of only -0.43% p.a.; i.e. he can improve the expected future Alpha performance by investing in previously top performing funds on average by 1.53% p.a.. The difference between deciles 1-8 and 9-10 is statistically significant as the t-test reveals.

Results still hold when considering average Alpha deciles instead of the absolute Alpha measure (compare column 6-9): The Alpha decile of the previously poorest performing funds is on average 4.80 and the Alpha decile of the previously best performing funds is on average 6.16. All average deciles are pairwise statistically different. If an investor purchases mutual funds in the top 20% of historical Alpha performance (deciles 9 and 10) he will expect the funds on average in decile of 6.13 in the following year. For comparison, investors who purchase mutual funds in deciles 1 to 8 of historical Alpha performance can expect the funds in the following year on average to be only in decile 5.40. This means, that investors can improve the future Alpha performance of their purchased mutual funds by 0.73 in terms of average deciles by purchasing funds in deciles 9 and 10 of past Alpha performance.

Additionally, I consider simple One-year Returns in the following year (columns 10-17). Results indicate that investors who invest in previously outperforming funds can expect higher returns in the future than investors who invest in previously poor performing mutual funds: Again, I observe a positive trend in the mean of the One-year Returns from decile 1 (mean of 3.55% p.a.) to decile 10 (mean of 10.69% p.a.). An investor who invests in the top 20% of previous Alpha performance can expect on average a future return of 9.78% p.a., whereas an investor who purchased mutual funds in deciles 1-8 of previous Alpha performance can expect on average only a return of 6.10% p.a.. Therefore, chasing historical performance improves expected future returns on average by 3.68% p.a.. Although the differences of two succeeding deciles are not statistically significant, the difference between decile 1-8 and 9-10 is significant at all common thresholds.

Again, results are confirmed by considering deciles instead of absolute measures in the following year. The average One-year return decile of funds in Alpha decile 1 is 5.27, whereas the average One-year Return decile of funds in Alpha decile 10 is 5.81 and investors can improve the expected average One-year Return decile by 0.29 when investing in the top 20% of historical Alpha performance.

The results do not depend on the specific performance measure used as the picture for the Appraisal ratio is very similar (compare panel B of table 5). I observe a positive trend along the previous Appraisal ratio deciles when considering the average Appraisal ratio in the following year. Investors who purchase mutual funds in the top 20% regarding historical Appraisal ratio generate higher future returns than investors who purchase funds in previous Appraisal ratio deciles 1 to 8. These results hold regardless considering future Appraisal ratios or simple returns and regardless considering absolute measures or deciles. Again, all differences of decile 1-8 and 9-10 are statistically significant.

Therefore, I can confirm the previous results of Kosowski, Timmermann, Wermers and White (2006) and Fischer, Hackethal and Meyer (2008) and conclude that it is reasonable to assume that performance persistence among German mutual funds exists.

In a second step I turn on a transaction-specific level and test whether these results still hold when considering only the actual mutual funds purchased by the private investors in my transactions data base. I use the same methodology, i.e. rank the purchased mutual funds by their historical performance deciles and display average performances of the following year by the previous deciles. Results are given in table 6.

Table 5: Performance persistence of all mutual funds in the German mutual fund universe

Table 5 presents results for research question 1. Funds are sorted into deciles[16] based on their performance over the prior year. Decile 10 includes the funds with the highest performance, while funds with the lowest performance are summarized in decile 1. The last two rows represent the deciles 1 to 8 and 9 to 10 respectively. The last column reports p-values of a parametric t-test. The analyzed time period is January 1997 – July 2007. Panel A presents results for Jensen's Alpha whereas Panel B shows results for the Appraisal ratio.

Panel A: Alpha Persistence of All Mutual Funds

Alpha Decile t	Alpha t + 1				Alpha Decile t + 1				One-year Returns t + 1				One-year Returns Decile t + 1			
	Obs.	Mean	Std. Dev.	p-value	Obs.	Mean	Std. Dev.	p-value	Obs.	Mean	Std. Dev.	p-value	Obs.	Mean	Std. Dev.	p-value
1	23,259	-1.25%	17.23%		23,259	4.80	2.54		23,422	3.55%	153.29%		23,422	5.27	2.41	
2	27,657	-1.28%	15.45%	0.866	27,657	4.90	2.20	0.000	27,715	4.81%	159.94%	0.366	27,715	5.34	2.13	0.001
3	29,262	-0.81%	14.56%	0.000	29,262	5.07	1.92	0.000	29,312	5.39%	156.75%	0.663	29,312	5.42	1.93	0.000
4	26,910	-0.85%	15.38%	0.788	26,910	5.28	1.74	0.000	26,949	5.53%	148.04%	0.916	26,949	5.47	1.79	0.003
5	27,503	-0.40%	13.06%	0.000	27,503	5.50	1.76	0.000	27,572	6.32%	143.63%	0.526	27,572	5.54	1.80	0.000
6	29,531	0.49%	18.46%	0.000	29,531	5.71	1.68	0.000	29,564	7.79%	159.45%	0.247	29,564	5.60	1.75	0.000
7	27,952	-0.07%	14.21%	0.000	27,952	5.85	1.74	0.000	28,010	6.99%	144.61%	0.525	28,010	5.65	1.80	0.002
8	28,166	0.54%	15.46%	0.000	28,166	5.98	1.95	0.000	28,251	7.89%	156.09%	0.478	28,251	5.68	1.96	0.035
9	28,655	0.21%	16.56%	0.013	28,655	6.11	2.21	0.000	28,776	9.00%	158.02%	0.395	28,776	5.77	2.16	0.000
10	24,313	2.16%	21.48%	0.000	24,313	6.16	2.55	0.008	24,476	10.69%	167.53%	0.232	24,476	5.81	2.48	0.117
1-8	220,240	-0.43%	15.56%		220,240	5.40	1.99		220,795	6.10%	152.95%		220,795	5.50	1.95	
9-10	52,968	1.10%	19.00%	0.000	52,968	6.13	2.37	0.000	53,252	9.78%	162.46%	0.000	53,252	5.79	2.31	0.000

Panel B: Appraisal Persistence of All Mutual Funds

Appraisal Decile t	Appraisal t + 1				Appraisal Decile t + 1				One-year Returns t + 1				One-year Returns Decile t + 1			
	Obs.	Mean	Std. Dev.	p-value	Obs.	Mean	Std. Dev.	p-value	Obs.	Mean	Std. Dev.	p-value	Obs.	Mean	Std. Dev.	p-value
1	23,291	-20.88	87.90		23,291	4.27	2.39		23,422	4.18%	138.22%		23,422	5.22	2.25	
2	27,679	-11.68	49.07	0.000	27,679	4.76	2.13	0.000	27,715	4.91%	158.32%	0.583	27,715	5.37	2.04	0.000
3	29,257	-6.87	19.40	0.000	29,257	4.98	1.90	0.000	29,312	5.33%	160.00%	0.752	29,312	5.46	1.91	0.000
4	26,885	-3.92	15.08	0.000	26,885	5.28	1.78	0.000	26,949	5.57%	151.61%	0.855	26,949	5.48	1.83	0.212
5	27,493	-5.09	17.72	0.000	27,493	5.46	1.78	0.000	27,572	6.06%	146.64%	0.701	27,572	5.56	1.84	0.000
6	29,527	-2.93	17.01	0.000	29,527	5.69	1.70	0.000	29,564	7.70%	163.82%	0.207	29,564	5.60	1.79	0.040
7	27,968	-2.42	10.27	0.000	27,968	5.83	1.77	0.000	28,010	7.34%	149.54%	0.780	28,010	5.65	1.85	0.001
8	28,193	-1.23	9.29	0.000	28,193	6.01	1.89	0.000	28,251	7.88%	156.54%	0.677	28,251	5.64	1.98	0.816
9	28,680	-0.11	8.92	0.000	28,680	6.32	2.07	0.000	28,776	8.99%	154.98%	0.394	28,776	5.73	2.12	0.000
10	24,275	4.60	25.14	0.000	24,275	6.55	2.32	0.000	24,476	10.17%	149.94%	0.374	24,476	5.83	2.34	0.000
1-8	220,293	-6.56	36.51		220,293	5.31	1.99		220,795	6.17%	153.72%		220,795	5.50	1.94	
9-10	52,955	2.05	18.39	0.000	52,955	6.42	2.19	0.000	53,252	9.53%	152.68%	0.000	53,252	5.78	2.22	0.000

[16] Note that the number of observations is not exactly the same for all deciles as Alpha performances may show same values at the corresponding thresholds.

Table 6: Performance persistence of all purchased mutual funds

Table 6 presents results for research question 2. Funds are sorted into deciles based on their performance over the prior year. Decile 10 includes the funds with the highest performance, while funds with the lowest performance are summarized in decile 1. The last two rows represent the deciles 1 to 8 and 9 to 10 respectively. The last column reports p-values of a parametric t-test. The analyzed time period is January 1999 – July 2007. Panel A presents results for Jensen's Alpha whereas Panel B shows result for the Appraisal ratio.

Panel A: Alpha Persistence of Purchased Mutual Funds

Alpha	Alpha t + 1				Alpha Decile t + 1				One-year Returns t + 1				One-year Returns Decile t + 1			
Decile t	**Obs.**	**Mean**	**Std. Dev.**	**p-value**	**Obs.**	**Mean**	**Std. Dev.**	**p-value**	**Obs.**	**Mean**	**Std. Dev.**	**p-value**	**Obs.**	**Mean**	**Std. Dev.**	**p-value**
1	3,118	-6.99%	22.35%		3,118	4.77	3.24		3,180	-7.15%	197.16%		3,180	5.38	3.05	
2	3,437	-2.99%	13.23%	0.000	3,437	4.85	2.60	0.312	3,461	0.14%	160.49%	0.097	3,461	5.55	2.64	0.014
3	3,814	-2.87%	13.41%	0.698	3,814	5.03	2.51	0.002	3,835	-0.87%	170.34%	0.796	3,835	5.47	2.56	0.192
4	3,976	-2.54%	13.23%	0.266	3,976	5.24	2.35	0.000	3,990	-0.80%	160.64%	0.987	3,990	5.48	2.44	0.885
5	4,207	-1.74%	12.67%	0.005	4,207	5.51	2.24	0.000	4,235	5.47%	156.00%	0.072	4,235	5.53	2.40	0.329
6	4,894	-1.72%	15.82%	0.955	4,894	5.60	2.28	0.058	4,910	3.75%	201.18%	0.652	4,910	5.56	2.39	0.557
7	5,002	-1.99%	13.92%	0.378	5,002	5.74	2.30	0.004	5,020	6.04%	157.20%	0.527	5,020	5.64	2.41	0.081
8	5,406	-2.17%	15.09%	0.514	5,406	5.93	2.37	0.000	5,422	7.24%	158.97%	0.697	5,422	5.67	2.41	0.612
9	5,889	-1.78%	16.44%	0.193	5,889	5.94	2.56	0.901	5,933	5.60%	168.09%	0.593	5,933	5.78	2.53	0.018
10	6,419	-1.56%	19.76%	0.490	6,419	6.22	2.98	0.000	6,502	9.18%	170.41%	0.240	6,502	5.85	2.85	0.116
1-8	33,854	-2.67%	15.09%		33,854	5.40	2.49		34,053	2.42%	170.53%		34,053	5.55	2.52	
9-10	12,308	-1.67%	18.25%	0.000	12,308	6.08	2.79	0.000	12,435	7.47%	169.31%	0.005	12,435	5.82	2.70	0.000

Panel B: Appraisal Persistence of Purchased Mutual Funds

Appraisal	Appraisal t + 1				Appraisal Decile t + 1				One-year Returns t + 1				One-year Returns Decile t + 1			
Decile t	**Obs.**	**Mean**	**Std. Dev.**	**p-value**	**Obs.**	**Mean**	**Std. Dev.**	**p-value**	**Obs.**	**Mean**	**Std. Dev.**	**p-value**	**Obs.**	**Mean**	**Std. Dev.**	**p-value**
1	2,491	-6.10	16.73		2,491	4.34	2.92		2,525	-8.27%	177.60%		2,525	5.35	2.82	
2	3,301	-5.95	16.50	0.731	3,301	4.84	2.60	0.000	3,325	-1.81%	180.36%	0.172	3,325	5.44	2.67	0.201
3	3,808	-5.80	14.98	0.686	3,808	5.07	2.49	0.000	3,832	2.28%	178.42%	0.337	3,832	5.50	2.59	0.310
4	4,024	-3.45	11.61	0.000	4,024	5.40	2.37	0.000	4,058	1.54%	174.44%	0.852	4,058	5.52	2.51	0.781
5	4,284	-3.02	11.15	0.090	4,284	5.46	2.29	0.227	4,316	2.25%	168.00%	0.849	4,316	5.54	2.52	0.733
6	4,904	-1.46	8.16	0.000	4,904	5.73	2.29	0.000	4,925	4.05%	176.36%	0.616	4,925	5.63	2.49	0.100
7	5,167	-1.33	8.96	0.449	5,167	5.91	2.28	0.000	5,186	1.75%	197.41%	0.536	5,186	5.63	2.49	0.901
8	5,535	-0.63	8.24	0.000	5,535	6.12	2.31	0.000	5,557	8.94%	171.12%	0.043	5,557	5.70	2.54	0.172
9	6,063	0.42	8.72	0.000	6,063	6.22	2.42	0.031	6,111	6.53%	164.91%	0.439	6,111	5.74	2.56	0.418
10	6,574	2.13	18.85	0.000	6,574	6.65	2.56	0.000	6,652	8.75%	162.45%	0.444	6,652	5.86	2.70	0.009
1-8	33,514	-3.02	11.94		33,514	5.48	2.46		33,724	2.27%	178.41%		33,724	5.56	2.56	
9-10	12,637	1.31	14.90	0.000	12,637	6.45	2.50	0.000	12,763	7.69%	163.63%	0.0028	12,763	5.80	2.64	0.000

Similar to the considerations of the whole German Mutual Fund market, I again observe a positive trend from the poorest performing funds (decile 1) to the best performing funds (decile 10). The results for the Alpha performance are displayed in panel A of table 6. An investor who purchases a mutual fund in decile 1 of previous Alpha performance can expect a mutual fund with an average Alpha of -6.99% p.a. in the following year. In contrast, an investor who purchases a mutual fund in decile 10 of previous Alpha performance can expect a fund with an average Alpha of -1.56% p.a.. Again comparing deciles 1-8 with deciles 9-10 makes the results even clearer: Investors investing in mutual funds belonging to the top 20% of historical Alpha performance can expect a future Alpha of -1.67% p.a., whereas investors purchasing funds in deciles 1 to 8 can expect only an future Alpha of -2.67% p.a.; i.e. investors can improve their future Alpha performance by 1.00% p.a. by chasing historical performance. This result is statistically significant at the 1% level.

Results hold when considering future Alpha deciles instead of the absolute measure: Investors who purchased a mutual fund in decile 1 can expect an underperforming fund in the following year with an average of deciles of 4.77. In contrast, investors who purchased a mutual fund in decile 10 can expect an outperforming fund in the following year, which is in an average decile of 6.22. Moreover, it is a winning strategy to purchase mutual funds belonging to the top 20% regarding Alpha performance: Mutual funds belonging to decile 9 and 10 are in an average Alpha decile of 6.08 in the following year, whereas mutual funds belonging to Alpha decile 1 to 8 are in the following year in an average Alpha decile of 5.40. Most results are pairwise statistically different.

Considering One-year Returns instead of Alpha performances in the following year (compare columns 10-18 of table 6, panel A) confirms the previous results: A positive trend along the Alpha deciles of the average One-year Return from -7.15% p.a. (decile 1) to 9.18% p.a. is observable. Moreover, investors who purchase mutual funds belonging to the top 20% of historical Alpha performance can expect on average a 5.05% p.a. higher return in the following year than investors who do not invest in the top 20%. Again, results still hold when I consider One-year Return deciles instead of the absolute performance measure.

When considering the Appraisal Ratio in panel B, results are qualitatively unchanged. Investors who purchase mutual funds belonging to the top 20% regarding the Appraisal ratio (deciles 9 and 10) in the following year obtain outperforming mutual funds, which have an average Appraisal ratio of 1.31. On the other hand, investors who purchase mutual funds belonging to decile 1 to 8, realize an average Appraisal ratio of -3.02 in the following year. From the poorest performing funds (decile 1) to the best performing funds (decile 10) again a positive trend is observable. The majority of the differences is statistically significant. Once again, the results hold regardless of considering One-year Returns instead of the Appraisal ratio and regardless of considering deciles instead of the absolute measures.

Summarizing the results of research question 1 and 2 I state that performance persistence within the German mutual fund market does exist and that investors seem to make smart investment decisions once they decide to purchase mutual funds by chasing historical performance. Consequently, investors who do not use historical performance as their decision criterion definitely make serious and costly investment mistakes. For a detailed analysis of the purchase criteria of private mutual fund investors, the reader is referred to Niebling (2010).

5.2 Identification of smart acting investors

Niebling (2010) shows that there are indeed investors who purchase mutual funds by chasing historical performance, but that there is as well a large group of investors who do not look at historical performance when choosing among mutual funds. As I have shown in the previous part of this paper, there is persistence in mutual fund performance. Thus, these investors make costly investment mistakes. The next logical step is to analyze which investors act smart and purchase mutual funds by chasing performance and which investors do not, i.e. which particular investors make investment mistakes. In order to understand the influence of socio-demographics and investor characteristics on the investment behavior, I use a regression model. The results are given in table 7.

The factors potentially affecting the smartness of private investors can be derived from the existing literature. It can surely be expected that experience influences trading behavior, as Grinblatt and Keloharju (2001) and Feng and Seasholes (2005) point out. On the other hand, Barber and Odean (2000) argue that excessive trading yields to overconfidence and thus influences investment behavior negatively. For my analysis I include the variables Age, Length of Customer Relationship and Trading Frequency measured on a 1 to 5 scale, where 1 indicates the lowest value in each case. Additionally, Vissing-Jorgensen (2003) argues that irrationality disappears with wealth. In order to capture this effect in my model, I include Average Trade Volume and the natural logarithm of Average Deposit Value. I use the average since the deposit value can change over time due to external effects others than investment success (e.g. purchase of additional securities). Furthermore, Barber and Odean (2001) show that overconfidence plays a crucial role in determining portfolio performance.

Their results actually indicate that men are more exposed to overconfidence and are thus more likely not to make smart investment decisions. As usual, Gender is coded as a dummy variable taking the value 1 if the investor is male.

Table 7: Impact of investor characteristics on investor-average Alpha deciles and Smartness

Table 7 shows results for research question 3. Regression coefficients from regression of investor characteristics on investor-average Alpha deciles and Smartness are displayed. Moreover, some investor-average fund characteristics are included as control variables. Dummy variables indicate if an investor is classified as male or married by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Average deposit value and average trade volume are proxies for wealth, whereas trading frequency and length of customer relationship are proxies for trading experience. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively. The analyzed time period is January 2003 – July 2007.

	Tobit-Regression 01	**Tobit-Regression 02**
Depending Variable	Investor Average Alpha Decile	Investor Average Smartness
Gender (Dummy; 1 = male)	-0.0193	0.0242
	(0.0258)	(0.0906)
Age	0.00919***	0.0237***
	(0.000853)	(0.00299)
Marital Status (Dummy; 1 = married)	-0.0181	-0.0996
	(0.0221)	(0.0775)
Log of Average Deposit Value	-0.00121	-0.0365
	(0.00819)	(0.0287)
Average Trade Volume	2.91e-06***	-3.27e-06
	(7.21e-07)	(2.51e-06)
Trading Frequency	-0.0964***	-0.224***
	(0.00828)	(0.0292)
Length of Customer Relationship	-0.0256***	-0.140***
	(0.00685)	(0.0240)
Riskclass	0.0180**	0.0417
	(0.00795)	(0.0279)
Investor Average Initial Charge	0.244***	
	(0.00766)	
Log of Investor Average Volume (TNA)	-0.133***	-0.199***
	(0.00785)	(0.0263)
Investor Average KAG-Top-Brand	-1.048***	-3.722***
	(0.0329)	(0.0969)
Constant	8.964***	25.50***
	(0.199)	(0.651)
Observations	19,423	19,235
Pseudo R-quared	0.047	0.016

Intuitively, including a variable measuring the risk-aversion of an investor is reasonable. Therefore I employ a variable called Riskclass, based on the self-reported assessment by investors when opening an account. The scale ranges from 1 (low risk-tolerance) to 6 (high risk-tolerance). Moreover, I include a dummy for married investors in the analysis, in order to capture further potential factors explaining investor Smartness. Finally, I incorporate investor averages of fund characteristics as additional control variables for determinants of investment decisions, namely Initial Charge, the logarithm of the Fund Volume (measured in TNA) and a dummy variable indicating whether a fund belongs to one out of six top-brand investment companies.

The second column of table 7 shows results of the Tobit-Regression on the average purchased Alpha decile. I find that age has a positive influence on the average purchased Alpha decile which is statistically significant. As age is a proxy for investment experience, I observe that experienced investors make more correct investment decisions. Moreover, the average trade volume affects the average purchased Alpha decile positively. This matches the findings of Vissing-Jorgensen (2003) as it is a proxy for wealth. Interestingly, the coefficient of the variable "Riskclass" is positive and statistically significant at the 5%-level. Therefore, investors, who assess themselves as more risky, purchase on average mutual funds with higher Alpha. A possible explanation is that experienced investors assess themselves more likely as risky as this assessment allows them to trade riskier securities (e.g. options or derivatives). On the other hand, Trading Frequency and Length of Customer Relationship influence the average purchased Alpha decile negatively. Hence, overconfidence is to the detriment of smart investment behavior. These results are in line with Barber and Odean (2000). Gender, Marital Status and the logarithm of the Average Deposit Value have no statistically significant influence on the average purchased Alpha deciles. The investor-average fund characteristics are included as control variables only. Interestingly, the investor-average Initial Charge has a positive and statistically significant influence on the average purchased Alpha decile. This is consistent with the results Niebling (2010) obtains, who finds that private investors are poised to pay higher initial charges for better performing mutual funds.

In column 3 of table 7 I present results for the Tobit-regression on the variable Smartness as defined in formula (3). The regression coefficients are very similar to the ones in Tobit-Regression 01. The only difference is that the variables "Average Trade Volume" and "Riskclass" are no longer statistically significant. Hence, if I take additional initial charge into account, the results remain very similar compared to measuring investors' Smartness solely by considering his ability to chase historical performance.

Summarizing the results for question 3, I find that smart investors are older, more experienced, wealthier and less overconfident than non-smart investors. On the other hand, Gender and Marital Status do not seem to have influence on the investment smartness.

5.3 The influence of smart mutual fund investment behavior on overall investment success

Finally, I study the economic impact of the variables Smartness and Average Decile purchased and address research question 4, i.e. the question whether investors who behave smart regarding mutual fund purchases are overall better investors. I measure overall investment success by the one-year portfolio return in the time from October 2006 till September 2007.[17] For this reason I perform a regression model, regressing the variables Investor Average Smartness and Investor Average Alpha Decile on the average portfolio return. Moreover, I define two additional dummy variables. Top 20 Alpha indicates whether an investor purchases on average mutual funds in the top 20% of Alpha performance. Top 20 Smartness indicates whether an investor has a Smartness value of more than 24. The underlying rationale is that investors who act smart will purchase on average mutual funds which are in decile 9 or 10 of previous Alpha performance. If an investor purchase on average mutual funds which are in decile 1 to 8 or have a Smartness value smaller than 24, I will assume that his investment decision is not based on historical performance. Of course, in this case single transactions can still be made in decile 9 and 10. However, the underlying assumption is that these single transactions are due to randomness as long as the average is not within the top 20%.

Additionally, several investor characteristics used already in the Tobit-Regressions 01 and Tobit-Regressions 02 are included. As I perform the regressions on portfolio returns in this subsection, I replace the self reported variable Riskclass with the real observable Portfolio Risk which can take values varying from 1 (low portfolio risk) to 5 (high portfolio risk)[18]. The main advantage of the variable portfolio risk is that it reflects the actual risk in the portfolio. On the other hand, the variable Riskclass is based on investors self assessment which, indeed, can differ from the actual portfolio risk significantly. Table 8 presents the results of this analysis.

[17] I have to deal with several outliers in the portfolio return data which are obviously due to data errors. Thus, I winsorize the data at the 1% level before performing regressions.

[18] I calculate the standard deviations of portfolio returns and rank the standard deviations within five groups from 1 (low risk) to 5 (high risk)

Regression 03 is the basic regression to explain abnormal portfolio performance for my dataset. Age, Average Trade Volume and Trading Frequency have a negative influence on the portfolio performance, indicating that successful investors are younger, purchase mutual funds with lower trade volume and trade more infrequent than non-successful investors.

Table 8: Impact of Investors' Smartness and Average Alpha Decile Purchased on Investors' portfolio performance

Table 8 shows results for research question 4. Regression coefficients from regression of the variables Smartness and investor-average Alpha decile on investors' average portfolio performance are presented. The dummy variables Top 20 Alpha and Top 20 Smartness indicate if an investor on average purchases funds which have an Alpha decile larger or equal than 9 or has a Smartness value larger than 24 respectively. Moreover, several investor-characteristics are included. Dummy variables indicate if an investor is classified as male or married by the bank's data warehouse. Trading frequency, length of customer relationship and portfolio risk take values from 1 (low) to 5 (high). Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively. The analyzed time period is January 1999 – July 2007 (regressions 03-05) and January 2002 – July 2007 (regressions 06-07) respectively.

	Reg 03	Reg 04	Reg 05	Reg 06	Reg 07
Depending Variable	Portfolio Performance	Portfolio Performance	Portfolio Performance	Portfolio Performance	Portfolio Performance
Investor Average Alpha Decile		0.00225*			
		(0.00133)			
Top 20 Alpha (Dummy)			0.0120*		
			(0.00695)		
Investor Average Smartness				0.000969**	
				(0.000399)	
Top 20 Smartness (Dummy)					0.0179***
					(0.00528)
Gender (Dummy; 1 = male)	-0.00543	-0.00541	-0.00540	-0.00209	-0.00199
	(0.00427)	(0.00427)	(0.00427)	(0.00424)	(0.00425)
Age	-0.000761***	-0.000787***	-0.000783***	-0.000734***	-0.000743***
	(0.000145)	(0.000146)	(0.000145)	(0.000150)	(0.000149)
Marital Status (Dummy; 1 = married)	0.00612	0.00607	0.00618	0.00965**	0.00978**
	(0.00414)	(0.00414)	(0.00413)	(0.00420)	(0.00420)
Log of Average Deposit Value	0.0501***	0.0500***	0.0502***	0.0458***	0.0460***
	(0.00294)	(0.00294)	(0.00294)	(0.00310)	(0.00309)
Average Trade Volume	-2.78e-07**	-2.75e-07**	-2.84e-07**	-3.32e-07	-3.51e-07
	(1.22e-07)	(1.23e-07)	(1.25e-07)	(3.41e-07)	(3.51e-07)
Trading Frequency	-0.00790***	-0.00764***	-0.00769***	-0.00578***	-0.00569***
	(0.00170)	(0.00171)	(0.00171)	(0.00177)	(0.00177)
Length of Customer Relationship	-0.00105	-0.00100	-0.00112	-0.00164	-0.00173
	(0.00122)	(0.00122)	(0.00122)	(0.00126)	(0.00126)
Portfolio Risk	-0.00154	-0.00182	-0.00190	-0.00247	-0.00274
	(0.00204)	(0.00206)	(0.00206)	(0.00225)	(0.00225)
Constant	-0.345***	-0.358***	-0.345***	-0.326***	-0.311***
	(0.0309)	(0.0317)	(0.0309)	(0.0332)	(0.0328)
Observations	21401	21401	21401	18203	18203
R-squared	0.058	0.058	0.058	0.050	0.051

On the other hand, Log Average Deposit Value affects the portfolio performance positively, indicating that successful investors are wealthier. These results are in line with the existing literature discussed earlier. The variables Gender, Marital Status, Length of Customer

Relationship and Portfolio Risk are not statistically significant and do not seem to have a major influence on the investment success.

In Regression 04 I add the average purchased Alpha decile as an additional independent variable. While all other coefficients remain qualitatively unchanged, the investor average Alpha decile has a small but positive influence on the portfolio performance. Hence, the ability of an investor to purchase mutual funds by chasing Alpha improves the investors' overall investment success. The fact that this effect is only small and only statistically significant at the 10%-level is not entirely surprising as the mere difference between the average Alpha deciles of purchased funds by private investors do not need to carry any information on the ability of an investor to chase performance. Hence, I follow a different approach and consider investors purchasing mutual funds from the two top deciles. Therefore, I mark those investors with a dummy equal to one if their average purchase decile is higher than 8 and label this variable as "Top 20".

Considering regression 05 I find that the Top 20 Alpha dummy does influence the portfolio performance statistically significantly and positively, whereas again all other coefficients remain qualitatively unchanged. The value of the coefficient allows me to state the economic impact of smart mutual fund investment behavior: Investors, who purchase mutual funds in the top 20% of historical Alpha performance on average, generate a 120bp higher portfolio return per annum than investors, who purchase mutual funds in the bottom 80% of historical Alpha performance on average.

Considering Regression 06 and 07[19] and adding the Investor Average Smartness and the top 20 Smartness dummy respectively yield to very similar results. Again, the variable Investor Average Smartness is statistically significant and has a positive influence on the portfolio return. The variable Top 20 Smartness has a clear positive influence on the portfolio return and is statistically significant at the 1%-level. I conclude that investors who have a Smartness value of more than 24 generate a 179bp higher portfolio return per annum than investors who have a Smartness value of less than 24.

So far I have studied the impact of investors' Smartness on the simple portfolio performance. Now, I will repeat the regression, but use the portfolios' Sharpe ratio as depending variable and thus take the portfolio risk component into account as well. The results which are

[19] Note that the number of observations is smaller for these regressions as the variable Smartness can only be calculated for a restricted set of investors. However, performing the regressions 01 – 03 on this restricted data set yields to qualitatively unchanged results.

shown in table 8 are very similar. Let me again analyze the basic regression (Regression 08) first. Age, Average Trade Volume, Trading Frequency, Length of Customer Relationship and Portfolio Risk affect the Sharpe ratio negatively; whereas the variable Marital Status and the logarithm of Average Deposit Value have a positive influence.

Table 9: Impact of Investors' Smartness and Average Alpha Decile Purchased on Investors' portfolio Sharpe ratio

Table 9 shows results for research question 4. Regression coefficients from regression of the variables Smartness and investor-average Alpha decile on investors' average portfolio Sharpe ratio are presented. The dummy variables Top 20 Alpha and Top 20 Smartness indicate if an investor purchases on average funds which have an Alpha decile larger or equal than 8 or has a Smartness value larger 24 respectively. Moreover, several investor-characteristics are included. Dummy variables indicate if an investor is classified as male or married by the bank's data warehouse. Trading frequency, length of customer relationship and portfolio risk take values from 1 (low) to 5 (high). Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively. The analyzed time period is January 1999 – July 2007 (regressions 08-10) and January 2002 – July 2007 (regressions 11-12) respectively.

	Reg 08	Reg 09	Reg 10	Reg 11	Reg 12
Depending Variable	Portfolios Sharpe Ratio	Portfolios Sharpe Ratio	Portfolios Sharpe Ratio	Portfolios Sharpe Ratio	Portfolios Sharpe Ratio
Investor Average Alpha Decile		0.00462***			
		(0.00141)			
Top 20 Alpha (Dummy)			0.00332		
			(0.00724)		
Investor Average Smartness				0.00216***	
				(0.000459)	
Top 20 Smartness (Dummy)					0.0299***
					(0.00613)
Gender (Dummy; 1 = male)	-0.00445	-0.00441	-0.00444	0.00219	0.00233
	(0.00572)	(0.00572)	(0.00572)	(0.00609)	(0.00609)
Age	-0.00124***	-0.00129***	-0.00124***	-0.00127***	-0.00126***
	(0.000194)	(0.000195)	(0.000194)	(0.000217)	(0.000217)
Marital Status (Dummy; 1 = married)	0.0108**	0.0107**	0.0108**	0.0117**	0.0119**
	(0.00482)	(0.00482)	(0.00482)	(0.00516)	(0.00516)
Log of Average Deposit Value	0.0461***	0.0459***	0.0462***	0.0453***	0.0456***
	(0.00213)	(0.00213)	(0.00214)	(0.00250)	(0.00250)
Average Trade Volume	-5.35e-07***	-5.29e-07***	-5.37e-07***	-7.88e-07	-8.20e-07
	(1.70e-07)	(1.71e-07)	(1.71e-07)	(5.53e-07)	(5.69e-07)
Trading Frequency	-0.0106***	-0.0101***	-0.0106***	-0.00941***	-0.00952***
	(0.00181)	(0.00181)	(0.00181)	(0.00197)	(0.00197)
Length of Customer Relationship	-0.00344**	-0.00334**	-0.00346**	-0.00326*	-0.00347**
	(0.00157)	(0.00157)	(0.00157)	(0.00170)	(0.00170)
Portfolio Risk	-0.112***	-0.113***	-0.112***	-0.113***	-0.114***
	(0.00183)	(0.00184)	(0.00185)	(0.00201)	(0.00201)
Constant	0.320***	0.292***	0.320***	0.283***	0.316***
	(0.0256)	(0.0268)	(0.0256)	(0.0303)	(0.0295)
Observations	21,401	21,401	21,401	18,203	18,203
R-squared	0.245	0.245	0.245	0.239	0.239

The addition of the investor average Alpha performance (Regression 09) has again a positive and statistically significant influence on the Sharpe ratio. The coefficient of the Alpha Top 20 dummy (Regression 10) is positive but not statistically significant. Again, all other results remain qualitatively unchanged compared to the basic regression 08.

In a last step, I study the influence of the variable Smartness on the Sharpe ratio in regression 11 and 12. Both the variable Smartness itself and the Smartness top 20 dummy affect the Sharpe ratio positively and are statistically significant. A smart investor who has a Smartness value of more than 24 generates on average a 299bp higher portfolio return in terms of the Sharpe ratio than a non-smart investor with a Smartness value of 24 or smaller.

These results imply that investors, who make smart mutual funds investment decisions and purchase funds by chasing historical performance, are not only likely to make better mutual fund investment decisions. They also have overall more investment success and are consequently better investors.

Given the higher significance of the variable Smartness I suggest to use this variable as ex-ante measure for assessing the overall investment success of private investors. Note again that this measure does not depend on potential randomness of stock markets returns as it is measured in advance (ex-ante).

6 Robustness

In order to check the validity of the results regarding my four research questions, I perform several robustness tests.

First, I exclude all investors who purchased only one fund in the analyzed period from my data set. After recalculating the regression model, it turns out that the results remain qualitatively unchanged. Investors who act smart and purchase mutual funds by chasing Alpha are still older, more experienced, wealthier and less overconfident than investors who do not act smart. In addition smart acting investors still generate a higher portfolio return on average and the economic impact also remains unchanged.

After not taking very infrequent traders into account, I investigate whether investors who are very frequent traders bias the results. In the data set a variable is included indicating if an investor is categorized as “heavy trader” by the banks’ data warehouse. Excluding all these heavy traders from the data set and repeating the analyses yields to qualitatively unchanged results for all research questions.

In the investor data set I can identify approximately 14% of all investors who received financial advice. For another robustness test I exclude these advised investors in order to validate whether financial advice skews the results. Again, repeating all regression models only for non-advised investors yield to qualitatively unchanged results.

As mentioned above I used a Tobit-regression model in order to analyze the impact of the investor characteristics on the investor-average purchased Alpha decile and the investor-average value of the variable Smartness, as the data is naturally censored. However, when using a conventional regression model the results remain qualitatively unchanged.

Finally, multi-collinearity does not seem to be a problem in my regression models as all variance-inflation-factors are reasonable small (between 1.02 and 1.23)[20].

Therefore, I state that the results of my research questions presented and discussed in section 5 are robust and are not due to potential data errors.

7 Conclusion

This paper contributes to three different strands of literature, namely mutual fund persistence, smart investment decision making and household finance. In contrast to earlier studies (e.g. Gruber (1996), Keswani and Stolin (2008)), I use a dataset of a German online brokerage house that allows me to analyze the investment behavior on an investor-specific level. Combining this dataset with data on the mutual fund universe from Morningstar and a German provider, VWD, and weekly mutual fund performance data from Thomson Financial Datastream, I am able to construct a dataset that contains more than 1.5m mutual fund transactions of roughly 44k distinct individual investors.

I focus on four major research questions. First, I contribute to the heavily discussed issue whether mutual fund performance is persistent or not (see Gruber (1996)). I show that there is persistence in mutual fund performance in the analyzed German mutual fund market.

Second, I investigate specific mutual fund transactions in order to test whether investors who purchase mutual funds by chasing historical performance indeed benefit from this strategy. I find that investors who purchase mutual funds belonging to the top 20% of historical Alpha performance can improve the performance of the purchased fund by 1.00%

[20] Note that multi-collinearity usually will be considered as present if VIF values are larger than 10.

p.a. in terms of Alpha and by 5.05% p.a. in terms of simple returns. Therefore, not chasing historical performance is a serious and costly investment mistake.

Third, I turn to investor-specific level examining which particular investor groups act smart and chase historical performance. With this analysis I contribute to the emerging body of literature on smart decision making (e.g. Elton, Gruber and Busse (2004) and Keswani and Stolin (2008)). I find that investors making smart mutual fund investment decisions are older, more experienced, wealthier and less overconfident than investors who do not make smart investment decisions. On the other hand, Gender and Marital Status do not seem to have influence on the investment behavior.

Finally, I discuss the economic impact of smart decision making and analyze whether investors who act smart and purchase mutual funds by chasing historical performance have more overall investment success. I show that investors who act smart when purchasing mutual funds generate on average a 179bp higher portfolio return per year than investors who do not act smart regarding mutual fund investment decisions. This makes my previous results on the mutual fund purchasing behavior and smart decision making even more valuable, as the outcomes of these analyses are not subject to any potential random realization of stock market returns (as in previous studies, e.g. Campbell (2006), Barber and Odean (2000) and Hackethal, Haliassos and Jappelli (2008)). The outcomes are rather indicators of superior investment sophistication and, therefore, I find an ex-ante measure to predict overall investment success which can be easily applied for future studies in which researchers need to measure investment success. These studies are not restricted to research on mutual fund investment, but can also be used for all kinds of questions concerning private investment behavior.

For example, someone could contribute to the issue whether financial advice helps private investors to enhance their portfolio returns by comparing the Smartness value of advised investors with the one of non-advised clients. Furthermore, it would be interesting to study whether investors can benefit from a learning effect when conducting the transactions. Again, someone could use the Smartness measure in order to measure the investment success.

Research in mutual funds remains an interesting domain even besides applying the Smartness measure to several research questions. For example, potential further research could deal with mutual fund marketing. Niebling (2010) shows that the majority of individual investors does not use historical performance as their decision criterion. He also finds that purchased funds have a clear above average fund volume and assumes that advertising works. It would be interesting to study the effects of marketing and advertising activities as well as the effect of news on the individual purchasing behavior in greater detail (compare Barber and Odean (2008)).

Beyond the scientific contribution of this paper, the results may also affect banks and policy makers in particular. Having shown that performance chasing is a wise strategy, policy makers might consider creating incentives to motivate investors and banks to invest into mutual funds that have performed well in the past. In the light of the introduction of MiFID EU Directive aimed at increasing financial market transparency and competition, which requires banks to gather information on the financial sophistication on a private investor, it might also be useful to look at the transaction history of a client to determine the investor’s financial sophistication. The potential of creating value for banks and customers by advising customers based on their financial sophistication has already been clearly proven (see e.g. Hackethal and Jansen (2007) and Fischer, Hackethal and Meyer (2008)).

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Do Advisors Help Investors to Make Better Investments?

Evidence from Investors' Mutual Fund Purchase Decisions

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Abstract:

Using account-level data on about 44k investors, this paper extends recent findings of Bergstresser, Chalmers and Tufano (2009) and contributes to the emerging literature on the role of financial advice. We find that unsophisticated investors are more likely to seek financial advice than sophisticated investors. Furthermore, we show that financial advisors do not help their clients to enhance the quality of their investment decisions. In fact, they tend to recommend mutual funds with high volume, belonging to a top-brand fund family and with less initial charges. As the past performance of a fund is not different for advised and non-advised clients, we conclude that advisors are much more salesmen than real advisors. The results hold when controlling for potential endogeneity issues.

Keywords: Financial Advice, Mutual funds, Fund performance, Household finance, Investment sophistication

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1 Introduction

The influence of financial advice on private investor's investment decisions is a highly relevant and heavily debated topic in both research and practice, since the vast majority of people relies on financial advice (DABBank (2004)). Given that financial advisors have been repeatedly and publically accused of misselling financial products (German Federal Ministry of Consumer Protection (2008)), policy makers have adopted measures like MiFID to enhance the quality of financial advice. However, a scientific debate on the influence of financial advice has only recently been started. The existing empirical literature on the influence of financial advice in Germany (Hackethal, Haliassos and Jappelli (2008)) and of mutual fund brokers in the United States (Bergstresser, Chalmers and Tufano (2009)), has only detected a small, albeit negative impact of financial advice on investment performance.

This paper is most closely related to and extends the recent work of Bergstresser, Chalmers and Tufano (2009) who compare mutual funds sold via the direct channel with mutual funds sold via the broker channel. They find that broker-sold funds have smaller risk-adjusted returns even before cost considerations than direct-sold funds. Consequently, they conclude that brokers do not add value to private investors' portfolios. As a potential explanation, Bergstresser, Chalmers and Tufano (2009) conjecture that advisors may provide other intangible assets or simply put client interests behind their own interests. They point out: *"Future research using account-level data […] may have more success identifying these less easily measured benefits of brokers".*

Having access to account level data allows us to extend the analyses of Bergstresser, Chalmers and Tufano (2009). We can clearly identify which single investors receive financial advice and which investors make their investment decisions on their own. In addition, we are able to compare private investors' investment behavior before and after they received financial advice. Using this methodology, this paper addresses the question whether financial advisors help their clients to arrive at better investment decisions. Moreover, this investor-specific approach allows us to analyze which particular sales arguments advisors use when selling mutual funds.

Additionally, this paper differs from the work of Bergstresser, Chalmers and Tufano (2009), as we use a different measure for assessing investment decision quality. We use the degree of which individual investors chase historical performance when choosing among mutual funds. This measure is proven to be an ex-ante proxy for overall investment success and therefore for investment sophistication (compare Niebling (2010b)). In contrast, existing studies on the role of financial advice, such as Bergstresser, Chalmers and Tufano (2009) and Hackethal, Haliassos and Jappelli (2008), always use ex-post returns in order to measure investment success. The big advantage of our approach compared to using ex-post returns is that the ex-ante measure is not subject to potential random realizations of stock market returns.

This paper builds on and contributes to two strands of literature on financial advice: First, we address the question which particular investors receive financial advice. At first view we confirm the former result (e.g. of Hackethal, Haliassos and Jappelli (2008)) that financial advisors are matched with older, wealthier and less overconfident investors. However, when applying our ex-ante measure for investment sophistication, we find that unsophisticated investors are more likely to ask for financial advice than sophisticated investors are. Note that these results are contradictory to Hackethal, Haliassos and Jappelli (2008), who show that financial advice is rather matched with more experienced investors.

Second, we investigate whether financial advice helps these clients to make better investment decisions. Our results generally confirm findings of Bergstresser, Chalmers and Tufano (2009) as we find that financial advisors do not improve private investors' investment sophistication. Extending Bergstresser, Chalmers and Tufano (2009), we show that advised investors purchase on average mutual funds which have a higher fund volume and which more likely belong to a top-brand fund family. However, we also show that financial advisors recommend mutual funds with lower initial charges, which is counterintuitive as advisors benefit from high initial charges by their commission model. These findings imply that financial advisors sell mutual funds which they believe clients would have purchased also without receiving advice. Hence, they are much more salesmen than advisors and seem to make the same investment mistakes as the private investors themselves make: They recommend high-volume and top-brand mutual funds instead of using historical performance as decision criterion.

These results are robust to endogeneity. In order to control for potential endogeneity issues, we perform a propensity matching as well as an event study, in which we compare the investment behavior of identical clients before and after the time they received financial advice.

The rest of the paper is organized as follows. In section 2 we summarize existing literature on financial advice and derive our research questions. Section 3 describes the data set we use in our analyses. In section 4 we give an overview of the statistical models and the methodology applied. Results on the questions who receive financial advice and whether financial advice can improve private investors' investment sophistication are displayed and discussed in section 5. In section 6 we describe additional robustness tests and section 7 draws conclusions.

2 Literature Review and Research Questions

There is only a small set of theoretical literature on the role of advice within the financial retail industry. The goal of these studies is to provide a guideline for reasonable regulation within the financial retail industry. For example, Ottaviani (2000) introduces a model of advice in which an informed advisor transmits information to an investor who is otherwise uninformed and has an uncertain degree of strategic sophistication.

Recently, Inderst and Ottaviani (2009) analyzed misselling of agents, i.e. the selling of financial products without considering the product suitability for the specific need of customers. The authors find that advisory firms' compliance standards are affected by several factors, such as the internal organization of a firms' sales process, the transparency of its commission structure and the steepness of its agents' sales incentives. Consequently, they conclude that political decision makers must take these factors into account when refining regulation in the financial retail industry.

Besides these theoretical papers, there are some studies which deal with empirical issues concerning financial advice. These studies can be differentiated into three strands, namely (i) literature on the issue which particular investors seek for financial advice, (ii) literature on the issue whether financial advisors can forecast future stock price returns and therefore can generate abnormal returns for private investors' portfolios and (iii) literature on the issue whether financial advisors can help investors to overcome behavioral biases.

In general, one could expect that financial advice is demanded by younger, less-educated and poorer investors, as financial advice can help these investors to overcome behavioral biases and to improve portfolio performance. However, Hackethal, Haliassos and Jappelli (2008) find that advisors are rather matched to richer, older and more experienced investors. They conclude that financial advisors are similar to babysitters, as they match with well-to-do households and offer a service that parents themselves could do even better. However, observed achievement of children with babysitters is usually better than the achievement of children without babysitters, for what apparently other contributing factors than the babysitters themselves are accountable. Moreover, Guiso and Jappelli (2006) show that overconfidence reduces the propensity to seek financial advice.

In this paper we will replicate these analyzes with our data set including additional investor-specific characteristics and restricting ourselves to mutual fund investors. Therefore, we formulate our first research question as follows:

<u>Question 1:</u> ***Which mutual fund investors ask for financial advice?***

For a long time, researchers have analyzed whether professionals have the ability to forecast the stock market (compare e.g. Cowles (1933), Barber and Loeffler (1993), Desai and Jain (1995)). For example, Womach (1996) investigates how stock prices proceed after "buy" or "sell" recommendations of U.S. brokerage firms. He finds that stock prices significantly react into the forecasted direction accompanied by volume increases. However, the author also documents that the total amount of "buy" recommendations exceeds the total amount of "sell" transactions by factor seven and concludes that brokers are reluctant to issue sell recommendations in order to avoid harming investment banking relationships and to maintain future information flows from managers. Metrick (1999) analyzes the quality of a set of investment newsletters and finds no evidence that a strategy of purchasing stocks recommended by the newsletters promises abnormal returns.

More recently, Bergstresser, Chalmers and Tufano (2009) compared mutual fund performance of funds sold via broker channel with funds sold via direct channel. They find that broker-sold funds have smaller risk-adjusted returns than direct-sold funds even before cost considerations and conclude that either brokers may provide other intangible benefits (e.g. increase in saving rates or increase in comfort with investment decisions) or brokers simply put clients' interest behind their own interest. These results are in line with the ones of Hackethal, Haliassos and Jappelli (2008) who show that the effect of financial advice is negative after controlling for endogeneity. Thus, investors who receive financial advice generate lower total and excess returns and also have higher portfolio risk and probability of losses than investors who do not receive financial advice.

However, Hackethal, Haliassos and Jappelli (2008) also find that financial advisors help their client to diversify their portfolios in a better way. This finding could imply that financial advisors may not improve investors' portfolio returns but can help investors to overcome behavioral biases. One specific behavioral bias is the disposition effect, i.e. the tendency of investors to sell winning investments too early and to hold on to losing investments for too long. Stuber (2008) shows that advised investors indeed display a significant lower disposition effect than unadvised investors. Moreover, Bergstresser, Chalmers and Tufano (2009) find evidence that funds sold by brokers (which are associated with financial advice) are more likely to invest in foreign mutual funds and conclude that financial advisors therefore help clients to fight the home bias.

All these existing pieces of literature have in common that they use ex-post portfolio returns as measure for investment success. Therefore, they are always subject to potential random realization of stock markets. In a recent paper, Niebling (2010b) has proven that the degree to which investors chase historical performance when choosing among mutual funds has a direct positive influence on the overall investment success. This result is a contribution to literature on mutual fund purchasing decisions. In this field of research, various authors show that mutual fund inflows are positively related to historical performance but that inferior performing mutual funds still receive net cash inflows. Hence, the majority of investors fail to flee from underperforming mutual funds (e.g. Gruber (1996), Sirri and Tufano (1998), Keswani and Stolin (2008) or Niebling (2010a). Consequently, Niebling (2010b) suggests to use mutual fund investment decision as an ex-ante measure for financial ability. The advantage of this ex-ante measure is that it is not subject to any potential realization of stock market returns, but is rather an indicator of superior investment sophistication. In this paper we will use this ex-ante measure in order to shed light on the question whether financial advisors help private investors to come to better investment decisions.

If advisors do not recommend mutual funds with the goal of increasing clients' investment sophistication, this in fact implies a "misselling" in the sense that Inderst and Ottaviani (2009) discuss the term in their recent theoretical work. Consequently, the next question is which other criteria financial advisors use as sales arguments in order to convince private investors. In a recent paper Niebling (2010a) analyzes mutual fund purchasing decisions of private investors in detail. He finds that investors rather use fund volume and the fact that a fund belongs to a top brand fund family as decision criterion when choosing among mutual funds. Therefore, the question arises whether advisors use the same criteria when recommending mutual funds to their clients.

In summary, our second research question is as follows:

Question 2: ***Do financial advisors help clients to increase their level of investment sophistication?***

3 Data

In order to compare the investment behavior of advised and non-advised investors, we use a comprehensive data set on an investor- and transaction-specific level. This data set has been supplied by a German discount brokerage house and contains in total more than 19m transactions of roughly 71k individual investors placed between January 1999 and July 2007. As we restrict ourselves for our analyses to mutual fund transaction, the relevant data set contains ~2.8m mutual fund transactions of ~48k distinct individual investors. The data base also contains several investor characteristics such as socio-demographic information as well as other information (e.g. risk class, deposit value, trading frequency). Unfortunately, these investor characteristics are not available for all investors which slightly reduce our data.

For sell transactions the choice set of an individual investor is limited to the funds he previously purchased and the actual transaction date might be determined by factors like liquidity needs or tax considerations instead of smart decision making. Therefore, our study exclusively focuses on mutual fund purchases, where investors choose funds from the entire mutual fund universe at a specific and individual date. Moreover, we exclude transactions which are part of mutual funds saving plans mainly due to two reasons: First, when setting up a saving plan, investors make the purchase decision only once in advance and then the mutual funds are purchased repeatedly and automatically by the bank. Second, saving plan investors usually cannot choose from the whole mutual funds universe, but can select only from a restricted set of mutual funds which are provided from the bank for saving plan purposes. Not considering sell and saving plan transactions leaves us with a data set of ~1.5m transactions of ~44k investors.

In table 1 some descriptive statistics of the investors are displayed. Marital Status, Advised and Heavy Trader are dummy variables and indicate whether an investor is classified as married, advised or heavy trader by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account on a scale from 1 (low) to 6 (high). Number of Portfolio Positions is a simple proxy for diversification following Benartzi and Thaler (2001). Another measure for diversification is the share of international equity in the equity portfolio (see Bluethgen et al. (2007)).

Table 1: Descriptive statistics

The table displays some descriptive statistics of the investor data we use for our studies. Dummy variables indicate if an investor is classified as male, as married, as a heavy trader or as an advised investor by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Number of Portfolio Positions and Share of International Equity are proxies for diversification.

	Obs	Mean	Median	Std. Dev.
Gender (Dummy; 1 = male)	43,880	84.31%		
Age	43,881	46.12	44.00	12.16
Marital Status (Dummy; 1 = marri	23,595	60.91%		
Riskclass	43,679	4.56	5.00	1.28
Heavy Trader (Dummy)	44,029	27.56%		
Deposit Value	44,028	55,802	36,296	131,441
Cash Value	44,029	34,637	15,139	86,061
Mutual Funds Trade Volume	44,029	4,206	2,557	14,273
Number of Trades	44,029	97	22	502
Number of Portfolio Positions	33,589	12.13	9.00	11.64
Share of International Equity	32,869	49%		
Length of Customer Rel. (years)	44,029	8.05	7.80	3.01
Advice	44,029	14.42%		

A comparison of the demographics with the ones provided by Deutsches Aktieninstitut (2004)[3] indicates that our sample of 44k investors represents approximately 0.6% of the whole mutual fund investor population in Germany. Investors in our sample are more likely to be male (84% compared to 58% in the population), are almost of the same average age (46 years compared to 47 years in the population) and have a higher average deposit value (€56k compared to €20k in the population). However, please note that the latter difference can be explained by the fact that the deposit value in the population is biased by Germans who rather own an investment portfolio (approximately 41% of the population) but do not invest in equity (only 16% of the population invest in stocks or mutual funds). Therefore, we believe that the gap will be significantly reduced when considering only investors who own equity (like the majority of investors in our data set). All in all, our sample is fairly representative for the mutual fund population in Germany.

In the year 2004 the online brokerage house decided to offer financial advice as an additional service for their customers. For this reason, the data set allows us to differentiate between advised and non-advised investors for transactions placed in the years 2005 to 2007. Moreover, we can perform an event study and compare the investors' behavior before and after the introduction of financial advice.

[3] Deutsches Aktieninstitut e.V. is a German Research Association of public listed companies and institutions.

In a second step of data preparation we enrich the data we obtain from the discount brokerage house with performance data of the German mutual fund market. We use the Morningstar database that has been proven to be of high quality in studies on the American mutual fund market (see Elton, Gruber and Blake (2001)). In order to calculate funds' relative performances to benchmark indices, we also need information to which particular peer group the fund belongs. These peer groups are also available via the Morningstar data base. Since Morningstar data is only available from 2002 to 2006, we supplement our database with funds' data that has been provided by two German suppliers, namely Hoppenstedt and VWD. Finally, the private investors purchase 254 funds that are not covered in one of our databases. In case no peer group was provided by any of the data providers, the mapping of funds into peer groups relies on regression techniques as they are also used in Koijen (2008). Essentially, this means that this paper relies on self-reported peer groups on which private investors have to rely when selecting mutual funds.

The weekly mutual fund return data was obtained from Thomson Financial Datastream and is dividend adjusted and net of fees, but does not include initial charges. Additionally, we need some information on the purchased mutual funds (e.g. fund volume, initial charge) which we obtain from Lipper/Reuters. Unfortunately, these data is only available for the years 2002 – 2008.

4 Model and Methodology

In order to measure the impact of financial advice it is crucial to measure the performance of mutual funds. We group all mutual funds into deciles based on Jensen's Alpha (see Jensen (1968)). The formula for the one-factor model is

$$r_i \quad r_f \qquad {}_i \qquad {}_i\, r_m \quad r_f \qquad {}_i \tag{1}$$

where r_i is the return of fund i, r_f is the return of a three month cash position, r_m is the return of a peer group's benchmark index, $_i$ is the sensitivity of fund i to the return on the benchmark index, $_i$ is the risk-adjusted return on fund i and $_i$ is the error term. The benchmark indices are chosen in accordance with a fund's peer group. As shown in table 2, this paper uses the according MSCI indices for all peer groups focusing on stocks, for bond funds Datastream indices are used and for money market funds indices provided by Citigroup are used.

In this paper we exclusively focus on Jensen's Alpha from the one-factor model, as recent studies have shown that results remain qualitatively unchanged once more sophisticated Alpha estimation techniques are used (see Carhart (1997), Gruber (1996) and Kosowski, Timmermann, Wermers and White (2006)). Moreover former analyses have shown that the results also remain qualitatively unchanged when we use both other risk-adjusted measures (e.g. the Alpha Persistence Ratio (APR) or the Appraisal Ratio) as well as simple return measures (compare Niebling (2010a) and Niebling (2010b)).

Using a rolling-window approach, the Alpha for each fund is calculated based on weekly observations between 1997 and 2008. The underlying assumption is that that a performance chasing investor (i.e. Alpha chasing investor) chooses among mutual funds by looking at last year's Alpha performance. In order to assure the comparability of risk-adjusted performances of mutual funds, we compare several peer groups which are presented in table 2.

Table 2: Definition of peer groups and peer group's benchmark indices
In this table the definitions of the 56 peer groups are given. The accordant peer group's benchmark indices are used for calculating the risk-adjusted performances (Jensen's Alpha) and for ranking the mutual funds into peer group specific deciles.

ID	Peer group	Peer group's benchmark index
Stock Market by Geography		
1	Stocks World	MSCI World
2	Stocks Europe	MSCI Europe
3	Stocks Germany	MSCI Germany
4	Stocks Spain	MSCI Spain
5	Stocks France	MSCI France
6	Stocks Switzerland	MSCI Switzerland
7	Stocks Italy	MSCI Italy
8	Stocks Scandinavia	MSCI Nordic Countries
9	Stocks UK	MSCI UK
10	Stocks Denmark	MSCI Denmark
11	Stocks Netherlands	MSCI Netherlands
12	Stocks Austria	MSCI Austria
13	Stocks Sweden	MSCI Sweden
14	Stocks Turkey	MSCI Turkey
15	Stocks Finland	MSCI Finland
16	Stocks Russia	MSCI Russia
17	Stocks North America	MSCI North America
18	Stocks Australia	MSCI Australia
19	Stocks Asia/ Pacific	MSCI AC Asia Pacific ex Japan
20	Stocks Japan	MSCI Japan
21	Stocks Emerging Markets	MSCI EM
22	Stocks Latin America	MSCI EM Latin America
23	Stocks Greater China	MSCI Golden Dragon
24	Stocks Singapore	MSCI Singapore
25	Stocks Thailand	MSCI Thailand
26	Stocks Korea	MSCI Korea
27	Stocks India	MSCI India
28	Stocks Brazil	MSCI Brazil
Stock Markets by Industry		
29	Stocks Information Technolo;	MSCI Information Technology

ID	Peer group	Peer group's benchmark index
Stock Markets by Industry (cont'd)		
30	Stocks Financial Markets	MSCI Financials
31	Stocks Materials	MSCI Materials
32	Stocks Energy	MSCI Energy
33	Stocks Health Care	MSCI Health Care
34	Stocks Consumer Goods	MSCI Consumer Staples
35	Stocks Industrial	MSCI Industrials
36	Stocks Utilities	MSCI Utilities
37	Stocks Media	MSCI Media
38	Stocks Biotech	MSCI Pharmaceuticals & Biotech
39	Stocks Real Estate	MSCI Real Estate
Money Markets by Geography		
40	Money Market EUR	CGBI WMNI 1MTH Euro debt
41	Money Market GBP	CGBI WMNI UK 1MTH Euro debt
42	Money Market USD	CGBI WMNI US 1MTH Euro debt
43	Money Market CAD	CGBI WMNI CN 1MTH Euro debt
44	Money Market CHF	CGBI WMNI SW 1MTH Euro debt
45	Money market AUD	CGBI WMNI AU 1MTH Euro debt
Bond Markets by Geography		
46	Bonds global (EUR)	CGBI WGBI WORLD 10 MKT ALL MATS
47	Bonds USD	CGBI USBIG Gvt-spons
48	Bonds CHF	SW Total all
49	Bonds GBP	UK Total all
50	Bonds AUD	AU Total all
51	Bonds JPY	JP Total all
52	Bonds DKK	DK Total all
53	Bonds CAD	CN Total all
54	Bonds SEK	SD Total all
55	Bonds NOK	NW Total all
56	Bonds Asia	CGBI ESBI 10 years

Having determined the Alpha performance for all mutual funds in any given week, we categorize the funds by their deciles using their peer-group specific past Alpha performance. Hence, in any given week and for every peer group the decile 1 contains the mutual funds with the poorest Alpha performance and decile 10 contains the mutual funds with the strongest Alpha performance. This means that we create a basis on that we can compare the mutual funds according to their relative performance demonstrated by the decile they join. Please note that it is not feasible to compare the performance measure of the mutual funds of different peer groups and different times directly with each other (for example the Alpha measures are always subject to different Betas). This is the reason why we use the decile approach. Finally, the performance information is combined with the transaction data containing all funds purchased by private investors.

Table 3: Definition of Initial Charge Groups

In this table the definitions and proportions of the three initial charge groups are displayed.

Initial Charge Group	Name	Definition	Proportion
1	No Initial Charges	Initial Charges = 0%	33%
2	Reduced Initial Charges	0% < Initial Charges < 5%	38%
3	Full Initial Charges	Initial Charges ≥ 5%	29%

In order to measure individual private investors' ability to make smart mutual fund purchasing decisions and therefore to measure investment sophistication, we construct a Smartness measure taking the Alpha decile as well as initial charges into account[4] (compare Niebling (2010b)). First, we classify all mutual funds into three different categories with respect to their initial charges, namely (i) mutual funds with no initial charges, (ii) mutual funds with reduced initial charges (initial charges larger than zero and smaller than 5%) and (iii) mutual funds with full initial charges (initial charges of 5% and larger) (compare table 3). Subsequently, we define a new variable "Smartness" assuming that smart investors (i) purchase the mutual funds with the highest historical Alpha performance and (ii) purchase the mutual funds with the lowest initial charge within the group of all funds with the highest historical Alpha performance:

$$\textit{Smartness} = 3 \text{ x } \textit{Alpha-decile} - \textit{Initial-charge-group} + 1 \qquad (2)$$

"Smartness" is a natural number between 1 and 30 and it holds that the larger the value of "Smartness", the smarter the investment decision according to our definition. Note that the historical Alpha has a stronger influence on the value of "Smartness" than the initial charge. Once "locked-in" into an Alpha decile it is not possible to change the decile by purchasing a fund with a low initial charge. In order to illustrate the intention behind the "Smartness" variable, some examples for the calculation of the variable are given in table 4.

[4] Please note that operating expenses are already factored into the Alpha measure.

Table 4: Examples for variable "Smartness"

Table 4 displays some examples for the variable "Smartness". The larger the variable "Smartness" is, the smarter appears the investment decision.

Alpha Deciles	Initial Charge Group	Smartness
10	1	30
10	3	28
9	1	27
1	3	1

As we want to measure the quality of an investors' mutual fund investment decision and not consider single transactions, which could be lucky draws, we calculate investors' averages for our analyses.

In order to address research question 1, i.e. to identify investor groups which seek for financial advice, we conduct a multiple regression model with the variable "Advice" as depending variable. As the variable "Advice" is a dummy variable indicating whether an investor receives financial advice, we use a Probit-Regression model. According to Hackethal, Haliassos and Jappelli (2008), we consider several investor characteristics as depending variables. Additionally, we include the investor-average purchased Alpha decile and the Smartness measure in order to measure investment sophistication. We also control for a couple of fund characteristics. We use the regression model:

$$Adv_i \quad Gen_i \quad Age_i \quad Mar_i \quad LN(DepVal)_i \quad TradeVol_i \quad TradeFreq_i \quad Len_i \quad Risk_i \quad PM_i \quad IC_i \quad LN(TNA)_i \quad TB_i \quad {}_i \tag{3}$$

where Adv_i is a dummy variable indicating whether an investor receives financial advice, Gen_i is a dummy variable indicating if the investor i is male, Age_i is the age of investor i, Mar_i is a dummy variable indicating if the investor i is married, $LN(DepVal)_i$ is the natural logarithm of the average deposit value of investor i, $TradeVol_i$ is the average fund trade volume of investor i, $TradeFreq_i$ is the trading frequency of investor i[5], Len_i is the length of the relationship of investor i with the bank, $Risk_i$ is the self-reported risk class[6] of investor i, PM_i is the investor-average of a given performance measure[7] of investor i, IC_i is the investor-average initial charge of investor i, $LN(TNA)_i$ is the natural logarithm of the investor-

[5] Measured on a scale from 1 (low trading frequency) to 5 (high trading frequency)

[6] On a scale from 1 (low risk) to 6 (high risk)

[7] In this regression we use Jensen's Alpha (defined in (1)) and the variable Smartness (defined in (2)) as performance measures.

average fund volume[8] of investor i, TB_i is the investor-average of a dummy variable indicating whether a fund belongs to one of the top mutual fund families and $_i$ is the error term.

In order to answer the central question of this paper, namely whether financial advice helps investors to come to better investment decisions, we perform a second regression model with the investor's average of the purchased Alpha decile and the average Smartness value of an investor, respectively, as depending variable. As both the purchased Alpha decile and the Smartness are censored variables (from 1 to 10 for the Alpha decile and from 1 to 30 for Smartness, respectively), we use a Tobit-Regression model. Depending variable is the dummy variable indicating if an investor receives financial advice. We also control for several investor characteristics and for a couple of fund characteristics. We use the regression model

$$PM_i \quad Adv_i \quad Gen_i \quad Age_i \quad Mar_i \quad LN(DepVal)_i \quad TradeVol_i$$
$$TradeFreq_i \quad Len_i \quad Risk_i \quad IC_i \quad LN(TNA)_i \quad TB_i \quad {}_i \tag{4}$$

where PM_i is the investor-average of a given performance measure[9] of investor i, Adv_i is the dummy variable indicating if the investor i receives financial advice, Gen_i is a dummy variable indicating if the investor i is male, Age_i is the age of investor i, Mar_i is a dummy variable indicating if the investor i is married, $LN(DepVal)_i$ is the natural logarithm of the average deposit value of investor i, $TradeVol_i$ is the average fund trade volume of investor i, $TradeFreq_i$ is the trading frequency of investor i[10], Len_i is the length of the relationship of investor i with the bank, $Risk_i$ is the self-reported risk class[11] of investor i, IC_i is the investor-average initial charge of investor i, $LN(TNA)_i$ is the natural logarithm of the investor-average fund volume[12] of investor i, TB_i is the investor-average of a dummy variable indicating whether a fund belongs to one of the top mutual fund families and $_i$ is the error term.

[8] Measured in Total Net Assets (TNA)

[9] In this regression we use Jensen's Alpha (defined in (1)) and the variable Smartness (defined in (3)) as performance measures.

[10] Measured on a scale from 1 (low trading frequency) to 5 (high trading frequency)

[11] On a scale from 1 (low risk) to 6 (high risk)

[12] Measured in Total Net Assets (TNA)

In order to account for potential endogeneity issues that may arise due to self-selection into financial advice (see Heckman, Ichimura and Todd (1998), we use two different approaches, namely (i) the propensity approach and (ii) an event study.

Using the propensity matching we are able to determine (almost) identical "statistical twins". As a consequence of the similarity of the pairs, the potential effect of a self-selection bias is reduced to a minimum. For every advised investor we determine a statistical twin based on the variables Age, Marital Status, Gender, Riskclass, Average Deposit Value, Average Cash, Average Mutual Fund Trade Volume and Length of Customer Relationship. Afterwards we compare the investment behavior of the advised investor with his statistical twin. This method is discussed in-depth by Titus and Marvin (2007) and has already been used in finance research (see Drucker and Puri (2005)).

As the online brokerage house from which we obtained our data set introduced the service of financial advice during the year 2004, we are able to study differences in the investment behavior of private investors before and after they receive financial advice. For that reason we consider two time periods, namely the time from January 2003 to June 2004 (before introduction of advice) and the time from January 2005 to June 2007 (after introduction of advice). In this event study we analyze the investment decisions of identical investors and thus results cannot be biased by factors others than the advice itself.

In existing literature on financial advice a third methodology for avoiding endogeneity issues is sometimes used, the so called "Two-Stage-Least-Square regression" (compare e.g. Hackethal, Haliassos and Jappelli (2008)). In a first step, this regression technique estimates the probability of seeking financial advice by regional data (such as population, average income, participation on elections, etc.). In a second step, it uses this probability of seeking of financial advice by regressing it on the respective depending variables. However, regional data from the destatis file[13] is available only for a grid of ~500 German regions which is, from our point of view, not detailed enough in order to derive reasonable findings. For that reason, conducting an event study seems to be superior to the two-stage least square procedure and we therefore decide not to use the Two-Stage-Least-Square regression.

[13] The destatis file contains a set of stuctural data on ~500 German regions and is provided by the German Federal Statistic Office.

5 Results and Discussion

5.1 *Identification of investors seeking for financial advice*

If we a-priori think about which investors may seek for financial advice, we will expect that these investors are younger, less experienced and less wealthy, as financial advisors can offer them guidance in order to improve portfolio performance and avoid investment mistakes. On the contrary, Hackethal, Haliassos and Jappelli (2008) find that financial advisors are rather matched with older, more experienced and wealthier investors. They argue that these investors can benefit from advisors' services by *"saving valuable time and/or by improving returns on sizeable investments"*. In this subsection we investigate which of these two cases apply for our data set and therefore address research question 1.

As described in section 4, we perform a probit-regression model analyzing several factors potentially affecting investors' use of a financial advisor. First of all, we include basic socio-demographic variables, such as Gender, Age and Marital Status. As usually Gender and Marital Status are dummy variables indicating whether the investor is male or married. Additionally, we include two variables measuring investors' wealth, namely Log of Average Deposit Value and Average Trade Volume as Vissing-Jorgensen (2003) argues that irrationality disappears with wealth. We surely can expect that investment experience is affecting investors' probability of seeking for financial advice (compare e.g. Feng and Seasholes (2005) and Grinblatt and Keloharju (2001)). On the other hand, Barber and Odean (2000) show that excessive trading yields to overconfidence. We include two variables measuring investment experience besides investors' age, namely Trading Frequency and Length of Customer Relationship.[14] Both variables are measured on a scale from 1 to 5, in which 1 indicates the lowest value. In order to map investors readiness to assume risk to our model we include the variable Riskclass which is self-reported by the investor when opening an account on a scale from 1 (low risk) to 6 (high risk).

Besides studying the affects of investor characteristics on the use of financial advice, we are also interested in the question whether investor sophistication has a positive or a negative effect on investors' probability to ask for financial advice. For that reason we include the variables Investor Averages Alpha Decile and Investor Average Smartness (defined in equation (2)) into the regression model. Niebling (2010b) proves that these measures are ex-

[14] Please note that we have no multi-collinearity issues in our regression analyses as all variance inflation factors are reasonable small.

ante proxies for overall investment success and hence for investment sophistication. Note that we conduct the regression models in the period from January 2003 to June 2004, which is the time before the online broker has introduced the offer of advice. Therefore, our results are not biased by effects resulting already from the advisory itself.

Table 5: Impact of investor characteristics on investors' probability to seek for financial advice

Table 5 presents results for research question 1. Regression coefficients from regression of investor characteristics on a dummy variable indicating whether an investor asks for financial advice are displayed. Moreover, some investor-average fund characteristics are included as control variables. Dummy variables indicate if an investor is classified as male or married by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Average Deposit Value and Average Trade Volume are proxies for wealth, whereas Trading Frequency and Length of Customer Relationship are proxies for trading experience. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively. The analyzed time period is January 2003 – June 2004.

	Reg 01 (Probit)	Reg 02 (Probit)	Reg 03 (Probit)	Reg 04 (Probit)
Depending Variable	Advice (Dummy)	Advice (Dummy)	Advice (Dummy)	Advice (Dummy)
Gender (Dummy; 1 = male)	-0.0414	-0.0441	-0.0425	-0.0453
	(0.0402)	(0.0402)	(0.0402)	(0.0402)
Age	0.0107***	0.0110***	0.0110***	0.0112***
	(0.00136)	(0.00136)	(0.00136)	(0.00137)
Marital Status (Dummy; 1 = married)	0.102***	0.0999***	0.101***	0.0985***
	(0.0330)	(0.0330)	(0.0330)	(0.0330)
Log of Average Deposit Value	0.146***	0.145***	0.146***	0.145***
	(0.0132)	(0.0132)	(0.0132)	(0.0132)
Average Trade Volume	3.31e-06**	4.19e-06***	3.64e-06**	4.41e-06***
	(1.50e-06)	(1.45e-06)	(1.49e-06)	(1.45e-06)
Trading Frequency	-0.0898***	-0.0916***	-0.0934***	-0.0928***
	(0.0131)	(0.0131)	(0.0131)	(0.0131)
Length of Customer Relationship	0.0575***	0.0579***	0.0570***	0.0574***
	(0.0112)	(0.0112)	(0.0112)	(0.0112)
Riskclass	-0.0659***	-0.0638***	-0.0642***	-0.0633***
	(0.0123)	(0.0123)	(0.0123)	(0.0123)
Investor Average Alpha Decile	0.0157			
	(0.0101)			
Investor Average Smartness		-0.00280		
		(0.00282)		
Top 20 Alpha (Dummy)			-0.129**	
			(0.0560)	
Top 20 Smartness (Dummy)				-0.0979**
				(0.0417)
Investor Average Initial Charge	-0.0351***		-0.0268***	
	(0.0107)		(0.0102)	
Log of Investor Average Volume (TNA)	0.0753***	0.0713***	0.0664***	0.0653***
	(0.0110)	(0.0108)	(0.0115)	(0.0111)
Investor Average KAG-Top-Brand	-0.398***	-0.381***	-0.418***	-0.403***
	(0.0441)	(0.0430)	(0.0440)	(0.0441)
Constant	-4.086***	-3.998***	-3.816***	-3.903***
	(0.295)	(0.291)	(0.298)	(0.293)
Observations	10529	10529	10529	10529
Pseudo R-squared	0.0593	0.0583	0.0696	0.0588

Results of these analyses are given in table 5. In all four regressions Age, Marital status, Logarithm of Average Deposit Value, Average Trade Volume and Length of Customer Relationship have a positive and statistically significant influence on investors' probability to seek for financial advice, whereas the variables Trading Frequency and Riskclass have a negative and statistically significant influence. Gender does not seem to affect the variable Advice as it is not statistically significant. These results indicate that investors who ask for financial advice are older, more likely to be married, more experienced, wealthier, less overconfident and more risk averse than investors who do not ask for advice. Therefore, we can confirm the results of Hackethal, Haliassos and Jappelli (2008) and reject the hypothesis that advisors help mainly younger and inexperienced investors to improve their investment decisions.

Let us now turn to the impact of investment sophistication on investors' probability to employ a financial advisor and therefore go beyond existing research on this topic. In regression model 1 and 2 we include the variables Investor Average Alpha Decile and Investor Average Smartness respectively. However, both variables do not seem to have any influence on investors' probability to seek for financial advice as both coefficients are not statistically significant. In order to generate a deeper insight into this issue we perform two additional regression models (regression 3 and 4) in which we include dummy variables indicating whether an investor purchases on average mutual funds in the top 20% of historical performance (regression 3) or has an average Smartness value of more than 24 (regression 4). The underlying assumption is that investors who indeed use historical performance as their decision criterion purchase on average mutual funds in the top 20% of historical performance (For a detailed discussion of this approach the reader is referred to Niebling (2010b)). Interestingly, both dummy variables are statistically significant and have a negative effect on investors' probability to ask for financial advice. This implies that unsophisticated investors are more likely to ask advisor for help in investment decisions than sophisticated investors are. Apparently, unsophisticated investors recognize that they have a need for financial advisory and therefore employ a financial advisor once it is provided by the bank.

In the light of these findings, the second research question becomes even more important: Can financial advisors indeed help these unsophisticated investors to come to better future investment decisions and to overcome behavioral biases? Do financial advisors help investors to increase their level of investment sophistication or do they use other sales arguments?

5.2 *Financial Advice and Investor Sophistication*

We now turn to our second research question, namely whether financial advisors help clients to make better investment decisions. A-priori, we would expect that advisors themselves are sophisticated and therefore indeed help clients to improve their investment success to such an extent that the clients are more likely to purchase mutual funds by chasing historical performance. Moreover, as these advisors are paid on a commission basis, we would also expect that they tend to sell mutual funds with higher initial charges, which reduces the value of the variable Smartness. Therefore, the question is which of these two effects – the improvement of the Alpha decile or the increase of initial charges – is the dominating one.

5.2.1 Evidence from Descriptive Analyses

In order to approach these questions, we first employ some descriptive statistics of the investor characteristics already discussed in subsection 5.1. Additionally, we discuss descriptive numbers of the investor averages of the purchased Alpha Decile and the variable Smartness respectively. Finally, we analyze descriptive numbers of investor averages of the fund characteristics Initial Charges, Annual Charges, Volume (measured in Total Net Assets) and Top-Brand Indicator, a Dummy variable indicating whether a mutual fund belongs to a top-brand fund family.

Results of this descriptive analysis are given in table 6[15]. Note that the analyzed time period is January 2005 to June 2007, as financial advice has been introduced by the bank during the year 2004[16].

Analyzing the results for the investor characteristics, we state that advised investors are more likely to be female, older, more likely to be married and assess themselves as more risk averse than non-advised investors. Moreover, advised investors seems to be wealthier as they have a higher average deposit value, a higher average cash value and trade on average a higher volume. Additionally, they seem to be more experienced as they have a longer relationship with the bank. All these results are statistically significant, but are not surprising given the findings from subsection 5.1 on the identification of investors seeking for financial advice.

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[15] These results and all following results are robust as several robustness checks reveal. An overview over all conducted robustness checks is given in section 6.

[16] For this reason results in table 6 differ slightly from the descriptive numbers presented in section 3 as in table 1 we considered the whole available time period from January 1999 to July 2007

Table 6: Descriptive statistics of advised investors vs. non-advised investors

Table 6 displays first, descriptive results for research question 2. In particular, descriptive statistics of the investor data for the subset of advised investors versus the subset of non-advised investors are presented. Dummy variables indicate if an investor is classified as married, as an advised investor or as a heavy trader by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Number of Portfolio Positions and Share of International Equity are proxies for diversification. Additional investor averages of the purchased Alpha decile and the variable Smartness which are both ex-ante proxies for investors' sophistication are calculated. Top20 Alpha Dummy and Top 20 Smartness Dummy indicate whether an investor purchases, on average, mutual funds in the top 20% of historical Alpha performance or with a Smartness value of more than 24 respectively. Finally, investor averages of some fund characteristics are displayed. The analyzed time period is January 2005 to June 2007.

	All Investors			Non-Advised Investor			Advised Investor			
	Obs.	**Mean**	**Std.Dev.**	**Obs.**	**Mean**	**Std.Dev.**	**Obs.**	**Mean**	**Std.Dev.**	**p-Value**
Investor-average Alpha Decile	34,964	6.88	1.82	29,200	6.84	1.88	5,764	7.09	1.45	0.000
Top20 Alpha Dummy	34,964	14.04%	34.74%	29,200	14.73%	35.44%	5,764	10.53%	30.70%	0.000
Investor-average Smartness	31,041	19.38	5.81	25,656	19.29	5.99	5,385	19.83	4.87	0.000
Top20 Smartness Dummy	34,964	31.96%	46.63%	29,200	33.39%	47.16%	5,764	24.72%	43.14%	0.000
Investor-average Initial Charge	31,041	4.10%	1.36%	25,656	4.11%	1.40%	5,385	4.08%	1.15%	0.112
Investor-average Annual Charge	34,294	1.36%	0.33%	28,569	1.37%	0.34%	5,725	1.33%	0.28%	0.000
Investor-average Volume (TNA, in M€)	34,403	3,184	3,920	28,671	3,187	3,993	5,732	3,170	3,533	0.765
Investor-average Top Brand Indicator	34,791	29.23%	33.13%	29,030	30.08%	34.19%	5,761	24.94%	26.70%	0.000
Gender (Dummy; 1 = male)	34,838	83.81%	36.84%	29,090	84.81%	35.90%	5,748	78.78%	40.89%	0.000
Age	34,839	45.69	12.20	29,091	45.16	11.90	5,748	48.38	13.32	0.000
Marital Status (Dummy; 1 = married)	20,309	60.15%	48.96%	16,396	59.19%	49.15%	3,913	64.20%	47.95%	0.000
Riskclass	34,756	4.52	1.28	29,024	4.57	1.29	5,732	4.26	1.20	0.000
Deposit Value	34,963	55,151	139,785	29,199	50,655	143,104	5,764	77,926	119,017	0.000
Cash Value	34,964	33,893	82,085	29,200	31,618	69,046	5,764	45,420	128,703	0.000
Mutual Funds Trade Volume	34,964	4,521	16,959	29,200	4,223	17,319	5,764	6,030	14,913	0.000
Lenght of Customer Rel. (years)	34,964	7.91	3.17	29,200	7.80	3.07	5,764	8.50	3.56	0.000
Number of Trades	34,964	75.26	427.46	29,200	83.84	464.37	5,764	31.80	117.06	0.000
Heavy Trader (Dummy)	34,964	25.14%	43.38%	29,200	30.00%	45.83%	5,764	0.54%	7.31%	0.000
Number of Portfolio Positions	25,332	11.90	11.30	21,750	11.81	11.52	3,582	12.47	9.86	0.001
Share of International Equity	24,887	49.71%	28.46%	21,351	49.54%	28.61%	3,536	50.70%	27.51%	0.024

When examining the variables Number of Trades and the Heavy Trader Dummy, we realize that advised investors dramatically trade less (30% of non-advised clients are classified as heavy traders by the banks' data warehouse, whereas this is the case for only 0.5% of advised clients). Following the line of argumentation of Barber and Odean (2000) who associate excessive trading with overconfidence, we can conclude that advised investors are less overconfident than their non-advised counterpars. Furthermore, advised investors have slightly more portfolio positions and a higher share of international equity. As both numbers are proxies for portfolio diversification (compare Bernatzi and Thaler (2001) and Bluethgen, Gintschel, Hackethal and Mueller (2007) respectively), we conclude that financial advisors may help their clients to diversify their portfolios and therefore to overcome this behavioral bias. These results are in line with the findings of Hackethal, Haliassos and Jappelli (2008).

Let us now turn to potential differences in investor sophistication between advised and non-advised customers displayed in table 6. We find that advised customers purchase mutual funds in an Alpha decile that is on average 0.23 higher and have a Smartness value that is on average 0.54 higher than non-advised investors. Hence, it seems as if advisors help their clients to purchase mutual funds by chasing historical performance. However, when considering the Top 20 dummy variables, we get a different picture. For advised investors the proportion of mutual funds in the top 20% of historical performance is smaller than for non-advised investors. Results are similar for the Top 20 Smartness Dummy. Given these simple descriptive analyses, this implies that advisors apparently help their clients to purchase higher Alpha deciles but that they do not help them to purchase the best performing mutual funds.

Finally, advised investors purchase mutual funds with lower annual charges and fund that are more likely belong to a top-brand fund family. Differences in initial charges and fund volume are not statistically significant in this descriptive analysis.

Summarizing results of these descriptive statistics, we find that financial advisors do not seem to help their clients to improve their investment sophistication, but they may help to overcome the behavioral bias of missing portfolio diversification. Moreover, we could not find that advisors tend to sell mutual funds with higher initial charges. We will shed more light on these questions by performing a multivariate analysis in the next subsection.

5.2.2 Evidence from Multiple Regressions

We now try to sharpen the results regarding research question 2 by performing a regression model regressing the Advice dummy variable on the Investor Average Alpha Decile and the Investor Average Smartness as well as on further potential purchase criteria. We also control for investor characteristics and for investor averages of fund characteristics in the model. Table 7 presents the respective results.

Before we study the influence of financial advice on the investment sophistication, let us briefly consider the effects of the investor characteristics on the Investor Average Alpha Decile and the Investor Average Smartness (regressions 05 and 06). Age and Average Trade Volume have a positive and statistically significant influence on the Investor Average Alpha Decile and the Investor Average Smartness respectively, whereas Trading Frequency and Length of Customer Relationship affect the depending variables negatively. Therefore, we can conclude that smart behaving and historical performance chasing (and hence more sophisticated) investors are older, more experienced, wealthier and less overconfident[17]. These results are in line with the findings of Niebling (2010b).

Let us now turn to the specific point of interest of this paper, namely the question whether and how financial advice effects the investor sophistication and other potential purchase criteria. First of all, consider regression 05 that uses the Investor Average Alpha Decile as depending variable. The coefficient of the Advice dummy variable is positive and statistically significant at the 1%-level. Consequently, financial advice affects the average purchased Alpha decile positively indicating that advisors indeed seem to help their clients to purchase mutual funds in a higher Alpha decile. However, when considering regression 06 which uses the Investor Average Smartness as depending variable, the effect of financial advice is no longer statistically significant. Hence, the positive influence of the advice disappears once also the costs of the advice are taken into account. Results change when looking at regression 07 and regression 08 where we use the Top20 Alpha Dummy and the Top20 Smartness Dummy respectively as depending variable. In both cases the Advice Dummy affects the respective Top20 Dummy negatively and statistically significantly.

[17] Excessive trading is a proxy for overconfidence, compare Barber, B.M., and T. Odean, 2000, "Trading is hazardous to your wealth: The common stock investment performance of individual investors", *Journal of Finance* 55, 773-806.

Table 7: Impact of financial advice on mutual fund purchasing criteria used by private investors

Table 7 shows results for research question 2. Regression coefficients from regressions of a dummy variable that indicates whether an investor receives financial advice on investor averages of potential mutual fund purchasing criteria are presented. Moreover, investor characteristics and investor averages of fund characteristics are included as control variables. Dummy variables indicate if an investor is classified as male or married by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Average Deposit Value and Average Trade Volume are proxies for wealth, whereas Trading Frequency and Length of Customer Relationship are proxies for trading experience. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively. The analyzed time period is January 2005 – June 2007.

	Reg 05 (Tobit)	Reg 06 (Tobit)	Reg 07 (Probit)	Reg 08 (Probit)	Reg 09	Reg 10	Reg 11 (Probit)
Depending Variable	Inv-avg Alpha Decile	Inv-avg Smartness	Top20 Alpha Dummy	Top20 Smartn. Dummy	Inv-avg Init. Charge	Inv-avg Volume	Inv-avg Top-brand
Advice (Dummy)	0.0872***	-0.126	-0.109***	-0.211***	-0.204***	0.205***	0.154***
	(0.0308)	(0.104)	(0.0368)	(0.0293)	(0.0223)	(0.0223)	(0.0273)
Gender (Dummy; 1 = male)	-0.0272	-0.0497	-0.0159	-0.0226	0.0552**	-0.0684***	0.0372
	(0.0307)	(0.103)	(0.0348)	(0.0282)	(0.0244)	(0.0255)	(0.0265)
Age	0.0106***	0.0293***	0.00629***	0.00406***	-0.00247***	-0.00818***	-0.00480***
	(0.00102)	(0.00345)	(0.00112)	(0.000950)	(0.000864)	(0.000885)	(0.000880)
Marital Status (Dummy; 1 = married)	-0.0138	-0.0309	-0.0466	-0.0215	0.0151	0.0453**	0.0150
	(0.0263)	(0.0885)	(0.0299)	(0.0238)	(0.0206)	(0.0219)	(0.0229)
Log of Average Deposit Value	0.00831	-0.0302	-0.0542***	-0.0510***	0.00307	0.0305***	0.0675***
	(0.0102)	(0.0344)	(0.0111)	(0.00932)	(0.00948)	(0.00948)	(0.00869)
Average Trade Volume	4.79e-06***	9.09e-06***	4.77e-06***	3.15e-06*	-6.60e-06**	-3.41e-06	-4.71e-06***
	(8.87e-07)	(2.99e-06)	(6.49e-07)	(1.64e-06)	(2.83e-06)	(2.83e-06)	(6.19e-07)
Trading Frequency	-0.0892***	-0.260***	-0.0709***	-0.0529***	0.00236	0.0325***	0.0803***
	(0.00993)	(0.0335)	(0.0114)	(0.00925)	(0.00814)	(0.00834)	(0.00868)
Length of Customer Relationship	-0.0275***	-0.134***	0.00802	-0.00150	-0.0230***	-0.0279***	-0.0424***
	(0.00817)	(0.0275)	(0.00912)	(0.00752)	(0.00659)	(0.00682)	(0.00702)
Riskclass	0.0140	0.0217	0.0144	-0.00628	-0.0170**	-0.0697***	-0.0382***
	(0.00947)	(0.0319)	(0.0107)	(0.00870)	(0.00762)	(0.00803)	(0.00820)
Investor AverageAlpha Decile					0.137***	-0.111***	-0.0841***
					(0.00797)	(0.00891)	(0.00654)
Investor Average Initial Charge	0.216***		0.178***			0.103***	0.0632***
	(0.00945)		(0.0125)			(0.00997)	(0.00767)
Log of Investor Average Volume (TNA)	-0.169***	-0.219***	-0.362***	-0.236***	0.0924***		-0.200***
	(0.00904)	(0.0302)	(0.00996)	(0.00818)	(0.00927)		(0.00909)
Investor Average KAG-Top-Brand	-1.231***	-4.563***	-0.535***	-0.941***	-0.997***	-0.492***	
	(0.0395)	(0.127)	(0.0454)	(0.0402)	(0.0395)	(0.0436)	
Constant	9.677***	25.52***	6.151***	5.074***	1.727***	22.04***	0.227
	(0.234)	(0.780)	(0.254)	(0.211)	(0.247)	(0.133)	(0.203)
Observations	17619	17619	17619	17619	17619	17619	17619
(Pseudo) R-squared	0.0381	0.0145	0.1605	0.0857	0.127	0.051	0.0588

Therefore, we confirm the results obtained by the descriptive analyses, namely that financial advisors may help their clients to purchase, on average, better performing mutual funds, but fail to sell their clients mutual funds belonging to the top performing funds regarding historical performance. They therefore fail to increase clients' investment sophistication.

Additionally, we perform three more regressions using the Investor Average Initial Charges (regression 09), the Investor Average Volume (regression 10) and the Investor Average Top-Brand Indicator (regression 11) as depending variables. As the Advice Dummy has a negative and statistically significant influence on the Investor Average Initial Charges, we conclude that advisors apparently sell their clients mutual funds with lower initial charges. This surprising finding is contradictory to our a-priori hypothesis that advisors are tempted to sell mutual funds with higher costs as they themselves benefit from these front-end loads by their commission model. Moreover, it turns out that financial advisors sell mutual funds which have a higher fund volume and are more likely to belong to a top-brand fund family as the Advice Dummy has a positive and statistically significant coefficient in both regressions 10 and 11.

Summarizing the results regarding the second research question so far, we state that financial advisors seem to use fund volume and funds' brand as major sales arguments and therefore make the same investment mistakes private investors obtain (compare Niebling (2010a)) when making mutual fund purchase decisions: Advisors do not recommend mutual funds by chasing historical performance to their clients and therefore they fail to improve their clients' investment sophistication. At least, financial advisors use initial charges as additional sales argument and hence help their clients to save money.

However, we used our whole data set in order to derive these findings. Thus, it could be that we have possible endogeneity issues within our analyses. For this reason we will perform two checks of endogeneity in the remaining subsections of section 5 in order to figure out whether our results still hold or change once checked for possible endogeneity.

5.2.3 Check for possible endogeneity I: Propensity approach

Potential endogeneity issues may arise due to clients' self-selection into financial advice. Therefore, we address the question whether the results we obtained so far are due to the advisors themselves or due to the clients they attract.

First of all, we conduct a propensity matching of the advised investors. For every investor who receives financial advice, the propensity algorithm seeks for a non-advised peer to such an extent that the advised investor and his peer have approximately the same age, gender, marital status, riskclass, wealth[18] and length of relationship with the bank. Consequently, we avoid that results are biased by other factors than the financial advice itself.

Considering the descriptive statistics which are presented in table 8, we find that advised investors tend to purchase mutual funds rather by chasing historical performance compared to their non-advised peers. An advised investor purchases a mutual fund in an average Alpha decile of 7.06, whereas the average Alpha decile of the mutual funds purchased by a non-advised investor purchases is 6.91. The difference is statistically significant.

Table 8: Descriptive statistics Propensity Approach

Table 8 displays additional results for research question 2. Descriptive statistics of the investor data for the subset of advised investors versus their non-advised peers are presented. For identifying the non-advised peers a propensity matching using the variables Gender, Age, Marital Status, Riskclass, Wealth and Length of Customer Relationship is conducted. Investor averages of the purchased Alpha decile and the variable Smartness which are both ex-ante proxies for investors' sophistication are reported. Top20 Alpha Dummy and Top 20 Smartness Dummy indicate whether an investor purchases on average mutual funds in the top 20% of historical Alpha performance or with a Smartness value of more than 24 respectively. Finally, investor averages of some fund characteristics are displayed. The analyzed time period is January 2005 to June 2007.

	Non-Advised Investor			Advised Investor			
	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	p-Value
Investor-average Alpha Decile	3,557	6.91	1.75	3,557	7.06	1.37	0.000
Top20 Alpha Dummy	3,557	12.57%	33.15%	3,557	8.83%	28.37%	0.000
Investor-average Smartness	3,557	19.46	5.79	3,557	19.70	4.77	0.058
Top20 Smartness Dummy	3,557	23.70%	42.53%	3,557	18.11%	38.51%	0.000
Investor-average Initial Charge	3,557	4.10%	13.78%	3,557	3.99%	1.19%	0.001
Investor-average Annual Charge	3,547	1.34%	0.34%	3,551	1.31%	0.29%	0.000
Investor-average Volume (TNA, in M€)	3,557	3,099	3,524	3,557	3,060	3,198	0.627
Investor-average Top Brand Indicator	3,557	33.25%	33.54%	3,557	26.30%	26.28%	0.000

However, when analyzing the Top 20 dummy results, we find that advised clients purchase less mutual funds belonging to the top 20% of historical Alpha (8.83%) performance than non-advised clients do (12.57%). Analyzing the Smartness value we get a similar picture. On the one hand, advised investors purchase on average mutual funds with a higher Smartness value than their non-advised counterparts (19.70 versus 19.46). On the other hand, they purchase less mutual funds belonging to the top 20% of Smartness value than non-advised investors do (18.11% versus 23.70%). Moreover, on average advised investors seem to purchase mutual funds with lower costs (initial charges as well as annual charges) and that less likely belong to a top-brand fund family than their non-advised peers.

[18] Measured by average deposit value, average cash and average mutual fund trade volume

Table 9: Impact of financial advice on mutual fund purchasing criteria used by private investors using propensity algorithm

Table 9 shows additional results for research question 2. Regression coefficients from regression of a dummy variable that indicates whether an investor receives financial advice on investor averages of potential mutual fund purchasing criteria are presented. Moreover, investor characteristics and investor averages of fund characteristics are included as control variables. For identifying the non-advised peers a propensity matching using the variables Gender, Age, Marital Status, Riskclass, Wealth and Length of Customer Relationship is conducted. Dummy variables indicate if an investor is classified as male or married by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Average Deposit Value and Average Trade Volume are proxies for wealth, whereas Trading Frequency and Length of Customer Relationship are proxies for trading experience. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively. The analyzed time period is January 2005 – June 2007.

	Reg 12 (Tobit)	Reg 13 (Tobit)	Reg 14 (Probit)	Reg 15 (Probit)	Reg 16	Reg 17	Reg 18 (Probit)
Depending Variable	Inv-avg Alpha Decile	Inv-avg Smartness	Top20 Alpha Dummy	Top20 Smartn. Dummy	Inv-avg Init Charge	Inv-avg Volume	Inv-avg Top-brand
Advice (Dummy)	0.0998***	-0.0594	-0.126***	-0.206***	-0.208***	0.211***	0.136***
	(0.0366)	(0.125)	(0.0450)	(0.0357)	(0.0285)	(0.0295)	(0.0338)
Gender (Dummy; 1 = male)	-0.0532	-0.226	0.0278	-0.0354	0.0686**	-0.0525	-0.0150
	(0.0427)	(0.146)	(0.0518)	(0.0413)	(0.0346)	(0.0357)	(0.0394)
Age	0.0117***	0.0271***	0.00542***	0.00115	-0.00434***	-0.00816***	-0.00336***
	(0.00141)	(0.00479)	(0.00163)	(0.00137)	(0.00113)	(0.00121)	(0.00129)
Marital Status (Dummy; 1 = married)	-0.0273	0.0188	-0.0774	-0.0199	-0.0108	0.0156	0.0136
	(0.0399)	(0.136)	(0.0482)	(0.0384)	(0.0317)	(0.0329)	(0.0369)
Log of Average Deposit Value	0.0138	-0.0196	-0.0668***	-0.0681***	-0.0102	0.0293*	0.106***
	(0.0150)	(0.0512)	(0.0172)	(0.0147)	(0.0145)	(0.0151)	(0.0134)
Average Trade Volume	7.03e-06***	1.22e-05**	9.76e-06***	6.45e-06***	-8.56e-06***	-6.83e-06*	-1.05e-05***
	(1.73e-06)	(5.91e-06)	(1.51e-06)	(2.39e-06)	(2.08e-06)	(3.91e-06)	(1.38e-06)
Trading Frequency	-0.0869***	-0.242***	-0.0811***	-0.0510***	-0.000489	0.0327***	0.0777***
	(0.0151)	(0.0514)	(0.0186)	(0.0149)	(0.0124)	(0.0124)	(0.0141)
Length of Customer Relationship	-0.0123	-0.144***	0.0248*	-0.00134	-0.0452***	-0.0303***	-0.0567***
	(0.0113)	(0.0384)	(0.0133)	(0.0110)	(0.00897)	(0.00956)	(0.0103)
Riskclass	0.0191	0.0697	0.0114	0.00479	-0.000787	-0.0520***	-0.00583
	(0.0141)	(0.0481)	(0.0170)	(0.0137)	(0.0117)	(0.0119)	(0.0129)
Investor AverageAlpha Decile					0.164***	-0.111***	-0.0655***
					(0.0131)	(0.0150)	(0.0109)
Investor Average Initial Charge	0.253***		0.229***			0.0738***	0.0529***
	(0.0146)		(0.0211)			(0.0159)	(0.0127)
Log of Investor Average Volume (TNA)	-0.172***	-0.217***	-0.356***	-0.229***	0.0688***		-0.220***
	(0.0144)	(0.0486)	(0.0165)	(0.0137)	(0.0153)		(0.0148)
Investor Average KAG-Top-Brand	-1.032***	-3.823***	-0.387***	-0.813***	-0.993***	-0.545***	
	(0.0630)	(0.206)	(0.0745)	(0.0669)	(0.0660)	(0.0716)	
Constant	9.358***	25.08***	5.898***	5.154***	2.306***	22.14***	-0.0963
	(0.365)	(1.224)	(0.412)	(0.345)	(0.411)	(0.208)	(0.329)
Observations	7114	7114	7114	7114	7114	7114	7114
(Pseudo) R-squared	0.039	0.011	0.1619	0.073	0.134	0.059	0.066

Solely regarding fund volume, no statistically significant difference is observable. Therefore, these descriptive statistics confirm pretty much the results of the descriptive statistics in subsection 5.1.

In a next step, we repeat the multiple regression analyses studying the effect of the Advice dummy on potential mutual fund purchasing criteria from subsection 5.2 with our dataset consisting of advised investors and their non-advised peers. Again, investor characteristics and investor averages of mutual fund characteristics are included as additional control variables. Results are presented in table 9. The Advice dummy in Regression 12 which uses the Investor Average Alpha decile as depending variable is positive and statistically significant at the 1%-level. This supports the findings from section 5.2 that clients who receive financial advice purchase on average mutual funds in a higher Alpha decile than their non-advised peers. However, when regressing on the Investor Average Smartness (compare Regression 13) the regression coefficient of the Advice Dummy is no longer statistically significant. Moreover, the Advice dummy affects both Top 20 dummy variables of the purchased Alpha decile (Regression 14) and the Smartness value (Regression 15) negatively and statistically significantly. Apparently, advised investors purchase less mutual funds belonging to the top 20% of historical performance and Smartness respectively than their non-advised counterparts. These results imply that financial advisors do not help their clients to chase historical performance. They rather reduce the investor sophistication of their clients.

However, advisors at least help their clients to reduce the costs of the mutual fund investments as indicated by the negative coefficient of the Advice Dummy when regressed on the Investor Average Initial Charges (Regression 16). Moreover, advised investors purchase on average mutual funds with a higher fund volume (compare Regression 17) that likely belong to a top-brand fund family (Regression 18).

Summarizing results of the analyses when using propensity matching, we confirm results obtained in subsections 5.1 and 5.2: Financial advisors do not help their clients to improve their investment sophistication. Advisors use fund volume, the fact that the fund belongs to a top-brand fund family and reduced initial charges as sales arguments.

5.2.4 Check for possible endogeneity II: Event study

In the final part of our analyses we perform a second check for potential endogeneity issues in the data set. We now analyze the investment behavior of identical investors before and after they receive financial advice. For that reason, we restrict the data set to investors who purchased mutual funds in the time period from January 2003 to June 2004 (before the introduction of advice by the bank) and in the time period from January 2005 to June 2007 (after introduction of advice by the bank) and have received advice in the second time period. It is obvious that by using this methodology, there cannot be factors other than the advice itself effecting changes in the investment behavior of these investors. Let us again first consider basic descriptive statistics which are presented in table 10. Analogous to former results, investors purchase, on average, mutual funds with higher Alpha deciles and higher Smartness values in the time after the introduction of financial advice compared to the time before the introduction.

Table 10: Descriptive statistics Event Study

Table 10 displays additional results for research question 2. Descriptive statistics of the investor data for the subset of advised investors are presented. These investors are analyzed in two time periods: Before the introduction of financial advice by the bank (January 2003 to June 2004) and after the introduction of financial advice (January 2005 to June 2007). Investor averages of the purchased Alpha decile and the variable Smartness which are both ex-ante proxies for investors' sophistication are reported. Top20 Alpha Dummy and Top 20 Smartness Dummy indicate whether an investor purchases on average mutual funds in the top 20% of historical Alpha performance or with a Smartness value of more than 24 respectively. Finally, investor averages of some fund characteristics are displayed.

	Before Intro. of Advice			After Intro. of Advice			p-Value
	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	
Investor-average Alpha Decile	2,899	6.84	1.65	2,899	6.96	1.37	0.002
Top20 Alpha	2,899	9.62%	29.50%	2,899	7.31%	26.04%	0.002
Investor-average Smartness	2,679	19.06	5.59	2,769	19.61	4.68	0.000
Top20 Smartness	2,899	25.25%	43.45%	2,899	20.70%	40.52%	0.000
Investor-average Initial Charge	2,679	3.91%	1.44%	2,769	4.08%	1.11%	0.000
Investor-average Annual Charge	2,889	1.27%	0.31%	2,889	1.34%	0.26%	0.000
Investor-average Volume (TNA, in M€)	2,836	2,931	2,862	2,890	3,480	3,633	0.000
Investor-average Top Brand Indicator	2,898	36.49%	33.83%	2,897	27.24%	26.71%	0.000

However, once the clients received financial advice, they purchase less mutual funds belonging to the top 20% of historical Alpha performance and Smartness value respectively compared to the time in which they did not receive advice. Moreover, average costs (initial charges as well as annual charges) are slightly higher after the introduction of advice. Furthermore, after receiving financial advice investors purchase, on average, funds with higher fund volume but that less likely belong to a top-brand fund family.

Finally, we again study the impact of the Advice Dummy variable on the Investor Average Alpha Decile, the Investor Average Smartness measure as well as on the other potential mutual fund purchase criteria. Results of these regression analyses are given in table 11.

Table 11: Impact of financial advice on mutual fund purchasing criteria used by private investors using an Event Stidy

Table 11 shows additional results for research question 2. Regression coefficients from regression of a dummy variable that indicates whether an investor receives financial advice on investor averages of potential mutual fund purchasing criteria are presented. The investors are analyzed in two time periods: Before introduction of financial advice by the bank (January 2003 to June 2004) and after introduction of financial advice (January 2005 to June 2007). Moreover, investor characteristics and investor averages of fund characteristics are included as control variables. Dummy variables indicate if an investor is classified as male or married by the bank's data warehouse. Riskclass is reported by the investors themselves when opening an account from 1 (low) to 6 (high). Average Deposit Value and Average Trade Volume are proxies for wealth, whereas Trading Frequency and Length of Customer Relationship are proxies for trading experience. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% level respectively.

	Reg 19 (Tobit)	Reg 20 (Tobit)	Reg 21 (Probit)	Reg 22 (Probit)	Reg 23	Reg 24	Reg 25 (Probit)
Depending Variable	Inv-avg Alpha Decile	Inv-avg Smartness	Top20 Alpha Dummy	Top20 Smartn. Dummy	Inv-avg Init Charge	Inv-avg Volume	Inv-avg Top-brand
Advice (Dummy)	-0.0264	-0.100	-0.0616	-0.181***	-0.0357	0.222***	0.157***
	(0.0470)	(0.173)	(0.0807)	(0.0581)	(0.0439)	(0.0417)	(0.0545)
Gender (Dummy; 1 = male)	0.0334	0.118	0.0208	-0.0251	-0.00704	-0.0190	-0.00727
	(0.0609)	(0.224)	(0.106)	(0.0754)	(0.0571)	(0.0549)	(0.0705)
Age	0.0123***	0.0368***	0.00632*	0.00793***	-0.00396**	-0.00639***	-0.00190
	(0.00203)	(0.00748)	(0.00329)	(0.00242)	(0.00196)	(0.00197)	(0.00235)
Marital Status (Dummy; 1 = married)	-0.0176	-0.129	0.103	0.0344	-0.00140	0.166***	0.0188
	(0.0521)	(0.192)	(0.0906)	(0.0643)	(0.0482)	(0.0472)	(0.0610)
Log of Average Deposit Value	-0.00228	-0.0799	-0.0552*	-0.0437**	0.00131	0.0229	0.0714***
	(0.0190)	(0.0699)	(0.0300)	(0.0220)	(0.0183)	(0.0182)	(0.0211)
Average Trade Volume	2.61e-05***	4.71e-05***	2.51e-05***	1.83e-05***	-2.98e-05***	-2.20e-05***	-2.08e-05***
	(4.12e-06)	(1.51e-05)	(5.06e-06)	(5.03e-06)	(6.67e-06)	(5.14e-06)	(4.36e-06)
Trading Frequency	-0.0547***	-0.304***	-0.0979***	-0.0488*	-0.0241	-0.0299*	0.150***
	(0.0211)	(0.0777)	(0.0365)	(0.0257)	(0.0200)	(0.0179)	(0.0248)
Length of Customer Relationship	-0.0208	-0.0628	0.00761	-0.00706	-0.00842	-0.0350**	-0.0269
	(0.0171)	(0.0629)	(0.0286)	(0.0211)	(0.0162)	(0.0154)	(0.0195)
Riskclass	0.0369*	0.133*	0.0512	0.0254	-0.0235	-0.0302	-0.0301
	(0.0204)	(0.0750)	(0.0349)	(0.0254)	(0.0196)	(0.0190)	(0.0238)
Investor AverageAlpha Decile					0.287***	-0.108***	-0.0325
					(0.0216)	(0.0239)	(0.0199)
Investor Average Initial Charge	0.334***		0.203***			0.123***	0.157***
	(0.0185)		(0.0367)			(0.0223)	(0.0221)
Log of Investor Average Volume (TNA)	-0.146***	-0.110	-0.461***	-0.249***	0.134***		-0.209***
	(0.0202)	(0.0738)	(0.0310)	(0.0247)	(0.0259)		(0.0244)
Investor Average KAG-Top-Brand	-0.588***	-2.937***	-0.271**	-1.268***	-0.725***	0.0950	-2.284***
	(0.0809)	(0.290)	(0.137)	(0.126)	(0.0954)	(0.0921)	
Constant	8.287***	22.13***	7.520***	4.841***	-0.137	21.84***	
	(0.500)	(1.827)	(0.762)	(0.598)	(0.658)	(0.273)	(0.565)
Observations	3124	3124	3124	3124	3124	3124	3124
(Pseudo) R-squared	0.0524	0.0102	0.2317	0.123	0.167	0.069	0.0817

Apparently, financial advice does not affect the average purchased Alpha decile as the coefficient of the Advice Dummy in Regression 19 is not statistically significant. This implies that we cannot find differences in the ability to purchase mutual funds by chasing historical performance of the analyzed investors before and after they received financial advice. When considering the Investor Average Smartness, results remain qualitatively unchanged (compare Regression 20). Again the respective regression coefficient is not statistically significant. Interestingly, in this event study even the Top20 Alpha Dummy variable is not affected statistically significantly by the Advice dummy (compare Regression 21). However, at least the Top 20 Smartness Dummy (Regression 22) is influenced negatively and statistically significantly by the Advice Dummy.

Thus, investors purchase less mutual funds which have, on average, a Smartness value of more than 24 once they received financial advice compared to the time they did not have a financial advisor and made their investment decisions by themselves. Therefore, our former results are confirmed so far that financial advisors do not help their clients to make better investment decisions. On the contrary, investors lose parts of their investment sophistication after receiving financial advice[19].

In this event study, even the effect that advised clients purchase on average mutual funds with lower initial charges is not observable, as the regression coefficient of the Advice Dummy in Regression 23 is not statistically significant at all common levels. The effect on the fund volume and the Top-Brand Dummy is the same as in the previous analyses (compare Regression 24 and Regression 25 respectively): Investors purchase on average mutual funds with a higher fund volume which belong more likely to a top-brand fund family once they receive financial advice.

All in all, with these analyses we find evidence that the results are not biased by potential endogeneity issues. The observed effects of financial advice on private investors' investment sophistication are solely due to the advisors themselves and not due to other factors affecting the investment behavior. Indeed, financial advisors do not help their clients to enhance their level of investment sophistication. They rather use fund volume and funds' brand as sales arguments.

[19] Please note once again, that both the ability to chase historical performance when purchasing mutual funds and the Smartness measure are ex-ante proxies for investment sophistication.

6 Robustness

In this paper we derive findings on the investment behavior and investment sophistication of private investors who receive financial advice which are counterintuitive and contradictory to our a-priori hypotheses. We also show that these results still hold when performing a propensity matching and an event study respectively and therefore account for potential endogeneity issues. In order to get even more confidence on our results, we perform several additional robustness checks which are described in this section.

First of all, we exclude all investors who have purchased only one mutual fund in the analyzed time periods from the data set. After recalculating the descriptive statistics as well as the regression models, it turns out that results remain qualitatively unchanged. Financial advisors still do not help their clients to purchase mutual funds belonging to the top 20% of historical performance. They still recommend mutual funds which are larger and are more likely to belong to a top-brand fund family.

After not taking very infrequent traders into account, we investigate whether investors who are very frequent traders bias the result. In the data set a variable is included indicating whether an investor is classified as "Heavy Trader" by the banks' data warehouse. Excluding all these heavy traders from the data set and repeating the analyses yields to qualitatively unchanged results for all research questions.

When we have constructed the data base we excluded all transactions which are part of mutual fund saving plans mainly due to two reasons: On the one hand, saving plan investors cannot choose from the whole available fund universe, and on the other hand, these investors make their investment decision only once in advance and then the funds are purchased automatically by the bank (compare section 3). However, we repeat all analyses with a data set including these saving plan transactions for robustness reasons. Again, all results remain qualitatively unchanged.

Moreover, when performing regressions on a dummy variable (i.e. regressions on the Advice Dummy in section 5.1 and regressions on the Top20 Alpha Dummy and the Top20 Smartness Dummy in section 5.2.) we always use a probit regression model. When calculating the same regression with a logit regression model, we do not obtain qualitative changes in the results. In addition, the propensity matching algorithm in section 5.2.3 uses a probit estimation technique. Again, when performing the propensity matching with a logit estimation results remain qualitatively unchanged.

Finally, multi-collinearity does not seem to be a problem in our regression models as all variance-inflation-factors are reasonably small.

7 Conclusion

This paper contributes to the strand of empirical literature on the role of financial advice within the financial retail industry. In particular, we extend the recent paper of Bergstresser, Chalmers and Tufano (2009). We use a dataset of a German online brokerage house that allows us to analyze the investment behavior on an investor- and transaction-specific level. Therefore, we can identify on single investor level which particular investors receive financial advice and which investors do not. Additionally, we are able to compare the behavior of investors in the time before and after they mandated a financial advisor.

All existing studies on the role of financial advice of which the authors are aware (e.g. Bergstresser, Chalmers and Tufano (2009); Hackethal, Haliassos and Jappelli (2008)) use ex-post portfolio returns in order to measure the quality of advice. In contrast, we use the degree to which investors chase historical performance when purchasing mutual funds in order to measure financial advisors' ability to improve their clients' investment sophistication in this paper. Niebling (2010b) proves that smart mutual fund decision making is an ex-ante measure for overall investment success and hence for superior investment sophistication. The advantage of this ex-ante measure compared to ex-post portfolio returns is that it does not have the problem of being potentially affected by random stock market movements.

We focus on two major research questions. First, we address the question which particular investors seek for financial advice. We find that investors who receive financial advice are older, more likely to be married, more experienced, wealthier, less overconfident and more risk averse. Additionally, we study the impact of investment sophistication on the probability to seek for financial advice. While the investor average purchased Alpha decile and the investor average Smartness value do not influence the probability to ask for advice, the Top20 Alpha dummy and the Top20 Smartness dummy, indicating whether an investor purchases on average mutual funds in the top 20% of historical Alpha performance or has an average Smartness value of more than 24, affects the Advice dummy negatively and statistically significantly. Apparently, unsophisticated investors are more likely to seek financial advice than sophisticated investors are.

Second, we turn to the question whether financial advisors help these clients to come to better investment decisions and hence increase clients' level of investment sophistication. We provide evidence that although advised investors purchase on average mutual funds in a higher Alpha decile, they purchase less funds belonging to the top 20% of historical performance and to the top 20% of the Smartness value respectively. Consequently, we conclude that advisors do not help their clients to increase their individual investment sophistication. Results still hold when checked for potential endogeneity issues. Hence, the fact that advisors do not recommend mutual funds that belong to the top 20% of historical performance is indeed due to the advisors themselves and not due to other factors affecting the investment behavior.

Moreover, we show that advice positively affects the investor average purchased fund volume and the investor average Top-brand Indicator. Hence, it seems as if advisors are more likely to recommend larger and well-known funds and are less likely to recommend funds which outperformed in the past. At least, advisors help their clients to save money to that extent that they recommend mutual funds with lower initial charges. Apparently, financial advisors use fund volume, the fact that the fund belongs to a top-brand fund family and reduced initial charges as sales arguments. These results also hold once checked for potential endogeneity. In their paper Hackethal, Haliassos and Jappelli (2008) conclude that financial advisors are like babysitters, as they offer a service that parents themselves could do better, but observed achievement of children with babysitters is usually better than the achievement of children without babysitters. With our results we can even go one step further: Financial advisors base investment recommendations on the same criteria private investors themselves seem to use (compare Niebling (2010a)). They recommend mutual funds which have higher fund volume and belong more likely to a top-brand fund family instead of looking at the funds' historical performance, which is proven to be a rational purchase criterion.

What do these results mean in practice? Apparently, financial advisors support their clients to that extent that they relieve them of the information gathering and fund choosing processes, but they do not choose better funds. A common explanation is that advisors are pushed to these poor investment recommendations by a misleading incentive model. However, we show that advisors recommend mutual funds which have lower initial charges. Therefore, the major problem seems to be that advisors sell mutual funds to their clients of which they believe clients would also purchase when left alone. Advisors are much more salesmen than advisors! Hence, political decision makers are urged to think about possibilities to enhance the sophistication of advisors and make it rewarding for financial advisors to sell the best funds.

There is much potential for future work regarding the role of advice in the financial retail industry. We have found some evidence that even if advisors do not increase overall investment sophistication they may help clients to better diversify their portfolios. Hence, it would be interesting to study the effect of financial advice on various known behavioral biases comprehensively. Additionally, someone could consider the role of fund marketing. Given our results, it seems as if not only the private investors themselves but rather the financial advisors are missleaded to purchase poorer performing funds by marketing.

Finally, future work could study the question whether the specific incentive model of the advisors influences the quality of the advice, i.e. whether advisors who do not work on a commission basis but get basic fees perform better in increasing clients' investment sophistication.

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Teil III

Lebenslauf

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