The Influence of XTFs on Risk and Return of Households' Investment Portfolios

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This thesis uses data of the Eurosystem's Household Finance and Consumption Survey and the Securities Holdings Statistics-Base of Deutsche Bundesbank. The results published and the related observations and analyses may not correspond to results or analyses of the data producers.

Geleitwort

Innerhalb des Forschungszweiges der Finanzmärkte im Allgemeinen sowie des Bereichs der Household Finance und des Entscheidungsverhaltens privater Haushalte im Kontext finanzmarktnaher Anlageformen im Besonderen wird noch immer sehr wenig die Portfoliobildung der privaten Haushalte einerseits und das Investment in die neueren Formen der passiven, weltweit breit streuende Marktindices abbildende Fonds, sogenannte XTFs, im Kontext des finanziellen Entscheidungsverhaltens privater Investoren andererseits analysiert. Man gewinnt den Eindruck, dass in der Literatur immer noch eher das modellhafte, wenig realitätsnahe und kaum empiriegeleitete Paradigma des Rationalverhaltens eines Homo oeconomicus dominiert, auch wenn in den letzten Dekaden verstärkt eine empirische und insbesondere experimentelle Finanzmarktforschung an Bedeutung gewinnt. Die vorliegende Arbeit geht den nicht einfachen Weg, diesen Mangel zu beheben, indem nicht nur statistisch-ökonometrische, sondern insbesondere ökonomische Aspekte des Portfolio-Entscheidungsverhaltens mit dem Fokus auf XTFs analysiert und hierbei auch interdisziplinär Ansätze berücksichtigt und gewürdigt werden. Hervorzuheben ist die nicht nur theoretische, sondern ebenso die fundierte empirische Analyse unter Nutzung umfassender Datenbasen der Deutschen Bundesbank.

Herr Wanger leistet mit der vorgelegten Dissertation einen Beitrag zur Schließung der bestehenden Forschungslücke und widmet sich daher einem zweigeteilten Forschungsziel:

(I) "To investigate whether XTFs enhance risk and return of household portfolios when taking multiple relevant asset classes into account – not only stocks."

(II) "To examine whether employing XTFs in household portfolios is reasonable when including practical constraints and risk measures that reflect households' actual investment situation and interpretation of risk more closely."

Im Gegensatz zum Großteil der bisherigen Forschung wird dabei der Fokus der Analyse auf das Investment in XTFs im Kontext realer Portfolios privater Haushalte gelegt und gleichzeitig die Effizienz real bestehender Portfolios privater Investoren hinsichtlich deren Veränderungspotential unter Rendite-Risiko-Gesichtspunkten (risikoadjustierte Performance) untersucht; unter intensiver Nutzung der von der Deutschen Bundesbank im Rahmen des Panel on Household Finances (PHF) zur Verfügung gestellten Daten. Der Deutschen Bundesbank und der zugehörigen Forschungseinheit sei für die großzügige Unterstützung ausdrücklich gedankt.

Die Dissertation von Herrn Wanger unterscheidet sich dabei in den forschungsleitenden Fragestellungen in einigen für die wissenschaftliche, aber genauso auch für die praktische Arbeit wesentlichen Aspekten von verwandten Arbeiten. Herr Wanger formuliert mit der genannten Zielsetzung seiner Arbeit drei Kernfragen als besonders relevant, die bereits sehr ähnlich im zweigeteilten Forschungsziel genannt werden:

(1) „Do XTFs enhance risk and return of household portfolios when taking multiple relevant asset classes of household portfolios into account?"

(2) "Do downside-risk measures help to explain the reluctance of households to invest in XTFs?"

(3) "Does reinvesting payouts in XTFs enhance the risk-return position of household portfolios?"

Im Unterschied zu bisherigen Arbeiten in diesem Themenfeld legt Herr Wanger den gut begründeten Fokus auf die direkte Verknüpfung der Forschung zu realen Portfolios privater Haushalte einerseits und zu Performanceanalysen der empirischen Finanzmarktforschung andererseits.

Die vorliegende Arbeit ist damit grundsätzlich im Forschungsgebiet der theoretischen und empirischen finanzwirtschaftlichen Forschung angesiedelt.

Der Dissertation gelingt nach ausführlicher und sorgfältig eingebrachter Grundlegung ein sehr guter Beitrag im Bereich Household Finance sowie hierbei insbesondere in den Teilgebieten Portfoliobildung der privaten Haushalte und Investment in neuere Formen der passiven, weltweit breit streuende Marktindices abbildende Fonds, sogenannte XTFs. Damit ist ein wichtiger Beitrag zur betriebswirtschaftlich, insbesondere finanzwirtschaftlich ausgerichteten theoretischen und empirischen Forschung zu Finanzmärkten und zum Risikoverhalten zu konstatieren.

Bamberg im Oktober 2021 Univ.-Prof. Dr. Andreas Oehler

Vorwort

Die vorliegende Arbeit ist während meiner Zeit als wissenschaftlicher Mitarbeiter und Doktorand am Lehrstuhl für Betriebswirtschaftslehre, insbesondere Finanzwirtschaft, der Otto-Friedrich-Universität Bamberg entstanden und wurde im Wintersemester 2020/2021 an der Fakultät Sozial- und Wirtschaftswissenschaften als Dissertation angenommen. Die Entstehung der Arbeit wäre ohne die Unterstützung zahlreicher Personen nicht möglich gewesen. Ihnen möchte ich hiermit herzlich danken.

Für die umfassende Betreuung, wissenschaftliche Begleitung und Förderung meines Promotionsvorhabens möchte ich mich bei Herrn Professor Dr. Andreas Oehler, meinem Doktorvater, besonders bedanken. Herrn Professor Dr. Thomas Egner möchte ich für die Übernahme des Zweitgutachtens meinen Dank aussprechen. Herrn Professor Dr. Karl-Heinz Gerholz danke ich dafür, dass er als dritter Prüfer meiner Disputation zur Verfügung stand.

Bei Herrn Dr. Martin Eisele möchte ich mich für die Bereitstellung der SHS-Daten der Deutschen Bundesbank bedanken.

Mein Dank gilt zudem meinen ehemaligen Kollegen, insbesondere Herrn Professor Dr. Tim Alexander Herberger, Herrn Dr. Florian Wedlich, Herrn Dr. Matthias Horn, Herrn Jonas Tobias Schmitz und Herrn Julian Schneider. Durch zahlreiche Anregungen, die konstruktive Zusammenarbeit und ein angenehmes Arbeitsklima haben Sie ebenfalls zum Gelingen dieser Dissertation beigetragen.

Des Weiteren möchte ich mich bei Freunden und Bekannten, die ich während meiner Zeit in Bamberg kennen gelernt habe, für die stete Motivation und den Zuspruch während der Anfertigung dieser Arbeit bedanken.

Mein größter Dank gilt meinen Eltern, Irmgard und Robert Wanger, sowie meiner Schwester Eva Wanger. Sie haben mich auf meinem bisherigen Weg in unschätzbarer Weise unterstützt und ermutigt. Ihnen widme ich diese Arbeit.

München im Oktober 2021 Hans Philipp Wanger

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List of Abbreviations

av.	Average
BF	Bond
BF	Bond Fund
BPT	Behavioral Portfolio Theory
c.f.	Confer (compare)
CAPM	Capital Asset Pricing Model
CASH	Cash
DAX	Deutscher Aktien Index
e.g.	Exempli gratia (for example)
ed.	Edition
Ed.	Editor
Eds.	Editors
et al.	Et alii (and others)
etc.	Et cetera (and so forth)
ETF	Exchange Traded Fund
f.	And the following one
ff.	Following pages
HFCS	Household Finance and Consumption Survey
HPT	Household Portfolio Type
i.e.	Id est (that is to say)
ISIN	International Securities Identification Number
LPM	Lower Partial Moment
LPM0	Lower Partial Moment Zero (Probability of Loss)
LPM1	Lower Partial Moment One (Expected Value of Loss)
$\sqrt{\text{LPM2}}$	Semi-Standard Deviation
MDD	Maximum Drawdown
M-LPM0	Mean-Lower Partial Moment Zero
M-LPM1	Mean-Lower Partial Moment One

M-LPM2	Mean-Lower Partial Moment Two
M-MDD	Mean-Maximum Drawdown
MSCI	Morgan Stanley Capital International
MV	Mean-Variance
NIE	New Institutional Economics
p.	Page
PHF	Panel on Household Finances
pp.	Pages
RD	Return Difference
REF	Real Estate Fund
RQ	Research Question
SD	Standard Deviation
SF	Stock Fund
SHS	Securities Holdings Statistics
SL	Security Lending
ST	Stock
SV	Savings
VALUEpf	Portfolio Value
XETRA	Exchange Electronic Trading
XTF	Plain-vanilla Exchange Traded Fund (ETF) which pursues a passive investment approach and replicates a broad, internationally diversified market index

List of Symbols

μ	Mean Return
σ	Standard Deviation of Returns
r_{SL}	Interest Rate for Security Lending
r_{SV}	Interest Rate on Savings
n	Degree of Risk Aversion
τ	Target Return
Φ	Utility Curve

1 Introduction

1.1 Motivation and Research Questions

One of the main implications of neoclassical finance theory[1] is that all investors should select the same well-diversified portfolio of risky securities. This portfolio is called market portfolio and includes all available risky securities, weighted in proportion to their market capitalization.[2] Investing in this way allows investors to maximize portfolio diversification by maximizing expected returns for a certain level of risk, and minimizing risk for a certain level of expected return, respectively.[3] Neoclassical finance assumes perfect and complete financial markets.[4] Since real-world financial markets are far from being perfect and complete,[5] investors are unable to acquire the neoclassical market portfolio in practice.[6] Approximations of the market portfolio usually rely on broad-based international market indices,[7] which can be obtained by investing in XTFs. "XTFs are plain-vanilla Exchange Traded Funds (ETFs) which pursue a passive investment approach and replicate a broad, internationally diversified market index."[8]

Studies in the field of household finance often report that households hold concentrated portfolios which, on average, underperform diversified market indices.[9] To increase the diversification of household portfolios and, in this context, to enhance risk and return, studies

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[1] The terms "standard finance" or "traditional finance" are also used in the literature (see e.g. Campbell (2006); Baker/Nofsinger (2010); Bloomfield (2010)).

[2] See Sharpe (1964); Jensen (1972); Fama (1972); Fama/French (2004); Perold (2004); Elton et al. (2014), pp. 292f.; Guiso/Sodini (2013), pp. 1424ff. This normative implication is based on the Capital Asset Pricing Model (CAPM) which assumes that investors are fully rational and reveal homogeneous expectations regarding risk and expected returns. The CAPM was developed by Sharpe (1964), Lintner (1965), and Mossin (1966) and presumes that investors can obtain portfolios with optimal risk-return trade-offs by investing one part of their funds in the market portfolio and the other part in a risk-free investment (see Tobin (1958); Sharpe (1964); Jensen (1972); Fama (1972); Fama/French (2004); Perold (2004)).

[3] This principle traces back to the "expected returns–variance of returns rule" of Markowitz (1952), p. 77.

[4] See Miller/Modigliani (1961); Oehler (2000b); Oehler/Unser (2002), p. 3, pp. 49ff.; Schmidt/Terberger (2006), pp. 57ff.; Franke/Hax (2009), pp. 154f.; Elton et al. (2014), pp. 290f. In this regard, complete markets means that every available asset can be traded. See chapter 2.1 for an explanation of perfect and complete financial markets.

[5] See Oehler (1991); (2000a); (2000b); Barberis/Thaler (2003), pp. 1055f.; De Bondt et al. (2008). Imperfect and incomplete markets are a key assumption of behavioral finance and economics (see chapter 2.3).

[6] See e.g. Roll (1977) regarding the impossibility to capture the neoclassical market portfolio in practice.

[7] See e.g. Fabozzi/Gupta/Markowitz (2009a), p. 42.

[8] Oehler/Wanger (2020), p. 1. In this context, "passive investment approach" means that the fund management refrains from making active investment decisions in terms of buying or selling securities to outperform a defined benchmark and only invests in the securities of the underlying index at the corresponding weights (see Bitz/Stark (2015), p. 232ff.). Independent from the definition in this thesis, the term XTF is used in different contexts as well (e.g. by Deutsche Börse AG (2019b) for the trading segment of ETFs). This thesis refers to the definition by Oehler/Wanger (2020). Separating XTFs as subsample of ETFs seems necessary since the ETF universe has grown extensively over the past decade and meanwhile includes many ETFs that follow rather active strategies (see e.g. Bioy et al. (2017); Investment Company Institute (2018a); (2019); Morningstar (2019)) which are contrary to the neoclassical market portfolio. Individual investors show poor ETF selection and use ETFs for excessive trading which harms risk and return of their portfolio (see Clifford/Fulkerson/Jordan (2014); Bhattacharya et al. (2017)).

[9] See Blume/Friend (1975); Kelly (1995); Barber/Odean (2000); (2001); Polkovnichenko (2005); Goetzmann/Kumar (2008).

recommend households to invest in XTFs.[10] XTFs are basically available for stocks and bonds, thereby only covering a fraction of all asset classes included in the neoclassical market portfolio.[11] Investing in XTFs causes transaction costs which are not considered in perfect and complete financial markets. In addition to the infeasibility of the neoclassical market portfolio, these constraints further limit the applicability of neoclassical predictions in practice.

Most studies examining household portfolios focus on their stock holdings.[12] The performance of a portfolio, however, mainly depends on the applied asset classes and the corresponding relative portfolio weights.[13] Since household portfolios involve multiple asset classes – not only stocks –[14] existing studies might miss out an important part of households' portfolios and estimate possible performance enhancements too narrowly.

Rather than evaluating risk in terms of neoclassical finance according to the return variance, individuals tend to distinguish between gains and losses and are more likely to be averse to losses than to gains.[15] Corresponding measures of risk that closer reflect households' interpretation are not taken into account by related investigations so far. Hence, important empirical evidence regarding the influence of XTFs on risk and return of household portfolios remains unclear. This doctoral thesis addresses this gap by pursuing the following two research goals:

- To investigate whether XTFs enhance risk and return of household portfolios when taking multiple relevant asset classes into account – not only stocks.
- To examine whether employing XTFs in household portfolios is reasonable when including practical constraints and risk measures that reflect households' actual investment situation and interpretation of risk more closely.

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[10] See Malkiel (2003a), (2003b); Huang/Lin (2011); Jacobs/Müller/Weber (2014); Bhattacharya et al. (2017); Elton/Gruber/de Souza (2019).

[11] This is based on the absence of appropriate benchmark indices and corresponding financial products in other asset classes than stocks and bonds, e.g., due to the lack of a broad-based international real estate index (see Jacobs/Müller/Weber (2014)) or ETFs that do not include derivatives as opposed to most commodity ETFs.

[12] See e.g. Blume/Friend (1975); Kelly (1995); Barber/Odean (2000); (2001); Grinblatt/Keloharju (2000); (2001a); (2001b); Polkovnichenko (2005); Goetzmann/Kumar (2008).

[13] See Brinson/Hood/Beebower (1986); (1995); Brinson/Singer/Beebower (1991); Ibbotson/Kaplan (2000); Hood (2005). Brinson/Hood/Beebower (1986); (1995) refer to this as "investment policy" and state that its influence on portfolio risk and return is much larger than the impact of market timing (over- or underweighting asset classes relative to their long-term weights) and security selection (active selection within an asset class). See also Bacon (2008), pp. 117ff. regarding an overview on performance attribution.

[14] See Arrondel et al. (2016), Badarinza/Campbell/Ramadorai (2016), and Guiso/Haliassos/Jappelli (2002) for an overview of household portfolios across different countries.

[15] See Kahneman/Tversky (1979); Thaler (1980); Benartzi/Thaler (1995).

As an exception to most existing studies which only focus on households' stock holdings, Calvet/Campbell/Sodini (2007) and von Gaudecker (2015) analyze multiple asset classes of household portfolios. Both studies find that most household portfolios in their sample reveal a much better diversification when taking mutual funds and cash holdings into account. Calvet/Campbell/Sodini (2007) conclude that "[t]he concentration of the stock portfolio […] is meaningless without a complete picture of the remaining constituents of the portfolio."[16] The authors also find that households who invest more aggressively incur higher losses but are not necessarily less diversified than households who invest less aggressively. However, Calvet/Campbell/Sodini (2007) and von Gaudecker (2015) do not compare the household portfolios in their sample with XTFs. In addition, both studies do not involve implementations of XTFs in household portfolios, thereby ignoring fees and transaction costs which can diminish benefits of diversification when employing XTFs.[17] Consequently, it remains unclear whether employing XTFs enhances risk and return of household portfolios when taking multiple relevant asset classes into account. Therefore, the first empirical analysis in this thesis examines the following research question:

RQ 1: Do XTFs enhance risk and return of household portfolios when taking multiple relevant asset classes of household portfolios into account?

Studies that investigate risk and return of household portfolios primarily rely on the variance or likewise the standard deviation of returns as (neoclassical) measure of risk.[18] The standard deviation implies, among others, that returns are normally distributed.[19] Normally distributed security returns, however, are hardly a tenable assumption.[20] Applying the standard deviation while returns are non-normally distributed, i.e. skewed, can lead to misinterpretations regarding the evaluation of risk. Prospect Theory by Kahneman/Tversky (1979) suggests that individuals do not evaluate deviations above and below the mean return equally as implied by the standard deviation but tend to differ between gains and losses relative to a certain reference point, e.g. a

[16] Calvet/Campbell/Sodini (2007), p. 724.
[17] See Rowland (1999); Jennings/Payne (2016).
[18] See e.g. Blume/Friend (1975); Kelly (1995); Grinblatt/Keloharju (2000); (2001a); (2001b); Polkovnichenko (2005); Goetzmann/Kumar (2008); Calvet/Campbell/Sodini (2007); (2009); Calvet/Sodini (2014); von Gaudecker (2015).
[19] See Markowitz (1959), p. 17ff.; Sortino/Satchell (2001), p. 3ff.; Bacon (2008), p. 82ff.
[20] See Mandelbrot (1963); French/Schwert/Stambaugh (1987).

target return. Thereby, individuals exhibit a higher sensitivity towards losses than towards gains – a phenomenon referred to as loss-aversion.[21]

Correspondingly, Unser (2000), Veld/Veld-Merkoulova (2008), and Holzmeister et al. (2019) find that households perceive risk rather in terms of downside-risk as reflected by different forms of Lower-Partial-Moments (LPMs). LPMs include, analogously to the reference point in Prospect Theory, an investor-specific target return from which risk is measured in terms of below-target-returns. The standard deviation can be interpreted as a special case of the general form of LPMs.[22] However, risk evaluations according to the standard deviation and LPM-based downside-risk measures differ from each other if returns are non-normally distributed and if the target return incorporated in the LPMs is different from the mean return as applied by the standard deviation.[23]

If risk evaluations according to downside-risk measures vary from risk evaluations according to the standard deviation, the evaluation of enhancements in risk and return might also differ. If enhancements in the risk-return trade-off that are based on LPMs are lower than those based on the standard deviation, XTFs might appear less attractive to households. This, in turn, may help to explain the reluctance of households to invest in XTFs.[24] Empirical analyses that compare possible enhancements from employing XTFs while taking the standard deviation as well as downside-risk measures into account are missing in pre-existing literature. Incorporating risk measures that reflect households' interpretation of risk more accurately when investigating possible enhancements from XTFs aims at the second research goal of this thesis. The second empirical analysis pursues the research question:

RQ 2: Do downside-risk measures help to explain the reluctance of households to invest in XTFs?

If a household decides to employ XTFs, the subsequent question of how to obtain a XTF portfolio arises. Existing studies mostly seem to assume that households establish a new XTF

[21] See Thaler (1980); Benartzi/Thaler (1995); Oehler (1992); (1994); (2000b); (2001b); (2011).
[22] See Harlow/Rao (1989); Harlow (1991).
[23] See Harlow/Rao (1989); Harlow (1991); Marmer/Ng (1993); Grootveld/Hallerbach (1999); Jarrow/Zhao (2006).
[24] According to Investment Company Institute (2018b), only six percent of American households own ETFs. In Germany, corresponding values range between five and 15 percent (see forsa (2016); Bhattacharya et al. (2017); Postbank AG (2018); Mai/Kaya (2019)).

portfolio from scratch.[25] Many households already hold a portfolio of financial assets.[26] In the extreme case, these households could switch their current portfolio to a XTF portfolio by selling their entire risky assets all at once and immediately reinvesting the available amount of money into XTFs. However, not every household might be willing and/or able to sell the entire risky assets all at once, for instance, if households feel overly attached to a certain security,[27] or if currently owned securities exhibit book-losses and households reveal the disposition to keep on holding these assets.[28] This asks for an alternative to switch existing household portfolios towards XTFs.

A feasible alternative is to take the payouts of an existing portfolio and reinvest them into XTFs. Thereby, the reinvested amounts are used to rebalance household portfolios (by purchasing XTFs). In this context, rebalancing means that the relative asset class weights of a portfolio are kept relatively stable over time.[29] In contrast to a one-time portfolio replacement, payouts can emerge in different amounts and irregularly which stretches the switch towards XTFs. Since transaction costs might offset possible increases in value of a reinvestment, they are a crucial factor when rebalancing portfolios with XTFs.[30] This challenges the recommendation to employ XTFs in practice and raises the question if, and if so, how far reinvesting payouts in XTFs enhances the risk-return position of household portfolios compared to reinvesting payouts according to households' current portfolio composition. This question addresses the second research goal of this thesis and has not been analyzed yet. The third empirical analysis therefore investigates:

RQ 3: Does reinvesting payouts in XTFs enhance the risk-return position of household portfolios?

[25] See e.g. Malkiel (2003b); Jacobs/Müller/Weber (2014); Bhattacharya et al. (2017); Elton/Gruber/de Souza (2019).
[26] See e.g. Arrondel et al. (2016), Badarinza/Campbell/Ramadorai (2016), and Guiso/Haliassos/Jappelli (2002).
[27] This phenomenon is also referred to as "endowment effect". Regarding the endowment effect, see Thaler (1980); Kahneman/Knetsch/Thaler (1990); Oehler (1992); (1995), pp. 32ff.; (2000b); (2002), pp. 857ff.; (2011).
[28] This behavior is based on the disposition effect (i.e. the tendency to sell assets with book profits and to keep assets with book losses) and can be associated with loss-aversion. Regarding the disposition effect, see Shefrin/Statman (1985); Kahneman/Knetsch/Thaler (1990); Oehler (1991); (1992); (1994); (1995), p. 32; (1999), pp. 72ff.; (2000b); (2002); (2011); Heilmann/Läger/Oehler (2001b); Oehler et al. (2003).
[29] See Donohue/Yip (2003).
[30] See Almadi/Rapach/Suri (2014); Dayanandan/Lam (2015); Horn/Oehler (2020).

For the three empirical analyses, two main data sets are applied: The Panel on Household Finances (PHF-) survey and the Securities Holdings Statistics (SHS-) base. Both data sets are provided by the German central bank (Deutsche Bundesbank) and are representative for the population of German households. The PHF-survey of 2014 reveals cross-sectional data on the distribution of wealth of 4,461 German households across multiple asset classes. The employed data of the SHS-base capture all stocks, debt securities, and mutual fund holdings of German households by their International Securities Identification Number (ISIN) on a monthly basis.[31] Portfolios of German households are approximated by assigning securities of the SHS-base to corresponding asset classes of stylized household portfolios which are drawn from the PHF-survey. Securities from the SHS-base are selected according to their aggregated market value of shares owned by German households, which is used as proxy for the distribution of a security among German households. In this way, risk and return of German households are estimated from January 2014 to December 2016. Different household portfolio compositions, like varying portfolio sizes (i.e. the number of securities per portfolio), are applied.

The main contribution of this thesis is to provide a more comprehensive picture of the effect of employing XTFs on risk and return of household portfolios by taking multiple relevant asset classes of households into account – not only stocks. As a further advantage, the conditions under which households employ XTFs are reflected more closely in comparison to previous studies. Furthermore, the empirical analyses are based on comprehensive data sets which are each representative for the German household sector.

The analyses contribute to the economic field of household finance. Household finance "asks how households use financial instruments to attain their objectives"[32] and distinguishes between normative and positive household finance. Normative household finance describes how households should make financial decisions; positive household finance describes how households actually make financial decisions. Essential in household finance are deviations that occur between households' ideal and observed behavior.[33] Prescriptions of normative models can serve as benchmark which households' actual behavior is tested against.[34] This thesis relies on the approach of positive household finance and provides implications for policymakers, regulators, financial advisors, and households alike.

[31] See Bade et al. (2017).
[32] Campbell (2006), p. 1553.
[33] See Campbell (2006); Guiso/Sodini (2013).
[34] See Guiso/Sodini (2013).

1.2 Research Outline

Chapter 2 to 4 lay the foundations for the subsequent empirical analyses conducted in chapter 5 to 7. Chapter 2 presents theoretical foundations. The descriptions begin with neoclassical finance theory and its restrictive assumptions. Along with the description of the following theories, i.e. the new institutional economics, market microstructure theory, financial intermediation as well as behavioral finance and economics, these previous assumptions are more and more relaxed to closer reflect households' actual portfolio choice.

The descriptions of theoretical foundations and the remaining chapters in this thesis are based on household portfolios. Besides individual investors, households represent another type of private investors.[35] Research in household finance frequently relies on the assumption that one individual out of all household members takes the main responsibility for financial decisions.[36] This thesis follows this approach. Descriptions in the remainder on the determinants of households' portfolio choice correspond to the finance responsible household member.

Chapter 3 surveys empirical characteristics of actual household portfolios and sets the implications of the theoretical frameworks presented in chapter 2 in an empirical context. While the distribution of households' wealth points out the role of financial assets compared to other asset classes in household portfolios, the second subchapter reviews asset diversification among households' financial assets. The last subchapter reveals insights on how far XTFs are already a component of household portfolios and carves out if, according to pre-existing financial research, XTFs represent a reasonable component of household portfolios.

Chapter 4 discusses portfolio selection in different risk-return-frameworks that are used in the empirical analyses and points out stages in a household's life cycle which might be particularly suitable to employ XTFs. The next subchapter explains the applied performance measure under consideration that multiple asset classes of household portfolios are included in the analysis. The last subchapter explains the two employed data sets and the way they are combined in order to estimate risk and return of household portfolios.

Chapters 5 to 7 describe the empirical analyses which address RQ1, RQ2, and RQ3. The construction of household portfolios in all three analyses relies on implications of chapter 3 regarding empirical household portfolio choice. Chapter 5 initially assumes the standard

[35] See Oehler (1995), pp. 6 for a categorization of ideal types of private investors and a differentiation of private investors from institutional investors.

[36] E.g., Kaustia/Conlin/Luotonen (2019) call this person the "finance responsible" person. European Central Bank (2016b) and Horn (2018), p. 7, refer to this person as "financial knowledgeable person".

deviation as measure of risk and examines whether XTFs can enhance risk and return of household portfolios (RQ1). Thereby, risk-return enhancements are ascertained using the performance measures established in chapter 4. Chapter 6 additionally includes the downside-risk measures described in chapter 4 and examines if the latter provide an explanation why households refuse to invest in XTFs (RQ2). Chapter 7 (RQ3) investigates whether reinvesting payouts in XTFs enhances the risk-return position of household portfolios compared to reinvesting payouts according to households' current portfolio composition and includes the risk measures employed in chapter 5 and 6.

Chapter 8 discusses the empirical analyses' results in the context of existing studies in the field of household finance, it outlines possible limitations to the results' generalizability, and concludes the thesis with implications for different stakeholders.

2 Theoretical Foundations

2.1 Neoclassical Finance

Neoclassical finance theory is centered around the efficient allocation of limited financial resources on financial markets.[37] In general, markets are places where market participants can trade goods. Financial markets,[38] in particular, are economic marketplaces where market participants can enter financial contracts[39] or trade securities.[40] Market prices coordinate the allocation of financial resources between market participants.[41]

A basic assumption of the neoclassical paradigm is that financial markets are perfect and complete. Perfect financial markets show the following characteristics:[42] The market price at which a financial contract or a security is traded is identical for all market participants (regardless of whether a market participant is on the buy- or sell-side). When making financial decisions (i.e. decisions whether to enter a financial contract or to trade a security)[43], market participants face no market barriers and are unable to influence market prices which qualifies them as price takers on financial markets. There are no transaction costs, no taxes, no costs for gathering and processing information, and market participants are perfectly informed. Market participants are rational decision makers who strictly maximize their expected utility and, thus, act as "clones" of the homo oeconomicus[44]. In complete financial markets, every amount and

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[37] See Fama (1970); Cezanne/Mayer (1998); Schmidt/Terberger (2006), p. 388.

[38] Financial markets can be divided into primary and secondary financial markets. On primary financial markets, financial contracts are issued or entered for the first time, while on secondary financial markets, financial contracts that are already issued or already exist are traded (see Oehler (2000d); (2004a); (2005b); Bitz/Stark (2015), p. 126; Hartmann-Wendels/Pfingsten/Weber (2019), p. 6). An example for a primary financial market is the Initial Public Offerings- (IPO)-market (see Herberger/Oehler (2011); Oehler et al. (2017); (2018) for an overview of the German IPO-market). The terms "financial markets" and "capital markets" are almost exclusively used interchangeably in the literature (see Wendt (2011), p. 12) which is why both terms are used as synonyms in this thesis. To avoid misunderstandings, the focus lies on financial markets, though.

[39] Financial contracts are defined as an agreement to exchange (claims for) present or future cash flows. Two fundamental types of financial contracts are (securitizations of) equity participations (e.g. stocks) and debt claims (e.g. loans). The two fundamental types of financial contracts represent first-order financial contracts. Financial contracts that use first-order financial contracts as object (underlying) are referred to as second- (or higher) order financial contracts or derivatives, respectively (see Oehler/Unser (2002), p. 17; Oehler (2004a); Hartmann-Wendels/Pfingsten/Weber (2019), p. 2). Not all financial contracts are automatically securities (e.g., in credit risk management different specifications are used) which securitize the legal position of a supplier of financial resources (see Oehler/Unser (2002), p. 17ff.). However, since households' security holdings (e.g. stocks, bonds etc.) play a key role in the subsequent analyses, this thesis focuses on financial contracts in terms of securities in the following.

[40] See Bitz/Stark (2015), pp. 1f.; Wendt (2011), pp. 11ff.; Hartmann-Wendels/Pfingsten/Weber (2019), pp. 2ff.

[41] See Fama (1970); Cezanne/Mayer (1998); Schmidt/Terberger (2006), p. 388; Hartmann-Wendels/Pfingsten/Weber (2019), pp. 17f.

[42] See Miller/Modigliani (1961); Oehler (2000b); (2005a); (2006a), pp. 298f.; (2006c), pp. 76f.; Oehler/Unser (2002), p. 3, pp. 49ff.; Schmidt/Terberger (2006), pp. 57ff.; Franke/Hax (2009), pp. 154f.; Elton et al. (2014), pp. 290f.

[43] See Bitz/Stark (2015), pp. 1f.

[44] See Oehler (2000b); (2002); (2004a); Thaler (2000); Kirchgässner (2008) on the concept of the "homo oeconomicus", or likewise the "homo economicus" or "rational man".

fraction of a cash flow can be traded regardless of its maturity and uncertainty associated with a cash flow.[45]

The major approach that describes rational decision-making behavior in neoclassical finance is the expected utility framework which is based on von Neumann/Morgenstern (1944).[46] The expected utility framework provides normative prescriptions of human decision-making behavior and relies on a system of axioms[47] that reflects preferences for a rational decision maker. The combination of the axioms allows establishing a utility function. Hence, if decision makers comply with the underlying axioms when deciding between different investment alternatives, they make rational decisions by choosing the alternative that maximizes their expected utility.[48]

The general situation under which rational decisions are made in normative neoclassical finance are decisions under risk.[49] Decisions under risk describe situations in which a decision maker knows the outcome of every possible alternative, i.e. all possible states of the nature, and the corresponding (subjective) probabilities of their occurrence.[50] In this context, financial risk can be specified as the threat which emerges from uncertainty about future states of the nature and it contains that a financial variable negatively deviates from its corresponding target value.[51]

[45] Oehler/Unser (2002), p. 3; Schmidt/Terberger (2006), pp. 57ff.

[46] See Oehler (1995), pp. 17f.; Rengifo/Trendafilov/Trifan (2014), p. 422. See Schoemaker (1982) for an overview regarding the literature on the expected utility framework.

[47] Further systems of axioms have been proposed in the literature which, however, are similar to the system in von Neumann/Morgenstern (1944) (see Schneeweiß (1963); Bamberg/Coenenberg/Krapp (2019), p. 88).

[48] See Oehler (1995), pp. 13ff.; Eisenführ/Weber/Langer (2010), pp. 248ff.; Ackert (2014), pp. 26f.

[49] See Markowitz (1959), p. 4; Rengifo/Trendafilov/Trifan (2014), p. 422, Ackert (2014), pp. 26f. Neoclassical finance assumes objective rationality. This means that there is no difference between the decision situation as perceived by the decision maker and reality, or all information about reality, respectively. However, objective reality is hardly realizable and, likewise, objective rationality or irrationality (see Eisenführ/Weber/Langer (2010), pp. 4f.; Bamberg/Coenenberg/Krapp (2019), p. 4). In the remainder, this thesis follows Eisenführ/Weber/Langer (2010), p. 4, who consider "rational" in terms of "more rational" and "irrational" in terms of "less rational".

[50] See Oehler/Unser (2002), pp. 10ff.; Laux/Gillenkirch/Schenk-Mathes (2018), pp. 32ff.; Bamberg/Coenenberg/Krapp (2019), p. 19. Situations under which decisions are made can generally be divided into situations under certainty and uncertainty. However, decisions in which the outcome of each alternative is known with certainty to the decision maker are hardly applicable in actual financial decisions. Uncertainty, in turn, provides a much better characterization of financial decisions (see Oehler/Unser (2002), pp. 10ff.; Laux/Gillenkirch/Schenk-Mathes (2018), pp. 32ff.). Consider, for example, possible uncertainty associated with the characteristic feature of financial contracts that the moment of payment and the moment of repayment diverge (see Bitz/Stark (2015), p. 2). Uncertain financial decisions can further be subdivided into decisions under risk and ambiguity. As opposed to decisions under risk, under ambiguity a decision maker is considerably limited in identifying all possible outcomes and in deriving corresponding probabilities. Probabilities can, rather than objective probabilities, be interpreted as subjective probabilities as they reflect the degree of individual belief for the occurrence of a possible outcome (see Oehler/Unser (2002), pp. 10ff.; Oehler et al. (2015), p. 33; Laux/Gillenkirch/Schenk-Mathes (2018), pp. 32ff., pp. 51ff.).

[51] See Bitz (1993), p. 642; Oehler/Unser (2002), p. 21; Oehler et al. (2015), p. 36.

Neoclassical finance models assume two objectives which are common to all (rational) financial decision makers. First, decision makers prefer higher over lower returns.[52] Second, in the context of uncertain situations in which financial decisions are assumed to be made, decision makers prefer stable returns and interpret deviations in terms of return variability as an undesirable thing – i.e. risk.[53] Decision makers are assumed to consider both objectives jointly and to be risk averse. In this context, risk averse means that in a decision between two securities of which the first is expected to bear less risk than the second while all other security features like expected returns[54] are equal, decision makers choose the first security.[55] In addition, decision makers accept higher risk only in exchange for higher (expected) returns as compensation. This indicates that risk and return are in conflict or trade-off to each other and implies that decision makers should, when making financial decisions, take both into account.[56]

To be able to evaluate whether an investment in a certain security represents a sound financial decision, Markowitz (1952) suggests measuring risk by the variance.[57] Following this, decision makers select securities according to the two parameters expected return and variance of returns which constitutes the framework referred to as mean-variance- (MV-) framework.[58] A key implication of Markowitz (1952) is that while the return for a portfolio of securities is the average of the return for each security (weighted by their contribution to the portfolio), risk is not the simple average.[59] This observation represents the foundation of the concept of diversification and suggests that decision makers should invest in a portfolio of securities rather than one single security. The goal of investors thereby is to obtain optimal portfolios, i.e. portfolios that maximize the return at their preferred level of risk (and vice versa).[60]

Subsequent questions that are essential in neoclassical finance models are: What are the consequences for the market prices of securities if all market participants follow the rule of

[52] See Markowitz (1952); (1959), p. 6. Likewise, Miller/Modigliani (1961), p. 412 describe that decision makers "prefer more wealth to less".
[53] See Markowitz (1952); (1959), p. 6.
[54] Since future returns of a possible investment alternative are not known with certainty, returns are, more precisely, "expected" returns (see Markowitz (1952); (1959), pp. 37ff.).
[55] See Ackert (2014), pp. 26ff.; Laux/Gillenkirch/Schenk-Mathes (2018), pp. 105ff.; Rengifo/Trendafilov/Trifan (2014), p. 422.
[56] See Markowitz (1952); (1959), p. 6; Elton et al. (2014), pp. 44ff.; Ackert (2014), pp. 26ff.
[57] Or likewise, the standard deviation of returns (see Markowitz (1952); (1959), p. 17ff.).
[58] Markowitz calls this the "expected returns–variance of returns rule" (see Markowitz (1952), p. 77) which provides the basis of Modern Portfolio Theory (see e.g. Ackert (2014), pp. 27ff.).
[59] See Ackert (2014), p. 28.
[60] See Markowitz (1952); (1959), p. 5, pp. 102ff.; Ackert (2014), pp. 27f.; Elton et al. (2014), pp. 42ff. If and how far diversification can enhance risk and return of a decision maker's portfolio largely depends on the correlation between the returns of the underlying securities. See chapter 4.1.1 for a more detailed description of the MV-framework.

Markowitz (1952)? How far can diversification reduce the risk of a portfolio in equilibrium financial markets and what returns – and thus security prices – can then be expected in dependence of risk? The basic model in neoclassical finance is the Capital Asset Pricing Model (CAPM) which was simultaneously developed by Sharpe (1964), Lintner (1965), and Mossin (1966).[61] The CAPM is based on the portfolio selection framework proposed by Markowitz (1952). Accordingly, market participants choose a portfolio from a collection or frontier of optimal portfolios that matches their preferred risk.[62] Tobin (1958) was able to simplify the process of portfolio selection. His approach assumes that market participants are able to borrow and lend unlimited amounts at the risk-free rate and, as market participants are perfectly informed, form the same (homogeneous) believes about risk and expected returns. Under these conditions, all market participants invest in the same optimal portfolio of risky securities (regardless of their risk preference). In addition, market participants divide their funds into an investment in the portfolio of risky securities and borrowing or lending, respectively, to adjust for individual risk preferences.[63] When selecting the optimal portfolio of risky securities, market participants employ a diversification strategy which enables eliminating some amount of risk (i.e. unsystematic risk), while the remaining amount of risk (i.e. systematic risk) cannot be diversified away. Thus, market participants are only compensated for taking systematic risk, but not unsystematic risk.[64]

In equilibrium state of the CAPM, the price (and consequently the expected return) of each risky security "must be such that investors collectively decide to hold exactly the supply of shares"[65]. As all market participants are assumed to hold the same optimal portfolio of risky securities, in equilibrium state, the optimal portfolio of risky securities is the so-called market portfolio, a portfolio that comprises all available risky securities weighted in proportion to their market capitalization.[66] As a result, the CAPM describes a linear function between risk and expected return. Market participants can obtain optimal portfolios along the straight line from the risk-free rate through the market portfolio which is identical for all market participants.[67] In

[61] See Elton et al. (2014), pp. 290ff.; Ackert (2014), pp. 29f.; Jensen (1972); Fama/French (2004); Perold (2004) for the rest of the paragraph.
[62] See Schmidt/Terberger (2006), pp. 345ff.
[63] See also Ackert (2014), p. 28; Steiner/Bruns/Stöckl (2017), p. 22. This concept is referred to as "separation-theorem" or "fund separation" in the literature (see Jensen (1972); Perold (2004); Fama/French (2004); Elton et al. (2014), p. 84).
[64] See Sharpe (1964); Schmidt/Terberger (2006), pp. 350f.; Elton et al. (2014), pp. 294ff.; Ackert (2014), p. 28.
[65] Perold (2004), p. 13.
[66] See Sharpe (1964); Jensen (1972); Fama (1972); Fama/French (2004); Perold (2004); Elton et al. (2014), pp. 292f.; Guiso/Sodini (2013), pp. 1424ff.
[67] See Sharpe (1964); Perold (2004); Elton et al. (2014), pp. 297ff. This straight line is referred to as the "capital market line" (see Sharpe (1964)).

equilibrium state, every security is correctly priced and security prices fully reflect all available information. Under these conditions, the price represents the only necessary signal for coordinating financial markets and for the optimal allocation of financial resources. In this state, financial markets are efficient.[68]

If market participants only consider security prices as relevant source of information, financial markets offer ideal investment conditions for them to efficiently allocate their funds.[69] Financial markets do not require every market participant to decide fully rational. As long as a sufficient number of market participants decides as if they were fully rational ("as-if" approach),[70] market inefficiencies are immediately exploited by the latter through arbitrage strategies, and market equilibrium state is immediately re-established.[71] As a consequence, there is no reason for market participants to deviate from the market portfolio in equilibrium. All information is reflected in security prices, systematically outperforming the market portfolio is not possible.[72]

In this regard, Fama (1970) argues that transactions costs, information that is not freely available to all investors, and disagreement among investors about the implications of available information are "not necessarily sources of market inefficiency, they are potential sources."[73] He hypothesizes that security prices fully reflect all available information (so-called Efficient Market Hypothesis). Empirical studies which test the hypothesis examine in how far security prices adjust to different subsets of available information. Fama (1970); (1991) divides these tests into three categories depending on the kind of available information:[74] Tests for return

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[68] See Fama (1970); (1991). In equilibrium, the price of a security can be subdivided into the price of time (i.e. the risk-free rate) and the price of risk (i.e. additional expected return per unit of risk taken) (see Sharpe (1964); Elton et al. (2014), pp. 293f.; Oehler/Höfer/Wendt (2013)). In neoclassical finance, the assumption that every amount of a financial contract or security is tradable at the market price implies that firms can raise any amount of funds and, consequently, finance any investment project. However, "the type of instrument used to finance an investment is irrelevant to the question of whether or not the investment is worth while" (Modigliani/Miller (1958), p. 292) as the choice of the capital structure does not affect the capital gains resulting from the investment project. Every choice between debt or equity instruments, i.e. the capital structure, is equivalent from the cost of capital point of view. In neoclassical finance, thus, no optimal capital structure exists (see Modigliani/Miller (1958); Miller/Modigliani (1961); see also Schmidt/Terberger (2006), pp. 62ff.; Franke/Hax (2009), pp. 340ff.).

[69] See Heilmann/Läger/Oehler (2000); Oehler/Heilmann/Läger (2000).

[70] See Oehler (1998a), p. 72; Oehler (2006b); (2011); (2012f); (2013d); (2013a); .

[71] See Fama (1970); Oehler (1991); (1992); (1995), p. 24; (2000b). Arbitrage strategies are characterized as a sequence of decisions that increase the wealth of a decision maker but do not require the decision maker to take any risk (see Oehler (2000b); Schmidt/Terberger (2006), p. 95). The assumption of a perfect and complete financial market further implies that financial contracts and securities are traded between market participants directly which makes financial intermediaries irrelevant in neoclassical finance (see Oehler (2005b), p. 217; Bitz/Stark (2015), p. 1; Hartmann-Wendels/Pfingsten/Weber (2019), pp. 17ff.). This changes, however, when relaxing the restrictive assumptions of neoclassical finance, which will be discussed in chapter 2.2.

[72] See Oehler (2000b); Elton et al. (2014), pp. 292ff.; Perridon/Rathgeber/Steiner (2017), pp. 291ff.

[73] Fama (1970), p. 388.

[74] See also Fama (1965); (2014); Oehler (1994); Wendt (2011), pp. 15ff. Fama changed the original titles of the three categories (weak, semi-strong, and strong form tests; see Fama (1970)) in his later publication (see Fama (1991)) into the terminology which is outlined in the text.

predictability, event studies, and tests for private information. Tests for return predictability investigate the forecast power of past security prices and other price-related factors.[75] Testing event studies investigates how quickly security prices adjust to the announcement of public information.[76] Tests regarding private information examine whether monopolistic access to information of certain investors is fully reflected in security prices.[77] Tests which cannot identify excess returns, i.e. higher expected returns compared to expected returns at the same risk in market equilibrium, would be in support of the hypothesis.[78]

Findings on market efficiency can be summarized as follows:[79] Empirical tests on return predictability (mostly on stock returns) find that future expected returns are in part predictable from past returns, dividend yields, and term-structure variables (etc.). For stocks, this can partly be related to autocorrelations[80] occurring over time. Event studies are, according to Fama (1991), p. 1602, the "cleanest evidence" for market efficiency. Security price reactions after stock splits, annual reports, or the issuance of new securities are mainly supportive for market efficiency. Tests on private information suggest that, among others, private information of corporate insiders or professional portfolio managers of mutual funds is not fully reflected in security prices.[81]

However, any test of market efficiency faces the problem that market efficiency is tested jointly with an underlying asset-pricing model (joint-hypothesis problem). A major drawback of market efficiency tests is that certain return patterns cannot be accurately attributed to either market inefficiency or an (potentially inadequately calibrated) asset-pricing model, which

[75] See for example studies on momentum and reversal strategies Jegadeesh/Titman (1993); Herberger/Kohlert/Oehler (2011); Herberger/Horn/Oehler (2020); Asness/Moskowitz/Pedersen (2013).
[76] Regarding the influence of political elections on security prices, see e.g. Oehler/Walker/Wendt (2013); Oehler/Horn/Wendt (2017a). For the impact of hedge fund announcements on stock prices see Oehler/Schmitz (2019); Schmitz (2019); Schmitz/Oehler (2020).
[77] On insider trading see for instance Oehler et al. (2016); Oehler/Heilmann/Läger (2000); Heilmann/Läger/Oehler (2001a).
[78] See Fama (1970).
[79] See Fama (1970); (1991); (2014); Ang/Goetzmann/Schaefer (2010); Elton et al. (2014), pp. 417ff.; Ţiţan (2015).
[80] On autocorrelations in stock returns see also Oehler (1994); (1995), pp. 279ff.; (2000a); (2000b); (2002), pp. 851ff.
[81] See e.g. Jaffe (1974); Seyhun (1986). Despite the tests in favor of market efficiency, return patterns that indicate limited market efficiency and cannot be explained by the predictions of neoclassical finance, so-called anomalies, frequently appear in financial markets over time (for an overview see Oehler (1992); (1995); (2013d) and chapter 2.3). However, market participants can hardly take advantage of anomalous over- or under-reactions of security returns as anomalies emerge randomly or in similar frequencies and are hard to identify from an ex-ante point of view (see e.g. Fama (1998); Malkiel (2003a)). This seems to be an even more serious problem from the perspective of private households since they typically gather and process less of the available information compared to professional market participants (see Oehler (1995), p. 5; Oehler/Kohlert (2009); Barber/Odean (2013); Oehler (2012e), p. 4; (2012f); (2012a); (2014a)).

means that testing market efficiency per se is not possible.[82] Moreover, unlike the assumptions of neoclassical finance theory, real-world market participants are subject to transaction and information costs. In this regard, Fama (1991), p. 1575, admits that "the extreme version of the market efficiency hypothesis is surely false."

As another issue, the neoclassical market portfolio is infeasible in practice. Constructing this portfolio would ideally require including all available assets (besides tradable financial securities, this also involves real assets like real estate, land, precious metals, etc.) as well as corresponding price and return data which are, however, largely unavailable.[83] As approximation of the neoclassical market portfolio, financial studies usually rely on broad, market capitalization-based market indices of tradable securities.[84] In the context of this thesis, this raises the question whether market indices achieve excess returns compared to household portfolios. Regarding this issue, there is broad acceptance among financial researchers that household portfolios are on average unable to outperform corresponding market indices.[85] This implies that if households stopped trading in order to outperform the market but rather bought and held a diversified portfolio at prices given by the market, they could obtain investment outcomes comparable to the market (portfolio).[86]

The descriptions in this chapter indicate that neoclassical finance models, on the one hand, provide a closed theoretical framework which allows deriving equilibrium states of financial markets. On the other hand, the incorporated assumptions regarding the absence of transaction costs, freely available information for all investors, or the possibility to borrow unlimited amounts at the risk-free rate seem incompatible with the conditions of real-world market participants which, in turn, limits their applicability in practice. Nevertheless, neoclassical models can serve as a benchmark to deduct deviations of actual financial decisions thereof.[87]

[82] See Fama (1991); (1998); (2014); Ackert (2014), pp. 30f.; Elton et al. (2014), p. 431. On the flip side, the joint-hypothesis problem led to a large number of proposed extensions to the original CAPM. These models aim to improve the explanation of security returns in relation to its risk by adding further risk factors to the market return in terms of Sharpe (1964) which is included in the CAPM. The CAPM is also called the one-factor capital asset pricing model. Among the most acknowledged extensions are the three-factor (see Fama/French (1992); (1993)), the four-factor (see Carhart (1997)), and the five-factor model (see Fama/French (2015)). However, while the additional explanatory power of the majority of the (many) proposed models appears to be relatively small, partly redundant, or unstable over time, the most important factor remains the expected return of the market portfolio (see Harvey/Liu (2019); Hwang/Rubesam (2019)).

[83] See Roll (1977). This also implies that the CAPM in a theoretical, neoclassical sense is not testable in practice.

[84] See Sharpe (1966); Goetzmann/Kumar (2008); Fabozzi/Gupta/Markowitz (2009a), p. 42.

[85] See e.g. Blume/Friend (1975); Kelly (1995); Barber/Odean (2000, 2001); Grinblatt/Keloharju (2000); (2009); Polkovnichenko (2005); Goetzmann/Kumar (2008); French (2008); Barber et al. (2009); von Gaudecker (2015). Thereby, studies mostly focus on households' stock holdings.

[86] See Malkiel (2003a); (2003b).

[87] See Oehler (2000b); (2005a), p. 29; Wendt (2011), pp. 20f.; Thaler (2016).

The research areas of new institutional economics, market microstructure, financial intermediation as well as behavioral finance and economics build upon neoclassical finance. They extend and modify its assumptions to closer approximate actual financial markets and market participants' decision-making behavior.[88]

2.2 New Institutional Economics, Market Microstructure, and Financial Intermediation

The field of New Institutional Economics (NIE) relaxes the neoclassical presumption that transactions are performed immediately and directly between perfectly informed market participants. Instead, NIE assumes limited mental capacities and asymmetrically distributed information to closer reflect the behavior of real-world market participants. Thus, as opposed to neoclassical finance, the features and the correct fulfilment of a transaction are to some extent uncertain to market participants.[89] To reduce the uncertainty and likewise the information asymmetries associated with decision alternatives and its outcomes, market participants establish institutions. Institutions are written and unwritten rules, laws, norms of behavior and beliefs, or contractual agreements that provide a framework to organize, among others, financial institutions or financial contracts.[90] NIE further assumes that establishing and utilizing such institutions induces – in contrast to neoclassical finance – transaction costs. Besides transaction costs for exchanging (financial) products on exchanges, these costs also include, e.g., the effort for gathering and processing information or for negotiating, monitoring, and enforcing the fulfillment of a (financial) contract.[91] Institutions allow incorporating arrangements that incentivize market participants in different intensities towards certain goals and aim to increase the efficiency of transactions on (financial) markets. The focus of NIE lies on microeconomic analyses of such institutions and its associated arrangements. Rather than a closed model or framework, NIE is assembled of various, partly overlapping approaches. Four major

[88] See Oehler (2005b), p. 218; (2006c), p. 77; Oehler/Reisch (2008); Richter/Furubotn (2010), pp. 2f.
[89] See Richter (1990); Oehler (2000b); (2002), pp. 845ff.; (2013d); Opper (2001); Menard/Shirley (2005), p. 1f.; Schmidt/Terberger (2006), pp. 386ff.; Oehler/Wendt (2017).
[90] See Opper (2001); Menard/Shirley (2005), p. 1f.; Schmidt/Terberger (2006), pp. 394f.; Richter/Furubotn (2010), pp. 7f.; Picot et al. (2015), p. 57. In the context of finance, institutions include, e.g., information asymmetries and risks associated with credit contracts (see Oehler/Unser (2002), pp. 197ff.), contracts between stakeholders and firms (see Oehler et al. (2011); Oehler/Schalkowski/Wendt (2011); (2012a); (2012b); (2013); (2014)), the relationship of stakeholders around an IPO, or mergers and acquisition transaction of a firm (see Walker et al. (2011); Oehler/Schalkowski/Wedlich (2015)), as well as relationships between market participants and analysts (see Höfer/Oehler (2013)).
[91] See Demsetz (1968); Richter/Furubotn (2010), pp. 13f., pp. 53ff.; Opper (2001); Menard/Shirley (2005), p. 1f.; Coase (2005); Schmidt/Terberger (2006), pp. 393f.

approaches of NIE are the Theory of Property Rights[92], Transaction Cost Theory[93], Information Economics[94], and the Principal Agent Theory[95].[96]

From the assumption of asymmetrically distributed information, the approaches of NIE derive discrepancies in the power of the involved contract parties to design and fulfill contracts, as well as differing extents to which the contract parties are (financially) affected by a decision.[97] Information asymmetries can occur prior to agreeing to a contract (ex-ante)[98], during the term of a contract (ex-interim)[99], and after maturity of a contract (ex-post)[100]. Informational disadvantages implicate the risk of deviations in market participants' expected outcomes. NIE suggests that market participants need to obtain additional information to reduce informational disadvantages and associated risks.[101] This, however, causes transaction costs (e.g. for gathering and processing information). Another possibility would be to include arrangements in a contract that incentivize the involved contract partners to act in the intended way. This induces monitoring or bonding costs.[102]

NIE assumes that – in contrast to neoclassical finance – market participants do not act fully rational although they want to act rational. After NIE, market participants are characterized by different initial states of knowledge and information while their ability to process information

[92] See Coase (1937); (1960); Alchian (1965); Demsetz (1964); (1967); Alchian/Demsetz (1972); (1973) regarding basic principles on the Theory of Property Rights.
[93] See Coase (1937); Williamson (1975); (1985) regarding the basis of the Transaction Cost Theory.
[94] See Stiglitz (1975); (1987); Rothschild/Stiglitz (1976) who substantially influenced this research area as well as Akerlof (1970) for the basic concept of "adverse selection" arising from uncertainty and asymmetrically distributed information between market participants regarding the quality of a tradable good.
[95] See Jensen/Meckling (1976); Fama/Jensen (1983); Pratt/Zeckhauser (1985) regarding the foundations of the Principal Agent Theory. See Oehler/Schalkowski (2013) for the Stewardship Theory which is based on and extends the Principal Agent Theory.
[96] See Richter (1990); Cezanne/Mayer (1998); Opper (2001); Menard/Shirley (2005), p. 1f.; Schmidt/Terberger (2006), pp. 396ff.; Wendt (2011), pp. 21ff.; Schalkowski (2013), p. 9; Wedlich (2017), p. 17. See Richter/Furubotn (2010), pp. 90ff.; Picot et al. (2015), pp. 56ff.; Ebers/Gotsch (2019), pp. 196ff. for a detailed description regarding the four main approaches of NIE.
[97] See Oehler/Unser (2002), pp. 197ff.; Oehler (2015d); Oehler/Wendt (2017).
[98] Ex-ante information asymmetries about the quality of a tradable good as well as the uncertainty associated with the asymmetry can induce adverse selection and impair market efficiency (see Akerlof (1970)).
[99] An example therefore is the "moral hazard" phenomenon (see Arrow (1963) on the foundations of moral hazard). In the context of financial contracts, this phenomenon can be described by a scenario in which one contract partner has an informational advantage and changes his behavior subsequently to entering a contract to improve his own position or outcome while impairing the position or increasing the costs of the other contract partner (see Schmidt/Terberger (2006), pp. 67f.).
[100] Examples for ex-post information asymmetries are, for instance, if the contract partners are differently affected by the economic consequences after maturity or terminating a contract, or if the fulfilment of the contract can hardly be verified ex-post (see Oehler (2005b); (2006a)).
[101] See Oehler (2006a); (2012a); (2012e), p. 4; (2012f); (2015d); (2017b); Oehler/Wendt (2017); Oehler/Höfer/Wendt (2014). One way to reduce information asymmetries between contract parties and associated risks is to employ scorings. In the context of the digital world and a proceeding digitalization, scorings are increasingly created automatically by algorithms in many areas of (financial) decision-making (see Oehler (2017b); (2021a)).
[102] See e.g. Oehler et al. (2015).

as well as their motivational and emotional capabilities are bounded (i.e. bounded rationality).[103] For better informed market participants, information asymmetries offer incentives to use their informational advantage to pursue their own objectives (e.g. to increase their outcome) while passing the costs on to less informed market participants, which constitutes opportunistic behavior. Opportunistic behavior is particularly attractive for informationally advantaged market participants if the counterparty can hardly recognize his advantage or can hardly protect himself from being exploited.[104] This is particularly serious in the context of financial contracts since most of the latter are credence goods. Credence goods can be characterized as goods at which the moment of payment and the moment of repayment diverge. Complete information about the features of a (financial) contract and its quality are, both before and after entering a contract, generally unavailable.[105] Consequently, information asymmetries can be reduced but not eliminated entirely,[106] and the decision of whether to enter a financial contract or not can rather be interpreted as a decision under ambiguity than a decision under risk.[107]

The descriptions on NIE imply that information asymmetries can have severe (negative) consequences for informationally disadvantaged market participants who want to trade financial contracts. This is particularly relevant in the context of households. On the one hand, households typically have informational disadvantages compared to professional market participants,[108] which hampers their ability to make sound financial decisions and achieve reasonable investment outcomes. On the other hand, professional market participants appear to take advantage of households' informational disadvantage.[109] Both aspects can add an explanation why household portfolios on average underperform a market portfolio (proxy).[110] In addition, information gathering, (fixed) participation and transaction costs,[111] as well as ambiguity aversion[112] can – as opposed to the neoclassical prediction that investors hold at least

[103] The concept of bounded rationality traces back to Simon (1955); (1956); (1957); (1990). See also Oehler (2000b); (2002); Picot et al. (2015), pp. 42ff.
[104] See Williamson (1985), pp. 47f.; Schmidt/Terberger (2006), p. 390.
[105] See Oehler (2011); (2012b); (2012d); (2013c), pp. 16f.; (2015d); Oehler et al. (2015), p. 39; Oehler/Höfer/Wendt (2013); Oehler/Wendt (2017); Bitz/Stark (2015), p. 2.
[106] See Schmidt/Terberger (2006), pp. 393f.
[107] See Oehler et al. (2015).
[108] See Oehler (1995), p. 5; Oehler/Kohlert (2009); Barber/Odean (2013); Oehler (2012e), p. 4; (2012f); (2012a); (2014a).
[109] See Linnainmaa (2010); Fecht/Hackethal/Karabulut (2018); Egan (2019).
[110] For an overview, see Barber/Odean (2013); Guiso/Sodini (2013), pp. 1471ff.
[111] See Haliassos/Bertaut (1995); Vissing-Jørgensen (2003).
[112] See Easley/O'Hara (2009); Epstein/Schneider (2010); Antoniou/Harris/Zhang (2015); Dimmock et al. (2016); Anantanasuwong et al. (2019). Another consequence from ambiguity aversion is that households might constrain the selection of possible security investments to local companies close to their residence since this gives them the feeling of familiarity and reduces ambiguity (see Baltzer/Stolper/Walter (2015)).

some amount of the market portfolio – motivate households to non-participate in risky investments at all and invest their entire funds in the risk-free investment instead.

The field of market microstructure analyzes the institutional and legal framework that leads to admissible and feasible transactions on financial markets.[113] Rather than frictionless markets and rational deciders as presumed by the neoclassical paradigm, the approaches of market microstructure – likewise to the approaches of NIE – interpret financial markets as institutions and market participants as asymmetrically informed individuals.[114] Central questions are how market participants' information processing and different arrangements of institutional frameworks affect the formation of prices and the efficiency of transactions.[115]

Market microstructure concentrates on security exchanges, i.e. trading platforms that provide the organizational, technical and legal infrastructure to balance supply and demand for financial contracts or securities.[116] The goal is to specify organizational structures[117] that facilitate the highest possible informational efficiency.[118] A necessary condition for informationally efficient security exchanges is operative functionality,[119] which is, in turn, mainly determined by the ability of an exchange to ensure liquidity.[120] Liquidity describes the possibility to immediately buy (and sell) large and small quantities of securities at any time without considerable additional price charges (price discounts).[121]

In the context of market microstructure, impediments to market liquidity like market frictions and transaction costs are of particular interest.[122] As opposed to the comprehensive definition of transaction costs according to NIE, market microstructure focuses more narrowly on costs associated with the transaction of a (financial) product on an exchange.[123] Trade impediments which are in contrast to frictionless markets as presumed by neoclassical finance indicate market imperfections that might limit households in practice when trading financial

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[113] See Oehler (1995), p. 22; (2000a); (2000b); (2002), p. 847.
[114] See Oehler (1995), p. 22; (1998a), pp. 73f.; (2000b); (2002), pp. 846ff.
[115] See O'Hara (1996), p. 1; Oehler (2000b); (2002), pp. 846ff.; (2006c); Stoll (2003), pp. 556f.
[116] See Oehler (2000c); (2006c), p. 80.
[117] Organizational structures particularly include the rules to obtain access to an exchange, trading rules, and the objects to be traded (see Oehler (1998a), p. 74; (2000c); (2001c); Oehler (2002), pp. 847f.).
[118] See O'Hara (1996), p. 1; Oehler (2000c); (2001c); (2006c); Oehler/Heilmann/Läger (2001). In this context, informational efficiency is considered in terms of Fama (1970), i.e., security prices reflect all relevant information.
[119] See Schmidt/Iversen/Treske (1993); Oehler (2001c); (2006c).
[120] See Theissen (1998), p. 45; Oehler (2001c); (2006c).
[121] See Oehler/Heilmann/Läger (2001); Oehler (2006c); Bernstein (1987); Theissen (1998), pp. 56ff.
[122] See Oehler (2001c); (2006c); Stoll (2003), p. 556.
[123] See O'Hara (1996), pp. 5f.; Stoll (2003), p. 556. The foundations on transaction costs in market microstructure studies, particularly the time dimension or immediacy of trading, trace back to Demsetz (1968).

securities.[124] Among others,[125] transaction costs, participation costs, and funding constraints are particularly relevant trade impediments from the perspective of households and, thus, for the subsequent analyses. Since the order values and the wealth of households are typically lower compared to those of other (professional) investors, transaction costs for the execution of an order are a relatively important factor when deciding whether to trade securities or not. Likewise, participation costs are particularly relevant as trading on security exchanges involves costs to get access to exchanges, e.g., account fees or minimum margin requirements.[126] Although neoclassical finance assumes unlimited borrowing at the risk-free rate, funding depends on an investor's (inherent) risk and is basically limited in practice.[127] This suggests for the subsequent empirical analyses to account for different risk and to distinguish between borrowing and lending rates.

The relaxation of the neoclassical presumptions by allowing for transaction costs, information asymmetries, and bounded rationality induces market frictions between the supply and demand for financial resources. Institutions whose primary purpose is to support market participants to overcome possible market frictions to close financial contracts in order to balance their financial needs are called financial intermediaries.[128] While financial intermediaries are irrelevant in neoclassical finance – perfect markets enable transactions between market participants directly – financial intermediaries are the basic institution in the savings-investment process if transaction costs, information asymmetries, and bounded rationality are taken into account.[129]

Financial intermediaries can be sub-classified as financial intermediaries in the narrow sense (e.g. banks, insurance companies, investment management companies, venture capital funds) and financial intermediaries in the broad sense (e.g. financial advisors and insurance brokers, rating agencies, security exchanges).[130] Financial intermediaries in the narrow sense distinguish from financial intermediaries in the broad sense as they take the role of a contract partner in

[124] See Vayanos/Wang (2013), pp. 1289ff.
[125] See Oehler (2000c); (2001c); (2006c); Vayanos/Wang (2013) regarding possible efficiency features and liquidity impediments of security exchanges.
[126] See Oehler (2000c); Vayanos/Wang (2013), p. 1291; Horn (2018), p. 17.
[127] See Vayanos/Wang (2013), p. 1291.
[128] See Oehler (2005b), pp. 212f.; (2006c); Wendt (2011), p. 39; Bitz/Stark (2015), pp. 2f.; Hartmann-Wendels/Pfingsten/Weber (2019), pp. 2f.
[129] See Gorton/Winton (2003), pp. 432ff.; Oehler (2004a); Wendt (2011), p. 39; Hartmann-Wendels/Pfingsten/Weber (2019), p. 10.
[130] See Oehler (2000c); (2004a); (2005b), pp. 212ff.; (2006a), pp. 306ff.; (2006c); Schalkowski (2013), pp. 19ff.; Bitz/Stark (2015), pp. 4ff.; Oehler/Horn/Wendt (2018a); (2018b); Hartmann-Wendels/Pfingsten/Weber (2019), pp. 3ff. for the rest of the paragraph.

financial contracts themselves. This includes contracts with both the supply-side (by borrowing from market participants) and the demand-side (by financing or lending to other market participants).[131] While offering borrowing and lending services, the major function of financial intermediaries in the narrow sense is to provide transformation services that aim at customizing information, nominal value, duration, and risk attributes of a financial contract according to the needs of the corresponding market participant.

Rather than acting as contract partners themselves, financial intermediaries in the broad sense, in turn, offer services that enable the formation of financial contracts, and offer cost-benefits or easier ways for market participants to close financial contracts between each other. The main functions of financial intermediaries in the broad sense are to induce matches between supply and (compatible) demand for financial contracts, as well as the reduction of possible information asymmetries (e.g. by providing specific information and financial advice to market participants).[132]

Financial intermediaries like banks or investment companies enable market participants to invest their savings in risk-free and risky securities.[133] These services of financial intermediaries in the narrow and broad sense are typically not provided by just one specific company or category of financial intermediaries. Financial systems rather consist of many financial intermediaries that are interconnected with each other. As a consequence, financial contracts may also be closed exclusively between financial intermediaries without a direct involvement of primary market participants of the demand- or supply-side.[134]

Given the considerable information asymmetries and uncertainty associated with portfolio choice situations, households usually have a high demand for information to reduce information asymmetries and to figure out appropriate investment solutions. To cover their information requirement, most households are dependent on high quality financial advice. High quality financial advice means that households receive information from financial intermediaries that fits to their knowledge, experience, and the requirements of their individual financial situation.[135]

[131] See Bitz/Stark (2015), pp. 4f.
[132] See Oehler (2000c); (2004a); (2005b), pp. 212ff.; (2006a), pp. 306ff.; (2006c); Schalkowski (2013), pp. 19ff.; Bitz/Stark (2015), pp. 4ff.; Hartmann-Wendels/Pfingsten/Weber (2019), pp. 3ff.
[133] See Horn (2018), p. 19; Hartmann-Wendels/Pfingsten/Weber (2019), pp. 19ff.
[134] See Oehler (2000c); (2004a); (2005b), pp. 212ff.; (2006a), pp. 306ff.; Hartmann-Wendels/Pfingsten/Weber (2019), p. 3.
[135] See Oehler (2011); (2015a); Oehler/Horn/Wendt (2016c); (2017b).

In accordance to their high demand for information, relying on financial advice is pervasive among households in many countries.[136] Contrary to high quality financial advice, high degrees of information asymmetries (e.g. associated with credence goods like financial products) create incentives for financial advisors to put their own interests above the interests of their clients. They could, e.g., maximize their income by selling financial products that involve high acquisition- or management-fees and pass the corresponding costs on to households.[137] Financial intermediaries further deviate from high quality advice by failing to assess relevant features of households' individual financial situation.[138]

In addition, establishing institutions as well as gathering and processing information about their clients for providing financial advice causes costs for financial intermediaries. To manage the trade-off between their own profitability and efficiency as well as the demand of their clients for high-quality and customized financial advice, it is a reasonable strategy from the perspective of financial intermediaries to offer products and financial advice that are sufficiently customized rather than entirely customized.[139] In this regard, an approach of financial intermediaries is to categorize their clients into a manageable number of types (e.g. three to five) according to the clients' preferred risk. Each type of client can then be assigned to a predefined portfolio composition that intends to match the client's preferred level of risk.[140] Considering this, it is no surprise that financial advisors tend to compose very similar portfolios instead of customized portfolios according to households' individual financial situation.[141]

The findings above imply that financial intermediaries have a considerable influence on households' portfolio choice and that household portfolios may not be tailor-made. This suggests for the subsequent analyses to investigate whether household portfolios reveal similar portfolio compositions and if they can be grouped into a reasonable number of portfolio types. The evidence outlined above further indicates that the outcome of financial advice in terms of household portfolios' risk and return may leave room for improvement.[142]

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[136] See, e.g., for Canada, The Investment Funds Institute of Canada (2012), for the United States, see Investment Company Institute (2013), and for Germany, see DAB Bank (2004); Hackethal et al. (2011).

[137] See Oehler (2004a); (2009); (2012a); (2012b); (2012d); (2012e); (2014b); (2015a); Bitz/Stark (2015), pp. 425ff.; Oehler/Kohlert (2008); (2009); Oehler/Kohlert/Jungermann (2009); Inderst/Ottaviani (2009); Fecht/Hackethal/Karabulut (2018); Egan (2019).

[138] See Rehkugler et al. (1992); Oehler/Kohlert (2008), pp. 91ff; (2009); Oehler/Kohlert/Jungermann (2009).

[139] See Oehler (2003a); (2003b); (2004b); (2005d) on customer satisfaction and the demands on quality and customer relationship management of retail banks.

[140] See Steiner/Bruns/Stöckl (2017), pp. 131ff. A further justification for this procedure is related to difficulties of clients to determine and express their own risk preferences.

[141] See Oehler/Kohlert (2008), pp. 91ff; (2009); Oehler/Kohlert/Jungermann (2009); Foerster et al. (2017).

[142] Research on financial advice largely points out existing information deficiencies and calls for improvements in the quality of financial advice (see Oehler (2004a); (2005a); (2006b); (2011); (2012a); (2012b); (2012d); (2012e);

2.3 Behavioral Finance and Economics

Behavioral finance and economics is "the study of how psychology impacts financial decisions in households, markets and organizations."[143] The major concern of this research field are analyses about the perception, processing and evaluation of information by market participants. Thereby, behavioral finance and economics builds upon neoclassical finance and is closely related to the approaches of NIE, market microstructure and financial intermediation. While institutional rules and information asymmetries constrain market participants' decision-making, the behavior exhibited by market participants, in turn, may lead to rule changes and the introduction of new rules. In this sense, the previous paradigms are rather complementing than contradicting each other.[144]

A key distinction from neoclassical presumptions is that behavioral finance and economics does not assume rational deciders and frictionless markets. The starting point, instead, is bounded rationality[145].[146] In this regard, Simon (1955) states that, instead of optimizing decision problems in terms of a rational decider, individuals rather choose alternatives that are "satisfactory" with regard to an individual "aspiration level".[147] Research further documents that individuals tend to ascertain possible outcomes of investment alternatives using heuristics, i.e. rules of thumb and intuitive probability evaluations that differ from the rules of probability theory. Consequently, systematic errors or behavior patterns that deviate from the predictions of expected utility theory assumed in neoclassical finance can occur – so-called "irrationalities", "anomalies", or "biases".[148] According to De Bondt et al. (2008), research approaches and models in behavioral finance and economics can be categorized into three blocks: (1) investor errors, (2) behavioral preferences, and (3) limits to arbitrage.

(2012f); (2013a); (2013b); (2013c); (2013d); (2014a); (2014b); (2015a); (2015b); (2015d); (2015e); (2015f); (2016a); (2016b); (2016c); (2017a); (2018); (2020); (2021b); (2021c); (2021d); (2021e); (2021f); (2021g); (2021h); Oehler/Horn/Wendt (2016b); (2016c); (2016d); (2017b); (2017c); (2020b); Oehler/Kohlert (2009); Oehler/Wendt (2016a); (2017); Oehler/Werner (2008); Wendt/Horn (2021); Wendt/Horn/Oehler (2021)). A possible approach would be to impart basic financial knowledge on a meta-level to households, supported by the information of independent "information navigators", in order to find adequate experts without becoming an expert oneself (see Oehler (2011); (2013a); (2013d); (2017b); (2021b); (2021f); (2021g); Oehler/Wendt (2017)).

[143] De Bondt et al. (2008), p. 2.

[144] See Oehler (2000a); (2000b); (2002); (2005c); (2011).

[145] The concept of bounded rationality traces back to Simon (1955) (see chapter 2.2 for a description).

[146] See Oehler (1991); (2000a); (2000b); Barberis/Thaler (2003), pp. 1055f.; De Bondt et al. (2008); Ackert (2014), p. 31f.

[147] Regarding this aspect, see also Selten (1990); Oehler (1995), p. 60; (2000b); (2002), p. 849; Ackert (2014), p. 31f.

[148] See Tversky/Kahneman (1974); Oehler (1991); (1992); (1994); (1995), pp. 26ff.; (2002), pp. 854ff.; Thaler (1990); De Bondt et al. (2008) for an overview. See also Wedlich (2017), pp. 127ff.; Oehler/Wedlich (2018); Oehler et al. (2018c) regarding the influence of investors' personality traits extraversion and neuroticism on their investment decisions, risk behavior, and return expectations.

(1) The block of investor errors includes erratic beliefs and cognitive errors of individuals as well as possible consequences at the market level.[149] In the context of financial research, a prominent bias from this block is the overconfidence bias which means that individuals overestimate their own knowledge and abilities.[150] Overconfidence is often associated with the behavior that investors trade excessively, which, however, causes considerable trading costs and leads to underperformance on average compared to the market (portfolio).[151] Accordingly, households would be better off by following a simple buy-and-hold strategy instead of engaging in active trading.[152]

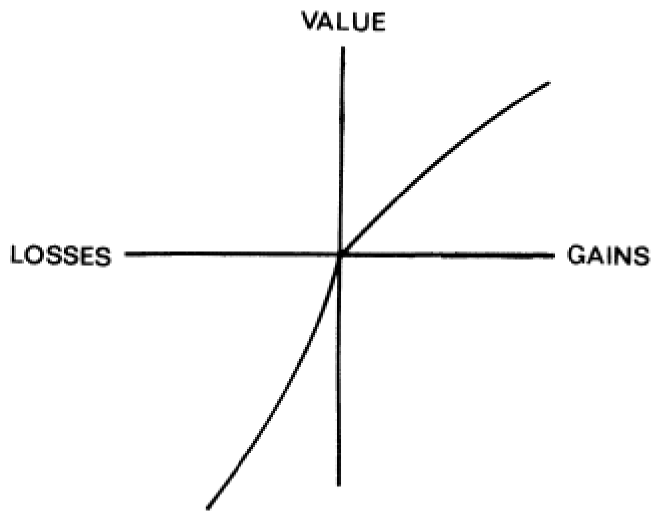
(2) The block of behavioral preferences captures investors' attitudes towards risk and return that do not comply with expected utility theory assumed in neoclassical finance.[153] One of the most widespread behaviorally-based preference frameworks is the Prospect Theory by Kahneman/Tversky (1979). Prospect Theory was proposed – in contrast to the normative models of neoclassical finance – as a descriptive model that intends to capture individuals' attitude towards risk under uncertainty.[154]

Prospect Theory has three main features:[155] First, in contrast to the neoclassical assumption that investors' utility is based on final states of wealth of decision alternatives, Prospect Theory assumes that utility is derived from gains and losses (i.e. changes in wealth) relative to a reference point that the investor considers to be convenient (for example, the status quo of a security or an investment position an investor seeks to attain[156]). Second, in the domain of gains, the value function is concave which shows that in this domain investors are risk averse. In the domain of losses, the value function is convex which implies that in this domain investors are risk-seeking. The course of the value function has a kink in the origin (see Figure 1). The second feature indicates that investors show a greater sensitivity towards losses than towards gains, a

[149] See De Bondt et al. (2008).
[150] See Oehler (1995), p. 38; (2000a); (2000b); (2002), p. 845; (2011); (2013d); Barberis/Thaler (2003), pp. 1065f; Glaser/Weber (2010), pp. 242ff.; Thaler (2016). Another well-documented biases is the so-called „home bias" which will be outlined in greater detail in chapter 3.2.
[151] See Odean (1998); Barber/Odean (2000); (2001); Barber et al. (2009); Graham/Harvey/Huang (2009).
[152] See Barber/Odean (2000); French (2008); Barber et al. (2009); Barber/Odean (2013), p. 1539, p. 1565; von Gaudecker (2015); Oehler/Horn (2019).
[153] See De Bondt et al. (2008).
[154] See Kahneman/Tversky (1979); Shiller (1999), pp. 1308f.; Barberis/Thaler (2003), p. 1069; De Bondt et al. (2008).
[155] See Kahneman/Tversky (1979); Shiller (1999), pp. 1308ff.; Barberis/Thaler (2003), pp. 1069ff.; De Bondt et al. (2008); Thaler (2016) for the rest of the paragraph.
[156] An investor's reference point according to Prospect Theory can vary from the mean return which is implicitly assumed as the "reference point" in the (neoclassical) standard deviation, which can result differing risk evaluations. This aspect is discussed in greater detail in the analsysis regarding RQ2.

behavior pattern which is referred to as loss-aversion[157]. Third, Prospect Theory assumes that investors overweight small probabilities and are more sensitive to differences in probabilities at higher probability levels. This yields a non-linear probability function and offers an explanation why individuals buy lottery tickets and invest in insurance contracts at the same time – which is, they overestimate small chances for a large gain.

Figure 1: Hypothetical value function according to Prospect Theory.



Source: Kahneman/Tversky (1979), p. 279.

Another key behavioral preference derived from Prospect Theory is mental accounting.[158] "Mental accounting is the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities."[159] In contrast to expected utility theory, individuals do not consider their wealth as one entity when making decisions, but rather rely on so-called mental accounts. Mental accounts can be characterized as groups of investments with similar outcome features that are jointly evaluated. The range of outcomes in each mental account defines account-specific reference outcomes from which gains and losses are ascertained.[160] Mental accounting has three main components:[161] First, the accounting

[157] See Kahneman/Tversky (1984). Several studies point out that investors assign approximately twice the weight to losses than they assign to gains which exhibits their loss-aversion (see Kahneman/Knetsch/Thaler (1990); Tversky/Kahneman (1992); Benartzi/Thaler (1995)).
[158] See Shiller (1999), pp. 1317ff.; De Bondt et al. (2008). In an earlier publication, Tversky/Kahneman (1981) use the term "psychological account". In reference to the terminology used in Thaler (1980), Kahneman/Tversky (1984) later suggest the term „mental account" (see Thaler (1999)).
[159] Thaler (1999), p. 183.
[160] See Kahneman/Tversky (1979); (1984); Tversky/Kahneman (1981); Thaler (1985); (1999).
[161] See Thaler (1999) regarding the three components of mental accounting.

system, which allows households to do ex-ante and ex-post cost-benefit analyses. The second component includes the assignment of financial activities, which involve both the sources and the uses of funds, to specific mental accounts. The third component of mental accounting is that the frequencies with which each mental account is evaluated vary.[162] Since gains and losses are evaluated within the frame of a certain mental account, they are no perfect substitutes for gains or losses of different mental accounts. As a result, mental accounting violates the economic principle of fungibility.[163]

In line with mental accounting, empirical research further suggests that households divide their wealth according to a hierarchy of mental accounts.[164] Shefrin/Thaler (1988) propose a hierarchy of three mental accounts, which consists of a current income account (which involves, e.g., money that is routinely spend each period), a current assets account (e.g. stocks, bonds, mutual funds, and other assets typically designated for saving), and a future income account (e.g. designated retirement accounts). While spending wealth on the current income account is assumed to be most tempting for households, spending wealth on the future income account is assumed to be least tempting. At the assignment of wealth to the mental accounts, households treat the components of their wealth as non-fungible.[165]

In the context of household portfolio choice, several implications can be drawn from the second block of behavioral finance and economics (behavioral preferences) according to De Bondt et al. (2008). First, since households tend to divide their wealth into mental accounts, it seems reasonable to pool and evaluate investments with similar outcome features jointly instead of evaluating the entire portfolio all at once. Second, because of the joint evaluation of similar investments, households likely refrain from compensating losses in one certain mental account with gains of a different mental account. This may lead to a pronounced unwillingness to take risks or the denial to invest in risky securities at all,[166] which points out the importance of loss aversion when evaluating household portfolio performance.[167] Third, it seems reasonable to exclude households from the subsequent analyses that have no or no significant "account" of

[162] Moreover, transactions are often evaluated separately, i.e. one at a time, rather than jointly together with other transactions (see Thaler (1999)).
[163] See Levin (1998); Thaler (1999).
[164] See Shefrin/Thaler (1988); Levin (1998); Thaler (1990); Graham/Isaac (2002).
[165] See Shefrin/Thaler (1988); Thaler (1990); (1999).
[166] See Benartzi/Thaler (1995); Thaler (1999); Dimmock/Kouwenberg (2010).
[167] This also motivates RQ2 which questions whether households can obtain enhancements in their risk-return position under consideration of loss-aversion and corresponding risk measures that reflect households' interpretation of risk more closely than the neoclassical standard deviation.

risky securities since these households are unlikely to transfer spendable money into a new mental account that includes different investments like, for example, XTFs.

(3) The block of limits to arbitrage examines possible limitations in the arbitrage process on financial markets.[168] In terms of neoclassical finance, Fama (1965) argues that arbitrageurs assure that security prices generally equal their values. Even if temporary discrepancies between price and value occur, sophisticated investors will immediately correct any mispricing. Proponents of behavioral finance and economics, in turn, assume that investors are imperfectly informed and that arising anomalies can cause market inefficiencies which makes arbitrage both costly and risky. This leads to limitations in the arbitrage processes and allows for deviations between security prices and values.[169] Examples which may produce such deviations are overreactions of speculative asset prices due to excess volatility,[170] as well as the tendency of investors – particularly due to their loss-aversion – to sell winners (i.e. securities that have increased in value since their purchase) too early and hold losers (i.e. securities that have declined in value since their purchase) too long.[171]

Studies of behavioral finance and economics further point out that while some sophisticated[172] (professional) investors might be able to exploit inefficiencies like (temporary) gaps between prices and values, ordinary investors are unable to do so.[173] This indicates that markets are not efficient in the sense that prices equal values, but that markets are efficient in the sense that they are hard to beat. Thus, although both the neoclassical and behavioral interpretation of market efficiency might seem conflicting, they agree that markets are hard to beat by ordinary investors like households.[174] As implication for household portfolio choice, the descriptions above substantiate the previous notion that households would – within hard-to-beat financial markets – be better off if they invest in a market portfolio proxy as reflected by XTFs.

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[168] See De Bondt et al. (2008).

[169] See Shiller (1999), pp. 1307ff.; Barberis/Thaler (2003), pp. 1060ff.; De Bondt et al. (2008); Statman (2014); (2017), pp. 3f.

[170] See for example Shiller (1979); (1981a); (1981b) for early evidence that speculative asset prices reveal persistent deviations from the efficient markets model. See also Oehler et al. (2019) regarding the influence of personality on price bubbles.

[171] This is the so-called "disposition effect" (see Shefrin/Statman (1985); Kahneman/Knetsch/Thaler (1990); Oehler (1991); (1992); (1994); (1995), p. 32.; (1999), pp. 72ff.; (2000b); (2002); (2011); Heilmann/Läger/Oehler (2001b); Oehler et al. (2003)).

[172] Financial sophistication denotes „the understanding of financial instruments and competence in taking sound financial decisions" (Guiso/Sodini (2013), p. 1401).

[173] See Barber/Odean (2013), pp. 1539ff.; Statman (2014).

[174] See De Bondt et al. (2008); Statman (2014); (2017), pp. 3f.

3 Characteristics of Household Portfolios

3.1 Distribution of Household Wealth

Neoclassical finance predicts that households divide their wealth in dependence on their preferred level of risk into an investment in the market portfolio and a risk-free investment.[175] Portfolios of less wealthy households should therefore just be a scaled-up version of more wealthy households.[176] This chapter intends to confront this theoretical prediction with empirical characteristics of household portfolios. Therefore, empirical research regarding the distribution of households' wealth across asset classes as well as the asset diversification within asset classes are reviewed. Eventually, implications for the recommendation to employ XTFs as well as the subsequent empirical analyses are drawn.

Households' total wealth mainly stems from two sources: Tangible wealth and human capital.[177] Human capital enables households to earn labor income and can be defined as the present discounted value of disposable labor income that an individual expects to earn over its remaining lifetime.[178] Human capital is non-tradable, it accumulates very slowly, and incurs substantial idiosyncratic and largely uninsurable risk. Human capital is hard to assess, not only from the perspective of empirical research, but even for households themselves since this would require drawing expectations about an individual's income over the entire lifetime, career prospects, health conditions, productivity and employment status, which are highly uncertain and hardly accurately determinable.[179] For most households, human capital represents the most important source of wealth (through labor income). Since human capital cannot be traded or liquidated, it cannot be transferred into tangible assets directly, which is why households typically accumulate tangible wealth by investing parts of their income through savings.[180] Given the difficulties in determining human capital wealth, its large variation across households, and its transfer into tangible wealth, the following descriptions focus on households' tangible wealth and, unless otherwise specified, leave out the term "tangible" for better readability.[181]

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[175] See chapter 2.1.
[176] See Guiso/Sodini (2013), p. 1407.
[177] See Oehler (1995), p. 115; Guiso/Sodini (2013), p. 1403; Zanella (2015).
[178] See Guiso/Sodini (2013), p. 1403; Zanella (2015).
[179] See Campbell (2006); Guiso/Sodini (2013), pp. 1400ff; Zanella (2015).
[180] See Campbell (2006); Guiso/Sodini (2013), p. 1403; Zanella (2015).
[181] To approximate differences in human capital, empirical studies frequently rely on households' monthly income (see e.g. Calvet/Campbell/Sodini (2007); (2009); von Gaudecker (2015)), which may, nonetheless, lead to estimation errors (see Horn (2018), p. 36).

Households can invest their savings into a broad range of assets. This range of assets is generally outlined in households' balance sheets. Accordingly, households can invest their savings into two categories of tangible assets: financial assets and real assets. Real assets essentially include real estate, vehicles, and private business wealth. Main categories of financial assets are cash and saving accounts, retirement plans and life insurance policies, investments in mutual funds, bonds, or individual stocks.[182] In developed countries, a major source of information regarding households' distribution of wealth among these assets are household surveys which cover households' balance sheets.[183] The latter are employed in the following to illustrate characteristic features of households' wealth distribution.

In developed countries, households' wealth widely differs. For instance, while households' total net wealth[184] amounts 109,000 Euro in the euro area on average, it ranges from about 51,000 in Germany to about 398,000 Euro in Luxembourg.[185] A common feature among many developed countries like the United States and the euro area, though, is that net wealth shows an unequally, right-skewed distribution, which means that wealth is heavily concentrated in the top part of households' wealth distribution.[186] In the euro area, 50 percent of the households below or at the median level hold only 12 percent of the net wealth, whereas the top decile owns 50 percent of the net wealth.[187] In the United States, households' average wealth in the top decile is more than 5,000 times higher than the average wealth of households in the bottom decile.[188]

Compared to financial assets, real assets represent the bulk of households' total (gross) wealth,[189] reaching a share of about 70 percent in the United States[190] and about 83 percent in the euro area[191] on average. Among real assets, households' main residence is the most

[182] See e.g. Guiso/Jappelli/Pistaferri (2002), p. 6; von Gaudecker (2015); Deutsche Bundesbank (2016); (2019a); European Central Bank (2016b); Badarinza/Campbell/Ramadorai (2016).

[183] See Guiso/Jappelli/Pistaferri (2002), p. 2; von Gaudecker (2015); Badarinza/Campbell/Ramadorai (2016); Arrondel et al. (2016). Prominent examples for household surveys are the Survey of Consumer Finances (United States), the Eurosystem's Household Finance and Consumption Survey (collection of consolidated household surveys of euro-area countries), the National Household Survey (Canada), the British Household Panel Survey (United Kingdom), and the Household, Income and Labour Dynamics in Australia Survey.

[184] Please note in this regard that the corresponding studies refer to net tangible wealth which is defined as the difference between total (gross) tangible assets and total liabilities (e.g. real estate mortgages, credit card debts, bank overdrafts, or other loans) (see e.g. European Central Bank (2017a); (2017b)).

[185] See Arrondel et al. (2016).

[186] See Campbell (2006); Guiso/Sodini (2013), pp. 1407ff.; Badarinza/Campbell/Ramadorai (2016); Arrondel et al. (2016).

[187] See Arrondel et al. (2016).

[188] See Guiso/Sodini (2013), p. 1407.

[189] See also Badarinza/Campbell/Ramadorai (2016) for an overview across multiple developed countries like Australia and Canada. Please note that the results in this publication may vary to the previously cited results for the United States and the euro area due to consolidation of the household surveys.

[190] See Guiso/Sodini (2013), p. 1407.

[191] See Bover et al. (2016); Arrondel et al. (2016); European Central Bank (2017a); (2017b).

important asset category across developed countries.[192] However, the participation rates and the relative portfolio share of the main residence largely vary, both across countries and within countries along the wealth distribution. In the second quintile of net wealth, for example, participation rates already exceed 90 percent in Spain, while they stay below 15 percent in Austria, Germany and France.[193] In the euro area as well as the United States, participation rates rise with wealth and are, in the top quintile of wealth, above 90 percent.[194]

A characteristic feature in the United States and the euro area is that among the top quintile of wealth, the relative portfolio share in real estate decreases while simultaneously the participation and wealth in private businesses sharply increases.[195] In the United States, the corresponding participation rates in private businesses rise from 22 percent in the 80th percentile of the wealth distribution to 70 percent in the top of the wealth distribution. In the euro area, participation rates increase from ten percent in the fourth quintile of wealth to 47 percent in the top five percent of the wealth distribution.[196] Another important real asset are vehicles. In the second quintile of the wealth distribution, participation rates already exceed 70 percent in the euro area and the United States. Relative portfolio shares in the first two quintiles are high but decline abruptly from the third quintile on.[197] The characteristics described above imply that, except for the wealthiest households, the main residence represents a dominant asset for most households as soon as they can afford it. While vehicles represent a relatively important asset for less wealthy households, private business wealth is mainly held by wealthy households.

According to balance sheets for average household portfolios across developed countries, most financial assets are held in cash and saving accounts, retirement plans and life insurance policies whereas the wealth allocated in mutual funds, bonds and stocks is relatively low.[198] Conditional on participation, the share of retirement plans and life insurance policies relative to households' financial wealth remains relatively stable across the wealth distribution and mostly ranges

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192 See Guiso/Jappelli/Pistaferri (2002), e.g. for the United States on pp. 188ff., or for Italy on pp. 264ff.; Campbell (2006); Guiso/Sodini (2013), pp. 1408f.; Arrondel et al. (2016); European Central Bank (2017a); (2017b).
193 See Arrondel et al. (2016); European Central Bank (2017a); (2017b). For the United States, Campbell (2006) and Guiso/Sodini (2013), pp. 1410f. find participation rates below ten percent among households in the first quintile of the wealth distribution.
194 See Campbell (2006); Guiso/Sodini (2013), pp. 1410f.; Arrondel et al. (2016); European Central Bank (2017a); (2017b).
195 See Campbell (2006); Guiso/Sodini (2013), pp. 1410f.; European Central Bank (2013); Bover et al. (2016).
196 See Campbell (2006) for the United States and Arrondel et al. (2016) for the corresponding values of the euro area.
197 See Campbell (2006); Guiso/Sodini (2013), pp. 1410f. for the United States and European Central Bank (2013) for the euro area.
198 See Badarinza/Campbell/Ramadorai (2016). The authors also document that in the allocation of households' financial wealth, other financial wealth (e.g. derivatives or hedge funds) only play a minor role. The following descriptions therefore abstract from these assets.

below the relative shares of cash and saving accounts as well as mutual funds, bonds and stocks across the wealth distribution.[199] However, a closer look across the wealth distribution in the remaining asset classes reveals differences. In the first wealth quintile in the euro area, 93 percent of the households already own cash and saving accounts, retirement plans and life insurances. While the relative portfolio share in these assets amounts, conditional on participation, 60 percent in the first wealth quintile, it decreases to 5 percent in the top five percent of the wealth distribution. Conversely, only 20 percent of the euro area households participate in risky financial assets like mutual funds, bonds, and stocks. While empirical evidence shows limited participation of less wealthy households in mutual funds, bonds, and stocks (only three percent in the first wealth quintile hold such assets), participation rates in mutual funds, bonds, and stocks steadily increase with wealth, reaching 44 percent (55 percent) in the fifth wealth quintile (top five percent of the wealth distribution) in the euro area.[200] A characteristic feature of household portfolios above the bottom part of the wealth distribution is that, conditional on participation, the relative portfolio share of financial assets tends to be u-shaped – a pattern that is often related to a crowding out effect related to the participation in real estate.[201] In the United States, higher participation rates in risky financial assets among more wealthy households are particularly in favor of stocks, reaching a rate of 20 percent in the fifth wealth quintile and thereby exceeds the participation rates of other financial assets like mutual funds or bonds.[202]

Empirical evidence presented above implies that asset participation is limited even among the wealthiest households. Moreover, participation in real and financial asset categories is far from being equally distributed across households' wealth distribution. Thus, portfolios of less wealthy households are hardly a scaled-up version of more wealthy households or households in the middle of the wealth distribution. This challenges neoclassical predictions and

[199] See Calvet/Campbell/Sodini (2007); Guiso/Sodini (2013), pp. 1413ff.; European Central Bank (2013); Arrondel et al. (2016).

[200] See Guiso/Jappelli/Pistaferri (2002), pp. 8ff.; Bover et al. (2016); Arrondel et al. (2016); European Central Bank (2013); (2017a); (2017b). Campbell (2006); Guiso/Sodini (2013), pp. 1413f. report a similar trend for the United States. See also Oehler (1995), pp. 166f.; (1998a), pp. 100f. regarding the inverse relation of relative portfolio shares between cash and saving account holdings as well as stock and bond holdings. Possible explanations for the widespread non-participation of less wealthy households in stocks include that they might particularly (compared to more wealthy households) suffer from fixed participation costs, e.g., information gathering and search costs or setup and running costs for a broker account (see Haliassos/Bertaut (1995); Vissing-Jørgensen (2003)). Barberis/Huang/Thaler (2006) and Dimmock/Kouwenberg (2010) further show that non-standard preferences like loss-aversion can partly explain why individuals decide to non-participate in the stock market. Loss-aversion may also lead to risk evaluations that deviate from those according to the neoclassical paradigm (see RQ2).

[201] See Cocco (2005); Yao/Zhang (2005); Guiso/Sodini (2013), pp. 1412f.; Laurinaityte (2018).

[202] See Guiso/Jappelli/Pistaferri (2002), pp. 8ff.; Campbell (2006); Guiso/Sodini (2013), pp. 1413f.

simultaneously represents a key result of empirical household research.[203] Comparisons of household survey data over time show that the characteristics of household portfolios remain relatively stable. As an exception, financial portfolios tend to become "riskier" as the participation in stocks as well as the average share of financial assets allocated towards stocks increased in the past years.[204]

The characteristic feature that less wealthy households show relatively high amounts invested in cash and saving accounts suggests that these amounts reflect the demand for liquid assets for the purpose of precaution. Moreover, households seem to move on to participate in (riskier) assets like mutual funds, bonds and stocks only after a sufficient level of wealth is achieved.[205] This indicates an implicit hierarchy of investments according to which households establish portfolios – a characteristic of the multi-layer portfolio framework[206] which will be outlined in the remainder in greater detail.

3.2 Asset Diversification

Once a household has decided to participate in a certain asset class, the subsequent question is how to diversify wealth within the asset class. The neoclassical paradigm predicts that all households should employ the same diversified market portfolio.[207] Empirical research, however, documents deviations of households' actual asset diversification from this prediction. Characteristic patterns of households' asset diversification will be presented in the following.

The main residence represents the largest component of wealth for the majority of households who can afford it.[208] Considering that this relatively large component of wealth is mostly committed into a single real estate, real estate wealth is rarely transacted upon wealth shocks.[209] The main motivating factor for investing in real estate is more the desire to own property than generating investment returns and further income.[210] In addition, real estate and private business wealth (the main wealth component of wealthy households) are highly specific and illiquid assets which usually include a non-monetary return component[211] that restricts price

[203] See Campbell (2006); Guiso/Sodini (2013), pp. 1413ff.
[204] See Guiso/Jappelli/Pistaferri (2002), pp. 8ff.; Guiso/Sodini (2013), pp. 1419ff.
[205] See Oehler (1995), pp. 166f.; (1998a), pp. 100f.
[206] See Oehler (2015c); (2021f); Oehler et al. (2018b).
[207] See chapter 2.1.
[208] See chapter 3.1.
[209] See Piazzesi/Schneider/Tuzel (2007); Piazzesi/Schneider (2009); Campbell (2006).
[210] See Deutsche Bundesbank (2015).
[211] See Hamilton (2000); Moskowitz/Vissing-Jørgensen (2002); Campbell (2006); Guiso/Sodini (2013), pp. 1400ff. In addition, real assets are frequently associated with considerable information asymmetries like adverse

determination and examining risk and return characteristics. As another issue, allocating wealth to retirement plans and life insurance policies offered by private life insurance companies differs from allocating wealth to mutual funds, stocks, and bonds offered by private banks in that the former primarily serve the purpose of risk prevention and provision for dependents while the latter instruments serve the purpose of achieving investment returns.[212] The research goals of this thesis are concerned with investment returns. Consequently, the descriptions on households' asset diversification focus on financial assets and abstract from real assets, retirement plans, and life insurance policies.

Studies on households' asset diversification predominantly examine their stock holdings. These studies often refer to Evans/Archer (1968) who point out that a sufficiently diversified portfolio consists of at least ten stocks since this reduces most of the idiosyncratic risk (idiosyncratic risk implies an increase in portfolio volatility without improving expected returns).[213] More recent publications find, however, that a much larger number of stocks – up to 300[214] – is necessary to obtain the level of diversification of a broad diversified index fund.[215] Empirical evidence, in contrast, documents that households only hold between two and four individual stocks on average which results in high levels of idiosyncratic risk.[216]

Studies that investigate households' broker accounts are able to examine detailed security holdings and trading activity. They also document low levels of diversification and high levels of idiosyncratic risk across a wide range of investors in their sample.[217] However, different studies indicate that most households do not own a broker account and, among households who do own a broker account, the wealth invested in these accounts represents only a small part of their entire financial wealth.[218] Polkovnichenko (2005) notices that a group of households who

selection problems described by Akerlof (1970). In the literature, real estate, private business wealth and human capital are frequently characterized as source of background risk, i.e. risk that is unavoidable since the underlying asset is non-tradable and non-insurable, and, due to market frictions and illiquidity, cannot be fully diversified away (see e.g. Heaton/Lucas (2000); Cocco (2005)).

212 See Bitz/Stark (2015), pp. 273ff.; Oehler (1995), pp. 66ff.; (1998a), pp. 79f. Therefore, the latter authors distinguish between financial assets in the broad sense (including retirement plans and life insurance policies) and financial assets in the narrow sense (excluding retirement plans and life insurance policies). In the same line, the authors also assign households' wealth at home loan banks to financial assets in the broad sense. Accordingly, this thesis concentrates on financial assets in the narrow sense.

213 See also Wagner/Lau (1971) regarding the effect of diversification on risk.

214 See Statman (2004).

215 In relation to decreasing costs for gathering a large number of stocks, the number of stocks required to attain a sufficiently diversified stock portfolio rose over time to about 15 (see Wagner/Lau (1971)), 30 (see Statman (1987)), 120 (see Statman (2003)), and 300 stocks (see Statman (2004)).

216 See Blume/Friend (1975); Kelly (1995); Barber/Odean (2000); (2001); Polkovnichenko (2005); Goetzmann/Kumar (2008); Odegaard (2017).

217 For example, Barber/Odean (2000); (2001); Goetzmann/Kumar (2008).

218 See Bilias/Georgarakos/Haliassos (2010); Anderson (2013).

invests in poorly diversified stock portfolios simultaneously invests large fractions of their wealth in stocks indirectly through mutual funds. Yet, he is unable to observe a wider range of asset classes of household portfolios including detailed security holdings – a common difficulty in household finance that impedes studying diversification and risk and return characteristics of household portfolios.[219]

A few studies, in turn, jointly observe households' investments in mutual funds, bonds and stocks as well as the "safe"[220] financial assets cash and saving accounts. Thereby, they provide a more comprehensive picture of households' asset diversification across multiple asset classes. These studies find that the majority of households achieves reasonable investment outcomes and diversification levels when taking mutual funds and safe financial assets into account. Nevertheless, a minority of households suffers from poor diversification and large losses.[221] Examining Swedish household portfolios, Calvet/Campbell/Sodini (2007) state that portfolios which exhibit high levels of idiosyncratic risk predominantly reveal concentrations in individual stocks while households with low levels of idiosyncratic risk mostly engage in mutual funds. Households in the middle of the idiosyncratic risk distribution prefer mutual funds and individual stocks which are more correlated with each other. The authors conclude that diversification is mainly obtained through mutual funds and that the relative share of risky financial assets invested in mutual funds is a better indication of diversification than the number of individual stocks.[222] However, it is unclear if the results on asset diversification of Swedish households apply to households in other countries as well (see RQ1).[223]

Empirical evidence shows that households who hold concentrated stock portfolios tend to keep the bulk of their financial wealth in safe financial assets and only allocate a minor part into risky financial assets so that potential losses from their risky investments only slightly affect their welfare.[224] Households with such a portfolio composition are typically less wealthy and less educated.[225] A possible reason why these households only invest a small portfolio fraction of their wealth into risk-bearing assets is that they are aware of their limited abilities regarding

[219] See e.g. Campbell (2006); Guiso/Sodini (2013), p. 1460.
[220] The quotes around "safe" indicate that the respective investments are only relatively safe compared to the other assets and that they are not riskless in a neoclassical sense in which default is not considered. For better readability, the quotes are left out in the following.
[221] See Calvet/Campbell/Sodini (2007); von Gaudecker (2015).
[222] See Calvet/Campbell/Sodini (2007).
[223] Regarding different points of selectivity in the Swedish data of Calvet/Campbell/Sodini (2007) set see, e.g., Campbell (2006); Christelis/Georgarakos/Haliassos (2013); von Gaudecker (2015).
[224] See Calvet/Campbell/Sodini (2007); Guiso/Sodini (2013), pp. 1462ff.; von Gaudecker (2015).
[225] See Goetzmann/Kumar (2008); Calvet/Campbell/Sodini (2007); (2009).

financial investments.[226] A possible explanation why these households invest in a small number of stocks nonetheless is that they reveal preferences for selecting stocks with highly skewed expected outcome and lottery-like characteristics.[227] The results above indicate that considering safe financial assets and mutual funds is essential for evaluating asset diversification as well as the risk and return of household portfolios.

Another characteristic phenomenon regarding households' asset diversification is the so-called home bias.[228] Home bias describes the preference of households to hold higher portions of domestic assets than predicted by the neoclassical market portfolio.[229] Empirical studies additionally report a local bias according to which households prefer stocks of companies that are close to their residence.[230] While many studies focus on home bias of households' stock holdings,[231] Tesar/Werner (1995), Oehler et al. (2007), and Oehler/Rummer/Wendt (2008) provide evidence that the home bias phenomenon exists among bonds and mutual funds as well. In either case, overweighting domestic or local assets and ignoring the benefits of diversifying internationally can have negative consequences for household portfolios in terms of higher risk and lower return.[232]

Over the past decades, correlations across international stock[233] and bond markets[234] have increased. In addition, degrees of firm-level internationalization have grown across several developed countries which indicates that investing in domestic blue-chip or mid-cap indices already provides high levels of internationalization.[235] This diminishes the importance of the home bias phenomenon and potential negative consequences on risk and return of household portfolios to some extent. Nevertheless, evidence suggests that households can still obtain benefits from international diversification.[236]

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226 See Polkovnichenko (2005); Calvet/Campbell/Sodini (2007); (2009).

227 See Mitton/Vorkink (2007); Goetzmann/Kumar (2008); Kumar (2009); Oehler/Schneider (2019); (2020). According to Kumar (2009), lottery stocks show high idiosyncratic volatility, high idiosyncratic skewness, and a low stock price.

228 See French/Poterba (1991); Cooper/Kaplanis (1994); Tesar/Werner (1995); Lewis (1999); Jeske (2001); Oehler (2001a); (2002), pp. 865f.; Oehler et al. (2007); Oehler/Rummer/Wendt (2008); Graham/Harvey/Huang (2009).

229 See Oehler/Rummer/Wendt (2008).

230 See Coval/Moskowitz (1999); Grinblatt/Keloharju (2001a); Zhu (2002); Baltzer/Stolper/Walter (2015).

231 See Cooper/Sercu/Vanpée (2013) for an overview regarding the equity home bias.

232 See Grubel (1968); Levy/Sarnat (1970); Solnik (1974); Levy/Lerman (1988); French/Poterba (1991); Errunza/Hogan/Hung (1999).

233 See Morana/Beltratti (2008); Baele/Inghelbrecht (2009); Bekaert/Hodrick/Zhang (2009); Christoffersen et al. (2012); Eiling/Gerard (2015). See also Chen (2018) regarding comovements of regional stock markets.

234 See Ilmanen (1995); Barr/Priestley (2004); Lamedica/Reno (2007); Engsted/Tanggaard (2007).

235 See Oehler/Wendt/Horn (2016); (2017); Oehler/Wendt (2016b).

236 See Goetzmann/Li/Rouwenhorst (2005); Driessen/Laeven (2007); Chiou/Lee/Chang (2009); Elton et al. (2014), pp. 256ff.

Explanations for the home or local bias include that transaction costs, institutional barriers for trading securities or gathering information might prevent households from investing abroad.[237] Among other reasons, increasing market comovements, high volume of cross-border capital flows and increasing digitalization suggest that transaction costs represent a less important factor for inducing home bias.[238] Different explanations, in turn, argue that households assuming or perceiving to have an informational advantage regarding domestic securities or a disadvantage regarding foreign securities are more likely to engage in domestic securities and ignore potential benefits from international diversification.[239] According to Graham/Harvey/Huang (2009), households with low perceived competence are less likely to invest in foreign assets. In addition, domestic investors tend to be more optimistic about the returns on domestic markets than foreign investors.[240] Baltzer/Stolper/Walter (2015) provide empirical support that, particularly in periods of increased market uncertainty, ambiguity-averse households tend to escape into familiar, local securities. Hence, the latter attempts to explain households' preferences to overinvest in domestic or local assets can largely be attributed to behavioral finance's concept of bounded rationality.[241]

The characteristic features of households' asset diversification imply that, on the one hand, households exhibit several investment biases that may make them feel safe and comfortable. On the other hand, these biases can severely harm the outcome to their investment decisions.[242] For the subsequent analyses, the findings outlined in this chapter suggest involving multiple asset classes of household portfolios (particularly safe financial assets and mutual funds) and applying household security holding data that closely reflects the actual security holdings of the underlying household population (e.g. to capture a potential home bias in security holdings).

3.3 XTFs as Component of Household Portfolios

In portfolio choice and asset diversification, an approach of households to reduce information asymmetries and address their high demand for information[243] could be to seek financial advice from a professional financial advisor. Considering empirical evidence, the benefit from

[237] See Rowland (1999); Glassman/Riddick (2001); Chan/Covrig/Ng (2005). See also Dahlquist et al. (2003) regarding the influence of corporate governance on home biased portfolios of investors.
[238] See French/Poterba (1991); Cooper/Kaplanis (1994); Tesar/Werner (1995); Lewis (1999).
[239] See Gehrig (1993); Brennan/Cao (1997); Oehler et al. (2007); Oehler/Rummer/Wendt (2008). In this context, see also Baars/Goedde-Menke (2019) regarding the concept of knowledge illusion.
[240] See Shiller/Kon-Ya/Tsutsui (1991); French/Poterba (1991).
[241] See Oehler et al. (2007); Oehler/Rummer/Wendt (2008); Baltzer/Stolper/Walter (2015).
[242] See Barber/Odean (2013), p. 1563.
[243] See Oehler (2011); (2015a); (2017a); Oehler/Horn/Wendt (2016c); (2017b).

financial advice in this regard, however, seems questionable. On the one hand, involving financial advice can increase the level of portfolio diversification compared to households which make autonomous financial decisions.[244] On the other hand, delegating financial decisions causes costs (e.g. for monitoring, commissions and fees) and gives rise to information asymmetries between typically better informed advisors and typically less informed clients. This can motivate financial advisors to take advantage of their clients.[245] Correspondingly, empirical research documents higher trading volume and higher fee expenses among portfolios that employ financial advice.[246] Compared to self-managed portfolios, employing financial advice largely does not lead to higher investment outcomes (net of costs).[247] According to von Gaudecker (2015), investment outcomes of portfolios that rely on financial advisors hardly vary from the investment outcomes when the advice stems from a household's private network.

Nonetheless, financial advisors exhibit a substantial impact on their clients' asset allocation. However, their recommendations often provide limited customization. Besides this, advisors who recommend portfolios that consist of fewer funds achieve better outcomes than those who recommend complex portfolios.[248] This might be related to the compensation structure of financial advisors which particularly provides incentives for advisors to recommend mutual funds with high fees.[249] Considering that the expenses for active mutual funds (e.g. for management fees, front-, and end loads) are usually higher than those for passive mutual funds,

[244] See Bluethgen et al. (2008); Kramer (2012); von Gaudecker (2015).
[245] See Inderst/Ottaviani (2009); Hackethal/Haliassos/Jappelli (2012); Inderst/Ottaviani (2012); Egan (2019).
[246] See Bluethgen/Meyer/Hackethal (2008); Hackethal/Haliassos/Jappelli (2012).
[247] See Kramer (2012); Hackethal/Haliassos/Jappelli (2012); Foerster et al. (2017). In contrast, a few studies find that financial advisors can indeed add value to clients' portfolios (see e.g. Zur/Itzhak (2001)). With the rise of the digital world and a proceeding digitalization, two further portfolio management services, social trading and robo-advisors, emerged. Social trading platforms provide a portfolio management service which allows retail investors, for example, to invest in wikifolio certificates. Oehler/Horn/Wendt (2016a) find, however, that the latter are on average unable to outperform the market. Robo-advisors offer an automated service to retail investors that helps them – under consideration of their perceived risk tolerance – to establish investment portfolios which usually consist of stock- and bond-ETFs. Typically the service of robo-advisors also includes an automated rebalancing of the established portfolios to keep the relative weights of the employed asset classes and the level of portfolio risk constant over time (see Horn/Oehler (2020); Oehler/Horn/Wendt (2020a)). Concerning retail investors' individual characteristics that influence their decision to employ a robo-advisor, see Oehler/Horn/Wendt (2020a). With regard to trading turnover and management costs of robo-advisors, the success of such an automated portfolio management service, however, can be doubted (see e.g. Horn/Oehler (2020)).
[248] See Foerster et al. (2017). The author further points out that advisors who advise a large number of clients with small portfolio sizes achieve worse outcomes than those with a few large clients.
[249] See Hackethal/Haliassos/Jappelli (2012); Kramer (2012); Christoffersen/Evans/Musto (2013); von Gaudecker (2015); Chalmers/Reuter (2015).

financial advisors are more likely to recommend active than passive mutual funds like index funds, ETFs and XTFs[250].[251]

The findings above suggest that active mutual funds are more common in household portfolios than XTFs (which are a subsample of ETFs). The latter is supported by further indications of empirical research. While only 14 percent of the worldwide mutual fund assets account for ETFs by 2018, the largest target region of the worldwide ETF assets is North America which accounts for 57 percent.[252] In the United States, passive mutual funds (ETFs and index funds) account for 21 percent of active mutual fund assets by the end of 2011. Among passive mutual funds, ETFs account for 73 percent and index funds for 27 percent. At the same time in Germany, passive mutual funds make up 20 percent of active mutual fund assets, whereas among passive mutual funds, ETFs represent 86 percent and index funds 14 percent of the fund assets.[253] This shows the dominant role of active mutual funds compared to passive mutual funds, as well as the dominant role of ETFs compared to index funds.[254] Over the past decade, assets under management of ETFs sharply increased relative to (active) mutual funds.[255] ETFs investing in global asset portfolios make up 14 percent of the worldwide ETF net assets as of 2018.[256] At the Exchange Electronic Trading (XETRA) exchange in Germany, the third largest trading volume in 2018 was induced by XTFs replicating the Morgan Stanley Capital

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[250] In a strict sense, index funds and ETFs are also mutual funds. This thesis, however, follows the approach of Deutsche Bundesbank (2018) by distinguishing them from active mutual funds. Index funds and ETFs differ in the sense that ETFs can be traded more flexible as they are continuously listed on exchanges while index funds are more constructed like mutual funds and can usually bought and sold only a few times per day via the investment company (which may include front- and end-loads). Besides passive ETFs, there are also active ETFs. However, the latter only represent a small fraction of ETFs. At the Exchange Electronic Trading (XETRA), which executes 89 percent of the ETF trading volume in Germany, only 44 active ETFs could be traded in 2019, while at the same time 1,461 passive ETFs (thereof: 738 stock ETFs, 400 bond ETFs, 25 commodity ETFs, and 298 other ETFs) were tradable (see Deutsche Börse AG (2019a)). Given the passive nature of XTFs which is of major concern in this thesis as well as the minor importance of active ETFs, this thesis abstracts from active ETFs unless otherwise specified, and refers to passive ETFs as "ETFs" for better readability.
Reasons why total expenses for ETFs are lower than for active mutual funds include that the creation process of ETF shares is more cost-efficient, that ETFs do not incur costs for active management, transfer agent fees, and front- or end-loads since ETF shares are mostly traded via exchanges (see Deutsche Bundesbank (2018)).

[251] See Bluethgen/Meyer/Hackethal (2008); Kommalpha (2009); Del Guericio/Reuter (2014). Regarding differences in fee expenses between active and passive mutual funds see also Malkiel (2013).

[252] See Deutsche Bundesbank (2018). The remaining shares of ETF target regions are 19 percent for Asia, 14 percent for Global, 9 percent for Europe, and 1 percent for other regions.

[253] See Bhattacharya et al. (2017). See also Kommalpha (2009) who include further index-linked financial instruments in their comparison.

[254] Given the major importance of ETFs over index funds, this thesis follows previous financial literature (see e.g. Bhattacharya et al. (2017)) and focuses only on ETFs.

[255] See Malkiel (2013); Deutsche Bundesbank (2018); Investment Company Institute (2018a); (2019). Between 2008 and 2018, for instance, the share of active mutual funds on total mutual fund assets decreased from 82 to 64 percent in the United States, while the share index funds and passive ETFs increased from ten and eight percent in 2008 to 18 percent each in 2018 (see Investment Company Institute (2019)).

[256] See Deutsche Bundesbank (2018). The remaining shares of ETF target regions are 19 percent for Asia, 57 percent for North America, 9 percent for Europe, and 1 percent for other regions.

International (MSCI) World stock market index. The largest trading volume was produced by ETFs replicating the major German stock index DAX.[257]

Empirical evidence on how far XTFs and the features pointed out above are reflected in household portfolios are scarce. As approximation, representative surveys among German bank clients indicate that the ownership rate of ETFs among the respondents is below ten percent.[258] Since financial advisors tend to recommend high-fee financial products rather than low-cost ETFs, ETF investors are more likely to be self-directed investors.[259] Compared to non-ETF investors and investors of actively managed mutual funds, respectively, ETF investors tend to be slightly younger, have a higher financial knowledge, and own a higher value and a greater variety of financial assets.[260] More specific, D'Hondt/Elhichou/Petitjean (2020) point out that these features also apply to retail XTF investors. The authors further find that retail XTF investors exhibit a longer investment horizon, a longer trading experience, hold a more diversified stock portfolio and trade these stocks more frequently.[261]

Among German retail investors, by far the largest share of ETF assets under management are invested in stock ETFs (over 90 percent). While German retail investors place the largest amount of their monthly ETF investments into ETFs which replicate the major German stock market index DAX, there is also a XTF among their top ten benchmark indices that replicates a broad, internationally diversified market index – the MSCI World stock market index.[262] Nevertheless, retail investors largely seem to (mis-)use ETF instruments for rather active investment strategies and do not improve their investment outcome compared to holding a well-diversified low-cost XTF on average due to poor ETF selection and timing.[263]

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[257] See Deutsche Börse AG (2019a). Similarly, in the United States most passive mutual fund assets were invested in domestic equity funds by the end of 2018 as 62 percent of passive mutual fund assets went into domestic equity funds (see Investment Company Institute (2019)). Besides the importance of XTFs, recent developments in the ETF market include (see Morningstar (2019)): strategic beta ETFs, thematic ETFs (see e.g. Methling/Nitzsch (2019)), and Environmental and Social Governance ETFs.

[258] See forsa (2016); Postbank AG (2018); Mai/Kaya (2019). Bhattacharya et al. (2017) find that 15 percent of the clients at a German retail broker traded at least one ETF between 2005 and 2010. In the United States, between about four and, more recently, eight percent of households own ETFs (see Investment Company Institute (2014); (2015); (2016a); (2017a); (2018a); (2019); (2020)).

[259] See Mai/Kaya (2019). This may also provide an explanation why ETF ownership rates in Bhattacharya et al. (2017) are higher compared to those reported by Postbank AG (2018) and Mai/Kaya (2019) since the former study excludes retail investor accounts that rely on financial advice and only include self-managed accounts.

[260] See Müller/Weber (2010); Bhattacharya et al. (2017); Investment Company Institute (2014); (2015); (2016a); (2017a); (2018a); (2019); (2020); D'Hondt/Elhichou/Petitjean (2020).

[261] The authors refer to XTFs in terms of "P-ETFs" (passive ETFs).

[262] See Bhattacharya et al. (2017).

[263] See Clifford/Fulkerson/Jordan (2014); Bhattacharya et al. (2017). The analysis of the latter study, however, is based on broker accounts which do not necessarily reflect households' entire investment portfolio (see chapter 3.2). Da Dalt et al. (2019) show that when purchasing a low-cost, passively managed ETF, Finnish retail investors are less likely to be contrarians and rather chase recent positive momentum than when purchasing common stocks.

Financial research outlined above suggests that active mutual funds seem to be more common in household portfolios than XTFs so far. In this regard, the question emerges whether active mutual funds can achieve higher investment outcomes than XTFs. Evidence from empirical studies shows large agreement on this question. Although some studies find timing skills of active mutual fund managers in the short-term,[264] active mutual funds are on average unable to (persistently) outperform a corresponding passive benchmark portfolio or low-cost ETF after expenses.[265] Moreover, even if some active mutual funds were able to persistently outperform their corresponding benchmark, the next question from a household's perspective would then be whether households could identify this group of active mutual funds and, in addition, if they could ascertain which of them will outperform in the future.[266] Therefore, academic studies widely conclude that the empirical results on active mutual fund performance "provide overwhelming support for low-cost indexing as an optimal strategy for individual investors"[267].[268]

The empirical findings presented above indicate that although households' investments in XTFs increased over the past decade, most households do not hold XTFs so far. The (smaller) group of households who currently employs XTFs seems to be younger, more experienced, wealthier, and exhibits longer investment horizons than households who do not invest in XTFs. The restrained distribution of XTFs across household portfolios can be associated with incentives of financial advisors to direct households' investments towards actively managed mutual funds rather than XTFs. Thereby, active mutual funds seem to induce higher costs and perform worse compared to XTFs on average.

[264] See e.g. Busse (1999); Bollen/Busse (2001); Jiang/Yao/Yu (2007).
[265] See e.g. Jensen (1968); Malkiel (1995); Malkiel (2003a); (2013); Carhart (1997); Carhart et al. (2002); Barras/Scaillet/Wermers (2010); Busse/Goyal/Wahal (2010); Fama/French (2010); Oehler et al. (2018a); Elton/Gruber/de Souza (2019). See Elton/Gruber (2013), pp. 1038ff.; Elton et al. (2014), pp. 682ff. for an overview. Oehler/Wendt (2007) also point out that governance conflicts among fund managers may impair mutual fund performance.
[266] See Elton/Gruber (2013), pp. 1042; Elton et al. (2014), pp. 683.
[267] See Malkiel (2013), p. 102.
[268] See e.g. Malkiel (2003a); Malkiel (2013); French (2008); Elton/Gruber/de Souza (2019).

4 Conceptual Foundations for the Empirical Analyses

4.1 Portfolio Selection Frameworks

4.1.1 Mean-Variance Framework

The principles of portfolio selection in neoclassical finance theory trace back to the "expected returns–variance of returns rule" of Markowitz (1952), p. 77. According to this rule, investors are rational deciders which exclusively consider risk and return in terms of the variance of returns (or likewise the standard deviation of returns) as well as the expected returns around the mean for selecting securities and for measuring the performance of a portfolio. This two-parameter framework is referred to as Mean-Variance (MV-) Framework.[269]

Taking risk in addition to return into account prevents investors from investing all the funds in the portfolio with the maximum expected return since "[t]he portfolio with maximum expected return is not necessarily the one with minimum variance."[270] Markowitz (1952); (1959) also realizes "that security returns are highly correlated, but not perfectly correlated, [which] implies that diversification can reduce risk but not eliminate it."[271] Thus, the rate at which investors can increase expected return while accepting more variance, or reduce variance while accepting less expected return, highly depends on the correlation between the involved securities.[272] Diversifying, which is pursued by this approach, means constructing a portfolio in such a way that portfolio risk is reduced without sacrificing return (and vice versa).[273]

Investors are assumed to prefer high (over low) returns and low (over high) risk. Therefore, they would evaluate a portfolio with less risk and higher return as superior compared to another portfolio which reveals higher risk and less return than the former portfolio.[274] Portfolios which are dominated by another portfolio in this way are referred to as "inefficient" while the remaining portfolios, i.e. portfolios that exhibit the maximum expected return for a given level of risk, are referred to as "efficient".[275] Determining the efficient portfolio for each level of risk

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[269] See Markowitz (1952); (1959), pp. 5ff.; Fabozzi/Gupta/Markowitz (2009b), pp. 15ff.; Elton et al. (2014), pp. 42ff. While the CAPM is mainly concerned with the effects of financial decisions of all market participants on security prices, the MV-framework focuses on the selection of portfolios according to individually preferred levels of risk (see Fabozzi/Gupta/Markowitz (2009b), p. 15).

[270] See Markowitz (1952), p. 79.

[271] Markowitz (1959), p. 5. There, he further states that "[i]f correlation among security returns were "perfect"–if returns on all securities moved up and down together in perfect unison–diversification could do nothing to eliminate risk."

[272] See Markowitz (1952); (1959), pp. 5ff.

[273] See Fabozzi/Gupta/Markowitz (2009b), pp. 26f.

[274] See Markowitz (1959), p. 6.

[275] See Markowitz (1959), pp. 6f.; Ackert (2014), pp. 27ff.; Elton et al. (2014), pp. 65ff.

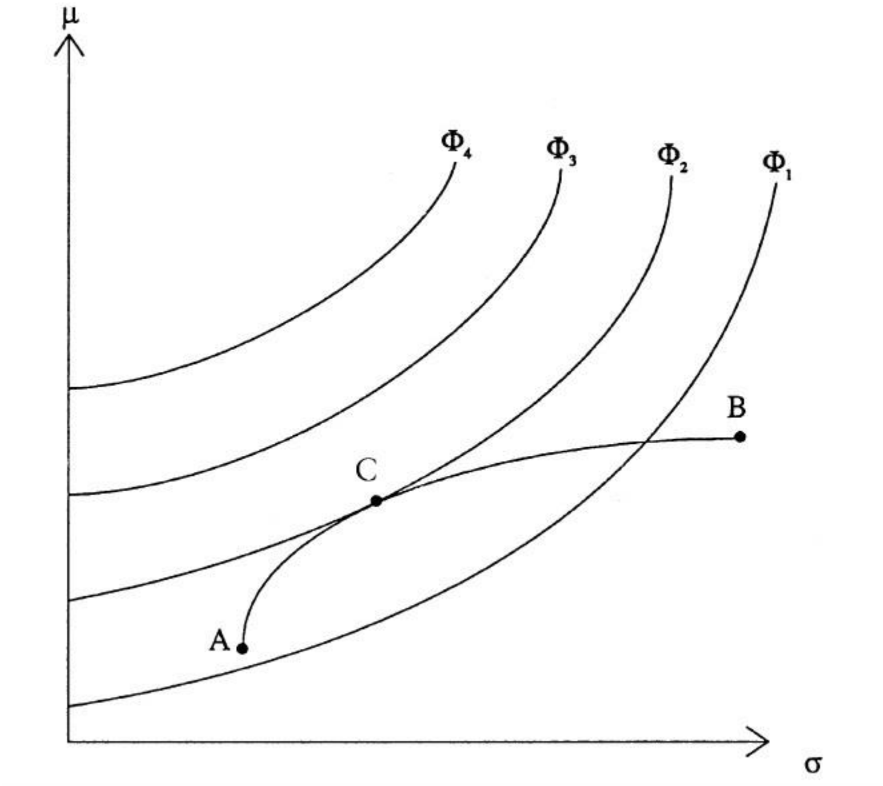
yields an infinite set of efficient mean-variance combinations which delineates the so-called efficient frontier.[276]

In a MV-framework, the goal of investors is to select – for the investment horizon of one specific period – the (one) portfolio from the set of efficient mean-variance efficient portfolios that maximizes the expected return at the preferred level of risk, or minimizes risk at their preferred level of return, respectively. This (one) portfolio represents an investor's optimal portfolio.[277] This optimal portfolio is individual for each investor since each investor receives a different utility from a certain risk-return trade-off. Figure 2 exemplary illustrates the determination of an investor's optimal portfolio in a diagram. The horizontal axis of the diagram represents risk (σ) and the vertical axis the expected mean returns (μ) of a portfolio. Utility curves (Φ_1, Φ_2, Φ_3, Φ_4) indicate the utility that an investor receives from different risk-return trade-offs. The investor's optimal portfolio (and thus the investor's maximum utility) is determined in point (C) where the investor's utility curve is tangent to the efficient frontier (AB). The closer the tangent point to the upper left corner of the diagram, the larger the utility of an investor ($\Phi_1 < \Phi_2 < \Phi_3 < \Phi_4$).[278] Risk is expressed in terms of the standard deviation since the standard deviation represents, rather than the variance of returns, the intuitively meaningful measure of risk.[279]

The difficulty of determining an investor's optimal portfolio accurately in practice is that real-world investors might be unable to precisely describe their utility function which is used to ascertain utility curves. However, "[i]t is unnecessary and uneconomical to require an "exact" solution."[280] Letting investors evaluate whether the risk-return combination of certain portfolios from a set of efficient portfolios are, given their tolerance of risk, appropriate for them provides a natural procedure and good approximation to identify an investor's optimal portfolio.[281]

[276] See Fabozzi/Gupta/Markowitz (2009b), pp. 17ff.; Ackert (2014), p. 28; Elton et al. (2014), pp. 65ff.; Perridon/Rathgeber/Steiner (2017), pp. 278f.
[277] See Fabozzi/Gupta/Markowitz (2009b), pp. 17ff.; Ackert (2014), p. 28.
[278] See Fabozzi/Gupta/Markowitz (2009b), pp. 16ff., pp. 34ff.; Steiner/Bruns/Stöckl (2017), pp. 13f.; Perridon/Rathgeber/Steiner (2017), pp. 284f.
[279] See Markowitz (1999).
[280] Markowitz (1959), p. 280.
[281] See Markowitz (1959), pp. 279ff.; (1991); Levy/Markowitz (1979); Fabozzi/Gupta/Markowitz (2009b), p. 36.

Figure 2: Determination of an investor's optimal portfolio in a MV-framework.



Source: Perridon et al. (2017), p. 285.

4.1.2 Portfolio Selection under Loss-aversion

4.1.2.1 Behavioral Portfolio Theory

A MV-framework might provide sound portfolio selection rules for rational deciders. However, households' financial decisions are largely inconsistent with rational decision-making and the concept of the homo oeconomicus.[282] Behavioral finance and economics emphasizes that households are much more likely to be loss-averse in terms of Prospect Theory.[283] This behavior is not reflected in a MV-framework which limits its applicability in practice. A framework that does take such behavior into account is the Behavioral Portfolio Theory (BPT) which is a positive portfolio theory that was introduced by Shefrin/Statman (2000).[284] BPT is based on Roy (1952)'s safety-first theory, SP/A theory of Lopes (1987), and a mental accounting structure, a feature of Prospect Theory by Kahneman/Tversky (1979). Mental accounting is

[282] See Oehler (1995), pp. 23ff.; (2004a); (2011); (2012e); (2013a); (2013d); Statman (2014); Thaler (2016); Oehler/Wendt (2017).
[283] See chapter 2.3.
[284] See Shefrin/Statman (2000); Das et al. (2010); Rengifo/Trendafilov/Trifan (2014), pp. 421ff.

used to incorporate the tendency of investors to make financial decisions based on gains and losses relative to a reference point which represents a basis of loss-aversion.[285]

Unlike the neoclassical prediction that investors consider their portfolio as a whole, BPT assumes that investors segregate their portfolio into several distinct mental accounts by which investors simplify financial decisions[286] and that investors act as if they overlook covariances between mental accounts[287]. Each mental account is matched with a different goal. These goals are associated with an aspiration level which generally ranges between low and high aspiration. Shefrin/Statman (2000) refer to avoiding poverty as low aspiration and a shot at riches as high aspiration. In dependence of the aspiration level, investors prioritize mental accounts in that low aspiration goals are assigned with high priority and high aspiration goals with low priority. In this way, investors resemble portfolios as layered pyramids in which current wealth is divided into, e.g., a bottom layer which is established to avoid poverty and a top layer for a shot at riches. The layered pyramid structure further implicates that an investor will not allocate wealth into the top layer until the goal of the bottom layer is accomplished (e.g. a certain level of wealth to avoid poverty).[288]

Shefrin/Statman (2000) suggest investment grade bonds or a risk-free investment for investors with low aspiration levels and stocks or lottery tickets for investors with higher aspiration levels. An implication thereof is that, while household portfolios which do not hold risky financial assets at all or allocate only a small fraction of their wealth in a small number of stocks[289] are inconsistent with the CAPM, they are consistent with BPT.[290]

The accomplishment of a goal depends on whether the portfolio of the mental account reaches a certain threshold level of return. For portfolio construction, BPT investors consider the expected return of a mental account and evaluate risk according to the probability of failing to reach the threshold level of return. For each mental account, a set of portfolios can be ascertained of which each portfolio exhibits the lowest probability of failing to reach the threshold level of return for a given expected return which, in turn, delineates an account-

[285] Shefrin/Statman (2000) present two versions of the BPT, a single-mental account version and a multiple mental account version. The mental accounting structure is used to expand the former version and model the latter.
[286] Covariances and joint probability distributions seem to impose difficulties on mental processing. Dividing joint probability distributions into mental accounts implicates a simplification of choices for households (see Tversky/Kahneman (1986)).
[287] See Kroll/Levy/Rapoport (1988); Jorion (1994).
[288] See Shefrin/Statman (2000); Das et al. (2010); Rengifo/Trendafilov/Trifan (2014), pp. 430ff.
[289] See chapter 3.1 and 3.2.
[290] See Shefrin/Statman (2000); Das et al. (2010).

specific efficient frontier. Thereof, investors select the portfolio that reflects their preferred trade-off between the latter two parameters best.[291]

Assuming the probability of failing to reach a threshold level of return as measure of risk constitutes a main difference between BPT and a MV-framework and implies a different understanding of portfolio efficiency.[292] Shefrin/Statman (2000) state that efficient portfolios according to BPT generally do not coincide with efficient portfolios according to a MV-framework. However, if the trade-off between risk and return in BPT embodies a value-at-risk type constraint and short-selling is allowed, portfolios are efficient according to both BPT and a MV-framework.[293] Alexander/Baptista/Yan (2017) compare both frameworks under consideration of estimation risk with regard to risk and return. They find that optimal portfolios selected with mental accounts outperform those selected in a MV-framework. Using stock price data from the United States, Pfiffelmann/Roger/Bourachnikova (2016) empirically compare asset allocations generated according to BPT and a MV-framework. Although the authors find in more than 70 percent of the cases that portfolios which are optimal according to BPT are also MV-efficient, they identify differences in the portfolio construction and conclude that both frameworks cannot be used interchangeably.

Since BPT assumes that certain assets are evaluated jointly while involving a risk measure that is supposed to reflect households' interpretation of risk more closely, it offers a generally useful approach with regard to RQ2. Studies reporting that a BPT-based- and a MV-framework might come to differing results, which is of interest regarding RQ2, suggests considering a MV- and a BPT-based framework. The next chapter presents a framework that is based on BPT and seems to be more suitable for the subsequent empirical analyses with regard to the employed household portfolios.

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[291] See Das et al. (2010). Oehler/Horn (2020) further investigate the relation between households‘ wealth and relative risk aversion in a BPT framework and Merton's consumption and portfolio choice model. The authors show that BPT provides a better fit than the consumption and portfolio choice model to explain households' financial risk taking. See also Oehler (1998b) regarding the question whether private investors employ increasing or decreasing relative risk aversion.

[292] See Rengifo/Trendafilov/Trifan (2014), pp. 430ff.; Statman (2017), p. 176. Holzmeister et al. (2019) conclude that in many countries the probability to experience losses is a more important risk measure compared to the variance of returns.

[293] See Das et al. (2010). Including short-selling constraints imposes only minor differences between portfolios of BPT and the MV-framework. Levy/Giorgi/Hens (2012) show that, although Prospect Theory violates some assumptions like the expected utility framework underlying the MV-framework and the CAPM, the MV-framework is not in contradiction to Prospect Theory and the CAPM is also intact in the framework of Prospect Theory.

4.1.2.2 Speculation-Portfolio of German Households

According to the multi-layer portfolio framework introduced by Oehler (2015c), households compile portfolios as layered pyramids in terms of a multiple mental account version of BPT. The approach categorizes households' financial assets into one of three portfolio layers – the basis-, additional-, or speculation-portfolio. The categorization depends on the goal that households want to achieve with a financial asset and allows comparing household portfolios among each other. The layers are arranged in decreasing order according to household’s financial needs[294]. Each layer represents a certain financial need which is specified by financial goals. Households can invest in the next upper layer as soon as the financial needs and goals of the previous layer are satisfied.[295]

While the bottom layer (i.e. the basis-portfolio) contains basic financial needs to prevent households from existence-threatening financial risks, investments in the middle layer (i.e. the additional-portfolio) aim to accomplish additional financial needs.[296] Investments in the top layer, the so-called speculation-portfolio, pursue the financial goal of speculation and further income and include the possibility of total loss. Speculation-portfolios involve households’ net wealth invested in cash accounts and further deposits, stocks (including stock funds), bonds (including bond funds), real estate funds, and other financial assets that primarily have an investment character (e.g. options, certificates).[297]

The speculation-portfolio offers a suitable framework for this thesis’ analyses for three main reasons. First, the speculation-portfolio contains a defined range of financial assets which allows an appropriate comparison of (sub-)portfolios among households. Second, XTFs can be categorized in the speculation-portfolio.[298] Thus, when deciding whether to invest in XTFs or

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[294] Regarding financial needs or likewise motives, see Oehler (1995), pp. 86ff.

[295] See Oehler (2015c); (2021f); Oehler/Horn/Wedlich (2018); Horn (2018), pp. 2f., pp. 49f.; Oehler/Horn (2019).

[296] Financial products which satisfy basic financial needs to prevent existence-threatening financial risks are, among others, liability and disability insurance, health care, or liquidity provisions. Additional financial needs can be covered by accident insurance or retirement provisions (see Oehler (2015c); (2021f); Oehler/Stellpflug (2015); Oehler et al. (2018b); Oehler/Horn/Wendt (2019)).

[297] See Oehler (2015c); (2021f); Oehler/Horn/Wedlich (2018); Horn (2018), pp. 49f.; Oehler/Horn (2019). Since the main motivation for households to invest in real assets like vehicles and own residence is often consumption and owning property instead of attaining investment returns (see Deutsche Bundesbank (2015); chapter 3.2), vehicles, real estate, and mortgage loans are not included in households’ speculation-portfolios within this thesis. In the context of the digital world, Cryptocurrencies (see Horn/Wendt (2021)) and Initial Coin Offerings (see Wendt/Horn (2021)) can also be categorized as investments in the speculation-portfolio.

[298] Depending on the financial needs and goals pursued with an investment in XTFs, households might also categorize XTFs in the additional-portfolio, e.g. when pursuing the goal of retirement provision with an investment in XTFs involving a specific threshold value for a certain point of time in the future (see Oehler (2016d); (2019); (2021f); Oehler et al. (2018b); Oehler/Horn/Wendt (2019)). This thesis analyzes investments in XTFs in terms of the financial goal of speculation and further income. This means that no specific threshold value is assigned with an investment in XTFs for a certain point of time in the future (see also chapter 3.2). Therefore, XTFs are categorized in the speculation-portfolio.

not, households likely include the performance of other financial assets of the speculation-portfolio (i.e. the same mental account) in their decision as they pursue the same goals with these assets.[299] In addition, combining assets which are jointly evaluated offers an appropriate frame for deriving a reference, or target return involved in the downside-risk measures. Third, the speculation-portfolio combines investments in financial assets which exhibit, rather than the assets in the basis- and additional-portfolio, frequent price fluctuations, continuous variability in risk and return, and incur the possibility of total loss.[300] Considering the investments in the speculation-portfolio is thus crucial when assuming loss-averse households which evaluate risk in terms of downside-risk measures, and for investigating the question whether employing XTFs in portfolios of such households leads to lower risk-return enhancements and a reluctance to invest in XTFs (see RQ2).

4.1.2.3 Mean-Downside-Risk Frameworks

The two parameters of portfolio selection, risk and return, are measured in most financial studies by the standard deviation (SD) of returns and the mean return. While the measurement of returns is less controversial,[301] there is more dispute about how households measure risk. In the context of loss-aversion, studies document that households evaluate risk in terms of several downside-risk measures,[302] which suggests considering the corresponding mean-downside-risk frameworks in the subsequent empirical analyses.

The SD assumes, among other things, normally distributed returns and does not involve skewness of returns. However, normally distributed returns are hardly a tenable assumption.[303] The asymmetrical nature of returns also becomes apparent by considering that securities like stocks and bonds can achieve unlimited gains but losses are limited to the invested amount of capital.[304] Furthermore, investors show preferences for asymmetric return distributions with

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[299] This is based on the tendency of households to consider assets with similar outcome features jointly (see Kahneman/Tversky, 1979; 1984; Tversky/Kahneman, 1981; Thaler, 1985; 1999), a behavioral feature that stems from the mental accounting structure and traces back to Prospect Theory (see Kahneman/Tversky, 1979; Thaler, 1999).

[300] See Horn (2018), p. 3.

[301] Since real-world investors are no clones of the homo oeconomicus, they may have different primary considerations for investing so that "[t]he appropriate definition of "return" may vary from investor to investor" (Markowitz (1959), p. 6). Some might, for instance, receive returns from satisfying non-monetary investment criteria like complying with ecological and socially responsible standards (see Oehler/Horn/Wendt (2018c); Oehler/Schalkowski/Wendt (2014)). Since these criteria are highly individual and hardly measurable across households, this thesis exclusively relies on returns in terms of cash flows.

[302] See e.g. Veld/Veld-Merkoulova (2008); Holzmeister et al. (2019).

[303] See Mandelbrot (1963); Fama (1965); Christie (1982); French/Schwert/Stambaugh (1987).

[304] See Grootveld/Hallerbach (1999).

positive skewness.[305] In order to raise the chance to obtain positively skewed returns, it can be attractive from an investor's perspective to abstain from expanding portfolio diversification.[306] Consequently, the preference for skewness can motivate households to refuse to invest into broad, internationally diversified XTFs.

As opposed to the SD which weights return variations around the mean equally, Prospect Theory by Kahneman/Tversky (1979) provides evidence that investors distinct between gains and losses relative to a specific reference point, or target return. Thereby, investors assign approximately twice the weight towards losses than towards gains which reflects loss-aversion.[307] An increased level of loss-aversion is associated with a lower probability that an investor participates in risky assets.[308] Studies argue that downside-risk, which means the returns that range below a specific target return of an investor, approximates investors' interpretation of risk more closely.[309] Downside-risk also seems to be a more intuitive interpretation of risk since only considering below-target-returns as an undesirable event is more comprehensible than the SD which also interprets returns above the mean as risk.

Several measures of downside-risk are documented among investors. Unser (2000) and Holzmeister et al. (2019) report that the Probability of Loss, i.e. LPM Zero (LPM0), represents individual investors' risk perception best. LPM0 describes the probability for the occurrence of below-target-returns. This measure is related to the safety-first theory by Roy (1952). The disaster level described in the safety-first theory is equivalent to the target return used in LPM0.

Veld/Veld-Merkoulova (2008) find that investors implicitly employ more than one risk measure and that investors' risk perception directly influences their selection of risky investments. The equivalent to the variance and the SD in a MV-framework are, in a mean-downside-risk framework, the semi-variance and the square root thereof, i.e. the semi-standard deviation or LPM Two ($\sqrt{\text{LPM2}}$). While bond-investors rather focus on LPM0, semi-variance is more often applied by stock-investors. Investors who care more about the underperformance relative to the market return than the initial price rather employ the Expected Value of Loss, i.e. the LPM One (LPM1). LPM1 denotes the probability of a below-target-return multiplied with the return

305 See Arditti (1967); Barberis/Huang (2008); Kumar (2009).
306 See Simkowitz/Beedles (1978); Conine/Tamarkin (1981); Hueng/Yau (2006); Mitton/Vorkink (2007); Kim (2015).
307 See Kahneman/Knetsch/Thaler (1990); Tversky/Kahneman (1992); Benartzi/Thaler (1995).
308 See Dimmock/Kouwenberg (2010).
309 See De Bondt (1998); Bertsimas/Lauprete/Samarov (2004); Holzmeister et al. (2019).

deviation from the target return. Veld/Veld-Merkoulova (2008) point out that the semi-variance most often represents investors' interpretation of risk.

The $\sqrt{\text{LPM2}}$ was, like the SD, proposed by Markowitz.[310] Both the SD and $\sqrt{\text{LPM2}}$ assume the same degree of risk aversion which allows comparing risk determined by both risk measures. The SD can be interpreted as a special case of $\sqrt{\text{LPM2}}$.[311] On the one hand, using $\sqrt{\text{LPM2}}$ would be equivalent to using SD if the underlying returns were symmetrically distributed and the target return of $\sqrt{\text{LPM2}}$ is identical to the portfolio's mean return.[312] On the other hand, both measures differ if the underlying returns are asymmetrically distributed and the choice of a household's target return does not correspond to the portfolio mean return.[313] Regarding the question which risk measure to employ first in the subsequent empirical analyses, Markowitz (1959) points out: "Clearly there are pros and cons on each side. The proper procedure, it seems to me, is to start with analyses based on variance. Analyses based on semi-variance, and those based on still other criteria […] can be considered after experience is gained with simpler measures."[314] The first empirical analysis (see chapter 5) accordingly starts by measuring risk by the SD. The subsequent analyses (see chapters 6 and 7) additionally employ downside-risk measures.

The LPM0, LPM1, and $\sqrt{\text{LPM2}}$ represent well-documented downside-risk measures and can be subsumed under the general notation of the LPMs.[315] The general LPM notation describes a basic mathematical expression that allows specifying the LPM0, LPM1 and $\sqrt{\text{LPM2}}$. Unser (2000), Veld/Veld-Merkoulova (2008), and Holzmeister et al. (2019) state that downside-risk measures better reflect investors' interpretation of risk than the variance or likewise the SD of returns, which is relevant regarding the investigation of RQ2. Correspondingly, this thesis controls for the LPM0, LPM1, and $\sqrt{\text{LPM2}}$ and includes, in addition to a MV-framework, a mean-LPM0 (M-LPM0)-, a mean-LPM1 (M-LPM1)-, and a mean-$\sqrt{\text{LPM2}}$ (M-LPM2)-framework.

Another risk measure which evaluates risk in terms of downside-risk is the Maximum Drawdown (MDD). The MDD is defined as the performance loss, measured from a previous peak or reference point.[316] The MDD measures risk in terms of returns. MDDs might therefore

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310 See Markowitz (1959), pp. 188ff.
311 See Harlow/Rao (1989); Harlow (1991).
312 See Harlow (1991).
313 See Ang/Chua (1979); Jarrow/Zhao (2006).
314 Markowitz (1959), p. 194.
315 See Bawa (1975); Fishburn (1977).
316 See Bacon (2008), p. 88; Bradford/Siliski (2016).

be well-understandable for households. Since the MDD is often published by financial service providers to investors, households might involve the MDD in their investment decisions. Furthermore, the MDD is suitable for risk evaluations against a target, or benchmark.[317] As opposed to LPM-based downside-risk measures, MDDs can cover different time periods.[318] Risk-return enhancements according to MDDs therefore cannot be compared directly with those of the LPM-based downside-risk measures. Nevertheless, MDDs allow controlling for a different downside-risk measure that might be applied by households. Therefore, the MDD is used as robustness measure for ascertaining possible enhancements from XTFs.

As target return from which households measure below-target-returns or downside-risk, financial research documents that households usually apply the initial price of an investment, the risk-free rate of return, or a corresponding market return.[319] Regarding this, Veld/Veld-Merkoulova (2008) note that market returns represent the most important target for households. As broad market returns are replicated by XTFs, they represent the reference or target to which household portfolios are compared in the subsequent empirical analyses. When assuming the returns of XTFs as target returns, downside-risk ("below-XTF-returns") expresses the opportunity costs that households incur because of holding their current portfolio instead of a portfolio of XTFs. In this context, it is important to notice that household portfolios might also outperform XTFs. Furthermore, employing XTFs to derive target returns allows conclusions about possible enhancements in risk and return and is therefore consistent with the research goals of this thesis.

4.1.3 Portfolio Selection over the Life Cycle

Portfolio selection in a MV-framework assumes that all households "have a common one-period investment horizon."[320] However, real-world households have to make numerous financial decisions over the life cycle. Depending on the phase in life in which a household is currently located, the relevance of an investment in XTFs may vary. A widespread recommendation of the financial industry is to invest considerable amounts of wealth in stocks at early ages and reduce the amount when households are getting older.[321]

[317] See Bradford/Siliski (2016).
[318] See Bacon (2008), p. 88.
[319] See Unser (2000); Veld/Veld-Merkoulova (2008).
[320] Fabozzi/Gupta/Markowitz (2009b), p. 30.
[321] See Guiso/Sodini (2013), p. 1479. Likewise, a common rule of thumb states that the share of wealth invested in stocks should be 100 minus the age of the investor. See also Howard/Yazdipour (2014), pp. 286f. for an example on life cycle financial planning.

In contrast to this, early models on portfolio selection over the life cycle presume that all households should participate in the stock market and keep the share of risky assets in their portfolio constant at all ages.[322] These models, however, are based on restrictive assumptions and are in contrast with empirical findings on households' actual portfolio rebalancing over the life cycle. Empirical evidence reveals that, first, instead of stock market participation at all ages, households' stock market participation tends to be constrained and exhibits a hump-shaped pattern over the life cycle. Second, with increasing age and conditional on owning risky assets, households' portfolio share invested in risky assets like stocks and mutual funds tends to vary little up to moderately away from risky assets.[323]

More detailed, Fagereng/Gottlieb/Guiso (2017) show that at early stages in life, households tend to enter the stock market, accumulate financial assets, and allocate a relatively large percentage of their financial wealth into stocks. The authors further find that as soon as households approach retirement, they tend to reduce the share of risky assets and exit the stock market around the date of retirement. Investing in XTFs increases the share of financial wealth allocated in risky financial assets. Consequently, employing XTFs as examined in this thesis' analyses seems to be most relevant for households at early stages in life[324] and, to a lesser extent, for households which intend to maintain their risky asset share as they age. More general, the results of the subsequent analyses are particularly relevant for households which reveal a long investment horizon.

4.2 Measurement of Household Portfolio Performance in a Mean-Variance Framework and in Mean-Downside-Risk Frameworks

In a MV-framework, households select portfolios using the two parameters risk and return. For any given level of return above the risk-free rate, households prefer the portfolio with the least risk.[325] The Sharpe Ratio which was introduced by Sharpe (1966) integrates this relation into one measure which is determined by the difference between a portfolio's mean return and the risk-free rate, divided by the SD of a portfolio. The Sharpe Ratio can be interpreted as the return

[322] See Merton (1969); (1971); Mossin (1968); Samuelson (1969).
[323] See Guiso/Haliassos/Jappelli (2002), pp. 15ff.; Guiso/Jappelli/Pistaferri (2002); Ameriks/Zeldes (2004); Guiso/Sodini (2013), pp. 1478ff.
[324] This is also consistent with empirical findings previously outlined in this thesis (see chapter 3.3). Moreover, Oehler (2012c) shows that young adults neither refuse more to make financial provisions, nor are they less interested in financial issues compared to older adults.
[325] See chapter 4.1.1.

of a portfolio per unit of risk.[326] The Sortino Ratio is the equivalent to the Sharpe Ratio in a downside-risk framework and is determined by the difference between a portfolio's mean return and the target return (only below-target-returns are considered), divided by the semi-standard deviation of a portfolio.[327]

The measured values of the Sharpe Ratio and the Sortino Ratio express performance as the relation between risk and return.[328] A drawback of these measured values is that the extent of performance is difficult to interpret.[329] This is particularly crucial when measuring the performance of household portfolios that include multiple relevant asset classes as in this thesis. In this case, the measured values of the Sharpe Ratio and the Sortino Ratio only provide limited information. Consider, for instance, a household portfolio that allocates most of the financial wealth into low risk financial assets (e.g. cash or savings account) and only a small fraction of financial wealth in a single stock. Although both performance measures might ascribe poor diversification and performance to the portfolio, it might in fact be very close to the efficient frontier.[330]

To overcome this shortcoming, the analyses in this thesis rely on the Return Difference (RD)[331] measure. The RD measure represents a modification of the Return Loss measure by Calvet/Campbell/Sodini (2007). Modifications are made to integrate and combine additional features that are relevant in the context of the subsequent analyses, for instance, the possibility to use the SD as well as the applied downside-risk measures as component of risk, or to incorporate differing borrowing and lending rates. The additionally integrated features are obtained from the Risk-adjusted Performance[332] and the Differential Return[333] measure. The following paragraphs describe the construction of the RD measure and its features.

Compared to the Sharpe Ratio and the Sortino Ratio which express performance as the relation between risk and return, the Return Loss measure by Calvet/Campbell/Sodini (2007) reveals performance in terms of returns. More specific, the Return Loss denotes the return that a household portfolio loses by not choosing a portfolio on the efficient frontier with the same level of risk. Risk is measured in terms of the SD. In graphical terms, the Return Loss describes

[326] See Sharpe (1966); (1994); Bacon (2008), pp. 67. Sharpe (1966) introduced the ratio for measuring mutual fund performance and originally proposed the term reward-to-variability ratio.
[327] See Sortino/van der Meer (1991); Sortino/Satchell (2001), pp. 176ff.
[328] See Wilkens/Scholz (1999); Scholz/Wilkens (2005); Bacon (2008), pp. 64ff.
[329] See Bacon (2008), pp. 67.
[330] See Calvet/Campbell/Sodini (2007); von Gaudecker (2015).
[331] See Oehler/Wanger (2020).
[332] See Modigliani/Modigliani (1997).
[333] See Wilkens/Scholz (1999); Scholz/Wilkens (2005); Bacon (2008), pp. 67ff.

the vertical distance between the efficient frontier and the position of a household portfolio in a $\mu - \sigma$ diagram.[334] Compared to the Sharpe Ratio and Sortino Ratio, the Return Loss allows quantifying the extent of performance and is therefore more appropriate for performance evaluations when multiple asset classes of household portfolios are included.

Return losses that are measured from a portfolio on the efficient frontier can conversely be interpreted as enhancements from a (household) portfolio's point of view. In this case, the procedure of the Return Loss measure can be used to determine the extent of additional return that is attainable by a portfolio compared to another portfolio with the same level of risk (henceforth: risk-return enhancements). Since this procedure seems generally appropriate for the subsequent analyses to determine risk-return enhancements of household portfolios, it represents the basis of the RD measure.

The Return Loss includes establishing an efficient frontier from which losses are ascertained.[335] However, the research questions in this thesis are interested in possible risk-return enhancements towards a specific benchmark or reference portfolio, i.e. a portfolio of XTFs. The Risk-adjusted Performance and the Differential Return are two alternative performance measures that also ascertain risk-return enhancements in terms of returns but compare an underlying portfolio against a specific benchmark or reference portfolio. The Risk-adjusted Performance and the Differential Return measure differ from each other in the basis of risk from which risk-return enhancements are determined. While the Risk-adjusted Performance measure assumes risk-adjusting the involved portfolios to the risk of the benchmark portfolio, the Differential Return measure requires risk-adjusting the benchmark portfolio to each single portfolio.[336] In the context of this thesis, an advantage of using the benchmark or reference portfolio as basis of risk is that the so-determined risk-return enhancements can be compared across all household portfolios. An advantage of using each single household portfolio as basis of risk is that the so-determined risk-return enhancements might reveal more relevant information from the perspective of a household. Since both alternatives seem to be relevant for the subsequent analyses, both alternative risk-adjustments are included in the RD measure.

Risk-adjusting thereby means that equal parts of all securities in a portfolio are shifted in the risk-free asset (decrease of risk), or that a certain amount is borrowed and invested in equal parts in all securities of a portfolio (increase of risk). This principle refers to the fund separation

[334] See Calvet/Campbell/Sodini (2007); von Gaudecker (2015).
[335] See Calvet/Campbell/Sodini (2007); von Gaudecker (2015).
[336] See Modigliani/Modigliani (1997); Wilkens/Scholz (1999); Scholz/Wilkens (2005); Bacon (2008), pp. 67ff.

by Tobin (1958).[337] The Risk-adjusted Performance and the Differential Return measure assume the SD as measure of risk. The principle of portfolio separation has also been shown for LPM-based downside-risk measures.[338] Hogan/Warren (1974), for instance, point out the validity of the portfolio separation for the semi-variance. Bawa/Lindenberg (1977) and Harlow/Rao (1989) demonstrate the relation for the Expected Value of Loss and arbitrary choices of portfolio target returns.[339]

Both the Risk-adjusted Performance and the Differential Return measure assume that the risk of a portfolio is adjusted at the risk-free rate. This means that households would borrow and lend at the same rate of return – an assumption that is hardly tenable for households in practice.[340] To examine the investment situation of real-world households more closely, the RD measure involves distinct borrowing and lending rates[341]. Overall, RDs determine performance as the difference in return between a household portfolio and a corresponding benchmark or reference XTF-portfolio at the same level of risk, while considering distinct borrowing and lending rates for risk-adjusting.[342]

Formula (1) and (2) provide an exemplary formal description of the RD measure. The example shows RDs that are based on the risk of a household portfolio ($\mathrm{RD_{HP}}$). The underlying measure of risk is specified in each of the subsequent analyses. μ_{HP} denotes the mean return of a household portfolio and ($\mu_{\mathrm{XTF,HP}}$) the mean return of a XTF portfolio which is risk-adjusted to the risk of the household portfolio:

(1) $\mathrm{RD_{HP}} = \mu_{\mathrm{XTF,HP}} - \mu_{\mathrm{HP}}$.

Thereby, $\mu_{\mathrm{XTF,HP}}$ is determined as follows:

[337] See chapter 2.1.
[338] Please note that different periods, which may constitute a MDD, prevent this downside-risk measure from risk-adjustments (see also chapter 4.1.2.3).
[339] In case of downside-risk measures, a risk-free investment represents the maximum attainable rate of return which (quasi certainly) does not fall below a certain level of target return (see e.g. Hogan/Warren (1974)).
[340] A comparison of security loans among large German banks in 2013 by Stiftung Warentest (2013), a leading German consumer foundation, reveals that households had to pay an annual rate of 5.5 percent on average for a security loan. In contrast, the average annual rate on cash deposits of German households, proxied by the average interest rate on overnight deposits of the household sector at German banks, amounts only 0.4 percent in 2013 (see Deutsche Bundesbank (2019c)).
[341] Regarding differing lending and borrowing rates see Matulich (1975).
[342] A formal description of the RD measure will be provided separately in the methodology chapters of each empirical analysis.

$$(2)\ \mu_{XTF,HP} = \begin{cases} r_{SL} + \frac{\mu_{XTF} - r_{SL}}{risk_{XTF}} risk_{HP}, \text{if } risk_{XTF} < risk_{HP} \\ r_{SV} + \frac{\mu_{XTF} - r_{SV}}{risk_{XTF}} risk_{HP}, \text{if } risk_{XTF} > risk_{HP} \\ \mu_{XTF}, \qquad\qquad\qquad \text{if } risk_{XTF} = risk_{HP} \end{cases}$$

where μ_{XTF} and $risk_{XTF}$ as well as μ_{HP} and σ_{HP} denote the mean return and the risk of the XTF- and the household portfolio, respectively. r_{SL} and r_{SV}, denote the fixed interest rate for security lending (SL) and savings (SV).[343]

4.3 Data Sources for the Empirical Analyses

4.3.1 Requirements and Availability of Household Portfolio Data

A main difficulty in household finance is that appropriate data is hard to obtain. Analyzing household portfolios ideally requires both representative and detailed data.[344] Representative means that the data sample at hand should adequately represent the entire underlying population. Detailed in this context means that for each household portfolio, the data should uncover the total financial wealth, the allocation of financial wealth across relevant asset classes, and its distribution across individual assets within each asset class. In addition to representativeness and a high level of detail, the data should track households over time.[345] However, such data requirements contrast with households' demand for financial privacy.[346]

Three fundamental data sources employed in empirical household finance are Swedish register data[347], broker account data[348], and household survey data[349], of which each has its own advantages and drawbacks.[350] Swedish register data used in Calvet/Campbell/Sodini (2007); (2009) are, as an exception, largely detailed and representative. However, Swedish households reveal several selective characteristics compared to households in many other countries.[351]

[343] The corresponding rates for r_{SL} and r_{SV} in formula (2) are usually incorporated with positive signs. For example, if a security lending rate of 5.5 percent is assumed, r_{SL} = 5.5 percent. See also Matulich (1975) for a graphical illustration of differing lending and borrowing rates in a $\mu - \sigma$ diagram.

[344] See Campbell (2006); Calvet/Campbell/Sodini (2007); Guiso/Sodini (2013), pp. 1460ff.; von Gaudecker (2015).

[345] See Campbell (2006); Calvet/Campbell/Sodini (2007).

[346] See Campbell (2006).

[347] See Calvet/Campbell/Sodini (2007); (2009). Register data for Finland is, although detailed, limited to households' stock holdings (see Grinblatt/Keloharju, 2000; 2001a; 2001b).

[348] See e.g. Barber/Odean (2000); (2001); Bhattacharya et al. (2017).

[349] See e.g. Guiso/Haliassos/Jappelli (2002); Polkovnichenko (2005); Graham/Harvey/Huang (2009), Kimball/Shumway (2010).

[350] See Campbell (2006); Calvet/Campbell/Sodini (2007); Guiso/Sodini (2013), pp. 1460ff.; von Gaudecker (2015) for the rest of the paragraph.

[351] Swedish household portfolios reveal exceptionally high stock market participation rates compared to many other countries (see Campbell (2006); Christelis/Georgarakos/Haliassos (2013); von Gaudecker (2015)). Further

Moreover, Swedish household data in Calvet/Campbell/Sodini (2007); (2009) capture the period from 1999 to 2002 and do not cover the following years in which assets under management of ETFs strongly increased.[352] Broker account data, on the one hand, reveal highly detailed information which allows quantitative analyses. On the other hand, different studies indicate that broker account data are hardly representative for households of a corresponding population and often cover only a small part of an entire household portfolio.[353] While broker account data are difficult to access for researchers, household survey data are better accessible and available for many developed countries.[354] Thereby, household surveys usually provide representative samples of a certain population and capture the amount of money invested across multiple asset classes. A main drawback of household survey data, however, is that detailed information on individual security holdings are not involved in the data which limits quantitative performance analyses.[355]

4.3.2 Combination of the Panel on Household Finances (PHF)-survey with the Securities Holdings Statistics (SHS)-base of Deutsche Bundesbank

Given that the requirements of ideal household portfolio data are high but appropriate data are hardly available, this thesis uses a novel approach to approximate household portfolios. The approach combines household survey data and household security holding data which are representative for the German household sector and stem from the same data provider, the German central bank (Deutsche Bundesbank). The two data sets are the Panel on Household Finances (PHF) and the Securities Holdings Statistics (SHS)-base.

The PHF-survey data were extracted from the second wave of the Household Finance and Consumption Survey (HFCS),[356] which is a collection of national household surveys from euro

specific features refer to national financial education programs and its relatively small country size which encourages diversifying internationally (see Campbell (2006)).

[352] See Bhattacharya et al. (2017); Bioy et al. (2017); Morningstar (2019); Investment Company Institute (2018a); Investment Company Institute (2018b); Deutsche Bundesbank (2018). Furthermore, the collection of Swedish register data was abolished in 2007 (see von Gaudecker (2015)).

[353] See Bilias/Georgarakos/Haliassos (2010); Anderson (2013). Bilias/Georgarakos/Haliassos (2010) report that less than 20 percent of American households own a broker account and that among households which do own a broker account, the wealth invested in such accounts represents only ten percent or less of the financial wealth.

[354] Prominent examples are the Survey of Consumer Finances for the United States and the Eurosystem's Household Finance and Consumption Survey for the euro area. The latter is a collection of consolidated household surveys which involves 19 euro-area countries in the third wave of 2017 (see European Central Bank (2020)).

[355] As an exception, von Gaudecker (2015) analyzes representative survey data of Dutch households which contain details on households' security holdings. However, security details are constrained to the largest portfolio holdings. Although this allows to mitigate some of the shortcomings of household survey data, it does not eliminate them.

[356] Data source: European Central Bank, Eurosystem Household Finance and Consumption Survey, second wave. Data access granted through the project: Can XTFs enhance Households' investment returns?; lead researcher: Oehler, A.; co-researchers: Horn, M., Wanger, H.P.

area countries which were consolidated by the European Central Bank.[357] The PHF-survey represents the German part of the HFCS and was conducted by Deutsche Bundesbank. Households participating in the survey were interrogated via face-to-face interviews which were administered by an interviewer who records replies using a computer. Survey participants were selected and contacted by region, municipality size, and anticipated wealth to assure obtaining a representative sample of German households.[358] The PHF-survey pursues an oversampling of wealthy households to accurately reflect the skewness of the wealth distribution related to the influence of a relatively small number of wealthy households and to capture exceptional features in asset holdings (e.g. certain financial assets that are predominantly owned by wealthy households).[359] Besides consistency checks that were already included in the computer assisted questionnaire, a range of quality and plausibility checks are performed subsequent to the conduction of the survey to minimize errors and inconsistencies in the data sample. This includes, for example, re-contacting a household to verify item values or imputation of missing values.[360]

The PHF-survey was executed from the beginning of the second quarter of 2014. Households' survey responses on their financial situation are assumed to rely on the previous quarter as of January 2014. This date is considered as start date for the subsequent empirical analyses. The initial sample of the PHF-survey includes 4,461 German households and captures, among others, the amount of money that households invest in cash (CASH) and savings (SV) (henceforth: "safe"[361] financial assets) as well as stock funds (SF), bond funds (BF), real estate funds (REF), individual bonds (BD) and individual stocks (ST) (henceforth: risky financial assets). Individual security holdings are not included in the PHF-survey data.[362] The total

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[357] See European Central Bank (2016b). The data employed in this thesis represents data of the second wave of the PHF-survey. The first wave of the PHF-survey was not employed since it could not be combined with appropriate security holding data of the SHS-base. At the time the first wave of the PHF-survey was conducted, i.e. in 2010, the SHS-base only provides security holding data on a quarterly basis which prevents proper portfolio return analyses; monthly security holding data is available since January 2013 (see Bade et al. (2017)). Data of the third wave of the PHF-survey, which was performed in 2017 (see European Central Bank (2020)), as well as more recent data of the SHS-base were not accessible at the time the empirical analyses of this thesis were conducted.

[358] See Knerr et al. (2015); European Central Bank (2016b). The applied survey mode is called Computer Assisted Personal Interview.

[359] Regarding possible consequences from inadequately considering the wealthy, see e.g. Eckerstorfer et al. (2016); Chakraborty/Waltl (2018); European Central Bank (2016b).

[360] See Knerr et al. (2015); European Central Bank (2016b).

[361] The quotes around "safe" indicate that the respective investments are only relatively safe compared to the other assets and that they are not riskless in a neoclassical sense in which default is not considered. For better readability, the quotes are left out in the following.

[362] Further fund types like "Hedge funds" or "Other fund types" are not considered in the subsequent analyses due to their limited relevance in households' portfolios. The questionnaire of the PHF-survey also includes sections that gather information on, among others, demographics, employment, real assets, and private business wealth (see European Central Bank (2016a); (2016b)). Since the research in this thesis focuses on a comparison of XTFs to households' financial assets mentioned above, further survey variables are not considered.

portfolio value (VALUEpf) is ascertained as the total amount of money that a household invests across all applied asset classes. The relative share of VALUEpf invested in a certain asset class represents the portfolios' asset class weight in percent (e.g. 30 percent of VALUEpf invested in CASH).

The SHS-base is a collection of monthly, obligatory reports from all financial institutions domiciled in Germany to the German central bank. The SHS-base is a full census, which means that "all financial institutions domiciled in Germany report all securities they hold in save custody for domestic and foreign customers."[363] Customers are divided into holder sectors. Holder sectors include, among others, non-financial corporations, insurance corporations and pension funds, investment companies, and German households. For security holdings of the German household sector, Deutsche Bundesbank approved data access.[364] Security holdings are collected by ISIN and include mutual funds, debt securities, and stocks. Deutsche Bundesbank performs a range of data quality checks when processing the reported data. The data quality checks involve (automated) plausibility checks concerning the consistency and completeness of the reports (e.g. existence and validity of ISINs), checks concerning aggregates by institutions (e.g. comparison of the reported security holdings with other statistics like monthly balance sheet statistics), and checks concerning aggregates by securities (e.g. comparison of the total holdings of a certain security across all investors with the outstanding amount).[365] Irregularities and implausibilities in the data should therefore be minimized.

The SHS-base does not distinguish between households' individual account holdings, i.e. the security names and the number of security shares stored in an individual account of a household are not revealed. However, Deutsche Bundesbank granted access to an additional variable, the aggregated market value of shares that all German households own of a certain security. Aggregated market values are composed by the aggregated number of shares which German households own of a certain security on aggregate (across all reporting financial institutions), multiplied by the current market price (end-of-month) in Euro. The special feature about aggregated market values is that they only involve shares which are held by German

[363] Bade et al. (2017), p. 4.
[364] Data source: Deutsche Bundesbank, Research Data and Service Centre, Securities Holdings Statistics-Base. Data access granted through the project: Can XTFs enhance the return of households' portfolios while keeping the portfolio-risk constant?; Project-ID: 2017\0103; lead researcher: Oehler, A.; co-researcher: Wanger, H.P.
The data privacy rules of Deutsche Bundesbank only allowed gathering security holdings of German households on aggregate. Further distinguishing security holdings, e.g. according to the reporting financial institutions was not permitted to prevent an identification and potential inferences on individual financial institutions and to keep the latter anonymous.
[365] See European Central Bank (2015); Bade et al. (2017).

households. Security shares that are held by other sector holders are not included. This means that aggregated market values show the amount of money that German households invest, for example, in a certain mutual fund or stock. Ranking all securities held by German households according to the aggregated market value represents a reasonable indication for the distribution of a security among German households. The larger the presumed distribution, the more likely that a certain security is owned by German households.[366]

Since the PHF-survey does not capture details on German households' security holdings which are necessary for estimating portfolio risk and return, security holdings of the SHS-base provide an appropriate complement to the PHF-survey for constructing household portfolios. In this way, the PHF-survey and the SHS-base are combined. Household portfolios are assembled by selecting securities from the SHS-base (according to aggregated market values) and by assigning them in the corresponding asset class of a household portfolio of the PHF-survey. Thereby, the approach combines strengths of household survey data with detailed security holding data of the same population.

In each empirical analysis, the construction of household portfolios is further specified. Portfolio constructions are varied, and different specifications are controlled for, e.g., the number of securities per portfolio or the weight of each security in a portfolio. Besides the PHF-survey and the SHS-base, Thomson Reuters Datastream was used to gather asset class information and price data for each security of the SHS-base. This allows categorizing the securities into the applied asset classes and calculating returns which are necessary to estimate risk and return of German household portfolios.

[366] Securities which are held at less than three institutions are excluded from the data set. They can barely be assumed to be representatively spread among German households.

5 The Capability of XTFs in Household Portfolio Optimization[367]

5.1 Methodological Approach

5.1.1 Construction of Household Portfolio Types

To evaluate whether XTFs can optimize household portfolios by enhancing their risk and return (see RQ1), this analysis first examines RDs.[368] RDs exhibit whether a portfolio of XTFs reveals higher returns than a corresponding household portfolio at the same level of risk. Secondly, this analysis investigates an extreme case of the recommendation to employ XTFs to examine the maximum effect of incorporating XTFs on risk and return of household portfolios. Therefore, the entire risky assets of household portfolios are sold all at once and replaced with a portfolio of XTFs. Then, changes in risk and return of household portfolios are ascertained (henceforth: portfolio replacement). Both investigations require constructing household portfolios and specifying a benchmark XTF portfolio from which possible enhancements can be measured.

Constructing household portfolios requires details on (i) asset class weights, (ii) security holdings, as well as (iii) assumptions about the portfolio size, i.e. the number of securities per portfolio. Asset class weights are derived using the PHF-survey.[369] Security holdings are assumed by employing the SHS-base.[370] Assumptions on portfolio size are deducted from existing studies.

(i) Asset class weights: Assumptions on asset class weights are based on previous observations that relying on the recommendation of financial advisors before making an investment decision is pervasive among households. Financial advisors seem to have a considerable influence on households' portfolio choice but compose, instead of tailored portfolios according to households' characteristics, very similar portfolios or categorize them into a manageable number types (according to households' preferred risk) and match each type with a predefined portfolio composition.[371] Therefore, this analysis relies on stylized portfolio compositions of households. To approximate the latter, clusters of household portfolios which show similar asset class concentrations (henceforth: Household Portfolio Types (HPTs)) are derived from the PHF-survey data.

[367] Substantial parts of this chapter and the corresponding appendices are obtained from Oehler/Wanger (2020).
[368] See chapter 4.2.
[369] Data source: European Central Bank, Eurosystem Household Finance and Consumption Survey, second wave. Data access granted through the project: Can XTFs enhance Households' investment returns?; lead researcher: Oehler, A.; co-researchers: Horn, M., Wanger, H.P.
[370] Data source: Deutsche Bundesbank, Research Data and Service Centre, Securities Holdings Statistics-Base. Data access granted through the project: Can XTFs enhance the return of households' portfolios while keeping the portfolio-risk constant?; Project-ID: 2017\0103; lead researcher: Oehler, A.; co-researcher: Wanger, H.P.
[371] See chapter 2.2.

For deriving HPTs, the initial PHF-data sample of 4,461 households is constrained to households that invest at least 1,000 Euros across SF, BF, REF, BD, and ST in total.[372] Leveraged households which exhibit negative liquidity in CASH, but positive amounts in the remaining asset classes as well as households who invest more than 90 percent of their total VALUEpf in safe financial assets[373] (i.e. CASH&SV) are also precluded. The excluded households are assumed to be barely interested or unable to invest in a portfolio of XTFs. The final sample includes 1,052 households.

Using the final sample of the PHF-data, household portfolios are grouped into clusters with similar asset class weights, i.e. HPTs. The relative amount that households allocate into each asset class (i.e. asset class weights) is used as separate variable in the cluster analysis. Due to the metric structure of the variables, the large size of the data sample, and since this analysis intends to identify heterogeneous portfolio types with distinct asset class concentrations, K-Means clustering is employed.[374] The number of clusters applied for K-Means clustering is derived from descriptive statistics and a correlation analysis of households' asset class weights as consistent relationships between certain asset classes can provide indications about the existence of a cluster. Several robustness checks are performed to test the validity of the cluster solution.[375]

(ii) Security holdings: Security holdings are assumed by choosing those securities from the SHS-base which are, according to the aggregated market value of shares, most widespread among German households. Therefore, for each asset class the securities with the highest aggregated market value of shares are selected. The number of selected securities depends on the applied portfolio size (several portfolio sizes are employed as robustness). Securities are equally assigned across the employed asset classes. For instance, for a HPT that consists of nine risky securities, three mutual funds, three bonds, and three stocks are selected. The selected securities reveal the highest market values of shares in each of the corresponding asset classes. In correspondence to the assumed starting date of the analysis in January 2014, securities are selected from the monthly subsample of the SHS-base as of January 2014. The weight of a security within its asset class is determined by the percentage of its market value relative to the market value of all securities in its asset class.[376]

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[372] See von Gaudecker (2015); Oehler/Horn/Wedlich (2018); Horn (2018), pp. 61f.; Oehler/Horn (2019) for a similar approach.
[373] See Oehler/Horn (2019).
[374] See Backhaus et al. (2016), pp. 453ff.
[375] See chapter 5.3, Appendix B, Appendix C, and Appendix D for details.
[376] See Table 34 in Appendix C for an example regarding the construction of the HPTs

When assigning securities from the SHS-base to the corresponding asset classes of the HPTs, mutual funds are further specified into stock funds (SFs), bond funds (BFs), and real estate funds (REFs).[377] Mutual funds that follow a mixed asset strategy are kept in the security sample since they rank among mutual funds with the highest aggregated market value of shares which points out their relevance in the portfolios of German households. Mixed funds are categorized into SFs or BFs according to return correlations with a range of stock and bond indices which cover a range of markets and sectors.[378] If the highest correlation value appears with one of the stock indices, the regarding mixed fund is categorized as SF (this applies analogously to categorizations into BFs). Aggregated market values of shares further point out the importance of REF in German households' portfolios. Ranking all mutual funds according to the aggregated market value reveals that five REFs rank among the top ten mutual funds. The large amount of money invested in REFs is, however, concentrated around a small number of REFs. The security sample from which securities are assigned to the HPTs contains only 42 REFs in total.

Security price data are obtained from Thomson Reuters Datastream in terms of total return prices to calculate monthly returns.[379] Securities for which no data are available were dropped from the dataset. HPTs are assumed to follow a buy-and-hold strategy.[380] If a security expires, the available amount of money is reinvested at the beginning of the subsequent month in a new security which is selected from the SHS-base, again, according to the highest market value in that month. Expiries of securities occur, for instance, when a bond matures, or a mutual fund is liquidated. At each reinvestment, fixed and proportional transaction costs are considered.[381]

Regarding CASH and SV, weighted average monthly interest rates on German households' deposits with different agreed maturities are applied. The interest rates as well as the outstanding amounts of deposits of the German household sector are provided by Deutsche Bundesbank (2019c). For CASH, interest rates on overnight deposits are assumed, while for

[377] See Appendix A.
[378] The applied indices as well as the categorization of the applied mixed funds are displayed in Table 25 and Table 26 in Appendix A.
[379] Total return prices include dividends and payouts and assume that the latter are reinvested in the same security at the closing price applicable on the ex-dividend date. Taxes and reinvestment charges are not considered in total return prices (see variable description of Thomson Reuters Datastream). Total return prices are obtained as daily data. First, daily discrete returns are determined. Then, daily discrete returns are transformed into daily log-returns and are accumulated to monthly log-returns. Finally, monthly log-returns are converted into discrete monthly returns. Total return prices represent an approximation since households, for instance, usually pay taxes when receiving payouts and incur transaction costs when reinvesting in practice. The latter aspect is considered in RQ3.
[380] This assumption is based on the findings that households show inertia (see Agnew/Balduzzi/Sunden (2003); Bilias/Georgarakos/Haliassos (2010)) and scarcely rebalance their financial portfolio (see Bonaparte/Cooper (2009); Brunnermeier/Nagel (2008)).
[381] See also chapter 5.1.3.

SV, interest rates on deposits with agreed maturities of up to one year, over one and up to two years, and over two years are employed. The weighted average monthly interest rate for SV is calculated by weighting the interest rates according to their outstanding amounts.

(iii) Portfolio size: Several portfolio sizes are deducted from the literature. In von Gaudecker (2015), 95 percent of the households analyzed in the study hold nine or less securities. Bhattacharya et al. (2017) distinguish between ETF- and non-ETF-investors and find that they store on average 12 and 10.9 securities, respectively, in their broker accounts.

Studies that analyze households' stock holdings document that the number of stocks ranges between one stock,[382] two stocks,[383] and more recently three stocks.[384] Investment Company Institute (2014); (2015); (2016a); (2017a); (2018a); (2019); (2020) shows that households mostly own between three and four mutual funds. Since all HPTs reveal a positive asset class weight for SF, BF and REF, at least one mutual fund is allocated into each mutual fund category. As future returns are unknown, employing an equal distribution of assets appears to be a reasonable strategy from the perspective of households.[385] As approximation of the total portfolio sizes as well as the number of individual securities for stocks and mutual funds reported in the studies above, a total portfolio size of nine risky securities, divided into three securities per asset class is assumed, i.e. three mutual funds, three bonds, and three stocks. The assumptions on portfolio size allow constructing the HPTs and calculating portfolio risk and return.

Several portfolio sizes are applied as robustness. Previous studies point out that a portfolio size of approximately 30 securities offers substantial reductions of unsystematic risk and a reasonable level of diversification.[386] To check whether XTFs enhance risk and return of household portfolios even when they are, according to these studies, considered to be diversified already, the analysis controls for a portfolio size of 27 securities, i.e. nine stocks, nine mutual funds and nine bonds. This comes close to a portfolio size of 30 securities and

[382] See Blume/Friend (1975).
[383] See Kelly (1995); Polkovnichenko (2005).
[384] See Goetzmann/Kumar (2008); Odegaard (2017).
[385] See Elton/Gruber (1977); De Wit (1998). An equal distribution of assets has been documented in empirical household portfolios (see e.g. Benartzi/Thaler (2001); Huberman/Jiang (2006); Baltussen/Post (2011)). In this regard, DeMiguel/Garlappi/Uppal (2009) point out that equally distributed portfolios can achieve reasonable investment outcomes compared to sophisticated portfolio optimization techniques.
[386] See Evans/Archer (1968); Statman (1987).

seems to be consistent with empirical observations that most households hold less than ten stocks,[387] and less than ten mutual funds.[388]

As additional robustness tests, a portfolio size between nine and 27 (i.e. 18 securities), as well as a large portfolio size of 297 securities is employed. A portfolio size of 18 securities might reveal information regarding successive changes in risk and return when increasing portfolio size. The portfolio size of 297 is based on Statman (2004) who outlines that a portfolio which consists of approximately 300 securities is sufficiently diversified. Testing for this portfolio size enables, analogously to a portfolio size of 27 securities, to control for the (hypothetical) case that households already hold a diversified portfolio in terms of portfolio size and allows investigating whether households can still optimize their portfolio by employing XTFs.

5.1.2 Methodology on Return Differences

RDs indicate if a XTF portfolio achieves higher risk-adjusted returns than the HPTs. Risk-adjusting a XTF portfolio to the risk of each HPT reveals risk-return enhancements based on the risk of the HPT portfolios. Since this case seems to be more relevant from the perspective of households than risk-adjusting the HPT portfolios to the risk of the XTF portfolio, the former case is used as base case scenario in the following. RDs that are based on the risk of the XTF portfolio are computed as robustness. The analysis in this chapter starts by employing the SD as measure of risk.[389]

As benchmark XTF portfolio, an easily investable buy-and-hold[390] portfolio is applied which consists of one stock XTF (60 percent) and one bond XTF (40 percent) (henceforth: 60/40 XTF portfolio).[391] Using a 60/40 stock/bond-ratio as benchmark asset class weights is based, in reference to Jacobs/Müller/Weber (2014), on portfolio compositions of professional investors[392] as well as the advice of large brokerage and investment firms.[393] The latter might provide an indication and serve as a reference for households in deriving portfolio weights for a XTF portfolio. Regarding the benchmark XTFs, the analysis employs XTFs which replicate

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[387] See Blume/Friend (1975); Kelly (1995); Polkovnichenko (2005); Goetzmann/Kumar (2008); von Gaudecker (2015).
[388] See von Gaudecker (2015); Investment Company Institute (2016b); (2017b).
[389] Downside-risk measures are additionally involved in the subsequent analyses (see chapter 6 and 7).
[390] The assumption is based on findings suggesting that households hardly benefit from a rebalancing strategy and are better of employing a simple buy-and-hold strategy (see French (2008); von Gaudecker (2015); Dayanandan/Lam (2015); Horn (2018), pp. 98ff.; Horn/Oehler (2020)).
[391] Since an appropriate benchmark index which sufficiently matches the characteristics of XTFs could not be identified for real estate, no real estate XTF is involved (see Jacobs/Müller/Weber (2014) for a similar approach).
[392] See Brinson/Hood/Beebower (1986); Ibbotson/Kaplan (2000).
[393] See Arshanapalli/Coggin/Nelson (2001); Annaert/De Ceuster/van Hyfte (2005).

appropriate indices that have been used as benchmark in financial studies before. The applied stock XTF replicates the Morgan Stanley Capital International World (MSCI World) Index (ISIN: LU0392494562),[394] while the bond XTF tracks the Markit iBoxx Euro Sovereign Index (ISIN: LU0290355717)[395].[396]

RDs (RD_{HPT}) between the mean return of the 60/40 XTF portfolio which is risk-adjusted to the SD of a HPT ($\mu_{XTF,HPT}$) as well as the mean return of the HPT (μ_{HPT}) are computed by:[397]

$$\text{(3)}\ RD_{HPT} = \mu_{XTF,HPT} - \mu_{HPT}.$$

Thereby, $\mu_{XTF,HPT}$ is computed as follows

$$\text{(4)}\ \mu_{XTF,HPT} = \begin{cases} r_{SL} + \frac{\mu_{XTF} - r_{SL}}{\sigma_{XTF}} \sigma_{HPT}, & \text{if } \sigma_{XTF} < \sigma_{HPT} \\ r_{SV} + \frac{\mu_{XTF} - r_{SV}}{\sigma_{XTF}} \sigma_{HPT}, & \text{if } \sigma_{XTF} > \sigma_{HPT} \\ \mu_{XTF}, & \text{if } \sigma_{XTF} = \sigma_{HPT} \end{cases}$$

where μ_{XTF} and σ_{XTF} denote the annual mean return and the SD of the 60/40 XTF portfolio, and μ_{HPT} and σ_{HPT} the annual mean return and the SD of each HPT, while r_{SL} and r_{SV} represent a fixed annual interest rate for security lending (SL) and savings (SV), respectively. Regarding r_{SV}, households are assumed to combine an investment in the 60/40 XTF portfolio with an investment in SV rather than CASH, i.e. households are assumed to prefer a longer-term safe financial asset with marginally higher fixed interest. In case of leverage, security lending is used to leverage an investment in the 60/40 XTF portfolio. Therefore, an annual interest rate of 5.5 percent is applied which was charged by German banks on average for security loans.[398]

5.1.3 Methodology on Portfolio Replacement

Portfolio replacements analyze the extreme case of implementing XTFs. The entire risky assets of a household portfolio are sold and the available amount of money is invested in the 60/40 XTF portfolio. All replacements are performed at the beginning of the observation period in January 2014, followed by a holding period until the end of the observation period in December

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[394] See Campbell (2006); Bhattacharya et al. (2017) for a previous application of the underlying benchmark index.
[395] See Jacobs/Müller/Weber (2014) for a previous application of the underlying benchmark index.
[396] This analysis follows Jacobs/Müller/Weber (2014) and avoids currency hedging which after Black/Litterman (1992) and Eun/Resnick (1994) had to be controlled for in international bond portfolios since this is difficult to implement from a household's perspective. The selected bond XTF thus exclusively contains euro-denominated constituents.
[397] See chapter 4.2 for a description of RDs as performance measure.
[398] See Stiftung Warentest (2013).

2016. For each replacement, fixed and proportional transaction costs for selling and buying securities are considered. As fixed transaction costs, 10 Euros per transaction are assumed which approximates the fixed amount that large German online brokers charged their clients.[399] Proportional transaction costs are assumed with 0.25 percent of the order value.[400] Subsequent to the replacements, the resulting levels of risk and return of a HPT are compared to those prior to the replacement.

5.2 Results

5.2.1 Risk and Return of Household Portfolio Types

Table 1 shows the average, median and standard deviation for the asset class weights of the 1,052 households in the final sample. Since households' participation rates and the amount of money invested in different asset classes might change with VALUEpf,[401] Table 1 is divided by quintile of VALUEpf.

Table 1: Households' asset class weights by quintile of VALUEpf

Quintile of VALUEpf		VALUEpf	CASH&SV	SF	BF	REF	BD	ST
Q1	average	18,300	55.7	14.3	5.5	3.9	4.5	16.1
	median	18,500	61.1	0.0	0.0	0.0	0.0	0.0
	SD	7,700	24.8	22.8	15.5	12.7	13.1	24.6
Q2	average	47,100	49.2	14.3	5.3	6.4	4.8	20.1
	median	47,500	52.4	0.0	0.0	0.0	0.0	9.3
	SD	10,100	25.5	21.4	13.1	16.5	15.2	26.7
Q3	average	87,600	49.3	12.4	3.8	7.0	7.3	20.1
	median	86,200	51.5	0.0	0.0	0.0	0.0	9.2
	SD	14,200	27.3	19.6	12.2	15.4	16.5	25.8
Q4	average	166,500	47.8	12.8	6.0	3.6	10.3	19.6
	median	162,100	49.4	3.2	0.0	0.0	0.0	10.3
	SD	33,200	26.8	18.7	13.5	8.7	20.0	23.3
Q5	average	746,300	36.2	12.0	5.4	3.6	14.9	27.9
	median	414,900	30.2	3.0	0.0	0.0	3.6	20.3
	SD	1,079,200	28.1	18.2	11.5	8.8	21.0	27.6

Notes: Using the final sample of 1,052 households of the PHF-survey of 2014, this table reports the average, median and standard deviation of households' total portfolio value (VALUEpf) in Euros and the relative amount of VALUEpf invested among the asset classes cash and savings (CASH&SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) in percent and divided by quintile (Q) of VALUEpf. Example: The mean allocation of households in the first quintile of VALUEpf into stocks is 16.1 percent.

[399] See Stiftung Warentest (2016).
[400] See Lynch/Balduzzi (2000).
[401] See e.g. Arrondel et al. (2016).

Median values of zero indicate that households invest disproportionally across the asset classes instead of allocating their wealth equally. When VALUEpf rises, the asset class weights of CASH and SF decrease while the asset class weight of ST increases. Higher exposures in ST associated with higher VALUEpf are in line with the finding in other studies that wealthier households reveal higher exposures in stocks.[402]

Since the construction of HPTs is based on the assumption that household portfolios reveal similar compositions,[403] portfolio compositions are also controlled for similarities by examining correlations between households' asset class weights, again, divided by VALUEpf (see Table 2). According to Table 2, three main significant correlations in households' asset class weights can be identified: First, the almost consistent and significant negative correlations between safe financial assets (CASH&SV) and most of the risky assets (SF, BF, BD and ST) across the quintiles of VALUEpf; second, the almost consistent and significant negative correlations between ST and the remaining asset classes; third, the significant negative correlations between SF and the two asset classes which represent individual assets, i.e. BD and ST. Since these three correlations imply characteristic relations in households' portfolio composition, they are used as indication for the number to be defined in the subsequent K-Means cluster analysis. According to the three main correlations, a three-cluster-solution is assumed.

Further statistics indicate possible concentrations of German households in cash and savings as well as stock funds, and stocks. The statistic on households' financial assets and liabilities of Deutsche Bundesbank (2014), for example, documents that German households invest about two thirds of their financial wealth in cash and savings (effective by the first quarter of 2014 and less of insurance and retirement plans). The next most important financial assets of households are mutual funds and stocks. A representative survey by forsa (2017) outlines that among financial assets, German households mainly employ safe financial assets, followed by mutual funds and individual stocks. Thus, while the correlation analyses imply a focus of households' investments either on safe financial assets, mutual funds or individual stocks, the additional statistics support the importance of those asset classes.

[402] See Campbell (2006); Arrondel et al. (2016).
[403] See chapter 2.2 and 5.1.1.

Table 2: Correlations between VALUEpf and asset class weights of households' portfolios

		CASH&SV	SF	BF	REF	BD	ST
Quintile 1	VALUEpf	0.113	0.013	-0.001	-0.086	0.029	-0.096
	CASH&SV		-0.372***	-0.247***	-0.181***	-0.099	-0.36***
	SF			-0.115*	-0.081	-0.191***	-0.335***
	BF				-0.044	-0.071	-0.215***
	REF					-0.073	-0.194***
	BD						-0.173**
Quintile 2	VALUEpf	-0.036	-0.048	0.008	0.032	0.049	0.021
	CASH&SV		-0.243***	-0.176**	-0.13*	-0.27***	-0.442***
	SF			-0.075	-0.177**	-0.156**	-0.334***
	BF				-0.098	-0.01	-0.195***
	REF					-0.11	-0.243***
	BD						-0.114*
Quintile 3	VALUEpf	-0.088	0.133*	-0.007	0.021	-0.089	0.039
	CASH&SV		-0.283***	-0.204***	-0.244***	-0.195***	-0.477***
	SF			-0.06	-0.114	-0.22***	-0.222***
	BF				0.008	-0.07	-0.173**
	REF					-0.073	-0.21***
	BD						-0.189***
Quintile 4	VALUEpf	-0.08	-0.068	0.016	0.105	0.128*	-0.012
	CASH&SV		-0.389***	-0.264***	-0.164**	-0.35***	-0.321***
	SF			0.078	0.034	-0.206***	-0.235***
	BF				0.071	-0.067	-0.307***
	REF					-0.071	-0.192***
	BD						-0.226***
Quintile 5	VALUEpf	-0.067	-0.112	0.067	-0.07	0.023	0.119*
	CASH&SV		-0.283***	-0.142**	-0.115*	-0.341***	-0.477***
	SF			0.082	0.046	-0.223***	-0.252***
	BF				-0.06	-0.058	-0.264***
	REF					-0.032	-0.184***
	BD						-0.233***

Notes: Using the final sample of 1,052 households of the PHF-survey of 2014, this table reports, divided by Quintile of VALUEpf, the Pearson correlation coefficients between households' total portfolio value (VALUEpf) in Euros and asset class weights, i.e. the relative amount of VALUEpf invested among the asset classes cash and savings (CASH&SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST). The symbols ***, **, and * denote the statistical significance at the one, five, and ten percent level, respectively. Example for Quintile 5: The Pearson correlation coefficient between CASH&SV and ST is -.477 with statistical significance at the one percent level.

The result of the three-cluster-solution of the conducted K-Means cluster analysis is illustrated in Table 3 and can be summarized as follows:

- HPT 1 represents the largest cluster by capturing approximately 44 percent of the 1,052 households and exhibits the lowest average VALUEpf. Particularly noticeable is the high exposure among the two safe financial assets, CASH and SV, which account together for 70.5 percent of VALUEpf, as well as the share of ST amounting close to ten percent of VALUEpf.
- HPT 2 consists of less households of the total sample (approximately 35 percent) which, in turn, reveal a higher average VALUEpf. HPT 2 exhibits the highest asset class concentration on SF by 25.4 percent of VALUEpf. Additionally, about one third of VALUEpf is invested among safe financial assets.
- HPT 3 includes, compared to the other HPTs, the least number of households (approximately 21 percent) and the least amount of VALUEpf invested in safe financial assets (25.0 percent). Furthermore, households assigned to HPT 3 allocate on average 63.7 percent of VALUEpf into ST and reveal the highest average VALUEpf.

Table 3: K-Means clustering (three-cluster-solution)

HPT (N=1,052)		VALUEpf	CASH&SV	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=463)	average	163,900	70.5	8.0	62.5	7.4	3.5	4.1	4.7	9.8
	SD	509,900	12.9	9.0	13.6	11.2	8.5	10.3	10.3	12.0
HPT 2 (n=366)	average	214,200	32.4	16.7	15.7	25.4	10.0	8.1	15.6	8.4
	SD	436,300	22.9	20.2	12.7	26.9	19.1	17.8	25.1	11.5
HPT 3 (n=223)	average	312,900	25.0	8.7	16.3	5.1	0.9	1.3	4.0	63.7
	SD	759,500	17.7	10.8	15.6	10.0	3.8	4.6	10.4	17.5

Notes: The table shows the results of K-Means clustering (three-cluster-solution) using the asset class weights of the 1,052 households of the final sample of the PHF-survey of 2014. The asset class weights, i.e. the relative amounts of households' total portfolio value (VALUEpf) in Euros invested among the asset classes cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) were applied as separate cluster variables. Each cluster represents a different Household Portfolio Type (HPT). For each HPT, the standard deviation and average asset class weight in percent of all households assigned to a respective cluster are reported.

As a first key result of this analysis, three HPTs are derived with asset class concentrations on cash/savings (HPT 1), mutual funds (HPT 2) and individual stocks (HPT 3).

5.2.2 Return Differences

RDs between the risk-adjusted 60/40 XTF portfolio and the three HPTs, based on the risk of each HPT, are presented in Table 4. The RDs are positive for all HPTs. This shows that the 60/40 XTF portfolio achieves higher risk-adjusted returns than all HPTs. HPT 1 shows the least amount of RDs of approximately 1.69 percentage points annual return. This is not surprising considering the relatively large portfolio concentration in CASH and SV as well as the low risk and return of HPT 1. RDs for HPT 2 are higher and reach approximately 2.48 percentage points annual return. The highest RDs can be obtained by HPT 3 of approximately 7.51 percentage points additional return per annum. The latter can be associated with modest returns of HPT 3 but relatively high risk. RDs indicate that the 60/40 XTF portfolio achieves higher returns in relation to its portfolio risk than HPT 3, which turns into large RDs after risk-adjusting the 60/40 XTF portfolio to the risk of HPT 3, even after controlling for leverage costs.

Table 4: Return Differences between the 60/40 XTF portfolio and the HPTs in [%]

	HPT 1		HPT 2		HPT 3	
	Risk	Return	Risk	Return	Risk	Return
60/40 XTF portfolio	8.30	10.68	8.30	10.68	8.30	10.68
60/40 XTF portfolio (risk-adj. to risk of HPT)	3.00	4.75	5.30	7.32	14.40	14.49
HPT	3.00	3.07	5.30	4.84	14.40	6.97
RD		1.69		2.48		7.51

Notes: This table shows the Return Differences (RDs) between the 60/40 XTF portfolio and the HPTs in percentage points of annual return for the period between January 2014 to December 2016 including (de-)leverage costs (minor deviations in RD due to rounding differences).

As a second key result of this analysis, RDs indicate that the 60/40 XTF portfolio achieves higher risk-adjusted returns than all stylized portfolios, even those with an asset class concentration on cash/savings (HPT 1) and mutual funds (HPT 2), and particularly those with concentrations on individual stocks (HPT 3). This suggests that an easily investable 60/40 XTF portfolio can enhance the risk-return trade-off of all stylized household portfolios.

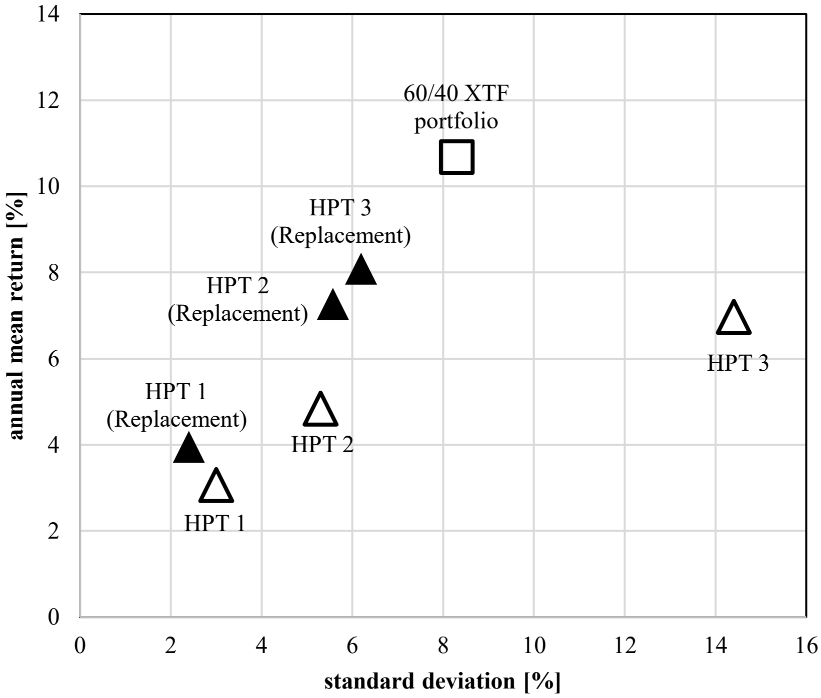
5.2.3 Portfolio Replacement

The results of the portfolio replacements are reported in Table 5. Although only about 30 percent of VALUEpf of HPT 1 are invested in risky assets, HPT 1 can increase returns by 0.89 percentage points while risk is simultaneously reduced by 0.60 percentage points. A reason therefore might be that a relatively large part of the risky assets of this HPT are invested in STs which might offer more potential for diversification than the assets of the remaining asset classes.

Despite its asset class concentration in mutual funds, HPT 2 can obtain the largest return increase of 2.43 percentage points. This might be associated with considerable asset class weights of BFs, REFs, and BDs which account in sum for approximately 30 percent of VALUEpf. Investments in the latter asset classes might yield lower returns than the benchmark XTF portfolio. Another reason might be a poor performance of SFs, which account for more than 25 percent of VALUEpf, compared to the applied XTFs. HPT 2 is the only experiencing a slight increase in risk after the portfolio replacement. However, given the return increase, the risk increase of 0.27 percentage points might be acceptable for households.

HPT 3 can obtain the highest risk reductions of all HPTs amounting to 8.21 percentage points. Returns can be increased by 1.12 percentage points. The relatively large risk reduction seems to be related to HPT 3's large allocation into individual stocks and an initial SD of 14.4 percent. Compared to the RDs of 7.51 percentage points, the return increase of 1.12 percentage points appears small. This can be linked to risk-adjustments. While determining RDs involves risk-adjusting, portfolio replacements, in turn, assume a simple implementation of the 60/40 XTF portfolio without adjusting for risk.

Table 5: Risk-return changes of Portfolio Replacement



	Risk	Return	Portfolio Replacement	
60/40 XTF portfolio	8.30	10.68	Risk	Return
HPT 1	3.00	3.07	2.40	3.95
			(-0.6)	*(0.89)*
HPT 2	5.30	4.84	5.57	7.27
			(0.27)	*(2.43)*
HPT 3	14.40	6.97	6.19	8.09
			(-8.21)	*(1.12)*

Notes: This table reveals the risk-return positions of the HPTs including and excluding the replacement of their entire risky assets with the 60/40 XTF portfolio (delta in parenthesis). The replacement is performed at the beginning of the observation period in January 2014 and includes fixed and proportional transaction cost. Subsequently, a buy-and-hold strategy is presumed until December 2016.

As third key result of this analysis, portfolio replacements lead to return increases in all stylized household portfolios and to risk reductions particularly in portfolios with concentrations on individual stocks (HPT 3).

5.3 Robustness Checks

5.3.1 Cluster Analysis

The first robustness check to validate the cluster solution controls for cluster homogeneity. Table 6 shows the corresponding F-values. F-values below one indicate that the intra-cluster variance is lower than the inter-cluster variance, which suggests a convenient homogeneity and fit of a cluster.[404] HPT 1 and HPT 3 show convenient intra-cluster homogeneity according to the F-values. For a few asset classes, HPT 2 exhibits F-values above one which indicates less intra-cluster homogeneity. An additional cluster partition, i.e. the K-Means four-cluster-solution (see Table 7), might increase intra-cluster homogeneity. When reviewing the four-cluster-solution, however, corresponding F-values (see Table 8) of HPT 2 do not consistently decline below one, i.e. overall no improvement is accomplished. The additional cluster of the four-cluster-solution, HPT 4, displays an asset class concentration on BD of 52.4 percent. Bond investments of the German household sector, however, account for only about 5.8 percent of their financial assets.[405] In addition, HPT 4 represents the smallest cluster with a cluster size of 107 households (total sample: 1,052 households) which suggests a minor relevance of this cluster and to maintain with the three-cluster-solution.

In addition to K-Means clustering, hierarchical clustering is applied as robustness. As this does not change the previous conclusions, a brief summary is provided here while details are presented in Appendix B. Using the elbow method and Dendogram indicates a three-cluster-solution as well. The three-cluster-solution of the hierarchical approach yields a very similar portfolio composition in terms of asset class weights compared to the K-Means clustering solution. This substantiates the previous results and suggests remaining with the cluster solution of the K-Means approach.

[404] See Backhaus et al. (2016), pp. 507ff.

[405] Own calculations based on data of Deutsche Bundesbank (2014), effective by the first quarter of 2014 and less of financial assets invested in insurance and retirement plans. German government bond holdings of German households also seem negligible compared to the holdings of the other domestic sectors. The respective share held by the German household sector decreased from 2.7 percent in January 2014 to 0.8 percent in December 2016 (own calculations based on data of Deutsche Bundesbank (2019d)).

Table 6: F-values for K-Means clustering (three-cluster-solution)

	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=463)	0.37	0.26	0.31	0.41	0.63	0.33	0.21
HPT 2 (n=366)	1.87	0.22	1.77	2.08	1.89	1.99	0.20
HPT 3 (n=223)	0.53	0.34	0.24	0.08	0.13	0.34	0.46

Notes: This table reports F-values for K-Means clustering (three-cluster-solution). F-values compare the intra-cluster variance with the overall variance for each cluster variable and allow conclusions about cluster homogeneity. F-values below one indicate that the intra-cluster variance is less than the inter-cluster variance and suggests high intra-cluster homogeneity (see for example HPT 1 and HPT 3). F-values are computed for households' asset class weights among cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) which are used as cluster variables.

Table 7: K-Means clustering (four-cluster-solution)

HPT (N=1,052)		VALUEpf	CASH&SV	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=453)	average	159,500	71.0	8.4	62.7	7.2	3.5	4.6	3.7	10.0
	SD	512,900	12.8	9.4	13.9	10.7	8.6	11.1	8.1	12.0
HPT 2 (n=270)	average	163,800	34.8	18.4	16.4	34.1	12.0	8.4	3.0	7.6
	SD	343,700	23.5	21.5	13.4	26.6	21.2	18.8	7.0	11.0
HPT 3 (n=222)	average	317,300	26.1	9.4	16.7	4.9	1.1	1.4	3.1	63.4
	SD	765,000	18.0	11.9	15.5	9.4	4.2	4.6	8.3	18.0
HPT 4 (n=107)	average	346,900	25.9	8.9	16.9	2.7	3.6	4.5	52.4	10.8
	SD	572,000	19.3	11.7	15.5	6.7	8.5	11.4	20.4	14.3

Notes: The table shows the results of K-Means clustering (four-cluster-solution) using the asset class weights of the 1,052 households of the final sample of the PHF-survey of 2014. The asset class weights, i.e. the relative amounts of households' total portfolio value (VALUEpf) in Euros invested among the asset classes cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) were applied as separate cluster variables. Each cluster represents a different Household Portfolio Type (HPT). For each HPT, the standard deviation and average asset class weight in percent of all households assigned to a respective cluster are reported.

Table 8: F-values for K-Means clustering (four-cluster-solution)

	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=453)	0.41	0.27	0.28	0.42	0.74	0.21	0.22
HPT 2 (n=270)	2.12	0.25	1.74	2.58	2.12	0.15	0.18
HPT 3 (n=222)	0.64	0.33	0.22	0.10	0.13	0.21	0.48
HPT 4 (n=107)	0.63	0.33	0.11	0.42	0.78	1.30	0.31

Notes: This table reports F-values for K-Means clustering (four-cluster-solution). F-values compare the intra-cluster variance with the overall variance for each cluster variable and allow conclusions about cluster homogeneity. F-values below one indicate that the intra-cluster variance is less than the inter-cluster variance and suggests high intra-cluster homogeneity (see for example HPT 1 and HPT 3). F-values are computed for households' asset class weights among cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) which are used as cluster variables.

5.3.2 Return Differences

Robustness tests of RDs include increasing portfolio sizes to examine if the 60/40 XTF portfolio can achieve higher risk-adjusted returns than the HPTs even when the HPTs are considered to be better diversified in terms of the number of securities per portfolio.[406] The analysis also controls for the influence of the HPTs' asset class weights and assumed securities on RDs. Therefore, three different versions of HPTs are established (henceforth: control portfolios). Control portfolios involve (i) an equal weighting of the HPTs' asset classes (i.e. 1/m portfolio), (ii) in addition to an equal weighting of the asset classes, an equal weighing of the HPTs' securities (i.e. 1/n portfolio), and (iii) a version of the HPTs which only contains their stock and bond holdings, weighted by a 60/40 ratio in correspondence to the 60/40 XTF portfolio (i.e. 60/40 portfolio).[407]

Each control portfolio is risk-adjusted to the risk of a HPT. If the risk-adjusted return of, for instance, the 1/m portfolio is higher after the adjustment than the return of the corresponding HPT, this indicates that the asset class weights applied in the HPT influence its returns (compared to an equal weighting of asset classes as implied by the 1/m portfolio). As a result, when RDs are measured towards the 60/40 XTF portfolio, RDs for the HPT are higher than the RDs for the 1/m portfolio. This indicates that a fraction of the RDs initially determined for the HPT relates to the choice of the asset class weights rather than the diversification of XTFs. Table 9 to Table 12 control for this influence and subtract such fractions from the RDs in cases they occur.[408] In this way, RDs are limited by control portfolios to the amount that can be attributed to diversification of XTFs. Except for a portfolio size of 297 securities,[409] however, RDs were not constrained by control portfolios. Overall, all RDs remain positive.

When increasing portfolio size, RDs of all HPTs stay positive and do not substantially vary from the RDs of the initial portfolio size of nine securities (see Table 9 to Table 12). In brief, for a portfolio size of nine securities, RDs reach 1.69 (2.48; 7.51) percentage points for HPT 1 (HPT 2; HPT 3) while for 18 securities, RDs are 1.46 (2.14; 6.63) percentage points for HPT 1

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406 See Evans/Archer (1968); Statman (1987); (2004).

407 See Table 34 and Appendix C for an illustration and description of control portfolios.

408 Cases in which the RD between a HPT and the 60/40 XTF portfolio was constrained since one of the control portfolios achieves higher risk-adjusted returns are outlined by positive values in the column "RD" in Table 9 to Table 12. The highest positive value represents the amount which is subtracted from the RDs.

409 The two exceptional cases are HPT 1 and HPT 2 that consist of 297 securities (see Table 12). Compared to both HPTs, the 1/n control portfolio achieves higher risk-adjusted returns for which the corresponding RDs are controlled for. A reason for the higher risk-adjusted returns of the 1/n portfolio might be that the latter implies an equal weighting of securities which might assign (compared to HPTs) higher weights to securities that reveal smaller market capitalizations (c.f. Table 27 regarding the applied securities). Nevertheless, the RDs of HPT 1 and HPT 2 stay positive and do not change the initial conclusion that they can obtain risk-return enhancements compared to the 60/40 XTF portfolio.

(HPT 2; HPT 3). HPTs that include 27 securities obtain RDs of 1.98 (3.01; 8.96) percentage points for HPT 1 (HPT 2; HPT 3) and HPTs with a large portfolio size of 297 securities achieve RDs of 1.68 (3.00; 7.27) percentage points for HPT 1 (HPT 2; HPT 3). Overall, this suggests that RDs and, thus, risk-return enhancements stay relatively robust when allowing for control portfolios and larger portfolio sizes.[410]

Table 9: Return difference (RD) based on the risk of HPTs (9 securities per HPT) [Jan. 2014 – Dec. 2016]

	Risk	Return	adjusted to risk of HPT 1		
HPT 1	3.00	3.07	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	9.02	5.66	3.00	2.82	-0.25
1/n	9.20	5.69	3.00	2.80	-0.27
60/40	13.26	6.11	3.00	2.47	-0.60
60/40 XTF portfolio	8.30	10.68	3.00	4.75	1.69
	Risk	Return	adjusted to risk of HPT 2		
HPT 2	5.30	4.84	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	9.02	5.66	5.30	3.90	-0.94
1/n	9.20	5.69	5.30	3.87	-0.97
60/40	13.26	6.11	5.30	3.29	-1.56
60/40 XTF portfolio	8.30	10.68	5.30	7.32	2.48
	Risk	Return	adjusted to risk of HPT 3		
HPT 3	14.40	6.97	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	9.02	5.66	14.40	5.76	-1.22
1/n	9.20	5.69	14.40	5.80	-1.18
60/40	13.26	6.11	14.40	6.17	-0.81
60/40 XTF portfolio	8.30	10.68	14.40	14.49	7.51

Notes: This table reveals the risk/return-positions of the HPTs, the 60/40 XTF portfolio, as well as the 1/m, 1/n and 60/40 portfolio for a portfolio size of nine securities and the period from January 2014 until December 2016 (left column). To determine the RDs, the latter four portfolios are risk-adjusted to the risk of the respective HPT (middle column). If the RDs (right column) for the 1/m, 1/n or the 60/40 control portfolios are positive (i.e. the control portfolio yields higher risk-adjusted returns than the HPT), the maximum of the positive RDs of the respective control portfolio is subtracted from the RD between the 60/40 XTF portfolio and the respective HPT. Example: The RD between the 60/40 XTF portfolio and the respective HPT is 7.51 percentage points without any subtraction since the RD between the 1/m, 1/n or 60/40 portfolio and respective HPT are negative.

[410] See Appendix C for robustness tests on RDs that are based on the risk of the 60/40 XTF portfolio.

Table 10: Return difference (RD) based on the risk of HPTs (18 securities per HPT) [Jan. 2014 – Dec. 2016]

	Risk	Return	adjusted to risk of HPT 1		
HPT 1	2.75	3.02	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	8.53	5.36	2.75	2.68	-0.34
1/n	8.37	5.38	2.75	2.71	-0.31
60/40	12.55	5.78	2.75	2.36	-0.65
60/40 XTF portfolio	8.30	10.68	2.75	4.48	1.46
	Risk	**Return**	**adjusted to risk of HPT 2**		
HPT 2	4.90	4.74	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	8.53	5.36	4.90	3.67	-1.06
1/n	8.37	5.38	4.90	3.73	-1.01
60/40	12.55	5.78	4.90	3.11	-1.63
60/40 XTF portfolio	8.30	10.68	4.90	6.88	2.14
	Risk	**Return**	**adjusted to risk of HPT 3**		
HPT 3	12.98	6.97	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	8.53	5.36	12.98	5.28	-1.69
1/n	8.37	5.38	12.98	5.31	-1.66
60/40	12.55	5.78	12.98	5.79	-1.18
60/40 XTF portfolio	8.30	10.68	12.98	13.60	6.63

Notes: This table reveals the risk/return-positions of the HPTs, the 60/40 XTF portfolio, as well as the 1/m, 1/n and 60/40 portfolio for a portfolio size of 18 securities and the period from January 2014 until December 2016 (left column). To determine the RDs, the latter four portfolios are risk-adjusted to the risk of the respective HPT (middle column). If the RDs (right column) for the 1/m, 1/n or the 60/40 control portfolios are positive (i.e. the control portfolio yields higher risk-adjusted returns than the HPT), the maximum of the positive RDs of the respective control portfolio is subtracted from the RD between the 60/40 XTF portfolio and the respective HPT. Example: The RD between the 60/40 XTF portfolio and the respective HPT is 6.63 percentage points without any subtraction since the RD between the 1/m, 1/n or 60/40 portfolio and respective HPT are negative.

Table 11: Return difference (RD) based on the risk of HPTs (27 securities per HPT) [Jan. 2014 – Dec. 2016]

	Risk	Return	adjusted to risk of HPT 1		
HPT 1	2.82	2.58	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	8.53	3.93	2.82	2.24	-0.34
1/n	8.46	3.33	2.82	2.05	-0.53
60/40	12.37	3.59	2.82	1.90	-0.68
60/40 XTF portfolio	8.30	10.68	2.82	4.56	1.98

	Risk	Return	adjusted to risk of HPT 2		
HPT 2	5.10	4.09	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	8.53	3.93	5.10	2.91	-1.17
1/n	8.46	3.33	5.10	2.56	-1.52
60/40	12.37	3.59	5.10	2.30	-1.78
60/40 XTF portfolio	8.30	10.68	5.10	7.10	3.01

	Risk	Return	adjusted to risk of HPT 3		
HPT 3	13.03	4.68	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	8.53	3.93	13.03	3.11	-1.57
1/n	8.46	3.33	13.03	2.16	-2.52
60/40	12.37	3.59	13.03	3.49	-1.19
60/40 XTF portfolio	8.30	10.68	13.03	13.63	8.96

Notes: This table reveals the risk/return-positions of the HPTs, the 60/40 XTF portfolio, as well as the 1/m, 1/n and 60/40 portfolio for a portfolio size of 27 securities and the period from January 2014 until December 2016 (left column). To determine the RDs, the latter four portfolios are risk-adjusted to the risk of the respective HPT (middle column). If the RDs (right column) for the 1/m, 1/n or the 60/40 control portfolios are positive (i.e. the control portfolio yields higher risk-adjusted returns than the HPT), the maximum of the positive RDs of the respective control portfolio is subtracted from the RD between the 60/40 XTF portfolio and the respective HPT. Example: The RD between the 60/40 XTF portfolio and the respective HPT is 8.96 percentage points without any subtraction since the RD between the 1/m, 1/n or 60/40 portfolio and respective HPT are negative.

Table 12: Return difference (RD) based on the risk of HPTs (297 securities per HPT) [Jan. 2014 – Dec. 2016]

	Risk	Return	adjusted to risk of HPT 1		
HPT 1	2.45	2.13	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	7.34	3.79	2.45	2.20	0.07
1/n	6.35	4.16	2.45	2.46	0.34
60/40	10.62	4.56	2.45	2.13	0.00
60/40 XTF portfolio	8.30	10.68	2.45	4.14	1.68

	Risk	Return	adjusted to risk of HPT 2		
HPT 2	4.38	2.83	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	7.34	3.79	4.38	2.83	0.00
1/n	6.35	4.16	4.38	3.30	0.47
60/40	10.62	4.56	4.38	2.71	-0.12
60/40 XTF portfolio	8.30	10.68	4.38	6.30	3.00

	Risk	Return	adjusted to risk of HPT 3		
HPT 3	11.26	5.26	Risk (risk-adj.)	Return (risk-adj.)	RD
1/m	7.34	3.79	11.26	2.88	-2.39
1/n	6.35	4.16	11.26	3.12	-2.15
60/40	10.62	4.56	11.26	4.50	-0.76
60/40 XTF portfolio	8.30	10.68	11.26	12.53	7.27

Notes: This table reveals the risk/return-positions of the HPTs, the 60/40 XTF portfolio, as well as the 1/m, 1/n and 60/40 portfolio for a portfolio size of 297 securities and the period from January 2014 until December 2016 (left column). To determine the RDs, the latter four portfolios are risk-adjusted to the risk of the respective HPT (middle column). If the RDs (right column) for the 1/m, 1/n or the 60/40 control portfolios are positive (i.e. the control portfolio yields higher risk-adjusted returns than the HPT), the maximum of the positive RDs of the respective control portfolio is subtracted from the RD between the 60/40 XTF portfolio and the respective HPT. Example: The RD between the 60/40 XTF portfolio and the respective HPT is 7.27 percentage points without any subtraction since the RD between the 1/m, 1/n or 60/40 portfolio and respective HPT are negative.

5.3.3 Portfolio Replacement

Tests regarding the robustness of portfolio replacements include, first, as for RDs, an increase in portfolio size (see Appendix D). While the general effect on risk and return of the HPTs remains stable, the extent of the changes in risk and return differs. For portfolio sizes larger than nine securities, the return increases are higher, and the risk reductions are lower. Only for HPT 1 which includes 297 securities, risk slightly rises. Less differences in risk between the HPTs and the 60/40 XTF portfolio seem to be in line with previous studies which correspondingly point out that an increase in portfolio size leads to a reduction in risk.[411]

Second, a portfolio replacement by 50 percent is conducted, i.e., only half of the amount invested in each security is replaced with the 60/40 XTF portfolio. This allows testing whether transaction costs might have a disproportionate impact on the results. However, both the risk reducing and the return increasing effect seem to be approximately half of the size compared to the initial (100 percent) portfolio replacement. Third, alternative stock/bond ratios of 25/75, 50/50, and 75/25 are incorporated in the benchmark XTF portfolio to control for different asset class weights which might represent a more favorable benchmark for households with a certain risk or stock/bond preference. The results, however, stay robust; none of the robustness ratios yields consistently superior risk-return enhancements compared to the 60/40 ratio.

[411] See Evans/Archer (1968); Statman (1987); (2003); (2004).

6 Downside-Risk Measures as Explanation for Households' Reluctance to Invest in XTFs[412]

6.1 Methodological Approach

RQ2 asks whether downside-risk measures can help to explain the reluctance of households to invest in XTFs. To answer that question, this analysis compares possible enhancements in the risk-return trade-off when risk is measured by the SD to possible enhancements when households show loss-aversion and evaluate risk according to downside-risk measures. Therefore, (i) risk-return positions of household portfolios are estimated, (ii) the calculation of the applied downside-risk measures is presented, (iii) individual benchmark XTF portfolios for each HPT are derived, and (iv) the determination of RDs according the employed risk-return-frameworks is outlined.

(i) Estimation of households' risk-return position: Since the allocation of assets across asset classes mainly determines a portfolio's overall performance,[413] it is crucial to consider multiple relevant asset classes of household portfolios. Most households rely on the recommendation of financial advisors[414] which, however, seem to build very similar portfolios instead of individualized portfolio compositions.[415] Considering that the three HPTs derived in the first empirical analysis take multiple relevant asset classes of household portfolios into account and represent stylized portfolio compositions of households, this analysis relies on the derived HPTs and their corresponding asset class weights.[416]

Regarding portfolio size (i.e. the number of securities per portfolio), this analysis follows the base case of the first empirical analysis[417] and applies nine risky securities per HPT, i.e., three mutual funds, three BDs and three STs. Mutual funds are, again, further divided into one SF, one BF, and one REF. In contrast to the first empirical analysis, this analysis takes all security holdings available in the data sample of the SHS-base[418] into account, i.e., security holdings are

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[412] Substantial parts of this chapter and the corresponding appendices are obtained from Wanger/Oehler (2019).
[413] See Brinson/Hood/Beebower (1986); (1995); Brinson/Singer/Beebower (1991); Hood (2005); Ibbotson/Kaplan (2000).
[414] See, e.g., for Canada, The Investment Funds Institute of Canada (2012), for the United States, see Investment Company Institute (2013), and for Germany, see DAB Bank (2004); Hackethal et al. (2011).
[415] See chapter 2.2.
[416] The HPTs are derived in chapter 5.2.1 from PHF-survey data, which were extracted from the second wave of the HFCS of the European Central Bank (Data source: European Central Bank, Eurosystem Household Finance and Consumption Survey, second wave. Data access granted through the project: Can XTFs enhance Households' investment returns?; lead researcher: Oehler, A.; co-researchers: Horn, M., Wanger, H.P.).
[417] See chapter 5.1.1. This analysis abstracts from increasing portfolio size and control portfolios since the first analysis suggests that the latter do not considerably change the results.
[418] Data source: Deutsche Bundesbank, Research Data and Service Centre, Securities Holdings Statistics-Base. Data access granted through the project: Can XTFs enhance the return of households' portfolios while keeping the portfolio-risk constant?; Project-ID: 2017\0103; lead researcher: Oehler, A.; co-researcher: Wanger, H.P.

not constrained to securities with the highest aggregated market value of shares owned by German households. This procedure largely extends the security sample from which securities are selected and assigned to the HPTs.

From the extended security sample, 1,000 random portfolios (each consisting of nine securities) are selected to compile HPTs. In correspondence to the first empirical analyses, a security's market value of shares relative to the market value of all securities in its corresponding asset class is assumed as indication for the distribution of a security among German households. The latter value is used again as probability for the selection of a security in the random sampling process. To avoid selection bias, each random portfolio is applied to every HPT. This means that the same randomly selected nine securities are weighted with the asset class weights of each HPT. As future price developments of securities are unknown, investing money in equal parts appears to be a reasonable strategy from the perspective of households.[419] An equal distribution of assets has been documented in empirical household portfolios.[420] Therefore, securities are equally weighted within the employed asset classes.

For each security of the SHS-base, asset class information and total return price data[421] are requested from Thomson Reuters Datastream. This allows categorizing each security into the asset classes SF, BF, REF, BD or ST, and to calculate monthly security returns.[422] If there were no data available or if a security could not be categorized clearly into one of the employed asset classes, the security was dropped from the data set. If securities reveal negative market values of shares, they are excluded from the first month the market value turns negative since this indicates bankruptcy and implies that this security cannot be purchased anymore.

The security sample of the SHS-base also includes mutual funds which follow a mixed asset strategy, i.e. mixed funds. Mixed funds are, according to the market value of shares, among the most widespread mutual funds of German households. Each mixed fund is categorized into SFs

[419] See Elton/Gruber (1977) De Wit (1998).
[420] See e.g. Benartzi/Thaler (2001); Huberman/Jiang (2006); Baltussen/Post (2011).
[421] Security returns using total return price data are calculated according to the same procedure as in the previous analysis (see chapter 5.1.1 and footnote 379).
[422] Compared to risky financial assets, CASH and SV reveal relatively low returns on average. Since the HPTs applied in this analysis all invest substantial amounts of VALUEpf in CASH and SV, inflation might have a considerable negative impact on household portfolio performance and might cause losses in real terms of returns which might also be crucial for loss-averse households assumed in this analysis. Consequently, this analysis refers to real returns and subtracts monthly inflation rates from all monthly (nominal) security returns. Monthly inflation rates for Germany were computed using monthly changes of the Harmonised Index of Consumer Prices as of Eurostat (2019). For the period between January 2009 and December 2013, the average monthly inflation rate amounts to 0.14 percent and 0.05 percent for the period between January 2014 and December 2016.

or BFs[423] according to return the correlations between a mixed fund and several stock and bond indices which cover a range of markets and sectors.[424] If the highest correlation value appears with one of the stock indices, the regarding mixed fund is categorized as SF (this applies analogously to categorizations as BFs). The initial sample from the SHS-base contains 1,970 mixed funds. Thereof, 49 mixed funds were excluded since they reveal less than three months of returns which prevents a proper calculation of correlations. From the remaining 1,921 mixed funds, 1,540 are assigned to SFs and 381 to BFs.

The resulting sample of security holdings is outlined in Table 13. The final sample contains 47,388 securities which includes 7,552 SFs, 3,267 BFs, 42 REFs, 22,225 BDs[425] and 14,302 STs. In correspondence to the first analysis, weighted (according to outstanding amounts) monthly interest rates on German households' deposits with agreed maturities of up to one year, over one and up to two years, and over two years are used as interest rates for SV, while interest rates on overnight deposits of German households are applied for CASH, respectively.[426]

[423] The categorization fits with the questionnaire of the PHF-survey since there, households who hold mutual funds are asked about the asset class which their mutual fund predominantly invests in (see European Central Bank (2016a)).
[424] See Table 25 in for the applied indices. The applied indices are the same as in the first analysis on RQ1.
[425] BDs include bonds with a fixed coupon (straight bonds and zero bonds) as well as bonds with a variable coupon (floating bonds and index linked bonds). Returns for the latter group of bonds are calculated using total return price data from Thomson Reuters Datastream. From the total 22,225 individual bonds in the sample, 14,291 are straight bonds, 1,247 are zero bonds, 6,660 are floating bonds, and 27 are index linked bonds.
[426] Own calculations; data obtained from Deutsche Bundesbank (2019c). See also chapter 5.1.1 and Table 14.

Table 13: Applied securities from the SHS-base of Deutsche Bundesbank

	SF	BF	REF	BD	ST
total number of securities in the sample	7,552	3,267	42	22,225	14,302
average number of securities with available return data per month	6,252	2,671	41	13,387	10,723
market value of security shares held by households (monthly average) [bn]	216.6	68.3	63.6	100.6	242.6
top 100 securities' market value of shares relative to asset class (monthly average)	53.8	62.2	100.0	20.6	76.2

Notes: The first row of this table shows the total number of securities in each asset class. The second row provides the average number of securities for which return data is available (monthly averages for the months between January 2014 and December 2016). The securities are obtained from Deutsche Bundesbank's SHS-base. The third row reveals for each asset class the aggregated market value of shares held by German households (monthly averages). The corresponding value for REFs outlines its importance in relation to the remaining asset classes, although it contains the least number of securities. The fourth row reveals, in terms of the market value of shares owned by German households, the percentage of the top 100 securities to the aggregated market value of all securities' shares of the regarding asset class. Each security's market value of shares relative to the market value of all shares of a certain asset class is used as proxy for the probability that a certain security is held by households. The values point out the importance of the top 100 securities for establishing HPTs. Example: The market value of the top 100 SFs accounts on average for 53.8 percent of the market value of shares invested in all securities in the sample.

The top 100 securities by market value of shares exhibit a major part in every asset class. For STs, they account on average for more than 75 percent of the market value of all STs. For BFs, they exceed 60 percent and for SFs 50 percent of the respective asset class’ market value. REFs are few, but the aggregated market value across all REFs indicates that they are an important component in German household portfolios compared to the remaining asset classes (e.g., REFs come close to the aggregated market value of BFs).[427]

The period over which returns are available can vary for each security and might be less than the 36 months covered by the observation period from January 2014 to December 2016. BDs show the largest difference between the entire number of available securities in this asset class and the average numbers of available securities per month, which implies that available data varies most often for BDs compared to the other asset classes (e.g. due to the maturity of a bond). For reinvesting an amount of money that is available after an expiry of a security, as in the first analysis, fixed transaction costs of 10 Euros per transaction[428] and proportional transaction cost of 0.25 percent of the order value are assumed.[429]

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[427] See Table 13.

[428] This reflects the approximate amount that large German online brokers charge their clients (see Stiftung Warentest (2016)).

[429] See Lynch/Balduzzi (2000).

(ii) Calculation of downside-risk measures: This analysis assumes downside-risk measures that reflect households' interpretation of risk closer than the SD, i.e. the LPM0, LPM1, $\sqrt{\text{LPM2}}$, and MDD.[430] The general notation of LPMs was introduced by Bawa (1975) and Fishburn (1977).[431] The mathematical expression of the general notation of LPMs can be used to specify the applied LPM-based downside-risk measures. It requires determining the degree of risk aversion (n), i.e. the weight an investor assigns to negative return deviations, and a target return (τ). The general LPM notation can be described by:

$$\text{(5) } \text{LPM}_{ni}(\tau) = \frac{1}{T}\sum_{t=1}^{T} \max\,[\tau - r_{it}, 0]^{n}.$$

Thereby, r_{it} denotes the (discrete) return of portfolio i in month $t(t = 1, \dots, T)$ and T the number of months. Depending on the definition of n, the general LPM notation allows expressing LPM0 (with $n = 0$), LPM1 (with $n = 1$), and $\sqrt{\text{LPM2}}$ (with $n = 2$), of portfolio i for a target return τ.[432] The three measures can be specified by:

$$\text{(6) } \text{LPM}_{n=0,i}(\tau) = \frac{1}{T}\sum_{t=1}^{T} \begin{cases} \max\,[\tau - r_{it}, 0]^{0}, & \text{if } (\tau - r_{it}) > 0 \\ 0, & \text{if } (\tau - r_{it}) \leq 0 \end{cases}$$

$$\text{(7) } \text{LPM}_{n=1,i}(\tau) = \frac{1}{T}\sum_{t=1}^{T} \max\,[\tau - r_{it}, 0]^{1}$$

$$\text{(8) } \sqrt{\text{LPM}_{n=2,i}(\tau)} = \sqrt{\text{semi} - \text{variance}_{i}(\tau)} = \sqrt{\frac{1}{T}\sum_{t=1}^{T} \max\,[\tau - r_{it}, 0]^{2}}.$$

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430 See downside-risk measures presented in chapter 4.1.2.3.

431 This general definition is also referred to as $\alpha - \tau$ model in the literature (see e.g. Fishburn (1977); Grootveld/Hallerbach (1999)).

432 While $n = 2$ implies risk-aversion and $n = 1$ risk-neutrality (see e.g. Fishburn (1977); Nawrocki (1999); Grootveld/Hallerbach (1999)), Fishburn (1977) states that the LPM model "may have a risk-seeking or 'gambling' aspect" (p. 119) when $n < 1$. Although households are usually assumed to be risk-averse (e.g. as reflected by the SD or $\sqrt{\text{LPM2}}$), risk evaluations according to LPM1 and LPM0 which implicate risk-neutrality and risk-seeking have also been documented among households in empirical studies (see e.g. Unser (2000); Veld/Veld-Merkoulova (2008); Holzmeister et al. (2019)). This is not necessarily contradictory since, while risk preferences of investors appear to remain relatively stable over time, they may temporarily vary, e.g. due to economic crises, emotions, stress, or changing stages in a life cycle (see e.g. Schildberg-Hörisch (2018)). More specific in the context of downside-risk, Crum/Laughhunn/Payne (1981) state that investors can reveal both risk-seeking and risk-averse behavior. While risk-seeking rather occurs in situations in which returns are below a corresponding target return, risk-averse behavior appears when returns are above a corresponding target return. Thus, when considering to sell a security that exhibits book-losses, for instance, households might evaluate the involved risk according to LPM0 and act temporarily risk-seeking (in reference to the convex value function in the domain of losses according to Prospect Theory; see Kahneman/Tversky (1979)). Another reason why employing several risk measures which reflect different risk preferences does not seem to be conflicting is that households' risk attitude and risk perception may diverge (see Nosić/Weber (2010); Oehler/Wedlich (2018); Oehler/Horn/Wedlich (2018)). E.g., Holzmeister et al. (2019) point out that the probability of loss (i.e. LPM0) represents households' risk perception best. They state that their result indicates that loss-aversion represents the most important component of decision-making under risk.

According to formula (5) to (8), risk emerges if the maximum value in square brackets is larger than zero. Such values occur in months in which the portfolio return is lower than the target return, i.e. $(\tau - r_{it}) > 0$. In months in which the portfolio return equals or exceeds the target return, no risk is assumed, i.e. $(\tau - r_{it}) \leq 0$. In this case, the value in square brackets turns zero. Following this procedure yields a series of monthly values which are either zero or positive. Each value of the series is weighted by the degree of risk aversion of the regarding LPM-based downside-risk measure. In LPM0, the resulting values are either zero or one. Finally, all weighted values are aggregated and divided by the number of months included in the observation period. Analogously to the relation between the SD and the variance, the square root is taken from the semi-variance to obtain $\sqrt{\mathrm{LPM2}}$.

In addition to the LPM-based downside-risk measures, the MDD is employed. According to Bradford/Siliski (2016), the MDD can be assembled by first calculating point-in-time drawdowns $\mathrm{D(T)}$, where r_{it} is the return of portfolio i in month t and r_{iz} is the return of portfolio i in month z:

$$\text{(9)}\quad \mathrm{D(T)} = \min\left(\frac{\prod_{i=0}^{T}(1+r_{it})}{\max\limits_{t\,\in\,0,\ldots,T-1}\prod_{z=0}^{t}(1+r_{iz})} - 1, 0\right).$$

In formula (9), the numerator shows the cumulative portfolio return at time T. The denominator indicates a high-water mark, i.e. the maximum realized cumulative return at any time $t < T$. After determining the time series $D = [D_0, D_1, \ldots, D_T]$ of point-in-time drawdowns, $\mathrm{MDD(T)}$ can be ascertained as the largest point-in-time drawdown (formally expressed by the minimum since drawdowns represent negative returns) determined in D:[433]

$$\text{(10)}\qquad \mathrm{MDD(T)} = \min_{t\,\in\,0,\ldots,T\,|\,D(T)\,\in\,D} \mathrm{D(T)} =$$

$$= \min_{t\,\in\,0,\ldots,T}\left[\min\left(\frac{\prod_{i=0}^{T}(1+r_{it})}{\max\limits_{t\,\in\,0,\ldots,T-1}\prod_{z=0}^{t}(1+r_{iz})} - 1, 0\right)\right].$$

As opposed to the SD, the MDD does not require any assumptions about the distribution of returns. In contrast to the LPM-based downside-risk measures, the MDD does not require a target return. The MDDs of the HPTs and the benchmark XTF portfolios can readily be compared to each other.

[433] See Bradford/Siliski (2016).

(iii) Benchmark XTF portfolios: Household portfolios are compared to benchmark XTF portfolios to ascertain risk-return enhancements from XTFs. For each HPT, an individual benchmark XTF portfolio is established. The construction of individual benchmark XTF portfolios relies on the previous assumption that the assets included in the HPTs represent investments in the speculation-portfolio. The latter concept involves that households' investments in the speculation-portfolio pursue the same goal and implies that households evaluate the performance of the investments included in the speculation-portfolio jointly.[434] Considering that speculation-portfolios differ across the HPTs, individual benchmark XTF portfolios are established for each HPT.

Individual benchmark XTF portfolios are derived according to the HPTs' asset class concentration[435] among stocks (ST and SF), bonds (BD und BF) and safe financial assets. HPTs' asset class weights are converted into well-replicable allocations across stocks, bonds, and safe financial assets to provide an easily investable benchmark XTF portfolio (see Table 14). In correspondence to the first empirical analysis, benchmark XTF portfolios follow a buy-and-hold strategy and employ one stock XTF and one bond XTF which cover the MSCI World Index and the Markit iBoxx Euro Sovereign Index, respectively.[436] As return of the safe investment, the interest rate on SVs is applied.[437]

In the analysis, possible risk-return enhancements of household portfolios are ascertained towards a corresponding benchmark XTF portfolio. Since the latter represent the reference, or target, to which household portfolios are compared, benchmark XTF portfolios are further applied for the deduction of target returns incorporated in the employed downside-risk measures.[438] As future returns are unknown,[439] households are thereby assumed to rely on past returns (i.e. returns prior to the beginning of the observation period in January 2014). The maximum pre-observation period that can be observed with regard to data availability covers the five-year-period from January 2009 to December 2013 (see Table 14).

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434 See chapter 4.1.2.2.

435 This assumes that households intend to maintain the risk of their current portfolio when employing XTFs. Since portfolio risk is heavily influenced by a portfolio's asset class concentration (see Brinson/Hood/Beebower (1986); (1995); Brinson/Singer/Beebower (1991); Hood (2005); Ibbotson/Kaplan (2000)), individual benchmark XTF portfolios are derived thereof.

436 ISIN of the applied stock XTF: LU0392494562; ISIN of the applied bond XTF: LU0290355717.

437 By choosing SV instead of CASH as benchmark for safe financial assets, this analysis relies on the assumption that households rather prefer investments with longer-term maturities and (marginally) higher fixed interest rates.

438 See also chapter 4.1.2.3 regarding the assumption to employ XTF portfolios to derive target returns for the applied downside-risk measures.

439 See e.g. Elton/Gruber (1977).

Table 14: Construction of HPT-specific benchmark XTF portfolios

Asset class weights of benchmark XTF portfolios				Reference period		Applied interest rate / XTF	
asset class	HPT 1	HPT 2	HPT 3	target return	risk / return	Index	interest rate / ISIN
SV (CASH + SV)	70.0	33.3	30.0	01/2009 - 12/2013	01/2014 - 12/2016	weighted average interest rate	German households' deposits with agreed maturities of up to one year, over one and up to two years, and over two years
Bond XTF (BF + BD)	10.0	33.3	0.0	01/2009 - 12/2013	01/2014 - 12/2016	Markit iBoxx Euro Sov. Index	LU0290355717
Stock XTF (SF + ST)	20.0	33.3	70.0	01/2009 - 12/2013	01/2014 - 12/2016	MSCI World Index	LU0392494562

Notes: This Table provides details on the construction of HPT-specific benchmark XTF portfolios that are used in this analysis to determine risk-return enhancements from XTFs. The asset classes in parentheses in the first column indicate which asset classes of an HPT are incorporated to derive a certain benchmark asset class weight. The asset class weights of the benchmark XTF portfolios are also applied in the pre-observation period to determine target returns for the LPM-based downside-risk measures. The pre-observation period represents the period with the maximum available return data that is common to the constituents of the benchmark XTF portfolios. Interest rate data on SV is gathered from Deutsche Bundesbank (2019c). Data on the stock XTF (MSCI World ETF) and bond XTF (Markit iBoxx Euro Sovereign Index ETF) are gathered from Thomson Reuters Datastream.

(iv) Determination of risk-return enhancements: Correspondingly to the first empirical analysis, possible enhancements in the risk-return trade-off of the HPTs are determined by RDs. For risk-adjusting portfolios, distinct rates for borrowing and lending are taken into account. As (quasi) risk-free investment (r_{SV}),[440] the monthly interest rate of SV between January 2014 and December 2016 of 0.06 percent is applied. The security lending rate (r_{SL}) amounts to a rate of 0.39 percent per month.[441]

RDs based on the risk of HPT portfolio i (RD_{HPTi}) can formally be described by:

$$(11) \qquad RD_{HPTi} = \mu_{BM,HPTi} - \mu_{HPTi}.$$

Thereby, RD_{HPTi} is ascertained by the mean return of the regarding benchmark XTF portfolio (μ_{BM}) which is risk-adjusted to the risk of HPT portfolio i ($\mu_{BM,HPTi}$), minus the mean return of

440 According to neoclassical finance, the risk-free investment bears no risk of default and is not included in the (market) portfolio of risky assets. Since the safe financial assets applied in this analysis (CASH and SV) exhibit return fluctuations which reflects risk, they are included in the HPTs. They are considered as “quasi” risk-free investment as opposed to the default-free risk-less investment in the sense of neoclassical finance. The monthly interest rate of SV used for r_{SV} is expressed in real terms, i.e. less of inflation.

441 The security lending rate is derived from a comparison of security loans offered by large German banks amounting to 5.5 percent per annum (see Stiftung Warentest (2013)). The monthly security lending rate used for r_{SL} is expressed in real terms, i.e. less of inflation.

the HPT portfolio i (μ_{HPTi}). Results for all risk measures are computed in monthly terms. $\mu_{BM,HPT}$ is determined for the SD and the LPM-based risk measures by:

$$\mu_{BM,HPTi} = \begin{cases} r_{SL} + \frac{\mu_{BM} - r_{SL}}{risk_{BM}} risk_{HPTi}, & \text{if } risk_{BM} < risk_{HPTi} \\ r_{SV} + \frac{\mu_{BM} - r_{SV}}{risk_{BM}} risk_{HPTi}, & \text{if } risk_{BM} > risk_{HPTi} \\ \mu_{BM}, & \text{if } risk_{BM} = risk_{HPTi} \end{cases} \tag{12}$$

Depending on the underlying risk measure, (risk) denotes the SD, LPM0, LPM1, or $\sqrt{LPM2}$.

6.2 Results and Discussion

6.2.1 Risk and Return of Benchmark and Household Portfolios

Table 15 illustrates the mean, median, skewness, and kurtosis of the three HPTs.[442] Each measure is first calculated separately for all 1,000 portfolios of a HPT. Then, the average, median, standard deviation, minimum, and maximum for each of the previous measures are ascertained. For example, in HPT 1 the maximum portfolio mean across all 1,000 HPT portfolios reaches approximately 1.32 percent of monthly return. Portfolios of HPT 1 exhibit on average the lowest mean return per month of approximately 0.15 percent, while portfolios of HPT 2 (HPT 3) achieve 0.22 percent (0.47 percent), respectively.

[442] From all monthly returns across the 1,000 portfolios included in a HPT, the highest and lowest 0.1 percent of returns are excluded as random checks suggested that some extreme outliers are driven by data errors and might lead to misinterpretations.

Table 15: Return distribution of HPT portfolios' monthly portfolio returns

HPT 1	Average	Median	Standard deviation	Minimum	Maximum
Mean [%]	0.1517	0.1426	0.0976	-0.0731	1.3151
Median [%]	0.0712	0.0639	0.1032	-0.2419	0.8069
Skewness	0.8212	0.8174	0.3513	-0.2471	2.4239
Kurtosis	1.3751	1.2033	1.0368	-0.7860	6.5954

Based on the Jarque-Bera test, the assumption that HPT 1's portfolio returns are normally distributed must be rejected for 34.1 percent (49.7 percent) of the portfolios at the 1 percent (5 percent) significance level.

HPT 2	Average	Median	Standard deviation	Minimum	Maximum
Mean [%]	0.2225	0.2106	0.1796	-0.1933	3.2168
Median [%]	0.1989	0.1894	0.1893	-0.3245	1.8202
Skewness	0.3951	0.3547	0.4129	-1.3723	2.7193
Kurtosis	1.0377	0.8646	1.0231	-1.1814	7.3659

Based on the Jarque-Bera test, the assumption that HPT 2's portfolio returns are normally distributed must be rejected for 14.0 percent (22.1 percent) of the portfolios at the 1 percent (5 percent) significance level.

HPT 3	Average	Median	Standard deviation	Minimum	Maximum
Mean [%]	0.4747	0.4787	0.4055	-0.9468	3.6759
Median [%]	0.4530	0.4358	0.4879	-1.4921	2.6271
Skewness	0.1026	0.1151	0.3824	-1.2305	1.4879
Kurtosis	0.1440	0.0129	0.7428	-1.1149	4.3461

Based on the Jarque-Bera test, the assumption that HPT 3's portfolio returns are normally distributed must be rejected for 2.9 percent (5.2 percent) of the portfolios at the 1 percent (5 percent) significance level.

Notes: The table presents the HPTs' portfolio mean, median, skewness and kurtosis between January 2014 and December 2016. Each of the measures was first calculated for all portfolios separately. Then, for each measure the average, median, standard deviation, minimum and maximum is provided. Example: Across all portfolios of HPT 3, the standard deviation of portfolio means is 0.4055 percent.

Differences in the risk evaluation according to the SD and the applied LPM-based downside-risk measures emerge if the target return applied in the downside-risk measures differs from the mean return employed in the SD, and if the portfolio returns are skewed and non-normally distributed.[443] To investigate whether differences in risk might occur due to skewed and non-normally distributed returns, each HPTs' portfolio return distribution is tested for normality using a Jarque-Bera test. Table 15 shows that portfolios of HPT 1 reveal on average the highest skewness value (0.82) compared to the skewness values of HPT 2 (0.40) and HPT 3 (0.10).

[443] See Harlow (1991); Jarrow/Zhao (2006).

According to the Jarque-Bera test, the assumption of normally distributed portfolio returns must be rejected for 34.1 percent (49.7 percent) of the portfolios of HPT 1 at the one (five) percent significance level. For portfolios of HPT 2, the assumption of normally distributed portfolio returns must be rejected for 14.0 percent (22.1 percent) and only 2.9 percent (5.2 percent) for portfolios of HPT 3 at the one (five) percent significance level, respectively. Thus, most portfolios of HPT 2 and HPT 3 seem to reveal normally distributed returns. The results of return skewness and the Jarque-Bera tests suggest that possible differences between the SD and the applied LPM-based downside-risk measures are more likely to occur for portfolios of HPT 1 than for portfolios of HPT 2 and HPT 3.

While the asset class weights of the benchmark XTF portfolio of HPT 2 are equally distributed among safe financial assets, bonds, and stocks, the benchmark XTF portfolios of HPT 1 and HPT 3 represent asset class concentrations of 70 percent in safe financial assets and stocks, respectively (see Table 14). The target returns applied in the LPM-based downside-risk measures are drawn from the five-year pre-observation period (i.e. January 2009 to December 2013) of each HPTs' benchmark XTF portfolio. The mean target returns for HPT 1 (HPT 2, HPT 3) amounts to 0.33 percent per month (0.52 percent, 0.87 percent). The target returns all differ from the average mean returns of the HPTs. Besides non-normally distributed returns, deviations between the target returns and the mean portfolio returns induce differences in risk between the SD and the applied LPM-based downside-risk measures.[444] Since portfolio returns of HPT 2 and HPT 3 seem to follow a normal distribution to a large extent (see Table 15), possible differences in risk can, for these HPTs, rather be associated with differing target and mean portfolio returns.

Risk and return characteristics of the benchmark XTF portfolios and the HPTs' portfolios are outlined in Table 16 and Table 17. Benchmark XTF portfolios are not (yet) risk-adjusted. The mean returns of all benchmark XTF portfolios (HPT 1: 0.32 percent; HPT 2: 0.54 percent; HPT 3: 0.80 percent) are higher than the mean returns of the corresponding HPT portfolios (HPT 1: 0.15 percent; HPT 2: 0.22 percent; HPT 3: 0.47 percent). Skewness values of the benchmark XTF portfolios are below the average skewness values of the corresponding HPT portfolios. This effect might be due to higher levels of diversification inherent to the employed benchmark XTF portfolios.[445]

[444] See Harlow (1991); Jarrow/Zhao (2006).
[445] See Hueng/Yau (2006); Mitton/Vorkink (2007); Kim (2015).

Table 16: Risk and return characteristics of benchmark XTF portfolios

	benchmark HPT 1	benchmark HPT 2	benchmark HPT 3
Mean value [%]	0.3210	0.5390	0.8030
Median [%]	0.1720	0.5640	0.7890
Skewness	0.4795	-0.0736	-0.1405
Kurtosis	0.9138	0.7599	0.7206
Standard deviation [%]	0.9645	1.5118	2.6103
LPM0 [%]	55.6	50.0	50.0
LPM1 [%]	0.3470	0.5319	0.9743
$\sqrt{\text{LPM2}}$ [%]	0.6218	1.0530	1.8859
MDD [%]	3.6813	6.2464	9.7569
Mean target return used in LPM-based risk measures [%]	*0.3250*	*0.5160*	*0.8650*

Notes: The table shows the mean value, median, skewness, kurtosis, standard deviation, Lower-Partial-Moment Zero (LPM0), LPM One (LPM1), LPM Two ($\sqrt{\text{LPM2}}$) and the Maximum Drawdown (MDD) of the monthly return distribution of each benchmark XTF portfolio for the period from January 2014 to December 2016. The target returns that are employed in the LPM-based risk measures represent the monthly mean return of the corresponding benchmark XTF portfolio between January 2009 to December 2013.

The benchmark XTF portfolios of HPT 1 and HPT 2 reveal slightly higher SDs (HPT 1: 0.96 percent; HPT 2: 1.51 percent) than the corresponding HPT portfolios on average (HPT 1: 0.89 percent; HPT 2: 1.43 percent). In contrast, when considering the LPM0, LPM1, $\sqrt{\text{LPM2}}$ and MDD as measure of risk, all benchmark portfolios exhibit lower risk than the corresponding HPT portfolios on average (see Table 16 and Table 17). This implies that loss-averse households which evaluate risk according to the employed downside-risk measures and would – instead of their current portfolio – hold the corresponding benchmark XTF portfolio, could obtain on average higher returns and less risk.

Table 17: Risk and return characteristics of HPTs' portfolios

	HPT 1	HPT 2	HPT 3
Mean value [%]	0.1517	0.2225	0.4747
Standard deviation [%]	0.8927	1.4330	3.5432
LPM0 [%]	65.1	63.7	55.0
LPM1 [%]	0.4312	0.6966	1.5888
$\sqrt{\mathrm{LPM2}}$ [%]	0.6611	1.1283	2.6669
MDD [%]	3.8220	6.5721	15.5763
Mean target return used in LPM-based risk measures [%]	*0.3250*	*0.5160*	*0.8650*

Notes: The table provides corresponding values for the mean, standard deviation, Lower-Partial-Moment Zero (LPM0), LPM One (LPM1), LPM Two ($\sqrt{\mathrm{LPM2}}$) and the Maximum Drawdown (MDD). The values represent averages across all portfolios of a HPT for the period of January 2014 to December 2016. The target returns that are employed in the LPM-based risk measures represent the monthly mean return of the corresponding benchmark XTF portfolio between January 2009 to December 2013.

6.2.2 Return Differences

Results on RDs according to a MV-, mean-LPM0 (M-LPM0)-, mean-LPM1 (M-LPM1)- and mean-$\sqrt{\mathrm{LPM2}}$ (M-LPM2)-framework are presented in the upper part of Table 18a to Table 18c. HPT 1 shows the least RDs on average (see Table 18a). If the benchmark XTF portfolio is risk-adjusted to the risk of HPT 1's portfolios (upper part of the Table 18a), RDs range between 0.14 percent and 0.15 percent monthly return. RDs for HPT 2 are generally higher than for HPT 1 (see Table 18b). The lowest RDs for HPT 2, amounting to 0.27 percent monthly return, occur in a MV-framework, while the highest average RDs, amounting to 0.36 percent, can be obtained in a M-LPM1-framework. RDs of HPT 3 are higher than those of the portfolios of HPT 2 (see Table 18c).

Table 18: Risk-return enhancements according to each applied risk measure

Part a: HPT 1

HPT 1	MV	M-LPM0	M-LPM1	M-LPM2
Mean return of benchmark portfolios (risk-adj.) [%]	0.2917	0.3052	0.2997	0.3063
Mean return of HPT 1 portfolios [%]	0.1517	0.1517	0.1517	0.1517
Mean RD [%]	0.1400	0.1535	0.1480	0.1546
	(0.0977)	(0.0972)	(0.0960)	(0.1011)
Two-sided Wilcoxon test between MV- and M-LPM-frameworks: p-value	- / -	< 0.001	< 0.001	< 0.001
Mean return of benchmark portfolio [%]	0.3210	0.3210	0.3210	0.3210
Mean return of HPT 1 portfolios (risk-adj.) [%]	0.1895	0.1388	0.1362	0.1367
Mean RD [%]	0.1315	0.1822	0.1848	0.1843
	(0.0912)	(0.1032)	(0.1073)	(0.1215)
Two-sided Wilcoxon test between MV- and M-LPM-frameworks: p-value	- / -	0.8006	< 0.001	< 0.001

	M-MDD
Mean MDD of HPT 1 portfolios [%]	3.8220
MDD of benchmark portfolio [%]	3.6813
Mean RD [%]	0.1407
	(1.0355)

Table 18: Risk-return enhancements according to each applied risk measure (continued)

Part b: HPT 2

HPT 2	MV	M-LPM0	M-LPM1	M-LPM2
Mean return of benchmark portfolios (risk-adj.) [%]	0.4893	0.5751	0.5798	0.5290
Mean return of HPT 2 portfolios [%]	0.2225	0.2225	0.2225	0.2225
Mean RD [%]	0.2668	0.3526	0.3573	0.3065
	(0.1563)	(0.1978)	(0.1912)	(0.1836)
Two-sided Wilcoxon test between MV- and M-LPM-frameworks: p-value	- / -	< 0.001	< 0.001	< 0.001
Mean return of benchmark portfolio [%]	0.5390	0.5390	0.5390	0.5390
Mean return of HPT 2 portfolios (risk-adj.) [%]	0.2459	0.2008	0.1914	0.2306
Mean RD [%]	0.2931	0.3382	0.3476	0.3084
	(0.1255)	(0.2040)	(0.2191)	(0.2669)
Two-sided Wilcoxon test between MV- and M-LPM-frameworks: p-value	- / -	0.0161	< 0.001	< 0.001

	M-MDD
Mean MDD of HPT 2 portfolios [%]	6.5721
MDD of benchmark portfolio [%]	6.2464
Mean RD [%]	0.3257
	(2.0276)

Table 18: Risk-return enhancements according to each applied risk measure (continued)

Part c: HPT 3

HPT 3	MV	M-LPM0	M-LPM1	M-LPM2		M-MDD
Mean return of benchmark portfolios (risk-adj.) [%]	0.9447	0.8388	1.0542	0.9672	Mean MDD of HPT 3 portfolios [%]	15.5763
Mean return of HPT 3 portfolios [%]	0.4747	0.4747	0.4747	0.4747	MDD of benchmark portfolio [%]	9.7569
Mean RD [%]	0.4700	0.3641	0.5795	0.4925	Mean RD [%]	5.8194
	(0.4032)	(0.4416)	(0.4912)	(0.4640)		(5.7669)
Two-sided Wilcoxon test between MV- and M-LPM-frameworks: p-value	- / -	< 0.001	< 0.001	< 0.001		
Mean return of benchmark portfolio [%]	0.8030	0.8030	0.8030	0.8030		
Mean return of HPT 3 portfolios (risk-adj.) [%]	0.3713	0.4652	0.3548	0.3888		
Mean RD [%]	0.4317	0.3378	0.4482	0.4142		
	(0.2858)	(0.4227)	(0.3163)	(0.3342)		
Two-sided Wilcoxon test between MV- and M-LPM-frameworks: p-value	- / -	< 0.001	< 0.001	0.0020		

Notes: The table provides, for each HPT, the mean (risk-adjusted) returns and mean Return Differences (RDs) which are determined in a mean-variance (MV), mean-Lower-Partial-Moment Zero (M-LPM0), mean-LPM One (M-LPM1), mean-LPM Two (M-LPM2) and mean-Maximum Drawdown (M-MDD) framework. Below the RDs, the standard deviation of RDs is placed into parentheses. Each table of a certain HPT is divided into two sections. The upper section reveals the RDs between the benchmark and the corresponding HPT portfolios while the benchmark XTF portfolio is risk-adjusted to the risk of the HPT portfolios (initial RD). The bottom section outlines the reverse case, i.e. RDs between the benchmark and the corresponding HPT portfolios while each HPT portfolio is risk-adjusted to the risk of its benchmark XTF portfolio (robustness RD). Cases in which the risk-adjusting would both increase the risk and reduce the return a HPT portfolio (due to (de-)leverage costs) are excluded. HPTs' portfolio means are based on monthly portfolio returns from January 2014 to December 2016. As robustness, RDs according to the MDD are also computed. Since the periods that constitute each MDD can vary, MDDs are not risk-adjusted. Example: When risk-adjusting the benchmark XTF portfolio of HPT 3 to the risk of all 1,000 HPT 3 portfolios, the average monthly mean return of the risk-adjusted benchmark XTF portfolios in a M-LPM2 framework is 0.9672 percent. Comparing this with the average mean return of the HPT 3 portfolios (0.4747 percent) yields an average RD of 0.4925 percent monthly return which implies an enhancement in risk-adjusted returns. Additionally, p-values are provided for a paired, two-sided Wilcoxon test which was used to test statistical difference between the RDs according to the MV- versus the employed downside-risk-return-frameworks.

As a first robustness test, RDs that are based on the risk of the respective benchmark portfolio are examined.[446] This represents the reverse case of the initial RDs and involves risk-adjusting the HPTs' portfolios to the risk of the corresponding benchmark XTF portfolio (see bottom part of Table 18a to Table 18c). For most HPTs' portfolios, this means deleveraging as they reveal higher risk than the benchmark portfolio. Overall, the robustness RDs remain positive. Deviations from the initial RDs mainly occur since the basis of risk is now on average lower and deleverage costs for risk-adjusting HPTs' portfolios differ from the costs to leverage the benchmark XTF portfolio (as implied by the initial RDs).

As a second robustness test, the analysis controls for risk-return enhancements according to the MDD (see upper part of Table 18a to Table 18c). As opposed to the other risk measures, the periods which define the MDD of a portfolio may spread over more than one month and the starting and ending month of each MDD can differ. Therefore, MDDs cannot be compared directly with the enhancements of the remaining risk measures. Nevertheless, the MDDs allow controlling for an additional, non-LPM-based downside-risk measure that indicates possible enhancements from XTFs in terms of returns. Controlling for the MDDs does not change the previous results. RDs according to the MDDs are positive for all HPTs which indicates that the benchmark XTF portfolio leads to smaller drawdowns than the corresponding HPT portfolios on average. While HPT 1 shows the least RDs, HPT 3 exhibits by far the largest RDs on average. So far, the results allow concluding that XTFs enhance the risk-return position of all HPTs on average, regardless of the applied risk measure.

To further investigate whether downside-risk measures help to explain the reluctance of households to invest in XTFs, RDs according to the applied downside-risk-return-frameworks are tested for statistical difference to the RDs of a MV-framework. Therefore, the first test checks whether the RDs of each risk-return-framework and HPT follow a normal distribution. According to the Shapiro-Wilk test, the assumption that RDs follow a normal distribution must be rejected at the one percent significance level for all risk-return-frameworks and HPTs. Based on this result, a (non-parametric) paired, two-sided Wilcoxon test is applied. The test shows that the assumption that RDs of the downside-risk-return-frameworks follow the same distribution as the RDs of a MV-framework must be rejected at the one percent significance

[446] Robustness RDs for the LPM-based downside-risk measures are ascertained analogously to formula (15) and (16) in Appendix C. As in the first analysis, cases in which risk-adjusting a HPT portfolio to the risk of the corresponding benchmark XTF portfolio would increase the HPT portfolio's risk and simultaneously reduce its return are excluded to avoid misinterpretations as it seems implausible from the perspective of a household to employ such a strategy.

level for all initial RDs (see upper part of Table 18a to Table 18c). Except for the M-LPM0-framework in HPT 1 and HPT 2, the test indicates the same result for the robustness RDs (see bottom part of Table 18a to Table 18c). Overall, most RDs of downside-risk-return-frameworks statistically differ from those of a MV-framework although the differences in terms of percentage points of return appear small.

An additional test is conducted to examine whether one of the downside-risk-return-frameworks yields consistently lower RDs across all HPTs compared to a MV-framework. For households which evaluate risk and return according to a specific downside-risk-return-framework, XTFs might in this case appear less attractive. Thus, the regarding downside-risk measure could help to explain why certain households refuse to invest in XTFs. To investigate this, a paired, one-sided Wilcoxon test is employed and the hypothesis that the RDs according to the downside-risk-return frameworks are statistically lower than those of a MV-framework is tested. Except for the RDs of two frameworks in HPT 3,[447] the test reveals that the RDs of the downside-risk-return-frameworks are not significantly lower. In contrast, most downside-risk-return-frameworks show statistically higher RDs compared to a MV-framework (see also mean RDs in Table 18a to Table 18c). This suggests the conclusion that none of the employed downside-risk measures can help to explain the reluctance of households to invest in XTFs. Instead of indicating fewer incentives to invest in XTFs, it rather appears more promising to invest in XTFs from the perspective of households that evaluate risk according to downside-risk measures.

Nevertheless, although most RDs of the downside-risk-return-frameworks range above those of a MV-framework, RDs do not seem to vary substantially in absolute terms, for example, mean RDs according to a MV- and M-LPM2-framework. Monthly RDs for HPT 1 of 0.14 and 0.15 percent return, respectively, translate into approximately 1.69 and 1.87 percent annual RD. Based on the VALUEpf of 163,900 Euros for HPT 1, the difference in RD of 0.18 percent translates into 292 Euros per annum which does not seem to represent a relevant amount relative to VALUEpf.[448] In addition, these values are computed ex-post. Considering that households have to derive expected portfolio returns under ambiguity ex-ante, these values could also be in the range of forecast errors. Thus, as opposed to statistically significant differences, RDs

[447] RDs in the M-LPM0- (initial and robustness RDs) and the M-LPM2-framework (only robustness RDs) of HPT 3 are statistically lower than those of a MV-framework at the one percent significance level.
[448] The corresponding annual amounts for HPT 2 and HPT 3 reach 1,053 and 891 Euros and suggest, given an initial VALUEpf of 214,200 and 312,900 Euros, respectively, the same conclusion.

seem insignificant in economic terms as they translate, in relation to VALUEpf, into negligible absolute amounts of Euros.

The result that RDs are similar and positive according to all applied risk-return-frameworks suggests that the employed XTF portfolios represent a reasonable approximation of the (optimal) market portfolio, regardless of the applied risk-return-framework. Das et al. (2010) and Pfiffelmann/Roger/Bourachnikova (2016) demonstrate that portfolios which are optimal in a BPT-related framework can also be MV-efficient. The results of this analysis point in the same direction since the economically insignificant RDs indicate that the employed benchmark XTF portfolios can optimize household portfolios in all applied risk-return-frameworks. As opposed to the studies above, however, optimal portfolios are represented by easily investable XTF portfolios rather than portfolios that are computed using portfolio optimization techniques. Jarrow/Zhao (2006) find little differences between optimal portfolios in a MV- and LPM-framework if portfolio returns are nearly normally distributed. This seems in line with the results of this analysis. Tests for normality of the HPTs' portfolio returns suggested that the latter largely follow normal distributions. The applied LPM-based downside-risk measures and the SD additionally yield similar results if the target and portfolio returns are close to each other.[449] This might also induce the resemblance of RDs across all applied risk measures. Although the target and the HPTs' portfolio returns are different, the difference might not be large enough to produce economically different RDs.

A reason for conflicting results with studies of Unser (2000), Veld/Veld-Merkoulova (2008), and Holzmeister et al. (2019) whose results would suggest differences between the applied (downside-)risk measures might be associated with different research goals and a different research design. For instance, while the experiments of Unser (2000) and Veld/Veld-Merkoulova (2008) ask participants from an ex-ante perspective to evaluate the risk of (hypothetical) security returns, this analysis determines (downside-) risk from an ex-post perspective.

Regarding the reluctance of households to invest in XTFs, two alternative explanations are possible. First, considering that relying on financial advice is prevalent among German households,[450] a reason why many households seem to refuse to employ XTFs might be that financial advisors barely recommend them to invest in XTFs since the incentive structure of

[449] See Harlow (1991); Jarrow/Zhao (2006).
[450] See DAB Bank (2004); Hackethal et al. (2011).

financial advisors typically motivates them to recommend high-fee products[451] instead of XTFs which typically charge lower fees.

Second, knowledge illusion might add an explanation. Baars/Goedde-Menke (2019) find that individuals tend to distinguish between different sources of risk based on their perceived expertise. Because perceived expertise does not necessarily coincide with the actual expertise of an individual, making decisions under risk can involve what the authors refer to as "knowledge illusion".[452] As one source of risk, they mention home bias. The authors argue that the higher expertise which individuals perceive for geographically close investments[453] can induce knowledge illusion since the preference for geographical proximity is usually not based on value-relevant information.[454] In this way, knowledge illusion increases the attraction of investments which are geographically close to the individual and can be associated with less diversified portfolios.[455] Hence, knowledge illusion can add an explanation why households refrain from XTFs since XTFs imply, as opposed to geographical proximity, investing internationally for which households perceive, in reference to Baars/Goedde-Menke (2019), fewer incentives and less expertise.

The goal of this analysis was to investigate whether households obtain less risk-return enhancements from employing XTFs under assumptions that approximate their actual risk evaluation more closely than a MV-framework which is applied in most existing studies. Less enhancements might offer fewer incentives for households to invest in XTFs which raises the question whether downside-risk measures can help to explain the reluctance of households to invest in XTFs.

Overall, the results show, first, that the risk-return enhancements according to each applied downside-risk measure are statistically different from the risk-return enhancements when the SD is the underlying measure of risk. However, none of the applied downside-risk measures leads to consistently lower risk-return enhancements compared to the SD. This suggests that none of the employed downside-risk measures can help to explain the reluctance of households to invest in XTFs. Second, all risk-return-frameworks, regardless of whether the SD or downside-risk is the underlying measure of risk, indicate that households can enhance their

[451] See Christoffersen/Evans/Musto (2013); von Gaudecker (2015); Chalmers/Reuter (2015); Egan (2019).
[452] Knowledge illusion might be influenced by an individual's available information. Oehler/Horn/Wendt (2020b) show in this regard that placebic information may increase an individual's perceived amount of relevant information which can lead to "information illusion".
[453] See Kilka/Weber (2000); Ackert et al. (2005).
[454] See Seasholes/Zhu (2010).
[455] See Dimmock et al. (2018).

portfolio performance by employing XTFs. This substantiates the common recommendation to employ XTFs[456] and suggests that the advice also holds true when households evaluate risk according to downside-risk measures.

[456] See Malkiel (2003a), (2003b); French (2008); Huang/Lin (2011); Jacobs/Müller/Weber (2014); Bhattacharya et al. (2017); Elton/Gruber/de Souza (2019).

7 The Impact of Reinvesting Payouts in XTFs on Risk and Return of Household Portfolios[457]

7.1 Methodological Approach

The analysis in this chapter aims to answer RQ3 which questions whether reinvesting payouts in XTFs enhances the risk-return position of household portfolios. The analysis relies again on the asset class weights of the HPTs derived in chapter 5.2.1.[458] Portfolios are constructed by assigning securities from the SHS-base[459] to the HPTs using the random sampling process according to chapter 6.1.

Portfolio replacements include selling the entire risky assets at once and investing the available amount of money in a XTF portfolio. They are a radical but rapid way to switch an existing portfolio to a XTF portfolio. Not every household might be willing and/or able to perform a portfolio replacement. This investigation assumes such households. Reasons why portfolio replacements might not be an option for a household include that the ownership of an asset can increase the asset's perceived value, and that households feel overly attached to a certain asset.[460] Households might expect a higher than the current market price for such assets which can motivate households to refuse to sell them. This behavior can also be associated with loss-aversion.[461] Loss-aversion can induce the disposition of households to keep assets with book losses in their account.[462] In addition, extra charges for premature terminations of an investment plan can prevent households from following a radical portfolio replacement. Households might also keep on holding their current assets since selling them would cause a high, immediate loss due to transaction costs which had to be compensated by uncertain gains of XTFs in the future.

A feasible alternative which does not require selling current assets is to use payouts from an existing portfolio's assets for investing in XTFs (henceforth: XTF-strategy). In this analysis, payouts include dividends, interest payments, as well as money that becomes available after an

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[457] Substantial parts of this chapter and the corresponding appendices are obtained from Wanger (2020).

[458] The HPTs are derived from PHF-survey data, which were extracted from the second wave of the HFCS of the European Central Bank (Data source: European Central Bank, Eurosystem Household Finance and Consumption Survey, second wave. Data access granted through the project: Can XTFs enhance Households' investment returns?; lead researcher: Oehler, A.; co-researchers: Horn, M., Wanger, H.P.).

[459] Data source: Deutsche Bundesbank, Research Data and Service Centre, Securities Holdings Statistics-Base. Data access granted through the project: Can XTFs enhance the return of households' portfolios while keeping the portfolio-risk constant?; Project-ID: 2017\0103; lead researcher: Oehler, A.; co-researcher: Wanger, H.P.

[460] This phenomenon is also referred to as "endowment effect". Regarding the endowment effect, see Thaler (1980); Kahneman/Knetsch/Thaler (1990); Oehler (1992); (1995), pp. 32ff.; (2000b); (2002), pp. 857ff.; (2011).

[461] See Kahneman/Tversky (1979); Thaler (1980); Benartzi/Thaler (1995); Oehler (1992); (1995), pp. 32ff.

[462] This behavior is based on the disposition effect, i.e. the tendency to sell assets with book profits and keep assets with book losses. Regarding the disposition effect, see Shefrin/Statman (1985); Kahneman/Knetsch/Thaler (1990); Oehler (1991); (1992); (1994); (1995), p. 32; (1999), pp. 72ff.; (2000b); (2002); (2011); Heilmann/Läger/Oehler (2001b); Oehler et al. (2003).

expiry of an asset (e.g. due to maturity of a bond or liquidation of a mutual fund). Payouts can emerge irregularly and in different amounts. In contrast to a one-time portfolio replacement, following the XTF-strategy stretches the switch to a XTF-portfolio in time.

Two further reinvestment-strategies are employed to evaluate possible enhancements from following the XTF-strategy: one benchmark- and one default-strategy. Portfolio replacements represent the most rapid portfolio switch to a XTF portfolio and have shown in chapter 5.2.3 to enhance risk and return of stylized household portfolios. Portfolio replacements are used as benchmark (henceforth: replacement-strategy) against which the XTF- and default-strategy are compared.

Correspondingly to the previous analyses, the replacement- and XTF-strategy invest available amounts of money into one stock XTF and one bond XTF.[463] The applied stock and bond XTF replicate the MSCI World Index and the Markit iBoxx Euro Sovereign Index, respectively. Both XTFs are accumulating instead of distributing payouts. Compared to distributing payouts, households are assumed to better exploit compound interest effects and to incur less transaction and monitoring costs when accumulating payouts.

The default-strategy reflects a continuation of the initial portfolio construction of the HPTs. When reinvesting payouts, one additional individual security is randomly selected from the SHS-base (henceforth: default-strategy). As in chapter 6, a security's market value of shares held by German households is used as probability for the selection of a security in the applied random sampling process. The default-strategy might be a relevant strategy for households that are overly confident about their abilities to estimate securities' risk and return development. While XTFs imply investing in terms of an "average" investor, overconfidence might motivate households to select individual securities by themselves.[464] Households might choose to self-select individual securities when they reveal preferences for domestic[465] or local assets[466]. In this regard, households might argue that investing in German large cap stocks provides reasonable degrees of internationalization which rather prevents than promotes disadvantages for portfolios from home bias.[467] An additional argument of households following the default-strategy might be that investing in many securities through XTFs is unnecessary, on the one hand, since a small number of individual securities might already reduce substantial amounts

[463] See chapter 5.1.3.
[464] See Odean (1998); Barber/Odean (2001).
[465] See French/Poterba (1991); Tesar/Werner (1995); Oehler/Rummer/Wendt (2008).
[466] See Baltzer/Stolper/Walter (2015).
[467] See Oehler/Wendt/Horn (2016); Oehler/Wendt/Horn (2017).

of portfolio risk and provide a sufficient level of diversification.[468] On the other hand, management fees might considerably reduce possible diversification benefits of XTFs.[469]

While the replacement-strategy invests in a stock/bond XTF portfolio at once, the XTF- and default-strategy reinvest successively through payouts. In all applied strategies, households are assumed to prefer keeping the current portfolio risk relatively stable and, thus, to rebalance payouts according to their portfolio's asset class weights at the beginning of the observation period.[470] In the XTF-strategy, payouts are rebalanced between a stock/bond XTF according to the current stock- (SF and ST) and bond-related (BF and BD) asset class weights of a HPT.[471] Since the benchmark XTF portfolios applied in the previous chapter are derived in this way, this analysis relies on the same asset class weights of benchmark XTF portfolios (see Table 19). Rebalancing according to the default-strategy considers all asset classes of the HPTs separately. Accordingly, payouts are reinvested in individual securities of the asset classes SF, BF, REF, BD, and ST.

Table 19: Benchmark XTF portfolios applied in the replacement- and XTF-strategy

Asset class weights of benchmark XTF portfolios				Reference period		Applied interest rate / XTF	
asset class	HPT 1	HPT 2	HPT 3	target return	risk / return	Index	interest rate / ISIN
SV	70.0	33.3	30.0	01/2009 - 12/2013	01/2014 - 06/2017	weighted average interest rate	German households' deposits with agreed maturities of up to one year, over one and up to two years, and over two years
Bond XTF	10.0	33.3	0.0	01/2009 - 12/2013	01/2014 - 06/2017	Markit iBoxx Euro Sov. Index	LU0290355717
Stock XTF	20.0	33.3	70.0	01/2009 - 12/2013	01/2014 - 06/2017	MSCI World Index	LU0392494562

Notes: On the left side, this table shows the asset class weights of the benchmark XTF portfolios which are used for target weights for rebalancing in the replacement- and XTF-strategy. The middle part of the table specifies the observation period in which risk and return of the benchmark XTF portfolios are ascertained. The pre-observation period is used to determine target returns for the applied downside-risk measures. The right side of the table provides details on the interest rate / XTFs that are employed in the asset classes of the benchmark XTF portfolios.

[468] See Evans/Archer (1968); Statman (1987).
[469] See Jennings/Payne (2016).
[470] See Brinson/Hood/Beebower (1986); (1995); Brinson/Singer/Beebower (1991); Hood (2005); Ibbotson/Kaplan (2000) regarding the influence of asset class weights on overall portfolio risk.
[471] To ascertain whether payouts are reinvested in the stock or bond XTF in the XTF-strategy, deviations between HPTs' current asset class weights and those of the corresponding benchmark XTF portfolio are examined. REFs are not involved in the applied benchmark XTF portfolios. In order to compare asset class weights, REFs included in the HPTs are considered in terms of a bond-related asset class since risk and return characteristics of REFs are assumed to be more similar to bond-related rather than stock-related asset classes.

In contrast to the total return price data employed in the previous two analyses, in this analysis, prices and payouts of each security in the SHS-base are gathered separately. Gathering payouts separately from security prices is necessary to ascertain the amount of money available for reinvesting according to the XTF- and default-strategy. Data are requested from Thomson Reuters Datastream. The available data allow an observation period from January 2014 until June 2017.[472] Securities for which no price data was available or which could not be clearly categorized into one of the employed asset classes were dropped from the data set.[473]

For each security, discrete monthly returns are computed.[474] Returns of BDs include end-of-month accrued interest.[475] Returns on CASH and SV are assumed using interest rates on German households' overnight deposits as well as deposits with agreed maturities of up to one year, over one and up to two years, and over two years (weighted according to outstanding amounts), respectively.[476] As in the previous analyses, mixed asset funds range among mutual funds with the highest market value of shares which indicates that mixed funds are particularly important in German household portfolios. Mixed funds are kept in the data set and categorized into SFs or BFs according to the correlation between each mixed fund's returns and the returns of stock and bond indices that cover a range of markets and sectors.[477] Of 2,915 mixed funds,

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472 For this data request, a six-month longer observation period is available compared to the observation periods in chapter 5 and 6. Since the XTF-strategy stretches the switch to XTF portfolios in time, an extended observation period is particularly useful and was therefore applied in the context of this analysis.

473 The availability of appropriate data on the amount of coupon payments and coupon dates of BDs was limited. Therefore, daily accrued interest data was gathered as approximation. A decline in accrued interest around zero is used to ascertain the amount and date of a coupon payment. Comparisons with BDs for which corresponding data was available showed only minor deviations, which suggested that the chosen procedure provides a reasonable approximation.

474 All HPTs exhibit substantial asset class weights in safe financial assets. The returns of safe financial assets are relatively low compared to the returns of assets in the remaining asset classes. Since inflation might offset the returns of safe financial assets and cause substantial losses in the HPTs which might be crucial for loss-averse households assumed in this analysis, this investigation refers to real returns and subtracts monthly inflation rates from all monthly nominal security returns. Monthly inflation rates for Germany are ascertained by monthly changes of the Harmonised Index of Consumer Prices as of Eurostat (2019).

475 For the approximation of coupon dates and coupon amounts of BDs, daily BD data was gathered (see footnote 473). To obtain monthly returns of BDs, first, daily returns are calculated based on total return index calculations of Thomson Reuters Datastream. The total return index $\mathrm{RI}_{s,d}$ for security s on day d is computed by $\mathrm{RI}_{s,d} = \mathrm{RI}_{s,d-1}(\frac{\mathrm{CP}_d+\mathrm{A}_d+\mathrm{C}_{s,(d-1;d)}}{\mathrm{CP}_{d-1}+\mathrm{A}_{d-1}})$, where $d-1$ denotes the previous trading day, CP_d the daily clean-price on day d, A_d the accrued interest on day d, and $\mathrm{C}_{s,(d-1;d)}$ indicates the coupon payments of bond s within $d-1$ and day d (see variable description of Thomson Reuters Datastream). Daily returns are then transformed into daily log-returns and were accumulated to monthly log-returns. Finally, monthly log-returns are converted into discrete monthly returns.

476 Own calculations; data obtained from Deutsche Bundesbank (2019c). See also chapter 5.1.1 and Table 19.

477 See Table 44 in Appendix E. If the highest correlation appears with one of the stock indices, the mixed fund is categorized as SF (and vice versa for BFs).

2,497 are categorized as SFs and 418 as BFs.[478] The final security sample involves 38,437 securities in total (10,217 SFs, 4,384 BFs, 64 REFs, 8,424 BDs,[479] and 15,348 STs).

Portfolios are constructed by selecting nine risky securities from the SHS-base using the random sampling process according to chapter 6.1 (one SF, one BF, one REF, three BDs, and three STs). The assumed portfolio size (i.e. the number of risky securities per portfolio) of nine risky securities represents the base case of the first empirical analysis.[480] Every selected portfolio is weighted with the asset class weights of each of the three HPTs to avoid selection bias. Within each asset class, securities are equally weighted. Following this procedure, 1,000 random portfolios per HPT are constructed. Portfolio returns are ascertained according to each applied reinvestment-strategy.

Reinvestments involve fixed transaction costs of 10 Euros[481] and proportional transaction costs of 0.25 percent of the order value[482]. In the XTF- and default-strategy, payouts are used for reinvesting. Payouts can vary in their amount and occur irregularly over time. An immediate reinvestment of every (even small amount of) payout might, on the one hand, reduce a loss of return arising from delaying the reinvestment of available amounts of money. On the other hand, immediately reinvesting every payout increases the amount of (fixed) transaction costs relative to the amount that is reinvested. As a balance to the trade-off between these effects, a threshold for of 1,000 Euros is assumed. The threshold amount implies transaction costs of 12.50 Euros. Payouts are accumulated and not reinvested until the threshold is reached.

To investigate the influence of transaction costs on the investment outcomes of each strategy, cumulative portfolio values at the end of the observation period are calculated, both including and excluding transaction costs. The securities and dates at which reinvestments take place are the same in both versions. In contrast to the replacement- and XTF-strategy, the default-strategy may involve reinvestments in BDs. If transaction costs are included, costs for accrued interests that must be paid to a former owner of a BD are involved. Since accrued interest costs lower the amount that is reinvested in a BD, corresponding interest claims are lower, and a loss of

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[478] 61 mixed funds were excluded from the data set since they contain less than three months of return which prevents proper calculations of correlations.
[479] BDs involve several sub-types of BDs, i.e. BDs with a fixed coupon (straight bonds and zero bonds) as well as bonds with a variable coupon (floating bonds and index linked bonds). The final sample contains 8,424 BDs in total, of which 4,611 are straight bonds, 426 are zero bonds, 3,245 are floating bonds, and 141 are index linked bonds.
[480] See chapter 5.1.1. This analysis abstracts from increasing portfolio size and robustness tests on control portfolios since the first analysis already indicates that the latter do not considerably change the results.
[481] This reflects the approximate amount that large German online brokers charge their clients (see Stiftung Warentest (2016)).
[482] See Lynch/Balduzzi (2000).

interest emerges. The amount of such interest losses is involved in cumulative portfolio values when transaction costs are excluded. Therefore, accrued interest costs are omitted, and the entire accumulated payouts are reinvested in the corresponding BD. At the first interest payment date after the reinvestment, interest payments are obtained proportionately to the passed holding period.[483] As a consequence, interests earned are higher if transaction costs are excluded. If transaction costs are included, the share of earned interest that corresponds to the amount of accrued interest costs represents a loss of interest which reduces cumulative portfolio values.

Risk-return enhancements are measured by RDs.[484] RDs are determined by risk-adjusting the benchmark portfolio which follows the replacement-strategy to the portfolios following the XTF- and default-strategy. Risk-adjustments are performed using distinct rates for borrowing and lending. As (quasi) risk-free investment (r_{SV}),[485] the average monthly interest rate of SV between January 2014 and June 2017 of 0.04 percent is applied. The security lending rate (r_{SL}) amounts to 0.39 percent per month.[486]

Several robustness checks are included. First, robustness RDs are determined. Therefore, portfolios following the XTF- and default-strategy are risk-adjusted to the risk of the corresponding benchmark portfolio.[487] Second, portfolio sizes are varied. Portfolios consisting of many individual securities might reveal less risk and higher levels of diversification compared to portfolios with less individual securities.[488] Hence, the effect on risk and return from reinvesting payouts in one additional security or one XTF might vary between portfolios with different portfolio sizes. Different portfolio sizes might also yield differing amounts and frequencies of payouts which can lead to different amounts and frequencies of reinvestments. This analysis relies on the portfolio sizes derived in chapter 5.1.1, i.e. HPTs consisting of 18, 27 and 297 risky securities are employed as robustness. Third, to check if the applied reinvestment-strategies yield different RDs in dependence of households' interpretation of risk,

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483 This procedure is equivalent to taking an interest-free loan amounting to the occurring accrued interest costs, investing it in the underlying BD at the reinvestment date, and paying it back at the first interest payment date after the reinvestment.
484 See chapter 4.2 and 6.1.
485 According to neoclassical finance, the risk-free investment bears no risk of default and is not included in the portfolio of risky assets. Since the safe financial assets applied in this analysis (CASH and SV) exhibit return fluctuations which reflects risk, they are included in the HPTs. They are considered as "quasi" risk-free investment as opposed to the default-free risk-less investment in the sense of neoclassical finance. The monthly interest rate of SV used for r_{SV} is expressed in real terms, i.e. less of inflation.
486 The security lending rate is based on a comparison of security loans offered by large German banks (see Stiftung Warentest (2013)). The monthly security lending rate used for r_{SL} is expressed in real terms, i.e. less of inflation.
487 Like in the first analysis, cases in which risk-adjusting a HPT portfolio to the risk of the corresponding benchmark XTF portfolio increases the HPT portfolio's risk and simultaneously reduces its return are excluded to avoid misinterpretations as it seems implausible from the perspective of a household to employ such a strategy.
488 See Evans/Archer (1968); Statman (1987).

downside-risk measures and corresponding risk-return-frameworks are applied in addition to the SD and a MV-framework, respectively. Since the LPM0, LPM1, $\sqrt{\text{LPM2}}$, and the MDD reflect households' interpretation of risk more closely than the SD,[489] a M-LPM0, M-LPM1, M-LPM2, and M-MDD-framework are used for robustness.

7.2 Results

Table 20 shows descriptive statistics for the applied benchmark XTF portfolios and the HPTs' portfolios following the XTF- and default-strategy. Overall, portfolios of HPT 1 show the lowest average mean return, those of HPT 2 reveal a higher and HPT 3 the highest average mean return. Within the HPTs, following the replacement-strategy reveals the highest mean return. The average mean returns of the XTF-strategy are higher than those of the default strategy in HPT 1 and HPT 3. In HPT 2, this relation is reversed. Mean returns of portfolios following the XTF- and default-strategy are tested for statistical difference. According to a paired Wilcoxon test, mean returns in HPT 1 and HPT 3 are statistically different at the one percent significance level while the mean returns of both strategies are not statistically different in HPT 2.[490]

Table 20: Descriptive statistics on benchmark XTF portfolios and portfolios of HPTs [Jan. 2014 to June 2017]

	reinvestment-strategy	portfolio mean [%]	SD of portfolio means [%]	median [%]	skewness	kurtosis
HPT 1	replacement-strategy	0.2610	n.a.	0.1570	0.5684	0.9582
	XTF-strategy [av.]	0.1736	0.2377	0.0918	0.7169	1.1208
	default-strategy [av.]	0.1594	0.2394	0.0697	0.7649	1.1542
HPT 2	replacement-strategy	0.4410	n.a.	0.4600	0.0862	0.6705
	XTF-strategy [av.]	0.2684	0.9997	0.2092	0.4098	1.2601
	default-strategy [av.]	0.2720	1.0116	0.2115	0.3778	1.1254
HPT 3	replacement-strategy	0.6920	n.a.	0.4710	-0.0142	0.6481
	XTF-strategy [av.]	0.5598	0.4238	0.5967	0.0756	0.3701
	default-strategy [av.]	0.5431	0.4232	0.5692	0.0850	0.3247

Notes: This table shows descriptive statistics of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (nine risky securities per portfolio).

489 See chapter 4.1.2.3 and 6.1.

490 Prior to the paired Wilcoxon test, a Shapiro-Wilk test was applied to test whether the mean returns of the portfolios following the XTF- and default-strategy follow a normal distribution. The test suggested that the assumption that the mean returns of both strategies follow a normal distribution must be rejected at the one percent significance level in all HPTs. Therefore, the non-parametric Wilcoxon test is applied for testing statistical difference. Since both strategies are based on the same randomly selected initial portfolios, a paired test was applied.

Besides the statistical difference, the extent of differences seems small. This suggests assessing whether the differences are significant in economic terms and relevant from the perspective of households. HPT 3 reveals the largest difference in mean returns between the XTF- and default-strategy. Compared to the initial VALUEpf of HPT 3 (312,900 Euro), the monthly difference in mean returns (0.0167 percent) translates into an absolute amount of 52 Euro per month (688 Euro per annum). These values appear negligible compared to the VALUEpf of HPT 3. Moreover, the values are determined ex-post. If a household wants to decide whether to follow the XTF- or the default-strategy and derives return expectations under ambiguity ex-ante, these values could also be in the range of forecast errors. This suggests that the differences in mean returns between the XTF- and default-strategy are insignificant in economic terms.

Table 21: Risk evaluation of benchmark XTF portfolios and portfolios of HPTs [Jan. 2014 to June 2017]

	reinvestment-strategy	SD [%]	LPM0 [%]	LPM1 [%]	√LPM2 [%]	MDD [%]
HPT 1	replacement-strategy	0.9225	57.1429	0.3671	0.6245	3.6725
	XTF-strategy [av.]	0.9624	64.3000	0.4266	0.6830	3.9410
	default-strategy [av.]	0.9333	65.1286	0.4285	0.6718	3.8549
HPT 2	replacement-strategy	1.4466	52.3810	0.5688	1.0356	6.2396
	XTF-strategy [av.]	1.5179	64.3476	0.6434	1.0658	6.0942
	default-strategy [av.]	1.5959	63.4905	0.6639	1.1138	6.4758
HPT 3	replacement-strategy	2.4920	54.7619	1.0081	1.8279	9.7489
	XTF-strategy [av.]	3.4154	53.8024	1.4555	2.5286	15.6805
	default-strategy [av.]	3.3896	54.1238	1.4596	2.5175	15.6648

Notes: This table shows the risk evaluation according to the applied risk measures of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (nine risky securities per portfolio).

The risk evaluation according to the SD and the applied downside-risk measures is outlined in Table 21. Portfolios of HPT 1 reveal the lowest risk values, while portfolios of HPT 2 show higher and those of HPT 3 the highest risk values on average. Across the applied risk measures and HPTs, the replacement-strategy reveals lower average risk than the XTF- and default-strategy in most cases. When comparing the XTF- and default-strategy, a paired Wilcoxon test indicates that across all risk measures, risk according to both strategies significantly varies from each other at the one percent significance level in almost all cases.[491] However, none of the

[491] In HPT 1 according to LPM1, risk between both strategies statistically varies at the five percent significance level. Prior to the paired Wilcoxon test, a Shapiro-Wilk test was applied to test whether the risk values of the

strategies shows consistently higher or lower risk compared to the other strategy. Thus, comparing the risk of the XTF- and default-strategy yields a mixed picture.

Table 22 illustrates the results on RDs. RDs show possible risk-return enhancements of portfolios following the XTF- or default-strategy towards the corresponding benchmark XTF portfolio. $\mathrm{RD_{HPT}}$ denotes RDs that are based on the risk of the HPTs' portfolios. $\mathrm{RD_{BM}}$ denotes the robustness RDs that are based on the risk of a HPT's corresponding benchmark XTF portfolio. HPT 1 shows the lowest RDs, while HPT 2 reveals higher RDs, and HPT 3 the highest RDs on average. Except for RDs of the XTF-strategy in HPT 2 according to a M-MDD-framework,[492] all RDs are positive, regardless of the basis of risk. This indicates that the benchmark XTF portfolios provide higher risk-adjusted returns than the XTF- and default-strategy. Employing the replacement- instead of the XTF- or default-strategy can thus enhance household portfolios' risk-return position. For instance, in a MV-framework, HPT 3 portfolios applying the replacement- instead of the default-strategy can obtain an increase in monthly return of approximately 26 basis points on a risk-adjusted basis.

portfolios following the XTF- and default-strategy follow a normal distribution. The test suggested that the assumption that the risk values of both strategies follow a normal distribution must be rejected at the one percent significance level in all HPTs. Therefore, the non-parametric Wilcoxon test is applied for testing statistical difference. Since both strategies are based on the same randomly selected initial portfolios, a paired test was applied.

[492] A reason therefore might be the asset class concentration by portfolios of HPT 2 on mutual funds. Holding multiple mutual funds might result in smaller drawdowns compared to the benchmark XTF portfolio which consists of only two XTFs. In addition, the period which defines a MDD may, as opposed to the other risk measures, spread over more than one month, and the starting and ending date of each MDD can differ. MDDs do not involve risk-adjusting. RDs for MDDs are ascertained by subtracting the MDD of the benchmark XTF portfolio from the MDD of a corresponding HPT portfolio. RDs according to MDDs cannot be compared directly with those of the other risk measures. Nevertheless, MDDs provide an additional robustness measure in terms of a non-LPM-based downside-risk measure.

Table 22: Return Differences (RDs) of HPT portfolios employing the XTF- and default-strategy [Jan. 2014 to June 2017]

	reinvestment-strategy	MV		M-LPM0		M-LPM1		M-LPM2		M-MDD
		RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD [%]
HPT 1	XTF-strategy [av.]	0.0560	0.0790	0.0684	0.1086	0.0640	0.1214	0.0662	0.1172	0.2685
	default-strategy [av.]	0.0659	0.0841	0.0816	0.1214	0.0775	0.1354	0.0799	0.1342	0.1824
	delta in RD: paired Wilcoxon-test (p)	*0.0099****	*0.0051****	*0.0132****	*0.0128****	*0.0135****	*0.014****	*0.0137****	*0.017****	*-0.0861****
HPT 2	XTF-strategy [av.]	0.1194	0.1661	0.1836	0.2063	0.1736	0.2307	0.1451	0.1932	-0.1455
	default-strategy [av.]	0.1231	0.1803	0.1785	0.2012	0.1730	0.2337	0.1468	0.2038	0.2361
	delta in RD: paired Wilcoxon-test (p)	*0.0036****	*0.0143****	*-0.005*	*-0.0051*	*-0.0006***	*0.003****	*0.0017****	*0.0106****	*0.3816****
HPT 3	XTF-strategy [av.]	0.2438	0.2641	0.1090	0.0844	0.2661	0.2500	0.2472	0.2417	5.9317
	default-strategy [av.]	0.2571	0.2728	0.1283	0.1045	0.2840	0.2621	0.2618	0.2519	5.9159
	delta in RD: paired Wilcoxon-test (p)	*0.0133****	*0.0087****	*0.0193****	*0.0201****	*0.0179****	*0.0121****	*0.0146****	*0.0101****	*-0.0157****

Notes: This table shows the RDs as average [av.] of 1,000 portfolios (nine risky securities per portfolio) following the XTF- and default-strategy for each of the applied risk-return-frameworks. RD_{HPT} denotes RDs that are based on the risk of the HPTs' portfolios. RD_{BM} denotes RDs that are based on the risk of a HPT's corresponding benchmark XTF portfolio. ***, **, and * indicate the one, five, and ten percent significance level of a paired, two-sided Wilcoxon test which was used to test statistical difference between the RDs according to the XTF- and default-strategy.

RDs of the XTF-strategy are lower than those of the default-strategy in most cases (see positive deltas in RDs in Table 22). Lower RDs imply that employing the XTF-strategy moves the HPTs closer to the corresponding benchmark XTF portfolio, which means that the XTF-strategy can enhance the risk-return position of HPTs that follow the default-strategy. A paired Wilcoxon test indicates that in HPT 1 and HPT 3, the RDs of the XTF- and default-strategy are significantly different from each other at the one percent significance level across all applied risk measures.[493] In HPT 2, RDs of the XTF-strategy are not consistently lower across all applied measures and do not significantly vary from the RDs of the default-strategy. A main reason therefore might be that while HPT 1 and HPT 3 show asset class concentrations on individual securities, HPT 2 focuses on mutual funds which might reveal similar risk-return characteristics throughout the observation period compared to XTFs. Additionally, the observation period might not be long enough to capture differences.

Differences in RDs are again tested for economic significance. According to a MV-framework, the largest difference in RDs occurs for HPT 3. In relation to the initial VALUEpf of HPT 3 (312,900 Euro), the monthly difference in RD (0.0133 percent) translates into an absolute amount of 42 Euro per month (536 Euro per annum). Analogously to the differences in mean returns, the absolute difference in RD appears insignificant compared to the VALUEpf of HPT 3 and might be in the range of forecast errors. Overall, the comparison of RDs between the XTF- and default-strategy suggests that the XTF-strategy leads to risk-return enhancements in the HPTs compared to the default-strategy. Nevertheless, within the observation period the amount of enhancements from employing the XTF- instead of the default-strategy seems to be small in absolute amounts of Euros.

Table 23 reports descriptive statistics on reinvestments. The number of transactions and reinvested amounts in the XTF- and default-strategy only involve purchases due to reinvestments. The replacement-strategy includes the selling of all nine risky securities and the purchase of two XTFs. Compared to HPT 1 and HPT 2, HPT 3 reveals one transaction less since only one (stock) XTF is purchased. The XTF-strategy involves less transactions and lower reinvestment amounts on average compared to the default-strategy. An explanation therefore is that the XTF-strategy reinvests payouts in two XTFs which accumulate earnings. The default-

[493] Prior to the paired Wilcoxon test, a Shapiro-Wilk test was applied to test whether the RDs of portfolios following the XTF- and default-strategy follow a normal distribution. The test suggested that the assumption that the RDs of both strategies follow a normal distribution must be rejected at the one percent significance level in all HPTs. Therefore, the non-parametric Wilcoxon test is applied for testing statistical difference. Since both strategies are based on the same randomly selected initial portfolios, a paired test was applied.

strategy, in turn, reinvests in individual securities which might yield payouts or expire during the observation period. This induces further reinvestments and higher reinvestment amounts. Portfolios that follow the default-strategy exhibit the highest number of individual risky securities per portfolio at the end of the observation period in June 2017 and the highest reinvested amounts relative to the initial VALUEpf. In HPT 2, approximately 25 percent of the initial VALUEpf are reinvested on average. This might be due to a relatively high asset class weight of HPT 2 in BDs which apparently expire more frequently than mutual funds or STs, which induces higher reinvestment amounts.

Table 23: Characteristics of reinvestments [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	January 2014 to June 2017			number of risky securities in June 2017
			number of transactions	sum of reinvested amounts [€]	in [%] of initial VALUEpf	
HPT 1	replacement-strategy	163,900	11.0	163,586	99.81	2.0
	XTF-strategy [av.]		4.4	10,838	6.61	8.6
	default-strategy [av.]		5.4	13,852	8.45	11.0
HPT 2	replacement-strategy	214,200	11.0	213,458	99.65	2.0
	XTF-strategy [av.]		7.5	39,806	18.58	8.6
	default-strategy [av.]		9.9	53,305	24.89	14.2
HPT 3	replacement-strategy	312,900	10.0	312,020	99.72	2.0
	XTF-strategy [av.]		10.7	38,868	12.42	8.6
	default-strategy [av.]		12.3	47,028	15.03	17.1

Notes: This table exhibits the initial VALUEpf by January 2014, the number of transactions, and the sum of reinvested amounts in Euro and in percent of the initial VALUEpf for each HPT's benchmark XTF portfolio and 1,000 HPT portfolios as average [av.] (nine risky securities per portfolio). The table also reveals the number of individual risky securities per portfolio at the end of the observation period.

In correspondence to its higher reinvested amounts, the default-strategy involves higher transaction costs than the XTF-strategy on average throughout the observation period (see Table 24). Since reinvestments in BDs seem to contribute to the higher reinvestment amounts in the default-strategy, they might also play an important role in transaction costs. Table 24 therefore divides transaction costs into selling-/purchase costs and accrued interest costs. Selling-costs only occur in the replacement-strategy; accrued interest costs only emerge in the default-strategy, i.e., if a new BD is purchased. Accrued interest costs account for more than half of the transaction costs in the default-strategy and are highest for HPT 2. This substantiates the previous notion that BDs are an important driver of reinvestments in HPT 2. Yet, when considering selling-/purchase costs separately, costs in the default-strategy are still higher on average than in the XTF-strategy.

Table 24: Influence of transaction costs on investment outcomes [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	sum of transaction costs [€]		cumulative VALUEpf until June 2017 [€]			cumulative return until June 2017 [%]		
			selling-/ purchase costs	accrued interest costs	including transaction costs	excluding transaction costs	difference in VALUEpf	including transaction costs	excluding transaction costs	difference in cumulative return
HPT 1	replacement-strategy	163,900	314	n.a.	182,562	182,942	380	11.39	11.62	0.23
	XTF-strategy [av.]		71	n.a.	175,356	175,436	80	6.99	7.04	0.05
	default-strategy [av.]		89	96	174,326	174,410	84	6.36	6.41	0.05
HPT 2	replacement-strategy	214,200	742	n.a.	256,542	257,462	920	19.77	20.20	0.43
	XTF-strategy [av.]		175	n.a.	234,732	234,910	178	9.59	9.67	0.08
	default-strategy [av.]		234	420	234,757	235,029	272	9.60	9.72	0.13
HPT 3	replacement-strategy	312,900	880	n.a.	412,739	413,969	1,230	31.91	32.30	0.39
	XTF-strategy [av.]		204	n.a.	390,157	390,392	235	24.69	24.77	0.08
	default-strategy [av.]		242	251	387,546	387,886	340	23.86	23.96	0.11

Notes: The left part of the table shows the initial VALUEpf by January 2014 and the sum of transaction costs that occur during the observation period (divided into selling-/purchase costs and accrued interest costs of BDs). Please note that selling-costs only occur in the replacement-strategy; accrued interest costs only emerge in the default-strategy, i.e., if a new BD is purchased. The middle part of the table reveals the cumulative VALUEpf at the end of the observation period in June 2017 (divided into VALUEpf including and excluding transaction costs as well as the difference between the latter). The right part of the table exhibits the characteristics of the middle part of the table in terms of returns. The values are presented for each HPT's benchmark XTF portfolio and as average [av.] of 1,000 HPT portfolios (nine risky securities per portfolio).

Cumulative portfolio values including and excluding transaction costs (see Table 24) show the impact of transaction costs on VALUEpf throughout the observation period. In each HPT, the replacement-strategy yields the highest cumulative VALUEpf. This is in line with the previous finding that benchmark XTF portfolios achieve higher risk-adjusted returns on average (see RDs in Table 22) compared to the HPTs' portfolios. While benchmark XTF portfolios reveal the highest cumulative returns, they also incur the highest losses in cumulative returns due to transaction costs. In HPT 2, for instance, cumulative returns decline by 0.43 percent due to transaction costs. An explanation therefore is that the replacement-strategy switches the entire portfolio at the beginning of the observation period. Since all transaction costs occur at the beginning, they accumulate to higher losses over time compared to reinvesting and incurring transaction costs successively as implied by the XTF- and default-strategy. This effect, however, depends on the observation period as well. Expanding the investment period induces further reinvestments (particularly in the default-strategy) and additional transaction cost which can exceed those of the replacement-strategy.

In HPT 1 and HPT 3, cumulative VALUEpfs and the returns of the XTF-strategy are higher than those of the default-strategy on average, regardless of whether transaction costs are included or excluded. In HPT 2, cumulative VALUEpfs and returns of the XTF-strategy are lower than those of the default-strategy. HPT 2 reveals a relatively high asset class weight in BDs. The bond XTF applied in the XTF-strategy reveals concentrations on government bonds.[494] The default-strategy employs individual BDs of the SHS-base which are assumed to be widespread among German households. According to stock market values of BD shares, German households seem to predominantly invest in domestic corporate bonds instead of government bonds.[495] A possible reason why cumulative returns are lower in the XTF-strategy might therefore be that the return of the applied bond XTF is lower than the return of the individual BDs employed in the default-strategy.

Nonetheless, the XTF-strategy incurs less losses in cumulative return due to transaction costs than the default-strategy. While transaction costs reduce cumulative returns of the XTF- and default-strategy to a similar extent in HPT 1, losses are higher for the default-strategy in HPT 2 and HPT 3. Since fees for XTFs are deducted from their fund assets, cumulative returns of the XTF-strategy are net of fees for XTFs. This weakens potential arguments to refrain from

[494] The applied bond XTF replicates the Markit iBoxx Euro Sovereign Index (ISIN: LU0290355717).
[495] See Table 27 in Appendix A.

investing in XTFs as they involve running fee costs and to self-select securities which do not bear running costs instead.

When increasing portfolio size (see Appendix E for corresponding tables), portfolio returns remain relatively stable in each strategy. For portfolio sizes of 18 and 27 securities, all RDs stay positive which means that for these portfolio sizes, the replacement-strategy yields higher risk-adjusted returns than the XTF- and default-strategy even when portfolios are considered to be better diversified. Risk as well as the RDs of the XTF- and default-strategy tend to decrease for larger portfolio sizes. For a portfolio size of 297 securities, RDs in HPT 3 are close to zero and some turn negative. This indicates that HPT 3 portfolios show on average similar or occasionally higher risk-adjusted returns than the corresponding benchmark XTF portfolio. Similar RDs suggest that the HPT 3 portfolios reveal levels of diversification which are similar to the corresponding benchmark XTF portfolios. This is in line with the findings of Statman (2004) who points out that a portfolio of approximately 300 securities provides reasonable diversification. RDs of the XTF-strategy remain lower than those of the default-strategy in most cases. This indicates that the XTF-strategy can by and large enhance the risk-return position of HPTs which follow the default-strategy, even when portfolios include more securities. The extent of enhancements, however, maintains low in absolute amounts of Euros.

An increase in portfolio size leads to a higher number of reinvestments and a higher amount of transaction costs. Reinvestment amounts decline slightly.[496] Cumulative VALUEpfs according to the XTF-strategy stay higher compared to those of the default-strategy in HPT 1 and HPT 3. Losses in terms of cumulative returns due to transaction costs maintain higher for the default- compared to the XTF-strategy. In the default-strategy, transaction costs increase more strongly than in the XTF-strategy and partly even offset an advance in cumulative returns which occurred excluding transaction costs.[497]

Overall, the results show that reinvesting payouts in XTFs yields risk-return positions which are by and large better compared to reinvesting payouts in individual securities according to households' current portfolio composition – particularly if the HPTs involve only a small number of securities. In absolute amounts of Euros, however, the amount of enhancements

[496] As an exception, reinvestment amounts increase for a portfolio size of 297 risky securities. A reason therefore might be that in this large portfolio size, securities (e.g. BDs) might expire more often than in a portfolio size of nine risky securities, which likely leads to higher reinvestment amounts.

[497] For a portfolio size of 27 securities in HPT 2, the default-strategy reveals a higher VALUEpf than the XTF-strategy excluding transaction costs. Including transaction costs, the XTF-strategy shows a higher VALUEpf which indicates that the previously higher VALUEpf of the default-strategy was offset by transaction costs (see Table 53 in Appendix E).

seems economically insignificant. The results further indicate that the default-strategy involves a higher investment turnover and that its investment outcomes are more heavily affected by transaction costs than those of the XTF-strategy. Compared to the XTF- and default-strategy, a radical portfolio replacement largely offers higher risk-adjusted returns after transaction costs.

7.3 Discussion

RDs capture the HPTs' portfolio diversification. In both reinvestment-strategies, risk and RDs tend to decline for larger portfolio sizes which implies an increase in diversification. This is in line with previous studies of Evans/Archer (1968); Wagner/Lau (1971); Statman (1987); (2004) which point out that increasing the number of securities in a portfolio leads to a reduction in portfolio risk and an increase in diversification, especially if a portfolio includes only a few securities prior to the increase. The latter effect might also contribute to the similarity in RDs between the XTF- and the default-strategy. Reinvestments according to the default-strategy, for instance, increase the portfolio sizes in HPT 3 from nine to 17.1 risky securities on average throughout the observation period (see Table 23).

The similarity in RDs might further be driven by return comovements of XTFs and individual securities included in the HPTs. Da/Shive (2018) document that arbitrageurs induce return comovements between ETFs and their underlying securities.[498] Likewise, Ben-David/Franzoni/Moussawi (2018) find that ETFs pass shocks on to their constituents and, thus, make them comove.[499] Hence, if securities included in the HPTs that follow the default-strategy are also included in the XTFs employed in the XTF-strategy, risk and return of both strategies and, thus, RDs tend to align. Another factor influencing the resemblance in RDs might be that the HPTs of both reinvestment-strategies do not differ enough from each other. Both strategies start with the same selected HPTs. The three-and-a-half-years observation period might be too short and the reinvested amounts too small to yield economically significant differences in RDs. According to the XTF-strategy in HPT 1, for example, only 6.61 percent of the initial VALUEpf were reinvested (see Table 23).

[498] A possible channel for arbitrageurs to exploit price discrepancies between XTFs and their underlying securities could be the closing auction in the creation/redemption process of XTFs (see e.g. Osterhoff/Overkott (2016)).

[499] The authors state that ETF arbitrage may transfer non-fundamental volatility to the underlying security basket. Glosten/Nallareddy/Zou (2020) add that this rather applies to large firms. They point out that for small firms with weak information environments, return comovements may not only be driven by non-fundamental factors, but also by an improved incorporation of short-term fundamentals in the prices of the underlying securities.

To provide an indication if (and if, how far) a higher reinvested amount leads to larger differences in RDs, a fixed monthly amount for reinvestments is added to all strategies and RDs are ascertained again. Additionally, cumulative returns including and excluding transaction costs are determined to investigate the influence of transaction costs on each strategy when reinvestment amounts are higher. The fixed monthly amount might represent, for example, monthly savings obtained from a households' monthly income. As an estimate, 200 Euros were assumed.[500]

After incorporating the fixed monthly amount in each strategy, RDs of the XTF-strategy decrease while those of the default-strategy increase.[501] Differences in RDs and, consequently, risk-return enhancements from following the XTF- instead of the default-strategy increase. However, in absolute amounts of Euros the enhancements remain insignificant.[502] Compared to the reinvestments without a fixed monthly amount, cumulative VALUEpfs and cumulative returns (both including and excluding transaction costs) increase in the XTF-strategy. In the default-strategy, cumulative returns decrease in some cases. Corresponding to the higher reinvestment amounts when including a fixed monthly amount, reductions (losses) in cumulative returns due to transaction costs increase in both strategies. However, losses in cumulative returns increase more strongly in the default- than in the XTF-strategy. While in the XTF-strategy, losses in cumulative return rose from 0.05 to 0.11 (0.08 to 0.12; 0.08 to 0.10) percent on average in HPT 1 (HPT 2; HPT 3), in the default-strategy losses in cumulative return increased from 0.05 to 0.53 (0.13 to 0.80; 0.11 to 0.73) percent.[503] Incorporating the fixed monthly amount suggests that losses in cumulative returns rise more quickly in the default- than in the XTF-strategy, and that higher reinvestment amounts are necessary to receive economically significant risk-return enhancements from employing the XTF- instead of the default-strategy.

[500] Incorporating an additional monthly fixed savings amount seems to be most relevant for households in their early ages since they are more likely to work and derive income from which they can obtain such an amount. For households that participated in the second wave of the PHF-survey (HPTs are derived from the same wave), Deutsche Bundesbank (2016) reveals that in the age group between 25 and 34, households earn an average annual net income of 25,200 Euro. This amount was divided by twelve to receive a monthly net income amount of 2,100 Euros. Multiplying the latter amount with an average savings ratio by German households during the observation period of 10 percent (own calculations; based on data of Deutsche Bundesbank (2019b)), a monthly fixed savings amount of 200 Euros was derived (rounded to hundred Euros).

[501] See Table 62 in Appendix E. An exception occurs when the MDD is the underlying risk measure.

[502] In a MV-framework, the largest difference in RDs occurs in HPT 2. Compared to the initial VALUEpf of HPT 2 (214,200 Euro), the monthly difference in RDs (0.0281 percent) translates into an absolute amount of 60 Euro per month (843 Euro per annum) which might, again, be in the range of forecast errors.

[503] See Table 63 in Appendix E.

Since reinvestment amounts increase over time and losses due to transaction costs are less severe for the XTF-strategy, the XTF-strategy probably yields economically significant risk-return enhancements over the default-strategy across longer investment periods. Possible cost advantages of the XTF-strategy might increase over time by the compound interest effect, which is essential for households intending to invest over the long-run.

Moreover, a portfolio of mainly two XTFs[504] that results from following the XTF-strategy is probably easier to manage than a portfolio that accumulated many individual securities over time as implied by the default-strategy. This might be important for households who want to switch from a reinvestment to a disinvestment strategy, e.g., after entering retirement, or for households who need or want to sell parts of the current portfolio for consumption. The XTF-strategy seems to be particularly appropriate for young adults and individuals of advanced age who already hold financial assets but are not able and/or willing to sell them all at once, who want to obtain an easy-to-manage XTF portfolio, but who also exhibit a sufficiently long investment horizon.

[504] Not every individual security that was included in a portfolio at the beginning might expire and be reinvested in XTFs. Therefore, a portfolio that employs the XTF-strategy over time might not entirely, but mainly consist of two XTFs in the sense that the XTFs represent a main share of the portfolio.

8 Discussion, Critical Appraisal, and Implications

The aim of the empirical analyses in the previous three chapters was to investigate the two research goals of this thesis:

- To investigate whether XTFs enhance risk and return of household portfolios when taking multiple relevant asset classes into account – not only stocks.
- To examine whether employing XTFs in household portfolios is reasonable when including practical constraints and risk measures that reflect households' actual investment situation and interpretation of risk more closely.

The analyses build on the foundations of neoclassical finance theory, NIE, market microstructure theory, financial intermediation, as well as behavioral finance and economics and involve empirical findings on characteristics of household portfolios. Two data sets of the German central bank (Deutsche Bundesbank), which are representative for German households, are combined: The PHF-survey and security holding data of the SHS-base.

The main advantage of the analyses in this thesis is that they include multiple asset classes of household portfolios – not only stocks. A further advantage is that the analyses are based on representative household portfolio data. Both factors enable a better approximation of household portfolios and allow investigating the influence of XTFs on risk and return of household portfolios more comprehensively compared to previous studies.

While RQ1 addressed the first research goal, the second research goal was pursued by RQ2 and RQ3.

RQ 1: Do XTFs enhance risk and return of household portfolios when taking multiple relevant asset classes of household portfolios into account?

Household portfolios are approximated by deriving stylized Household Portfolio Types (HPTs) from clustering German household portfolio data obtained from the PHF-survey. Three HPTs are identified which reveal asset class concentrations on cash/savings (HPT 1), mutual funds (HPT 2) and individual stocks (HPT 3). Correlation analyses, statistics on financial assets and liabilities of Deutsche Bundesbank (2014), and survey results by forsa (2017) are in support of the ascertained HPTs and the corresponding asset class concentrations of German households. While HPT 1 reveals the least amount of VALUEpf, HPT 3 reveals the highest VALUEpf which is in line with previous findings stating that less wealthy households tend to focus on cash/savings and more wealthy households reveal higher exposures in stocks.[505]

RDs indicate that all HPTs can enhance their risk-return trade-off from a 60/40 stock/bond XTF portfolio. Thereby, the portfolio cluster which contains most households of the data sample (i.e. HPT 1 with a focus on cash/savings) can obtain the least enhancements while the portfolio cluster which contains the least number of households and shows the highest concentration on individual stocks (HPT 3) can obtain the largest enhancements. This is in line with Calvet/Campbell/Sodini (2007) and von Gaudecker (2015) who report that most households in their sample incur slight return losses while a small group of households who invest more aggressively incur higher return losses and, thus, could obtain larger enhancements compared to the market portfolio.

Portfolio replacements analyze the extreme case in which the entire risky assets of a household portfolio are sold at once and replaced with a 60/40 XTF portfolio while including transaction costs. Contrary to RDs, portfolio replacements do not involve risk-adjusting. They examine the scenario in which households simply replace all risky assets in their portfolio with a 60/40 XTF portfolio at once without adjusting for a portfolio's current risk. Within the observation period, portfolio replacements lead to enhancements in both risk and return of all stylized portfolios except HPT 2. The slight increase in SD of HPT 2 (0.30 percentage points), however, seems acceptable in exchange for the increase in (expected) annual return of 2.40 percentage points. Hence, the analysis indicates that an entire replacement of a portfolio with an easily investable XTF portfolio can, without risk-adjusting, by and large enhance risk and return of the stylized household portfolios.

RQ 2: Do downside-risk measures help to explain the reluctance of households to invest in XTFs?

In statistical terms, RDs that are based on the downside-risk measures LPM0, LPM1, and $\sqrt{\text{LPM2}}$ are significantly different from the RDs that are based on the SD. However, these differences seem insignificant in economic terms as they translate, in relation to VALUEpf, into negligible absolute amounts of money which could be in the range of forecast errors. In

[505] See Campbell (2006); Guiso/Sodini (2013), pp. 1407ff.; European Central Bank (2016c); (2017a); (2017b); Arrondel et al. (2016).

addition, none of the applied downside-risk measures leads to consistently lower (and significant) RDs compared to the SD on average. This analysis concludes that none of the employed downside-risk measures can help to explain the reluctance of households to invest in XTFs.

This seems conflicting at first with Unser (2000), Veld/Veld-Merkoulova (2008), and Holzmeister et al. (2019) who point out that households perceive risk, as opposed to the SD, mostly in terms of downside-risk which would suggests that differences in households' risk evaluation and RDs across the applied risk-return-frameworks occur. However, reasons for the similarity in RDs might be that the former studies pursue different research goals and a different research design, e.g., by using experiments instead of household portfolio data or by capturing households' risk evaluation from an ex-ante instead of an ex-post perspective.

The finding that RDs are similar and positive across all applied risk-return-frameworks, on the flip side, suggests that the applied XTF portfolios represent a reasonable proxy of the (optimal) market portfolio for households, regardless of the underlying risk measure and corresponding risk-return-framework. In line with Jarrow/Zhao (2006), Das et al. (2010), and Pfiffelmann/Roger/Bourachnikova (2016), portfolios which are optimal in a MV-framework can also be optimal in a M-LPM- and BPT-framework, respectively.

An alternative explanation why households refuse to invest in XTFs relates to the observation that relying on financial advice is prevalent among German households.[506] Since financial advisors are typically subject to an incentive structure that motivates them to recommend high-fee products,[507] they might refrain from recommending households low-fee products like XTFs. Another influencing factor regarding households' reluctance to employ XTFs can be associated with the concept of knowledge illusion by Baars/Goedde-Menke (2019). This concept involves that individuals tend to distinguish between different sources of risk based on their perceived expertise. Since XTFs imply diversifying internationally but households perceive higher expertise for geographically close investments,[508] households might refuse to invest in XTFs as they perceive more expertise and incentives to invest in geographically close investments.

Nevertheless, although none of the employed downside-risk measures can help to explain the reluctance of households to invest in XTFs, all applied risk-return-frameworks indicate that households can obtain risk-return enhancements from employing XTFs. This substantiates the

[506] See DAB Bank (2004); Hackethal et al. (2011).
[507] See Christoffersen/Evans/Musto (2013); von Gaudecker (2015); Chalmers/Reuter (2015); Egan (2019).
[508] See Kilka/Weber (2000); Ackert et al. (2005).

widespread recommendation to employ XTFs[509] and suggests that the advice also holds true if households evaluate risk according to downside-risk measures.

RQ 3: Does reinvesting payouts in XTFs enhance the risk-return position of household portfolios?

The results on RQ3 show that reinvesting payouts in XTFs yields risk-return positions which are by and large better than those when payouts are reinvested in individual securities according to households' current portfolio composition. In absolute amounts of Euros, however, the amount of differences between the XTF- and default-strategy seem economically insignificant. The similarity might be influenced by the effect that increasing the number of securities in a portfolio induces risk reductions and diversification increases, particularly for small portfolio sizes.[510] If the portfolio size of a HPT is small, reinvesting in an additional security by following the default-strategy might yield risk reductions and diversification increases close to those when the XTF-strategy is employed.

Comovements between XTFs and their constituents[511] might contribute to similar risk-return enhancements of the XTF- and default-strategy towards benchmark XTF portfolios. If a HPT following the default-strategy includes constituents of the XTFs applied in the XTF-strategy (e.g. German blue chip stocks), risk and return of both strategies might align. Additionally, the three-and-a-half-years observation period might not be long enough to reveal economically significant differences between the XTF- and default-strategy.

The results further indicate that the default-strategy involves higher investment turnover and that its investment outcomes are more heavily affected by return losses due to transaction costs compared to the XTF-strategy. Over a longer investment period, further occurring reinvestments likely increase return losses in the default-strategy and raise advantages in the XTF-strategy which may be intensified by the compound interest effect. The XTF-strategy therefore seems more favorable for households in the long-run than the default-strategy.

[509] See Malkiel (2003a); (2003b); French (2008); Huang/Lin (2011); Jacobs/Müller/Weber (2014); Bhattacharya et al. (2017); Elton/Gruber/de Souza (2019).
[510] See Evans/Archer (1968); Wagner/Lau (1971); Statman (1987); (2003); (2004).
[511] See Da/Shive (2018); Ben-David/Franzoni/Moussawi (2018).

Taking a long-term perspective, a portfolio that mainly consists of two XTFs – resulting from the XTF-strategy – might also be easier to manage than a portfolio that has accumulated many individual securities over time as implied by the default-strategy. For instance, if a household wants to switch from a reinvestment to a disinvestment strategy, e.g. after retirement, or if a household wants to sell a certain amount of securities for consumption. Consequently, the XTF-strategy might be particularly appropriate for young adults and individuals of advanced age who already hold financial assets but are not able and/or willing to sell them all at once, who want to obtain an easy-to-manage XTF portfolio, but who also exhibit a sufficiently long investment horizon.

Empirical research in the field of household finance faces the difficulty that appropriate data is hard to access.[512] This imposes specific constraints to each study which require making assumptions that may limit the analyses' results. This thesis is also based on some crucial assumptions: First, it relies on stylized portfolio compositions and a number of assumptions regarding the construction of household portfolios (e.g. the number of securities per HPT). Thus, the corresponding estimations of risk and return of household portfolios do not capture the entire diversity of individual household portfolios. Considering that the entire diversity of individual household portfolios is hard to grasp, deriving stylized portfolio compositions in terms of the HPTs represents an approximation. As such, HPTs might not reflect the portfolio composition of every existing household. However, since the HPTs are derived from representative empirical household portfolio data, they likely provide a good estimation and reflection of many existing household portfolios.

Second, the results may be driven by idiosyncratic effects of the assets assumed in the HPTs during the observation period. Hence, the effect of employing XTFs might be over- or underestimated from an ex-ante perspective. However, as the results stay robust for different portfolio sizes (see chapter 5.3.2), the positive effect on household portfolio performance from investing in XTFs seems to remain. Additional effects may arise from home-biased security selections in the HPTs (e.g. due to a dominant role of German large-cap stocks)[513]. However, investing in German blue-chip stocks provides a reasonable degree of internationalization and rather prevents than promotes home-bias.[514]

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[512] See Campbell (2006); Calvet/Campbell/Sodini (2007); Guiso/Sodini (2013), pp. 1460ff.; von Gaudecker (2015).
[513] C.f. Table 27 regarding the securities applied in chapter 5.
[514] See Oehler/Wendt/Horn (2016); (2017); Oehler/Wendt (2016b).

Third, the observation period might not be long enough so that the ascertained results might deviate from the influence of XTFs on risk and return of household portfolios in the long-run. For instance, if a certain stock market which has a major impact on the applied stock XTF, but not on the HPTs, performs exceptionally well during the observation period, RDs might overestimate the enhancements in risk and return from employing XTFs. An advantage of the data applied in this thesis, however, is that they are, in contrast to many other studies, based on representative household portfolio data. As a special feature, the SHS-base reveals German households' security holdings by ISIN and provides a proxy for the distribution of each security among German households in terms of the aggregated market values of shares which are owned by German households (excluding all shares owned by foreign investors or other sectors like non-financial corporations and investment companies).[515] As the PHF-survey does not capture German households' security holdings which are necessary for estimating portfolio risk and return, combining the PHF-survey with security holding data of the SHS-base is considered as a best estimate for constructing German household portfolios that consist of multiple asset classes.

This thesis is the first that combines data of the PHF-survey with security holding data of the SHS-base. Since the HFCS also includes household surveys of other euro area countries and the European Central Bank expanded the collection of household security holding data to other euro area countries[516], further research could apply the approach of this thesis and combine both data sets for other European countries to investigate household portfolios. Future studies could use more recent security holding data of the SHS-base, which was not accessible at the time the analyses of thesis were performed.[517] Among others, this would allow applying an extended observation period and checking the robustness of this thesis' results, for instance, whether the extent of enhancements from employing XTFs remains stable over time. Including more recent security holding data could also be used to investigate reinvestment-strategies for household portfolios using XTFs for a longer investment period. This could provide an indication about the period of time after which reinvesting payouts in XTFs might yield economically significant risk-return enhancements, which would be particularly useful for households that reveal long investment horizons.

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[515] See Bade et al. (2017).

[516] Collecting security holding data of different sector holders from domestic banks by other European central banks started in 2014 (see European Central Bank (2015); Bade et al. (2017)).

[517] See chapter 4.3.2 regarding the availability of the employed data sources.

The results in this thesis exhibit relevant findings for different stakeholders. The deduction of stylized household portfolio compositions can be useful for regulators, policy makers and financial advisors. They provide estimations of each portfolio type's risk and return characteristics which can be used when assessing the impact of certain regulations and policies on different household portfolio types, or when establishing portfolio recommendations for households that exhibit a certain portfolio composition, respectively. Investigating RDs can help financial advisors and households to estimate, depending on a household's portfolio composition and interpretation of risk, the extent of return enhancements that are attainable from an easily investable XTF portfolio with similar risk.

Moreover, the performance of XTF portfolios might serve as a benchmark for households against which they can compare (recommendations of financial advisors to employ) actively managed mutual funds or active investment strategies. The investigation of portfolio replacements might be relevant for financial advisors and households who raise concerns that replacing their (clients') risky assets with an easily investable XTF portfolio without risk-adjusting increases portfolio risk, and that the involved transaction costs offset potential enhancements. The results of this thesis on portfolio replacements can mitigate such concerns as they indicate risk reductions and return increases, regardless of the stylized portfolio composition, which implies that employing XTFs has a positive influence on risk and return of German household portfolios.

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Appendix

Appendix A: Data Preparation (chapter 5.1.1)

Appendix B: Robustness Checks on Cluster Analysis (chapter 5.3.1)

Appendix C: Robustness Checks on Return Differences (chapter 5.3.2)

Appendix D: Robustness Checks on Portfolio Replacement (chapter 5.3.3)

Appendix E: Methodology / Robustness Checks on Reinvestment Strategies (chapter 7)

Appendix A

In the three empirical analyses of this thesis, multiple relevant asset classes of household portfolios are included, i.e. the safe financial assets cash (CASH) and savings (SV) as well as the risky financial assets stock funds (SFs), bond funds (BFs), real estate funds (REFs), individual stocks (STs) and individual bonds (BDs). When assigning German households' security holdings from the SHS-base to these asset classes, securities that are reported by less than three financial institutions are excluded from the sample since these securities can hardly be assumed as representatively held by German households. Restrictions in the data policy of Deutsche Bundesbank restricts obtaining a separate identifier for the asset class of each security in the SHS-base. Instead, corresponding asset class information is gathered from Thomson Reuters Datastream.

Among mutual funds with the highest aggregated market values of shares there are a range of mutual funds which follow a mixed asset strategy which points out the relevance of such mixed funds in the portfolios of German households. Mixed funds are assigned to SF or BF according to their correlation with stock- and bond-indices that cover different subcategories. The applied indices as well as the categorization of mixed funds in the first empirical analyses (see chapter 5) are displayed in Table 25 and Table 26.

Table 25: Applied Stock and Bond indices for categorization of Mixed Funds

num.	Index category	Name	Ticker
1	Stock index	MSCI NORTH AMERICA E	MSNAMRE
2	Stock index	MSCI EUROPE E	MSEROPE
3	Stock index	MSCI AC ASIA PACIFIC E	MSAAPFE
4	Stock index	MSCI EM E	MSEMKFE
5	Stock index	MSCI AC WORLD :SM E	MSZAWFE
6	Stock index	MSCI AC WORLD :L E	MSLAWFE
7	Stock index	S&P 500/CITIGROUP PURE VALUE	SP05PVA
8	Stock index	S&P 500/CITIGROUP PURE GROWTH	SP05PGR
9	Stock index	S&P 500 DIVIDENDS ARISTOCRATS	SP5DIAR
10	Stock index	DAX 30 PERFORMANCE	DAXINDX
11	Stock index	EURO STOXX	DJEURST
12	Stock index	MSCI AC WORLD E	MSACWFE
13	Bond index	IBOXX EURO CORPORATES	IBCRPAL
14	Bond index	IBOXX EURO OVERALL	IBEURAL
15	Bond index	IBOXX EURO LIQUID SOVEREIGNS GLOBAL	IBELSVE
16	Bond index	IBOXX EURO LIQUID SOVEREIGNS CAPPED 2.5 - 5.5	IBELSCD
17	Bond index	IBOXX EURO LIQUID SOVEREIGNS CAPPED 5.5 - 10.5	IBELSCE
18	Bond index	IBOXX EURO LIQUID SOVEREIGNS CAPPED 10.5+	IBELSCC
19	Bond index	S&P MUNICIPAL BOND HIGH YIELD INDEX	SPMUBHY
20	Bond index	S&P 500 HIGH YIELD CORP BOND INDEX	SP5HYBI
21	Bond index	IBOXX EURO HY FIXED RATE	IBEHYFR

Notes: The table outlines details and tickers to the applied stock and bond indices which are used to calculate return correlations with mixed funds. Corresponding return data is gathered from Thomson Reuters Datastream.

Table 26: Categorization of Mixed funds into Stock and Bond funds

original category	categorized	ISIN	Name
Mixed fund	Bond fund	FR0010135103	CARMIGNAC GESTION PATRIMOINE FCP 3 D C
Mixed fund	Bond fund	DE0005896864	DEKA STIFTUNGEN BALANCE
Mixed fund	Bond fund	LU0364818897	UNION INVESTMENT UNIPROFIANLAGE 2016
Mixed fund	Bond fund	LU0139429517	DWS DB OPPORTUNITY
Mixed fund	Bond fund	LU0279509904	ETHNA-DEFENSIV A
Mixed fund	Bond fund	DE000A0B71B7	NORDINVEST NORD.INV. GESELL.NORDSELECT
Mixed fund	Bond fund	LU0383797551	UNION INVESTMENT LX. UNIGARANT COMD.2017
Mixed fund	Bond fund	LU0395794307	JPMORGAN INV.FUNDS GLB. INCOME FUND A DS.
Mixed fund	Bond fund	LU0255639139	NORDEA 1 ABSOLUTE RETURN FD.AP EUR
Mixed fund	Stock fund	LU0136412771	ETHNA-AKTIV A
Mixed fund	Stock fund	LU0323578657	FLOSSBACH VON STORCH STRATEGIE MTPL.OPPS.R
Mixed fund	Stock fund	LU0425202842	DWS INV.DB PRIVMANDAT COMFORT PRO DEUT
Mixed fund	Stock fund	DE000A0M0341	PIONEER INVT.HVB VERM DEP PRIVAT BALANCE PI
Mixed fund	Stock fund	DE000A0RPAM5	UNION INV.GESELL.MBH PRIVATFONDS KONTROLLIERT
Mixed fund	Stock fund	DE0005896872	DEKA EUROLAND BALANCE
Mixed fund	Stock fund	LU0425202925	DWS INV.DB PRIVMANDAT COMFORT PRO GLOB
Mixed fund	Stock fund	LU0321021312	DRESDNER VERMMGT WACA EUR DIS D
Mixed fund	Stock fund	DE0008491044	UNION INV.PRIVATFONDS UNIRAK
Mixed fund	Stock fund	LU0272367581	DWS VORSORGE PREMIUM
Mixed fund	Stock fund	DE000DK1CHH6	DEKA INVESTMENT GMBH EUROLAND BALANCE TF
Mixed fund	Stock fund	LU0185900692	DEKASTRUKTUR 4 ERTRAG PLUS
Mixed fund	Stock fund	LU0185900775	DEKASTRUKTUR 4 WACHSTUM
Mixed fund	Stock fund	DE000A0M0358	PIONEER INVT.HVB VERM DEP PRIV WACHSTUM PI
Mixed fund	Stock fund	LU0097711666	INTL.FD.MAN.LBBW BALANCE CR20
Mixed fund	Stock fund	DE0008476250	KAPITAL PLUS A (EUR)
Mixed fund	Stock fund	LU0163675910	SAUREN GLOBAL DEFENSIV A
Mixed fund	Stock fund	GB00B1VMCY93	M &.G OPTIMAL INCOME A H ACC EUR

Notes: The table reveals the categorization of mixed funds into stock and bond funds according to the highest correlation with one of the stock- and bond-indices in Table 25.

After categorizing securities from the SHS-base in the asset classes employed in this analysis, securities are matched with price data and (discrete) monthly returns are calculated.[518] Returns for stocks and mutual funds are calculated using total return price data (including dividends and payouts) which are gathered from Thomson Reuters Datastream. Bonds are calculated using the clean price, coupon payments, and accrued interest.[519]

Next, all securities within a certain asset class are ordered by their aggregated market value of shares in January 2014, i.e. the beginning of the observation period. Thereof, those securities are selected into the HPTs which reveal the highest aggregated market value of shares (e.g., for

[518] The analysis is thereby based on the assumption that households are price takers.
[519] See e.g. Dbouk/Kryzanowski (2009). Due to limited data availability, total return price data are used for calculating returns of bonds with variable coupon payments. The total return index $\mathrm{RI}_{s,d}$ for security s on day d is computed by Datastream according to $\mathrm{RI}_{s,d} = \mathrm{RI}_{s,d-1}(\frac{\mathrm{CP}_d+\mathrm{A}_d+\mathrm{C}_{s,(d-1;d)}}{\mathrm{CP}_{d-1}+\mathrm{A}_{d-1}})$, where $d-1$ denotes the previous trading day, CP_d the daily clean-price on day d, A_d the accrued interest on day d, and $\mathrm{C}_{s,(d-1;d)}$ indicates the coupon payments of bond s within $d-1$ and day d (see variable description at Thomson Reuters Datastream for details).

a portfolio size of nine securities, which includes three ST, the top three ST according to the aggregated market value of shares are obtained). The aggregated market value of shares of a security relative to the aggregated market value of all shares included in a certain asset class of a household portfolio determines the security's weight within the asset class of a household portfolio. This is consistent with the previous assumption that the larger the aggregated market value of shares, the larger the distribution and importance of a security among households.

During the observation period until December 2016, some securities expire (e.g. due to the maturity of a bond or liquidation of a mutual fund). In this case, households are assumed to reinvest the available amount in the subsequent month. Accordingly, a security of the same asset class is selected which reveals the highest aggregated market value of shares in the corresponding month. In each reinvestment, transaction costs are considered. For a portfolio size of nine securities, zero stocks, two bonds, and zero mutual funds were reinvested; for a portfolio size of 18 securities, zero stocks, five bonds, and zero mutual funds were reinvested; for a portfolio size of 27 securities, zero stocks, five bonds, and zero mutual funds were reinvested (see Table 27 for details).[520]

[520] The only stock reinvestment that occurs refers to an exchange of shares in June 2015 (CH0024899483 to CH0244767585, see https://www.ubs.com/global/de/about_ubs/media/global/legal-structure.html) which was accepted by most of the stockholders (see https://www.boerse-online.de/nachrichten/aktien/gut-90-prozent-der-ubs-aktionaere-nehmen-an-aktientausch-teil-1000392110). Therefore, the new shares of this company are applied for reinvestment.

Table 27: Securities applied in the first empirical analysis

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
1	*BD*	DE000CZ29DB9	COMMERZBANK 2009 G/R 31/03/14	2014-01	2014-03	3	x	x	x	x
2	*BD*	DE000HSH4QN3	HSH NORDBANK AG 2014 2% 24/01/19 REG.S	2014-04	2016-12	33	x	x	x	x
3	*BD*	DE000A1R08U3	THYSSENKRUPP 2013 4% 27/08/18 1	2014-01	2016-12	36	x	x	x	x
4	*BD*	DE000A1G49F1	UNICREDIT BANK IRE. 2012 G/R 29/12/15 REG.S	2014-01	2015-11	23	x	x	x	x
5	*BD*	XS0576395478	FMC FINANCE VII SA 2011 5 1/4% 15/02/21 REG.S	2015-12	2016-12	13	x	x	x	x
6	*BD*	DE000A1ALVC5	DTBK.CAP.FDG.TST.XI 2009 9 1/2% PERP. EARLY	2014-01	2015-03	15		x	x	x
7	*BD*	DE0001137438	BUNDESREPUB.DTL.BSA 2013 1/4% 11/09/15	2015-04	2015-08	5		x	x	x
8	*BD*	XS1271836600	DEUTSCHE LUFTHANSA 2015 5.125%(F/R)08/75 REG.S	2015-09	2016-12	16		x	x	x
9	*BD*	DE000CB83CE3	COMMERZBANK AG 2011 6 3/8% 22/03/19 773	2014-01	2016-12	36		x	x	x
10	*BD*	DE000CB59FV0	COMMERZBANK AG 2008 6 1/4% 30/09/14 667	2014-01	2014-08	8		x	x	x
11	*BD*	DE000A1YCQ29	DEUTSCHE LUFTHANSA 2015 5.125%(F/R)08/75 REG.S	2014-09	2016-12	28		x	x	x
12	*BD*	DE000A0GNPZ3	ALLIANZ FINANCE II 2006 5 3/8% PERP.	2014-01	2016-12	36			x	x
13	*BD*	XS0326869665	BAYERISCHE LB. 2007 5 3/4% 23/10/17 761	2014-01	2016-12	36			x	x
14	*BD*	DE000A1MA9H4	THYSSENKRUPP 2012 4 3/8% 28/02/17 1	2014-01	2016-12	36			x	x
15	*BD*	XS0438813536	DEUTSCHE LUFTHANSA 2009 6 1/2% 07/07/16 2	2014-01	2016-06	30				x
16	*BD*	DE000A2AASM1	PROKON RGTV.EGN.EG. 2016 3 1/2% 25/06/30	2016-07	2016-12	6				x
17	*BD*	DE000A0TU305	DT.BK.CONTG.CAP.IV 2008 8% PERP. REG.S	2014-01	2016-12	36				x
18	*BD*	DE0001141547	BUNDESREPUB.DTL. BO 2009 2 1/4% 11/04/14 154	2014-01	2014-03	3				x
19	*BD*	DE000CB0BWA6	COMMERZBANK AG 2014 G/R 26/03/19 323	2014-04	2016-12	33				x
20	*BD*	DE000A0T61L9	THYSSENKRUPP FIN. 2009 8 1/2% 25/02/16 2	2014-01	2016-01	25				x
21	*BD*	XS0731681556	VW INTL FIN NV 2012 3 1/4% 21/01/19 REG.S	2016-02	2016-12	11				x
22	*BD*	DE000A1G3U23	UNICREDIT BANK IRE. 2012 G/R 04/05/16 REG.S	2014-01	2016-04	28				x
23	*BD*	DE000A1R02E0	HORNBACH BAUMARKT 2013 3 7/8% 15/02/20 REG.S	2016-05	2016-12	8				x
24	*BD*	XS0419185789	DEUTSCHE LUFTHANSA 2009 6 3/4% 24/03/14 1	2014-01	2014-02	2				x
25	*BD*	DE000HSH4PF1	HSH NORDBANK AG 2014 G/R 26/08/19 REG.S	2014-03	2016-12	34				x
26	*BD*	XS0214238239	THYSSENKRUPP 2005 4 3/8% 18/03/15	2014-01	2015-02	14				x
27	*BD*	DE000A14J579	THYSSENKRUPP 2015 1 3/4% 25/11/20 REG.S	2015-03	2016-12	22				x
28	*BD*	DE000A0AD8E5	HAMBURGER SPARK.AG 2009 G/R 17/03/14 517	2014-01	2014-02	2				x
29	*BD*	XS0205537581	ARGENTINA 2003 G/R 31/12/38 PAR BON	2014-03	2016-12	34				x
30	*BD*	DE000A0GMHG2	PORSCHE INTL.FNG. 2006 3 7/8% 01/02/16	2014-01	2016-01	25				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
31	*BD*	XS1064049767	WUERTT.LEB.AG 2014 5.25%(F/R) 07/44	2016-02	2016-12	11				x
32	*BD*	DE000DB2KVT4	DEUTSCHE BK AG LDN 2010 2.6%(F/R) 08/15 REG.S	2014-01	2015-07	19				x
33	*BD*	DE000A14J587	THYSSENKRUPP 2015 2 1/2% 25/02/25 REG.S	2015-08	2016-12	17				x
34	*BD*	DE000HSH4L33	HSH NORDBANK AG 2013 G/R 17/10/18 REG.S	2014-01	2016-12	36				x
35	*BD*	DE000CZ31PX3	COMMERZBANK AG 2011 5%(F/R) 03/18 Q	2014-01	2016-12	36				x
36	*BD*	DE000A0DTY34	DEUTSCHE BK.TST.CO. 2005 6%(F/R) PERP. EARLY	2014-01	2014-12	12				x
37	*BD*	DE0001137420	BUNDESREPUB.DTL.BSA 2013 ZERO 12/06/15	2015-01	2015-05	5				x
38	*BD*	DE000DB2KVR8	DEUTSCHE BK AG LDN 2010 2.6%(F/R) 07/15 REG.S	2015-06	2015-06	1				x
39	*BD*	DE000A1R0TU2	BILFINGER SE 2012 2 3/8% 07/12/19 REG.S	2015-07	2016-12	18				x
40	*BD*	DE000A1TM5X8	HOCHTIEF AG 2013 3 7/8% 20/03/20	2014-01	2016-12	36				x
41	*BD*	DE0001118446	BUNDESREPUB.DTL.BSB 2008 G/R 01/12/14 2008/29	2014-01	2014-11	11				x
42	*BD*	DE0001141570	BUNDESREPUB.DTL. BO 2010 2 1/4% 10/04/15 157	2014-12	2015-03	4				x
43	*BD*	DE0001141588	BUNDESREPUB.DTL. BO 2010 1 3/4% 09/10/15 158	2015-04	2015-09	6				x
44	*BD*	XS0968913342	VW INTL FIN NV 2013 5.125%(F/R)PERP. REG.S	2015-10	2016-12	15				x
45	*BD*	DE000A0Z12Y2	THYSSENKRUPP 2009 G/R 18/06/14 2	2014-01	2014-05	5				x
46	*BD*	DE0001141562	BUNDESREPUB.DTL. BO 2010 2 1/2% 27/02/15 156	2014-06	2015-01	8				x
47	*BD*	DE000A12TZ95	HOCHTIEF AG 2014 2 5/8% 28/05/19	2015-02	2016-12	23				x
48	*BD*	XS0759200321	FRESENIUS SE & CO. 2012 4 1/4% 15/04/19 REG.S	2014-01	2016-12	36				x
49	*BD*	DE000CZ29DA1	COMMERZBANK 2009 G/R 03/03/14	2014-01	2014-02	2				x
50	*BD*	XS0542369219	RHEINMETALL AG 2010 G/R 22/09/17	2014-03	2016-12	34				x
51	*BD*	DE000HSH3PX6	HSH NORDBANK AG 2011 G/R 05/11/15	2014-01	2015-10	22				x
52	*BD*	DE000DB7XJJ2	DEUTSCHE BANK AG 2015 2 3/4% 17/02/25	2015-11	2016-12	14				x
53	*BD*	DE000CZ29SX1	COMMERZBANK 2009 G/R 30/09/14 IHS55	2014-01	2014-08	8				x
54	*BD*	XS0938218400	STADA ARZNEIMITTEL 2013 2 1/4% 05/06/18	2014-09	2016-12	28				x
55	*BD*	DE000CZ31PQ7	COMMERZBANK AG 2011 G/R 14/03/17 1 EARLY	2014-01	2015-02	14				x
56	*BD*	DE000HSH3537	HSH NORDBANK AG 2013 G/R 06/08/18	2015-03	2016-12	22				x
57	*BD*	DE000CB83GA2	COMMERZBANK AG 2011 5%(F/R) 04/18 Q	2014-01	2016-12	36				x
58	*BD*	DE000DB2KX53	DEUTSCHE BK AG LDN 2011 G/R 10/02/16	2014-01	2016-01	25				x
59	*BD*	XS0997941355	K&S AG 2013 4 1/8% 06/12/21 REG.S	2016-02	2016-12	11				x
60	*BD*	XS0225369403	BAYER AG 2005 5%(F/R) 07/05 EARLY	2014-01	2015-06	18				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
61	*BD*	XS1013954646	FRESENIUS SE & CO. 2014 2 3/8% 01/02/19 REG.S	2015-07	2016-12	18				x
62	*BD*	DE000CZ31PM6	COMMERZBANK AG 2011 G/R 17/02/17 1 EARLY	2014-01	2015-01	13				x
63	*BD*	DE000HSH4R03	HSH NORDBANK AG 2014 G/R 16/07/19 2137	2015-02	2016-12	23				x
64	*BD*	DE000HSH35M8	HSH NORDBANK AG 2012 G/R 21/06/17	2014-01	2016-12	36				x
65	*BD*	DE0001118362	BUNDESREPUB.DTL.BSB 2008 G/R 01/09/14 P1 /p	2014-01	2014-08	8				x
66	*BD*	NO0010313356	NORWAY 2006 4 1/4% 19/05/17 NST 472	2014-09	2016-12	28				x
67	*BD*	DE0001118529	BUNDESREPUB.DTL.BSB 2009 G/R 01/07/15 2009/07	2014-01	2015-06	18				x
68	*BD*	DE000A11QR65	BAYER AG 2014 3%(F/R) 07/75 REG.S	2015-07	2016-12	18				x
69	*BD*	XS0456708212	EVONIK INDUSTRIES 2009 7% 14/10/14 REG.S	2014-01	2014-09	9				x
70	*BD*	DE0001030500	BUNDESREPUB.DTL. AN 2006 1 1/2% 15/04/16 INDXLK.	2014-10	2016-03	18				x
71	*BD*	DE000A2AAPF1	THYSSENKRUPP 2016 2 3/4% 08/03/21 REG.S	2016-04	2016-12	9				x
72	*BD*	DE0001141554	BUNDESREPUB.DTL. BO 2009 2 1/2% 10/10/14 155	2014-01	2014-09	9				x
73	*BD*	DE000CZ31P11	COMMERZBANK AG 2011 G/R 26/04/17 2 EARLY	2014-10	2015-03	6				x
74	*BD*	XS0477568637	FMC FINANCE VI SA 2010 5 1/2% 15/07/16 REG.S	2015-04	2016-06	15				x
75	*BD*	XS1433512891	OTTO GMBH & CO.KG 2016 2 1/2% 16/06/23 5	2016-07	2016-12	6				x
76	*BD*	DE000DB2KX61	DEUTSCHE BK AG LDN 2011 2.7%(F/R) 02/16 REG.S	2014-01	2016-01	25				x
77	*BD*	XS1044496203	HBGCM.FIN.LX. 2014 2 1/4% 12/03/19 REG.S	2016-02	2016-12	11				x
78	*BD*	DE000CZ22EH9	COMMERZBANK AG 2009 5% 30/10/17	2014-01	2016-12	36				x
79	*BD*	XS0520759803	HBGCM.FIN.LX. 2010 6 3/4% 15/12/15 S	2014-01	2015-11	23				x
80	*BD*	XS0520938647	NORDDEUTSCHE LB. 2010 6% 29/06/20 558	2015-12	2016-12	13				x
81	*BD*	DE000A0TKUU3	HBGCM.FIN.LX. 2007 5 5/8% 04/01/18	2014-01	2016-12	36				x
82	*BD*	XS0873432511	FRESENIUS SE & CO. 2013 2 7/8% 15/07/20 REG.S	2014-01	2016-12	36				x
83	*BD*	XS0458230082	HEIDELBERGCMNT FIN. 2009 7 1/2% 31/10/14 REG.S	2014-01	2014-10	10				x
84	*BD*	XS1109110251	DEUTSCHE LUFTHANSA 2014 1 1/8% 12/09/19 REG.S	2014-11	2016-12	26				x
85	*BD*	XS0447977801	FRAPORT FF ARPT 2009 5 1/4% 10/09/19 REG.S	2014-01	2016-12	36				x
86	*BD*	XS0482703286	FRANZ HANIEL & CIE 2010 G/R 01/02/17 5	2014-01	2016-12	36				x
87	*BD*	DE000CZ226Y9	COMMERZBANK AG 2010 3 7/8% 22/03/17	2014-01	2016-12	36				x
88	*BD*	DE000CZ29SW3	COMMERZBANK 2009 G/R 17/09/14 IHS54	2014-01	2014-08	8				x
89	*BD*	DE000HSH4M65	HSH NORDBANK AG 2014 G/R 09/07/19 2008	2014-09	2016-12	28				x
90	*BD*	XS0503554627	CELESIO FINANCE BV 2010 4 1/2% 26/04/17	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
91	*BD*	DE000CB898R7	COMMERZBANK 2009 G/R 17/02/14 694	2014-01	2014-01	1				x
92	*BD*	DE000A1R0410	THYSSENKRUPP 2014 3 1/8% 25/10/19 REG.S	2014-02	2016-12	35				x
93	*BD*	DE0001135085	BUNDESREPUB.DTL. AN 1998 4 3/4% 04/07/28	2014-01	2016-12	36				x
94	*BD*	DE000CZ29DC7	COMMERZBANK 2009 G/R 16/04/14	2014-01	2014-03	3				x
95	*BD*	DE000CZ43Y57	COMMERZBANK AG 2014 G/R 28/02/19 318	2014-04	2016-12	33				x
96	*BD*	XS0953199634	CONTINENTAL AG 2013 3% 16/07/18 REG.S	2014-01	2016-12	36				x
97	*BD*	DE000A1MA9X1	HOCHTIEF AG 2012 5 1/2% 23/03/17	2014-01	2016-12	36				x
98	*BD*	XS0210318795	DT.TKOM.INTL.FIN. 2005 4% 19/01/15	2014-01	2014-12	12				x
99	*BD*	XS0968913268	VW INTL FIN NV 2013 3.875%(F/R)PERP. REG.S	2015-01	2016-12	24				x
100	*BD*	FR0011052117	RENAULT SA 2011 4 5/8% 25/05/16	2014-01	2016-04	28				x
101	*BD*	DE000NLB8K69	NORDDEUTSCHE LB. 2016 3 1/2% 30/03/26	2016-05	2016-12	8				x
102	*BD*	DE000A0AD8Q9	HAMBURGER SPARK.AG 2009 F/R 05/14 518	2014-01	2014-04	4				x
103	*BD*	XS1013955379	FRESENIUS SE & CO. 2014 3% 01/02/21 REG.S	2014-05	2016-12	32				x
104	*BD*	NO0010226962	NORWAY 2004 5% 15/05/15 NST 471	2014-01	2015-04	16				x
105	*BD*	XS1206541366	VW INTL FIN NV 2015 3.5%(F/R) PERP. REG.S	2015-05	2016-12	20				x
106	*BD*	XS0458230322	HBGCM.FIN.LX. 2009 8% 31/01/17 REG.S	2014-01	2016-12	36				x
107	*BD*	DE000WLB27H2	ERSTE ABWLANSTALT. 2009 4% 05/05/15	2014-01	2015-02	16				x
108	*BD*	XS0211637839	ALLIANZ FINANCE II 2005 4.375%(F/R)PERP. EARLY	2015-03	2016-12	20				x
109	*BD*	XS0470518605	VW INTL FIN NV 2009 3 1/2% 02/02/15 A11/09-	2014-01	2015-01	13				x
110	*BD*	DE000HSH4GG8	HSH NORDBANK AG 2013 G/R 04/04/18 1 EARLY	2015-02	2016-03	14				x
111	*BD*	XS1048589458	DUERR AG 2014 2 7/8% 03/04/21	2016-04	2016-12	9				x
112	*BD*	DE000HSH3XX0	HSH NORDBANK AG 2012 G/R 12/10/17 1481	2014-01	2016-12	36				x
113	*BD*	DE000CZ29SZ6	COMMERZBANK 2009 G/R 29/10/14 IHS57	2014-01	2014-09	9				x
114	*BD*	FR0011321447	RENAULT SA 2012 4 5/8% 18/09/17	2014-10	2016-12	27				x
115	*BD*	DE000A1EWGX1	DUERR AG 2010 7 1/4% 28/09/15	2014-01	2014-08	8				x
116	*BD*	DE000DB7XHP3	DEUTSCHE BANK AG 2014 6% PERP. REG.S	2014-09	2016-12	28				x
117	*BD*	DE000A1G77B1	UNICREDIT BANK IRE. 2012 G/R 27/03/15 REG.S	2014-01	2015-02	14				x
118	*BD*	DE000CZ225X3	COMMERZBANK AG 2010 4%(F/R) 11/17 Q	2015-03	2016-12	22				x
119	*BD*	DE000A1A55G9	DAIMLER AG 2009 4 5/8% 02/09/14 REG.S	2014-01	2014-08	8				x
120	*BD*	DE000CZ22EQ0	COMMERZBANK 2010 G/R 02/02/15 82	2014-09	2015-01	5				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
121	*BD*	DE000DB9ZKK9	DEUTSCHE BK AG LDN 2011 3.5%(F/R) 10/16 REG.S	2015-02	2016-09	20				x
122	*BD*	US912828UF54	US TREASURY NOTE 2012 1 1/8% 31/12/19 T-2019	2016-10	2016-12	3				x
123	*BD*	DE0001118388	BUNDESREPUB.DTL.BSB 2008 G/R 01/10/14 2008/23	2014-01	2014-09	9				x
124	*BD*	XS0985874543	HBGCM.FIN.LX. 2013 3 1/4% 21/10/20 REG.S	2014-10	2016-12	27				x
125	*BD*	XS0542298012	RWE AG 2010 4.625%(F/R)PERP. EARLY	2014-01	2015-08	20				x
126	*BD*	DE000A1ZBEM8	UNICREDIT BANK IRE. 2014 G/R 11/02/19	2015-09	2016-12	16				x
127	*BD*	XS0459131636	FRANZ HANIEL & CIE 2009 G/R 23/10/14 REG.S	2014-01	2014-09	9				x
128	*BD*	DE000CB83HU8	COMMERZBANK AG 2012 10% 30/01/17 272	2014-10	2016-12	27				x
129	*BD*	XS0801261156	SCHAEFFLER FIN BV 2012 6 3/4% 01/07/17 EARLY	2014-01	2014-04	4				x
130	*BD*	XS0972058175	OTTO GMBH & CO.KG 2013 3 3/4% 17/09/20	2014-05	2016-12	32				x
131	*BD*	FR0010809236	RENAULT SA 2009 6% 13/10/14 30	2014-01	2014-09	9				x
132	*BD*	FR0010957282	PEUGEOT SA 2010 5% 28/10/16	2014-10	2016-09	24				x
133	*BD*	XS1387174375	HEIDELBERGCEMENT AG 2016 2 1/4% 30/03/23 REG.S	2016-10	2016-12	3				x
134	*BD*	XS0441800579	GE CAP.EUR.FDG. 2009 4 3/4% 30/07/14	2014-01	2014-06	6				x
135	*BD*	XS1048428442	VW INTL FIN NV 2014 4.625%(F/R)PERP. REG.S	2014-07	2016-12	30				x
136	*BD*	XS0478802548	HEIDELBERGCEMENT AG 2010 6 1/2% 03/08/15 REG.S	2014-01	2015-07	19				x
137	*BD*	DE000A11QR73	BAYER AG 2014 3.75%(F/R) 07/74 REG.S	2015-08	2016-12	17				x
138	*BD*	DE000HSH3WM5	HSH NORDBANK AG 2010 G/R 14/07/14	2014-01	2014-06	6				x
139	*BD*	DE0001135275	BUNDESREPUB.DTL. AN 2005 4% 04/01/37	2014-07	2016-12	30				x
140	*BD*	DE000CZ29SY9	COMMERZBANK 2009 G/R 15/10/14 56	2014-01	2014-09	9				x
141	*BD*	XS0723509104	FMC FINANCE VIII 2012 5 1/4% 31/07/19 REG.S	2014-10	2016-12	27				x
142	*BD*	XS0214851874	VENEZUELA 2005 7% 16/03/15	2014-01	2015-02	14				x
143	*BD*	DE000DB2KYD2	DEUTSCHE BK AG LDN 2011 G/R 24/02/16	2015-03	2016-01	11				x
144	*BD*	XS0259604329	LINDE FINANCE 2006 7.375%(F/R)07/66 EARLY	2016-02	2016-06	5				x
145	*BD*	DE000A11QGR9	SIXT SE 2014 2% 18/06/20	2016-07	2016-12	6				x
146	*BD*	XS0503278847	STADA ARZNEIMITTEL 2010 4% 21/04/15 REG.S	2014-01	2015-03	15				x
147	*BD*	DE000A1E8V89	SIXT SE 2010 4 1/8% 25/10/16	2015-04	2016-09	18				x
148	*BD*	DE000HSH4FT3	HSH NORDBANK AG 2013 2% 06/09/18	2016-10	2016-12	3				x
149	*BD*	XS0675221419	FMC FINANCE VIII 2011 6 1/2% 15/09/18 REG.S	2014-01	2016-12	36				x
150	*BD*	DE000CZ29D27	COMMERZBANK 2009 G/R 18/08/14 IHS26	2014-01	2014-07	7				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
151	*BD*	XS0212694920	TURKEY 2005 5 1/2% 16/02/17	2014-08	2016-12	29				x
152	*BD*	DE0001134922	BUNDESREPUB.DTL. AN 1994 6 1/4% 04/01/24	2014-01	2016-12	36				x
153	*BD*	DE000NLB2HC4	NORDDEUTSCHE LB. 2013 4 3/4% 02/10/23	2014-01	2016-12	36				x
154	*BD*	DE000WLB6KU0	LANDESBANK HESSEN 2009 3%(F/R) 10/15 S	2014-01	2015-09	21				x
155	*BD*	XS1213831362	STADA ARZNEIMITTEL 2015 1 3/4% 08/04/22	2015-10	2016-12	15				x
156	*BD*	DE000CZ29D01	COMMERZBANK 2009 G/R 21/07/14 10	2014-01	2014-06	6				x
157	*BD*	DE0001137404	BUNDESREPUB.DTL.BSA 2012 ZERO 12/12/14	2014-07	2014-11	5				x
158	*BD*	DE000A1H3VN9	KTG AGRAR SE 2011 7 1/8% 06/06/17 DEFAULT	2014-12	2016-12	25				x
159	*BD*	DE000CZ29D35	COMMERZBANK 2009 G/R 01/09/14 IHS27	2014-01	2014-08	8				x
160	*BD*	DE000DB2KYE0	DEUTSCHE BK AG LDN 2011 2.7%(F/R) 02/16 REG.S	2014-09	2016-01	17				x
161	*BD*	XS0969344083	CONTINENTAL AG 2013 3 1/8% 09/09/20 REG.S	2016-02	2016-12	11				x
162	*BD*	DE000CB83HX2	COMMERZBANK AG 2012 9 1/2% 14/03/17 275	2014-01	2016-12	36				x
163	*BD*	DE000CZ29S12	COMMERZBANK 2009 F/R 09/14 Q	2014-01	2014-08	8				x
164	*BD*	XS0997941199	K&S AG 2013 3 1/8% 06/12/18 REG.S	2014-09	2016-12	28				x
165	*BD*	DE0001118560	BUNDESREPUB.DTL.BSB 2009 G/R 01/12/15 2009/11	2014-01	2015-11	23				x
166	*BD*	XS1026109204	FRESENIUS SE & CO. 2014 4% 01/02/24 REG.S	2015-12	2016-12	13				x
167	*BD*	DE0001135259	BUNDESREPUB.DTL. AN 2004 4 1/4% 04/07/14	2014-01	2014-06	6				x
168	*BD*	DE000HSH4XX8	HSH NORDBANK AG 2012 G/R 14/09/17 1668	2014-07	2016-12	30				x
169	*BD*	XS0234434222	HENKEL & CO.KGAA AG 2005 5.375%(F/R)11/04 EARLY	2014-01	2015-10	22				x
170	*BD*	DE000HLB2DM0	LANDESBANK HESSEN 2015 3% 18/11/25	2015-11	2016-12	14				x
171	*BD*	DE000WLB69D3	LANDESBANK HESSEN 2009 3%(F/R) 01/15 S	2014-01	2014-12	12				x
172	*BD*	XS1002933072	HBGCM.FIN.LX. 2013 3 1/4% 21/10/21 REG.S	2015-01	2016-12	24				x
173	*BD*	XS0847087714	OTTO GMBH & CO.KG 2012 3 7/8% 01/11/19 REG.S	2014-01	2016-12	36				x
174	*BD*	DE000CZ29DH6	COMMERZBANK 2009 G/R 19/05/14	2014-01	2014-04	4				x
175	*BD*	DE000HLB02N4	LANDESBANK HESSEN 2013 4% 06/11/23	2014-05	2016-12	32				x
176	*BD*	DE000HSH4MQ5	HSH NORDBANK AG 2013 G/R 14/05/18 REG.S	2014-01	2016-12	36				x
177	*BD*	DE000TUAG059	TUI AG 2005 8.625%(F/R)PERP. EARLY	2014-01	2015-04	16				x
178	*BD*	DE0001141596	BUNDESREPUB.DTL. BO 2011 2% 26/02/16 159	2015-05	2016-01	9				x
179	*BD*	XS0912992160	O2 TELF.DTL.FNZ. 2013 1 7/8% 22/11/18 REG.S	2016-02	2016-12	11				x
180	*BD*	XS0974356262	HAPAG LLOYD AG 2013 7 3/4% 01/10/18 EARLY	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
181	*BD*	DE0001135283	BUNDESREPUB.DTL. AN 2005 3 1/4% 04/07/15	2014-01	2015-06	18				x
182	*BD*	DE000A1HE6A8	UNICREDIT BANK IRE. 2013 G/R 28/02/18	2015-07	2016-12	18				x
183	*BD*	DE000DZ1JB11	DZ BK.AG.DZG.FF.AM 2013 3% 30/12/19 REG.S	2014-01	2016-12	36				x
184	*BD*	XS0478803355	HBGCM.FIN.LX. 2010 7 1/2% 03/04/20 REG.S	2014-01	2016-12	36				x
185	*ST*	DE000BASF111	BASF	2014-01	2016-12	36	x	x	x	x
186	*ST*	DE0007236101	SIEMENS	2014-01	2016-12	36	x	x	x	x
187	*ST*	DE0007100000	DAIMLER	2014-01	2016-12	36	x	x	x	x
188	*ST*	DE000BAY0017	BAYER	2014-01	2016-12	36		x	x	x
189	*ST*	DE0008404005	ALLIANZ	2014-01	2016-12	36		x	x	x
190	*ST*	DE0005557508	DEUTSCHE TELEKOM	2014-01	2016-12	36		x	x	x
191	*ST*	DE0005140008	DEUTSCHE BANK	2014-01	2016-12	36			x	x
192	*ST*	DE000ENAG999	E ON N	2014-01	2016-12	36			x	x
193	*ST*	DE0007164600	SAP	2014-01	2016-12	36			x	x
194	*ST*	DE000CBK1001	COMMERZBANK	2014-01	2016-12	36				x
195	*ST*	CH0038863350	NESTLE 'R'	2014-01	2016-12	36				x
196	*ST*	DE0008430026	MUENCHENER RUCK.	2014-01	2016-12	36				x
197	*ST*	DE0005552004	DEUTSCHE POST	2014-01	2016-12	36				x
198	*ST*	DE0007037129	RWE	2014-01	2016-12	36				x
199	*ST*	DE0007664039	VOLKSWAGEN PREF.	2014-01	2016-12	36				x
200	*ST*	DE0006483001	LINDE	2014-01	2016-12	36				x
201	*ST*	DE0005190003	BMW	2014-01	2016-12	36				x
202	*ST*	DE0007010803	RATIONAL	2014-01	2016-12	36				x
203	*ST*	DE0008232125	DEUTSCHE LUFTHANSA	2014-01	2016-12	36				x
204	*ST*	DE000KSAG888	K + S	2014-01	2016-12	36				x
205	*ST*	CH0012005267	NOVARTIS 'R'	2014-01	2016-12	36				x
206	*ST*	DE0006048432	HENKEL PREF.	2014-01	2016-12	36				x
207	*ST*	DE0007500001	THYSSENKRUPP	2014-01	2016-12	36				x
208	*ST*	GB00B03MLX29	ROYAL DUTCH SHELL A	2014-01	2016-12	36				x
209	*ST*	US0378331005	APPLE	2014-01	2016-12	36				x
210	*ST*	US4592001014	INTERNATIONAL BUS.MCHS.	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
211	*ST*	CH0012032048	ROCHE HOLDING	2014-01	2016-12	36				x
212	*ST*	DE0006048408	HENKEL	2014-01	2016-12	36				x
213	*ST*	DE000PAH0038	PORSCHE AML.HLDG.PREF.	2014-01	2016-12	36				x
214	*ST*	DE0006231004	INFINEON TECHNOLOGIES	2014-01	2016-12	36				x
215	*ST*	NL0000235190	AIRBUS	2014-01	2016-12	36				x
216	*ST*	DE0005785604	FRESENIUS	2014-01	2016-12	36				x
217	*ST*	FR0000120578	SANOFI	2014-01	2016-12	36				x
218	*ST*	DE0005470405	LANXESS	2014-01	2016-12	36				x
219	*ST*	US3696041033	GENERAL ELECTRIC	2014-01	2016-12	36				x
220	*ST*	DE0005190037	BMW PREF.	2014-01	2016-12	36				x
221	*ST*	DE0005439004	CONTINENTAL	2014-01	2016-12	36				x
222	*ST*	DE0005200000	BEIERSDORF	2014-01	2016-12	36				x
223	*ST*	DE000A0DJ6J9	SMA SOLAR TECHNOLOGY	2014-01	2016-12	36				x
224	*ST*	DE0005937007	MAN	2014-01	2016-12	36				x
225	*ST*	DE0005772206	FIELMANN	2014-01	2016-12	36				x
226	*ST*	DE000A1EWWW0	ADIDAS	2014-01	2016-12	36				x
227	*ST*	FR0000120271	TOTAL	2014-01	2016-12	36				x
228	*ST*	DE0005229942	BERTELSMANN GSH.15.00%	2014-01	2016-12	36				x
229	*ST*	DE0005790430	FUCHS PETROLUB PREF.	2014-01	2016-12	36				x
230	*ST*	DE0005785802	FRESENIUS MED.CARE	2014-01	2016-12	36				x
231	*ST*	US1912161007	COCA COLA	2014-01	2016-12	36				x
232	*ST*	DE0007664005	VOLKSWAGEN	2014-01	2016-12	36				x
233	*ST*	DE000LED4000	OSRAM LICHT	2014-01	2016-12	36				x
234	*ST*	DE0007251803	STADA ARZNEI N	2014-01	2016-12	36				x
235	*ST*	NL0000009355	UNILEVER DR	2014-01	2016-12	36				x
236	*ST*	DE0007042301	RHOEN-KLINIKUM	2014-01	2016-12	36				x
237	*ST*	DE0008402215	HANNOVER RUCK.	2014-01	2016-12	36				x
238	*ST*	US5949181045	MICROSOFT	2014-01	2016-12	36				x
239	*ST*	DE0007037145	RWE PREF.	2014-01	2016-12	36				x
240	*ST*	CH0002497458	SGS 'N'	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
241	*ST*	DE0005810055	DEUTSCHE BOERSE	2014-01	2016-12	36				x
242	*ST*	DE0006599905	MERCK KGAA	2014-01	2016-12	36				x
243	*ST*	US7427181091	PROCTER & GAMBLE	2014-01	2016-12	36				x
244	*ST*	DE0005545503	DRILLISCH	2014-01	2016-12	36				x
245	*ST*	DE0005408884	LEONI	2014-01	2016-12	36				x
246	*ST*	US5801351017	MCDONALDS	2014-01	2016-12	36				x
247	*ST*	DE000A0Z2ZZ5	FREENET	2014-01	2016-12	36				x
248	*ST*	DE0005158703	BECHTLE	2014-01	2016-12	36				x
249	*ST*	DE0007165607	SARTORIUS	2014-01	2016-12	36				x
250	*ST*	DE0006766504	AURUBIS	2014-01	2016-12	36				x
251	*ST*	NO0010096985	STATOIL	2014-01	2016-12	36				x
252	*ST*	DE0005909006	BILFINGER BERGER	2014-01	2016-12	36				x
253	*ST*	ES0178430E18	TELEFONICA	2014-01	2016-12	36				x
254	*ST*	DE0007297004	SUEDZUCKER	2014-01	2016-12	36				x
255	*ST*	US7170811035	PFIZER	2014-01	2016-12	36				x
256	*ST*	FI0009000681	NOKIA	2014-01	2016-12	36				x
257	*ST*	DE0007257503	CECONOMY	2014-01	2016-12	36				x
258	*ST*	DE0005229504	BIJOU BRIGITTE MODISCHE ACCESSOIRES	2014-01	2016-12	36				x
259	*ST*	DE0005089031	UNITED INTERNET	2014-01	2016-12	36				x
260	*ST*	CH0012221716	ABB LTD N	2014-01	2016-12	36				x
261	*ST*	GB0007980591	BP	2014-01	2016-12	36				x
262	*ST*	DE000TUAG000	TUI	2014-01	2016-12	36				x
263	*ST*	DE0005878003	DMG MORI	2014-01	2016-12	36				x
264	*ST*	DE0005501357	AXEL SPRINGER	2014-01	2016-12	36				x
265	*ST*	US23317H1023	DDR	2014-01	2016-12	36				x
266	*ST*	DE0007235301	SGL CARBON	2014-01	2016-12	36				x
267	*ST*	CH0024899483	UBS 'R' DEAD - 28/08/15	2014-01	2015-06	18				x
268	*ST*	CH0244767585	UBS GROUP	2015-07	2016-12	18				x
269	*ST*	US30231G1022	EXXON MOBIL	2014-01	2016-12	36				x
270	*ST*	US17275R1023	CISCO SYSTEMS	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
271	*ST*	DE0006602006	GEA GROUP	2014-01	2016-12	36				x
272	*ST*	DE0006335003	KRONES	2014-01	2016-12	36				x
273	*ST*	CA0679011084	BARRICK GOLD (NYS)	2014-01	2016-12	36				x
274	*ST*	CH0038389992	BB BIOTECH N	2014-01	2016-12	36				x
275	*ST*	DE0006632003	MORPHOSYS	2014-01	2016-12	36				x
276	*ST*	DE0007314007	HEIDELB.DRUCKMASCHINEN	2014-01	2016-12	36				x
277	*ST*	DK0060534915	NOVO NORDISK 'B'	2014-01	2016-12	36				x
278	*ST*	DE0007480204	DEUTSCHE EUROSHOP	2014-01	2016-12	36				x
279	*ST*	DE000WCH8881	WACKER CHEMIE	2014-01	2016-12	36				x
280	*ST*	US4581401001	INTEL	2014-01	2016-12	36				x
281	*ST*	US4781601046	JOHNSON & JOHNSON	2014-01	2016-12	36				x
282	*ST*	DE0006202005	SALZGITTER	2014-01	2016-12	36				x
283	*ST*	DE0006047004	HEIDELBERGCEMENT	2014-01	2016-12	36				x
284	*ST*	GB0000566504	BHP BILLITON	2014-01	2016-12	36				x
285	*BF*	FR0010135103	CARMIGNAC GESTION PATRIMOINE FCP 3 D C	2014-01	2016-12	36	x	x	x	x
286	*BF*	DE0008491069	UNION INV.PRIVATFONDS UNIEURORENTA	2014-01	2016-12	36		x	x	x
287	*BF*	DE0009750174	UNION INV.PRIVATFONDS UNIKAPITAL NET	2014-01	2016-12	36			x	x
288	*BF*	DE0008471400	ALLIANZ RENTENFONDS - A - EUR	2014-01	2016-12	36				x
289	*BF*	LU0294219869	FT INVEST GLOBAL BOND A EUR H1 C	2014-01	2016-12	36				x
290	*BF*	LU0089559057	UNION INVESTMENT LX. UNIEUROKAPITAL NET	2014-01	2016-12	36				x
291	*BF*	LU0496363937	FRANK.TMPLTN.INV.FUND. GLB.BD.AH1 Y DS.EUR	2014-01	2016-12	36				x
292	*BF*	DE000DK0AYK1	DEKA RENTEN REAL	2014-01	2016-12	36				x
293	*BF*	DE0009771980	DEKA EUROPABOND TF	2014-01	2016-12	36				x
294	*BF*	LU0649391066	DWS ZINSEINKOMMEN EUR	2014-01	2016-12	36				x
295	*BF*	LU0355142794	UNIGAR+BEST OA 2014 A DS.D	2014-01	2014-06	6				x
296	*BF*	LU0395794307	JPMORGAN INV.FUNDS GLB. INCOME FUND A DS.	2014-07	2016-12	30				x
297	*BF*	LU0097169550	UNION INVESTMENT LX. UNIEUROASPIRANT A	2014-01	2016-12	36				x
298	*BF*	DE0005896864	DEKA STIFTUNGEN BALANCE	2014-01	2016-12	36				x
299	*BF*	DE0008476532	DWS INVESTMENT SLT.RENT	2014-01	2016-12	36				x
300	*BF*	LU0337414485	BANTLEON OPPORTUNITIES L PA	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
301	*BF*	LU0168093226	UNION INVESTMENT LX.UNI ER.KP.CORPORATES NET A	2014-01	2016-12	36				x
302	*BF*	LU0364818897	UNION INVESTMENT UNIPROFIANLAGE 2016	2014-01	2016-06	30				x
303	*BF*	LU0255639139	NORDEA 1 ABSOLUTE RETURN FD.AP EUR	2016-07	2016-12	6				x
304	*BF*	LU0139429517	DWS DB OPPORTUNITY DEAD - Liquidated	2014-01	2016-12	36				x
305	*BF*	LU0337413677	BANTLEON INVEST SA OPPS. S PA	2014-01	2016-12	36				x
306	*BF*	DE0008491085	UNION INV.PRIVATFONDS UNIKAPITAL	2014-01	2016-12	36				x
307	*BF*	LU0145656475	DEUTSCHE INVEST I EURO BONDS (SHORT) LD	2014-01	2016-12	36				x
308	*BF*	LU0365363810	UNION INV.LX.UNIGARANT PLUS BST.OF ASS.2014 II	2014-01	2016-09	9				x
309	*BF*	LU0107368036	DEKA-BASISSTRATEGIE RENTEN CF	2014-10	2016-12	27				x
310	*BF*	LU0542579023	OPPENHM.ASTMGMT.SVS.SARL CASH PLUS	2014-01	2016-12	36				x
311	*BF*	DE0008491028	UNION INV.PRIVATFONDS UNIRENTA	2014-01	2016-12	36				x
312	*BF*	LU0034353002	DEUTSCHE FLOATING RATE NOTES LC	2014-01	2016-12	36				x
313	*BF*	LU0454734905	DWS INV.SA RENDITE GARANT 2015	2014-01	2015-10	22				x
314	*BF*	DE0008475047	ALLIANZ EURO RENTENFONDS - A - EUR	2015-11	2016-12	14				x
315	*BF*	LU0279509904	ETHNA-DEFENSIV A	2014-01	2016-12	36				x
316	*BF*	DE000A0B71B7	NORDINVEST NORD.INV. GESELL.NORDSELECT	2014-01	2016-10	34				x
317	*BF*	LU0272368639	DWS INV.VORSORGE RENTENFONDS 10Y	2016-11	2016-12	2				x
318	*BF*	DE0008476516	DWS VERM R LD	2014-01	2016-12	36				x
319	*BF*	LU0383797551	UNION INVESTMENT LX. UNIGARANT COMD.2017	2014-01	2016-12	36				x
320	*BF*	DE0008471913	ALLIANZ MOBIL-FONDS - A - EUR	2014-01	2016-12	36				x
321	*BF*	DE0008471079	COMINVEST ASTMGMT. PUBLIKFD.ADIG ADIRENTA	2014-01	2015-07	19				x
322	*BF*	LU0272368126	DWS INV.VORSORGE RENTENFONDS 15Y	2015-08	2016-12	17				x
323	*BF*	FR0010149120	CARMIGNAC GESTION SECURITE FCP CAP.	2014-01	2016-12	36				x
324	*SF*	DE0008491051	UNION INV.PRIVATFONDS UNIGLOBAL	2014-01	2016-12	36	x	x	x	x
325	*SF*	DE0009848119	DWS TOP DIVIDENDE LD	2014-01	2016-12	36		x	x	x
326	*SF*	DE0008474503	DEKAFONDS	2014-01	2016-12	36			x	x
327	*SF*	LU0136412771	ETHNA-AKTIV A	2014-01	2016-12	36				x
328	*SF*	LU0323578657	FLOSSBACH VON STORCH STRATEGIE MTPL.OPPS.R	2014-01	2016-12	36				x
329	*SF*	DE0008474511	ARIDEKA	2014-01	2016-12	36				x
330	*SF*	LU0425202842	DWS INV.DB PRIVMANDAT COMFORT PRO DEUT	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size 9	18	27	297
331	*SF*	LU0048578792	FIDELITY FUNDS EUR.GW. FD.A GLB.CERT.	2014-01	2016-12	36				x
332	*SF*	DE0008476524	DWS VERM. FUNDS I LD	2014-01	2016-12	36				x
333	*SF*	DE000A0M0341	PIONEER INVT.HVB VERM DEP PRIVAT BALANCE PI	2014-01	2016-12	36				x
334	*SF*	DE000A0RPAM5	UNION INV.GESELL.MBH PRI VATFONDS KONTROLLIERT	2014-01	2016-12	36				x
335	*SF*	DE0008491002	UNION INV.PRIVATFONDS UNIFONDS	2014-01	2016-12	36				x
336	*SF*	DE0005896872	DEKA EUROLAND BALANCE	2014-01	2016-12	36				x
337	*SF*	LU0425202925	DWS INV.DB PRIVMANDAT COMFORT PRO GLOB	2014-01	2016-12	36				x
338	*SF*	LU0321021312	DRESDNER VERMMGT WACA EUR DIS D	2014-01	2016-12	36				x
339	*SF*	DE0009757740	UNION INV.PRIVATFONDS UNIEUROAKTIEN	2014-01	2016-12	36				x
340	*SF*	DE0008490962	DWS DEUTSCHLAND LC	2014-01	2016-12	36				x
341	*SF*	DE0008474008	DWS INVESTA LD	2014-01	2016-12	36				x
342	*SF*	DE0008471012	FONDAK - A - EUR	2014-01	2016-12	36				x
343	*SF*	DE0008491044	UNION INV.PRIVATFONDS UNIRAK	2014-01	2016-12	36				x
344	*SF*	LU0272367581	DWS VORSORGE PREMIUM	2014-01	2016-12	36				x
345	*SF*	LU0114760746	FRANK.TMPLTN.INV.FUNDS TMPLTN.GW.EUR A AC.	2014-01	2016-12	36				x
346	*SF*	DE000DK1CHH6	DEKA INVESTMENT GMBH EUROLAND BALANCE TF	2014-01	2016-12	36				x
347	*SF*	GB0030932676	M&G GLOBAL THEMES A EURO ACC	2014-01	2016-12	36				x
348	*SF*	DE0005933931	ISHARES CORE DAX UCITS ETF (DE)	2014-01	2016-12	36				x
349	*SF*	LU0185900692	DEKASTRUKTUR 4 ERTRAG PLUS	2014-01	2016-12	36				x
350	*SF*	FR0010148981	CARMIGNAC GESTION INVESTISSEMENT FCP 2 D C	2014-01	2016-12	36				x
351	*SF*	LU0185900775	DEKASTRUKTUR 4 WACHSTUM	2014-01	2016-12	36				x
352	*SF*	DE000A0M0358	PIONEER INVT.HVB VERM DEP PRIV WACHSTUM PI	2014-01	2016-12	36				x
353	*SF*	LU0097711666	INTL.FD.MAN.LBBW BALANCE CR20	2014-01	2016-12	36				x
354	*SF*	LU0090707612	UNION INVESTMENT LX. UNIEUROSTOXX 50 A	2014-01	2016-12	36				x
355	*SF*	DE0008476250	KAPITAL PLUS A (EUR)	2014-01	2016-12	36				x
356	*SF*	LU0163675910	SAUREN GLOBAL DEFENSIV A	2014-01	2016-12	36				x
357	*REF*	DE0009809566	DEKA IMMOBILIENEUROPA	2014-01	2016-12	36	x	x	x	x
358	*REF*	DE0009805507	DEUTSCHE IMMOBILIEN FON. NR 1	2014-01	2016-12	36		x	x	x
359	*REF*	DE0009805515	DEUTSCHE IMMOBILIEN FON. GRUND	2014-01	2016-12	36			x	x
360	*REF*	DE0009807016	COMMERZ GRUNDBESITZ INV. GESELL.HAUSINVEST EUPA.	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
361	*REF*	DE0009801423	WESTINVEST GESELL.FOR INV.FON.INTERSELECT	2014-01	2016-12	36				x
362	*REF*	DE0007483612	DEKA IMMOBILIENGLOBAL	2014-01	2016-12	36				x
363	*REF*	DE0009807008	DB REAL ESTATE INV. GRUNDBESITZ INVEST	2014-01	2016-12	36				x
364	*REF*	DE0006791809	KAN AM GRUNDINVEST FONDS IN LIQ	2014-01	2016-12	36				x
365	*REF*	DE0009807057	GRUNDBESITZ GLOBAL RC	2014-01	2016-12	36				x
366	*REF*	DE0009805002	CS EUROREAL A EUR	2014-01	2016-12	36				x
367	*REF*	DE0009802306	SEB IMMO INVEST P LIQ	2014-01	2016-12	36				x
368	*REF*	DE0009805556	DEUTSCHE IMMOBILIEN FON. GLOBAL	2014-01	2016-12	36				x
369	*REF*	DE0009846451	AXA IMMOSELECT LIQ	2014-01	2016-12	36				x
370	*REF*	DE0008007998	DEGI INTERNATIONAL LIQ	2014-01	2016-12	36				x
371	*REF*	DE0009807800	DEGI EUROPA LIQ	2014-01	2016-12	36				x
372	*REF*	DE000A1CUAY0	WERTGRUND WOHN SELECT D	2014-01	2016-12	36				x
373	*REF*	DE000A0YFRV7	CATELLA REAL EST.AG KPL. MAX	2014-01	2016-12	36				x
374	*REF*	DE000A0DJ328	TMW PROPERTY INVESTMENT IMMOBILIEN WELTFONDS	2014-01	2016-12	36				x
375	*REF*	DE0009802314	SEB IM.INV.GESELLSCHAFT IMMOPTF.TAR.RET.FON.	2014-01	2016-12	36				x
376	*REF*	DE0009820068	ILE.IM.INSTITUT INTER IMMOPROFIL	2014-01	2016-12	36				x
377	*REF*	DE0009772616	UBS (D) EUROINVEST IMMOBILIEN	2014-01	2016-12	36				x
378	*REF*	DE000A0MY559	CATELLA REAL ESTATE AG FOCUS NORDIC CITIES A	2014-01	2016-12	36				x
379	*REF*	DE000A0F6G89	MORGAN STANLEY P2 VALUE	2014-01	2016-12	36				x
380	*REF*	DE000A0M98N2	CATELLA REAL ESTATE BOUWFONDS EUR.RESD.	2014-01	2016-12	36				x

Table 27: Securities applied in the first empirical analysis (continued)

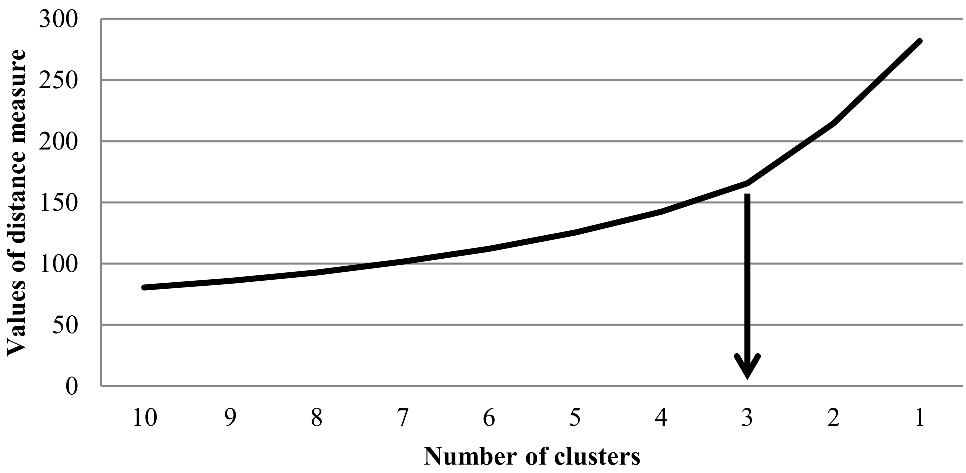
#	Asset class	ISIN	Name	First date	Last date	# obs.	Portfolio size			
							9	18	27	297
381	*REF*	DE0006791817	KANAM GRUND KPL. US GRUNDINVEST FONDS	2014-01	2016-12	36				x
382	*REF*	DE000SEB1A96	SEB GLOBAL PROPERTY FUND LIQ	2014-01	2016-12	36				x
383	*REF*	DE0009751354	CSUI.ASTMGMT.CS PR.DYM.	2014-01	2016-12	36				x
384	*REF*	DE000A0ETSR6	DEGI GLOBAL BUSINESS LIQ	2014-01	2016-12	36				x
385	*REF*	AT0000622980	CONSTANTIA REAL ESTATE A	2014-01	2016-12	36				x
386	*REF*	DE000A0CARS0	KANAM GRUND SPEZFD. GESELL.GRUNDINVEST FON.	2014-01	2016-12	36				x
387	*REF*	DE000A0J3GM1	AXA IMMOSOLUTIONS LIQ	2014-01	2016-12	36				x
388	*REF*	DE000A0RHEG6	WARBURG INVEST KPL.MBH SELEKT I FONDS	2014-01	2015-09	21				x
389	*REF*	AT0000A08SH5	ERSTE IMMOBILIENFONDS T	2015-10	2016-12	15				x
390	*REF*	AT0000615158	CONSTANTIA REAL ESTATE T	2014-01	2016-12	36				x

Notes: This table documents the securities applied in the first empirical analysis of this thesis (see chapter 5) and includes the asset class categorization of a security across stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST), a security's ISIN, the period in which a security (its returns) are employed, as well as the assumed portfolio sizes in which a security is involved.

Appendix B

In addition to K-Means clustering, hierarchical clustering is performed as robustness. Using the elbow criterion (see Table 28) and a corresponding Dendogram (see Table 29), a three-cluster-solution is, like for K-Means clustering, derived for hierarchical clustering. Both the three-cluster-solution (see Table 30 and Table 31) and, as further robustness, the four-cluster-solution (see Table 32 and Table 33) of the hierarchical approach yield very similar portfolio compositions in terms of asset class weights compared to those of the K-Means clustering approach which supports the initial results of the K-Means approach.[521]

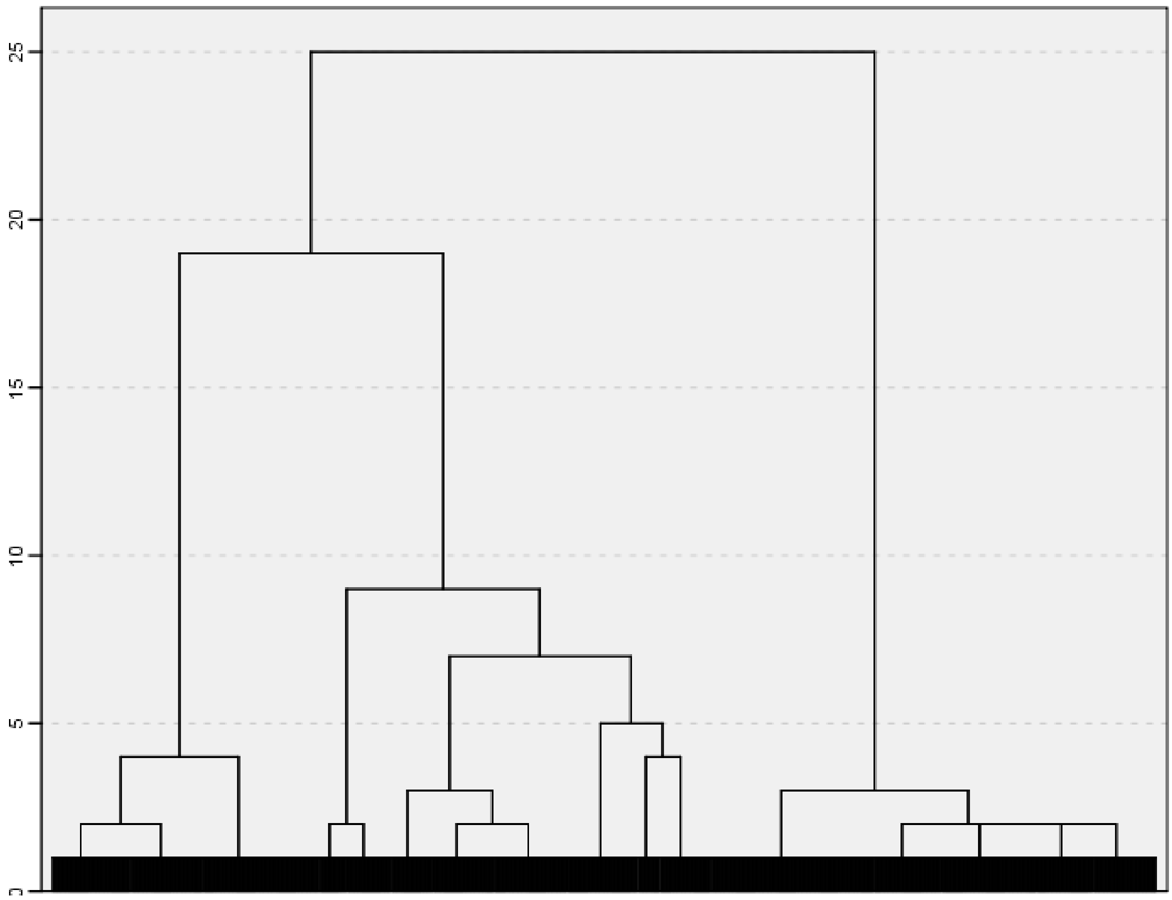
Table 28: Elbow criterion regarding the hierarchical clustering approach



Notes: The figure shows the values of the distance measure of hierarchical clustering using households' asset class weights from the final sample of the PHF-survey. The squared Euclidean distance is employed as distance measure and Ward's algorithm to fuse cases. The number of clusters is derived from the position the curve reveals a sharp bend. Accordingly, a three-cluster-solution is derived.

[521] The analysis also controls for quantitative measures for deducting the number of clusters. Therefore, CH-Index values are calculated (see Caliński/Harabasz, 1974). Milligan/Cooper (1985) compared 30 stopping rules for determining the “optimal” number of clusters. They found superior partitioning results of the Caliński/Harabasz-statistic, which compares the intra- and inter-cluster variance and computes an index value for each cluster solution. The results on the CH-Index indicate a four-cluster-solution. However, due to the minor relevance of the fourth cluster (see above) and the robustness of the three-cluster-solution, the analysis remains with the three-cluster-solution.

Table 29: Dendogram of hierarchical clustering approach



Notes: The figure shows the Dendogram of hierarchical clustering using households' asset class weights among cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) from the final sample of the PHF-survey. The squared Euclidean distance is employed as distance measure and Ward's algorithm is used to fuse cases. From the scaled distances (see values along the ordinate between 0 and 25), a three-cluster-solution can be derived which is indicated by the large distance at the position the tree divides into three branches or clusters, respectively.

Table 30: Hierarchical clustering (three-cluster-solution)

HPT (N=1,052)		VALUEpf	CASH&SV	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=424)	average	169,200	71.1	7.1	64.0	7.8	3.3	3.1	5.2	9.4
	SD	531,700	12.4	6.8	13.3	11.8	8.4	7.2	10.9	11.3
HPT 2 (n=373)	average	183,900	37.3	18.6	18.6	23.1	10.0	8.5	13.8	7.4
	SD	399,700	24.5	20.9	14.6	27.3	19.1	18.9	25.0	11.5
HPT 3 (n=255)	average	328,300	23.9	7.1	16.7	7.5	1.4	2.6	5.6	59.1
	SD	735,700	17.0	7.7	16.4	11.9	4.5	7.1	11.5	20.4

Notes: The table shows the results of hierarchical clustering (three-cluster-solution) using the asset class weights of the 1,052 households of the final sample of the PHF-survey of 2014. The asset class weights, i.e. the relative amounts of households' total portfolio value (VALUEpf) in Euros invested among the asset classes cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) were applied as separate cluster variables. Each cluster represents a different Household Portfolio Type (HPT). For each HPT, the standard deviation and average asset class weight in percent of all households assigned to a respective cluster are reported.

Table 31: F-values for Hierarchical clustering (three-cluster-solution)

	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=424)	0.21	0.24	0.34	0.40	0.31	0.38	0.19
HPT 2 (n=373)	2.01	0.29	1.82	2.08	2.15	1.97	0.20
HPT 3 (n=255)	0.27	0.37	0.35	0.11	0.30	0.42	0.62

Notes: The table reports F-values for hierarchical clustering (three-cluster-solution). F-values compare the intra-cluster variance with the overall variance for each cluster variable and allow conclusions about cluster homogeneity. F-values below one indicate that the intra-cluster variance is less than the inter-cluster variance and suggests high intra-cluster homogeneity (see for example HPT 1 and HPT 3). F-values are computed for households' asset class weights among cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) which are used as cluster variables.

Table 32: Hierarchical clustering (four-cluster-solution)

HPT (N=1,052)		VALUEpf	CASH&SV	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=424)	average	169,200	71.1	7.1	64.0	7.8	3.3	3.1	5.2	9.4
	SD	531,700	12.4	6.8	13.3	11.8	8.4	7.2	10.9	11.3
HPT 2 (n=305)	average	143,700	39.9	20.3	19.6	28.1	10.9	10.2	3.4	7.5
	SD	291,000	24.8	22.0	15.1	27.8	20.4	20.5	8.7	11.7
HPT 3 (n=255)	average	328,300	23.9	7.1	16.7	7.5	1.4	2.6	5.6	59.1
	SD	735,700	17.0	7.7	16.4	11.9	4.5	7.1	11.5	20.4
HPT 4 (n=68)	average	364,100	25.5	11.2	14.3	0.8	5.7	1.0	60.2	6.9
	SD	680,000	19.3	13.1	11.6	2.7	10.6	4.1	21.4	11.0

Notes: The table shows the results of hierarchical clustering (four-cluster-solution) using the asset class weights of the 1,052 households of the final sample of the PHF-survey of 2014. The asset class weights, i.e. the relative amounts of households' total portfolio value (VALUEpf) in Euros invested among the asset classes cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) were applied as separate cluster variables. Each cluster represents a different Household Portfolio Type (HPT). For each HPT, the standard deviation and average asset class weight in percent of all households assigned to a respective cluster are reported.

Table 33: F-values for Hierarchical clustering (four-cluster-solution)

	CASH	SV	SF	BF	REF	BD	ST
HPT 1 (n=424)	0.21	0.24	0.34	0.40	0.31	0.38	0.19
HPT 2 (n=305)	2.22	0.31	1.89	2.37	2.51	0.24	0.20
HPT 3 (n=255)	0.27	0.37	0.35	0.11	0.30	0.42	0.62
HPT 4 (n=68)	0.78	0.19	0.02	0.64	0.10	1.44	0.18

Notes: The table reports F-values for hierarchical clustering (four-cluster-solution). F-values compare the intra-cluster variance with the overall variance for each cluster variable and allow conclusions about cluster homogeneity. F-values below one indicate that the intra-cluster variance is less than the inter-cluster variance and suggests high intra-cluster homogeneity (see for example HPT 1 and HPT 3). F-values are computed for households' asset class weights among cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST) which are used as cluster variables.

Appendix C

The analysis controls for the influence of the asset class weights and securities of HPTs on RDs by involving three different versions of HPTs, i.e. control portfolios. The following list provides a description of the construction of the employed control portfolios (see also Table 34 for an exemplary illustration of the construction of the HPTs and the control portfolios):

- 1/m portfolio, where m describes the number of asset classes. This portfolio contains the same (number of) securities and security weights within each asset class as the initial HPTs, but uses equal asset class weights for stocks, bonds and mutual funds (SF, BF and REF within mutual funds are again equally weighted).

- 1/n portfolio, where n denotes the number of securities within a specific asset class. This portfolio builds upon the 1/m portfolio, but in addition equally weights the securities within each asset class.

- 60/40 portfolio uses weights of 60 and 40 percent for stocks and bonds, respectively, does not involve any other asset classes, but includes the same (number of) stocks and bonds as the initial HPTs. This portfolio was constructed to compare its performance in correspondence to the composition of the 60/40 XTF.

Table 34: Illustration of the construction of the control portfolios and HPTs

	Safe Financial Assets		Mutual Funds				
Portfolio Label	CASH	SV	SF	BF	REF	BD	ST
1/n (27)	0%	0%		33.3%		33.3%	33.3%
			11.1%	11.1%	11.1%		
				(equally weighted)		(equally weighted)	(equally weighted)
				(9)		(9)	(9)
1/m (27)	0%	0%		33.3%		33.3%	33.3%
			11.1%	11.1%	11.1%		
				(agg. market value)		(agg. market value)	(agg. market value)
				(9)		(9)	(9)
60/40 (18)	0%	0%		0%		40%	60%
				(agg. market value)		(agg. market value)	(agg. market value)
				(0)		(9)	(9)
HPT 1 (27)	8.0%	62.5%		15.0%		4.7%	9.8%
			7.4%	3.5%	4.1%		
				(agg. market value)		(agg. market value)	(agg. market value)
				(9)		(9)	(9)
HPT 2 (27)	16.7%	15.7%		43.5%		15.6%	8.4%
			25.4%	10.0%	8.1%		
				(agg. market value)		(agg. market value)	(agg. market value)
				(9)		(9)	(9)
HPT 3 (27)	8.7%	16.3%		7.3%		4.0%	63.7%
			5.1%	0.9%	1.3%		
				(agg. market value)		(agg. market value)	(agg. market value)
				(9)		(9)	(9)

Notes: This Table illustrates the construction of the control portfolios and the HPTs and refers to an exemplary portfolio size of 27 securities (see number of securities in parenthesis). Each frame represents a portfolio. The weights of the included asset classes are reported in the upper part of each portfolio in [%]. In the middle, the distribution of securities within each asset class is described. The number in parentheses below shows the number of securities within each asset class. The employed asset classes are cash (CASH), savings (SV), stock funds (SF), bond funds (BF), real estate funds (REF), bonds (BD) and stocks (ST).

To examine, if one of the control portfolios achieves higher returns than a corresponding HPT, each control portfolio is risk-adjusted to the risk of the corresponding HPT. Thereby, costs for (de-)leverage are applied analogously to RDs and risk-adjusted returns are calculated for the 1/m ($\mu_{1/m,HPT}$), 1/n ($\mu_{1/n,HPT}$), and 60/40 ($\mu_{60/40,HPT}$) portfolio. Then, the maximum RD between the HPTs and all risk-adjusted control portfolios (CP), $RD^{max}_{CP,HPT}$, are determined by:

$$(13) \qquad RD^{max}_{CP,HPT} = \max\begin{cases}\mu_{1/m,HPT} & -\mu_{HPT},\\ \mu_{1/n,HPT} & -\mu_{HPT},\\ \mu_{60/40,HPT} & -\mu_{HPT}.\end{cases}$$

If one of the control portfolios yields a higher return than the respective HPT, i.e. if $RD^{max}_{CP,HPT} > 0$, the overall RD between the risk-adjusted 60/40 XTF portfolio and the corresponding HPT (RD_{HPT}) is reduced by this amount. More detailed, RD_{HPT} is computed by:

$$(14) \qquad RD_{HPT} = \mu_{XTF,HPT} - \mu_{HPT} - \max\,[0; RD^{max}_{CP,HPT}].$$

In formula (3) the subtraction of max $[0; RD^{max}_{CP,HPT}]$ was left out as none of the control portfolios changes the general conclusions. Table 9 to Table 12 show the RDs in detail across all applied portfolio sizes including the control portfolios.

As additional robustness, the analysis controls for RDs that are based on the risk of the 60/40 XTF portfolio (and not on the risk of the HPTs) (see Table 35 to Table 38). Therefore, the HPTs as well as the control portfolios are risk-adjusted to the risk of the benchmark 60/40 XTF portfolio. Correspondingly, (de-)leverage costs for risk-adjusting the HPTs and control portfolios are applied. The overall RD between the 60/40 XTF portfolio and $\mu_{HPT,XTF}$, RD_{XTF}, is computed by:

$$(15) \qquad RD_{XTF} = \mu_{XTF} - \mu_{HPT,XTF} - \max\,[0; RD^{max}_{CP,XTF}].$$

The risk-adjusted returns of the HPTs ($\mu_{HPT,XTF}$) and analogously the control portfolios ($\mu_{1/m,XTF}, \mu_{1/n,XTF}, \mu_{60/40,XTF}$) are computed according to:

$$(16) \qquad \mu_{HPT,XTF} = \begin{cases} r_{SL} + \frac{\mu_{HPT}-r_{SL}}{\sigma_{HPT}}\sigma_{XTF}, & \text{if } \sigma_{HPT} < \sigma_{XTF}\\ r_{SV} + \frac{\mu_{HPT}-r_{SV}}{\sigma_{HPT}}\sigma_{XTF}, & \text{if } \sigma_{HPT} > \sigma_{XTF}\\ \mu_{HPT}, & \text{if } \sigma_{HPT} = \sigma_{XTF}\end{cases}$$

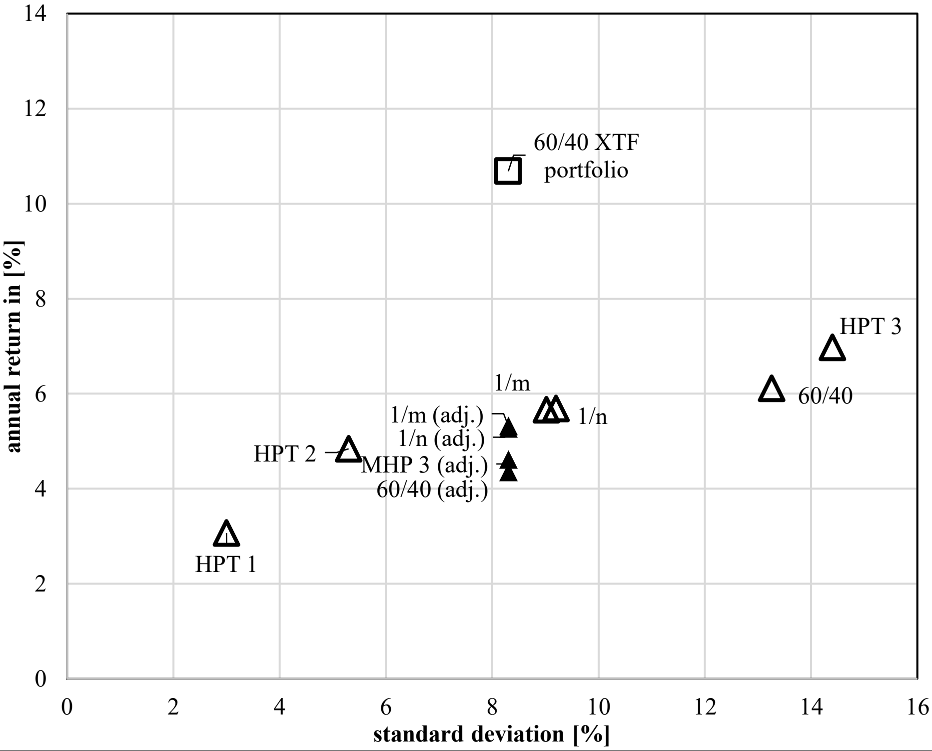
Then again, possible return increases for risk-adjusted HPTs are subtracted from the risk-adjusted control portfolios. Therefore, the maximum return difference between the risk-adjusted HPTs and the risk-adjusted control portfolios ($RD^{max}_{CP,XTF}$) which are based on the risk of the benchmark XTF portfolio are computed as follows:

$$(17) \qquad RD^{max}_{CP,XTF} = \max\begin{cases}\mu_{1/m,XTF} & - \mu_{HPT,XTF},\\ \mu_{1/n,XTF} & - \mu_{HPT,XTF},\\ \mu_{60/40,XTF} & - \mu_{HPT,XTF}.\end{cases}$$

Since the risk of HPT 1 and HPT 2 is below the risk of the 60/40 XTF portfolio, those HPTs need to be leveraged. However, the assumed annual security lending rate of 5.5 percent[522] for leverage is higher than the annual mean returns of HPT 1 and HPT 2. Thus, increasing leverage would imply both a reduction in returns and an increase in risk for HPT 1 and HPT 2. Since it seems unlikely that households would follow such a strategy, both HPTs are not risk-adjusted and no corresponding RDs are determined. To avoid misinterpretations, these cases are excluded from the analysis and only RDs for HPT 3 are presented. Checking for the control portfolios indicates that the returns of the 1/m (1/n; 1/m) control portfolio exceed those of HPT 3 by 0.71 (0.38; 0.38) percentage points for a portfolio size of nine (18, 27) securities. Taking this into account when ascertaining RDs, RDs for HPT 3 range between 5.34 and 6.82 percentage points for all portfolio sizes. A main reason for the difference between these RDs and the initial RDs that are based on the risk of HPT 3 is likely the impact of (de-)leverage costs. Nevertheless, the general conclusion that the 60/40 XTF portfolio obtains reasonably higher returns than HPT 3 does not change.

[522] See Stiftung Warentest (2013).

Table 35: Return difference (RD) based on the risk of the 60/40 XTF portfolio (9 securities per HPT) [Jan. 2014 – Dec. 2016]

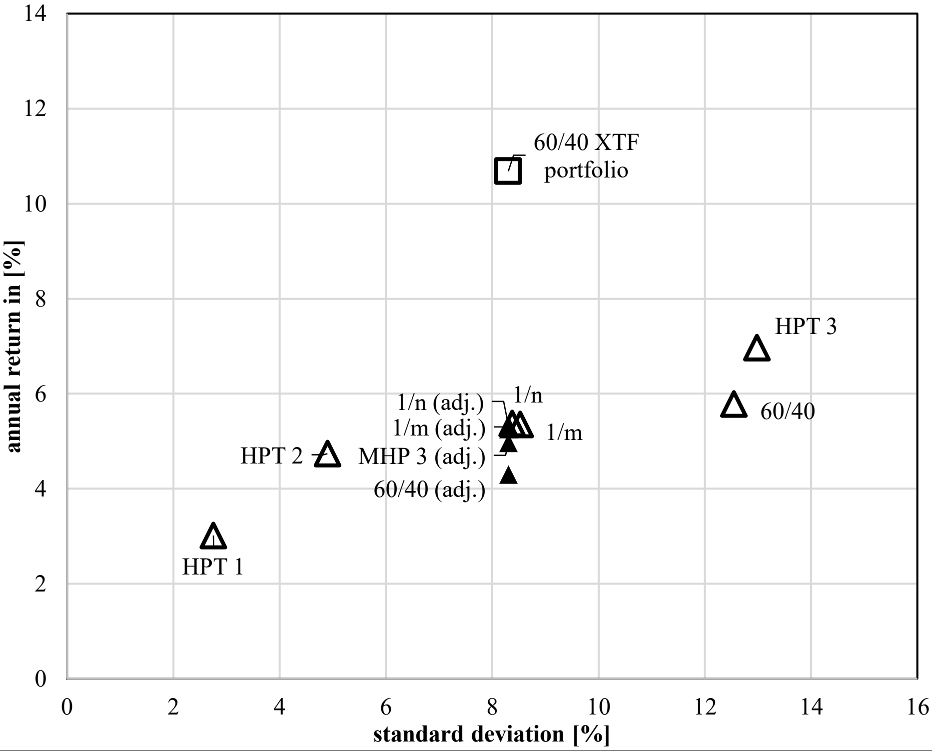


	Risk	Return	adjusted to risk of XTF	
60/40 XTF portfolio	8.30	10.68	Risk (risk-adj.)	Return (risk-adj.)
HPT 1	3.00	3.07	8.30	- / -
HPT 2	5.30	4.84	8.30	- / -
HPT 3	14.40	6.97	8.30	4.61
1/m	9.02	5.66	8.30	5.32
1/n	9.20	5.69	8.30	5.27
60/40	13.26	6.11	8.30	4.35

RD between	1/m (I)	1/n (II)	60/40 (III)	XTF (IV)
HPT 1	- / -	- / -	- / -	- / -
HPT 2	- / -	- / -	- / -	- / -
HPT 3	0.71	0.66	-0.26	5.36

Notes: The upper part of the Table reports the (risk-adjusted) risk/return-positions of the HPTs and the control portfolios of a portfolio size of nine securities between the period from January 2014 until December 2016. The bottom part of the Table shows the RDs between the (I) 1/m control portfolio, (II) 1/n control portfolio and the (III) 60/40 control portfolio and the HPTs, as well as the overall RD between the (IV) 60/40 XTF portfolio and the HPTs (including (de-)leverage costs). HPTs for which the cost of leverage exceeds their mean portfolio return are not risk-adjusted and no corresponding RDs are calculated. The RD in (IV) checks for the control portfolios by subtracting the maximum of positive return increases from (I), (II), or (III). Example: The RD between the 60/40 XTF portfolio and HPT 3 is 5.36 percentage points and was reduced by the maximum positive RD of 0.71 percentage points in (I).

Table 36: Return difference (RD) based on the risk of the 60/40 XTF portfolio (18 securities per HPT) [Jan. 2014 – Dec. 2016]

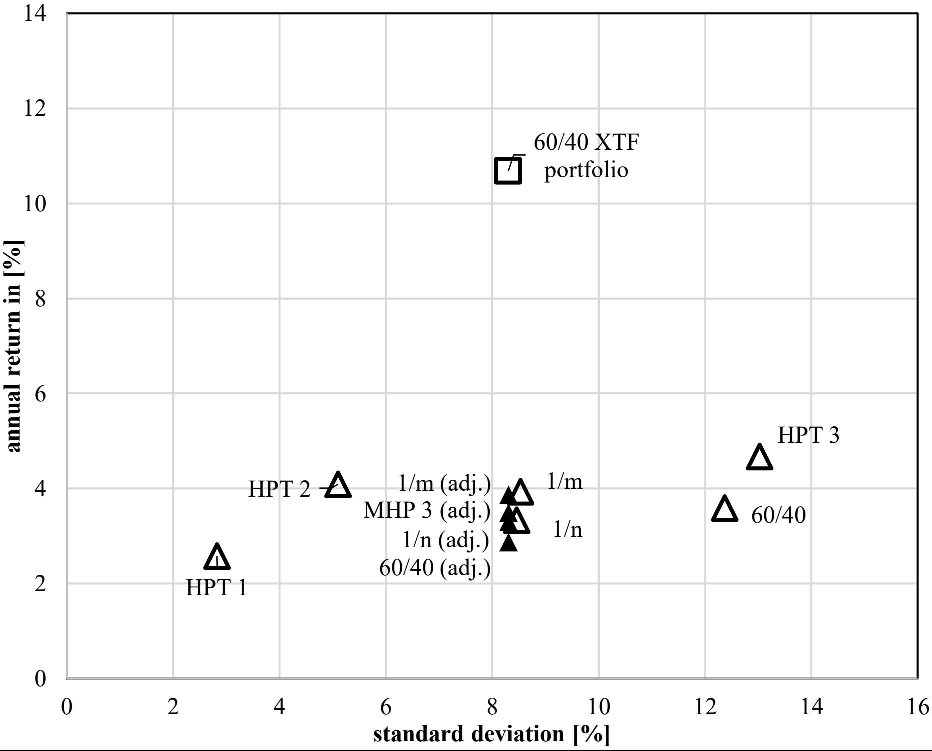


	Risk	Return	adjusted to risk of XTF	
60/40 XTF portfolio	8.30	10.68	Risk (risk-adj.)	Return (risk-adj.)
HPT 1	2.75	3.02	8.30	- / -
HPT 2	4.90	4.74	8.30	- / -
HPT 3	12.98	6.97	8.30	4.96
1/m	8.53	5.36	8.30	5.25
1/n	8.37	5.38	8.30	5.34
60/40	12.55	5.78	8.30	4.30

RD between	1/m (I)	1/n (II)	60/40 (III)	XTF (IV)
HPT 1	- / -	- / -	- / -	- / -
HPT 2	- / -	- / -	- / -	- / -
HPT 3	0.29	0.38	-0.66	5.34

Notes: The upper part of the Table reports the (risk-adjusted) risk/return-positions of the HPTs and the control portfolios of a portfolio size of 18 securities between the period from January 2014 until December 2016. The bottom part of the Table shows the RDs between the (I) 1/m control portfolio, (II) 1/n control portfolio and the (III) 60/40 control portfolio and the HPTs, as well as the overall RD between the (IV) 60/40 XTF portfolio and the HPTs (including (de-)leverage costs). HPTs for which the cost of leverage exceeds their mean portfolio return are not risk-adjusted and no corresponding RDs are calculated. The RD in (IV) checks for the control portfolios by subtracting the maximum of positive return increases from (I), (II), or (III). Example: The RD between the 60/40 XTF portfolio and HPT 3 is 5.34 percentage points and was reduced by the maximum positive RD of 0.38 percentage points in (II).

Table 37: Return difference (RD) based on the risk of the 60/40 XTF portfolio (27 securities per HPT) [Jan. 2014 – Dec. 2016]

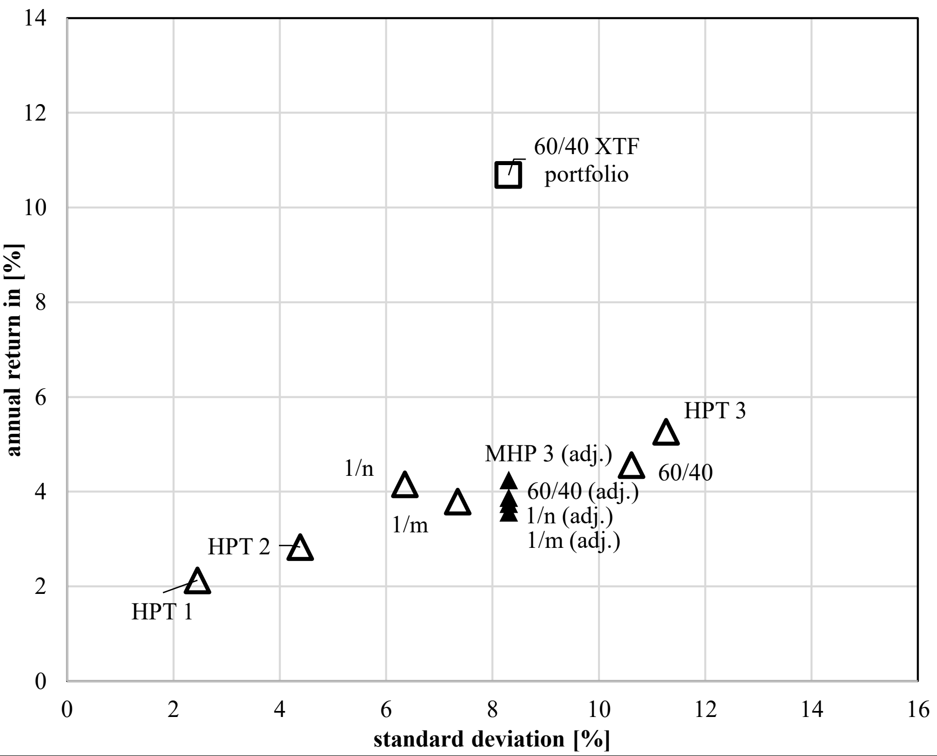


	Risk	Return	adjusted to risk of XTF	
60/40 XTF portfolio	8.30	10.68	Risk (risk-adj.)	Return (risk-adj.)
HPT 1	2.82	2.58	8.30	- / -
HPT 2	5.10	4.09	8.30	- / -
HPT 3	13.03	4.68	8.30	3.49
1/m	8.53	3.93	8.30	3.87
1/n	8.46	3.33	8.30	3.29
60/40	12.37	3.59	8.30	2.87

RD between	1/m (I)	1/n (II)	60/40 (III)	XTF (IV)
HPT 1	- / -	- / -	- / -	- / -
HPT 2	- / -	- / -	- / -	- / -
HPT 3	0.38	-0.19	-0.62	6.82

Notes: The upper part of the Table reports the (risk-adjusted) risk/return-positions of the HPTs and the control portfolios of a portfolio size of 27 securities between the period from January 2014 until December 2016. The bottom part of the Table shows the RDs between the (I) 1/m control portfolio, (II) 1/n control portfolio and the (III) 60/40 control portfolio and the HPTs, as well as the overall RD between the (IV) 60/40 XTF portfolio and the HPTs (including (de-)leverage costs). HPTs for which the cost of leverage exceeds their mean portfolio return are not risk-adjusted and no corresponding RDs are calculated. The RD in (IV) checks for the control portfolios by subtracting the maximum of positive return increases from (I), (II), or (III). Example: The RD between the 60/40 XTF portfolio and HPT 3 is 6.82 percentage points and was reduced by the maximum positive RD of 0.38 percentage points in (I).

Table 38: Return difference (RD) based on the risk of the 60/40 XTF portfolio (297 securities per HPT) [Jan. 2014 – Dec. 2016]



	Risk	Return	adjusted to risk of XTF	
60/40 XTF portfolio	8.30	10.68	Risk (risk-adj.)	Return (risk-adj.)
HPT 1	2.45	2.13	8.30	- / -
HPT 2	4.38	2.83	8.30	- / -
HPT 3	11.26	5.26	8.30	4.25
1/m	7.34	3.79	8.30	3.57
1/n	6.35	4.16	8.30	3.74
60/40	10.62	4.56	8.30	3.87

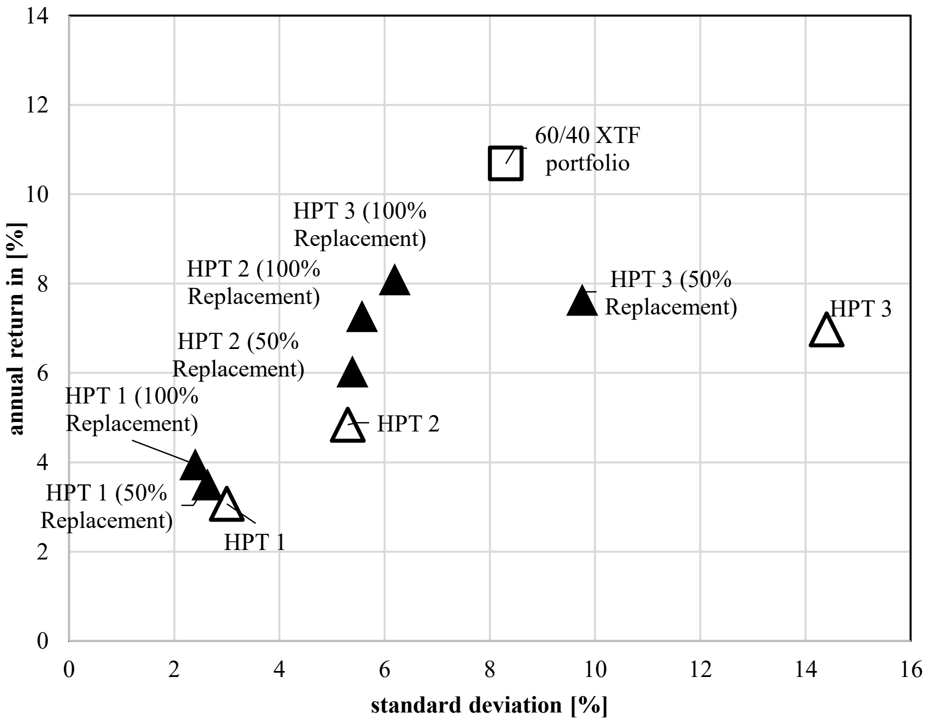
RD between	1/m (I)	1/n (II)	60/40 (III)	XTF (IV)
HPT 1	- / -	- / -	- / -	- / -
HPT 2	- / -	- / -	- / -	- / -
HPT 3	-0.68	-0.51	-0.38	6.43

Notes: The upper part of the Table reports the (risk-adjusted) risk/return-positions of the HPTs and the control portfolios of a portfolio size of 297 securities between the period from January 2014 until December 2016. The bottom part of the Table shows the RDs between the (I) 1/m control portfolio, (II) 1/n control portfolio and the (III) 60/40 control portfolio and the HPTs, as well as the overall RD between the (IV) 60/40 XTF portfolio and the HPTs (including (de-)leverage costs). HPTs for which the cost of leverage exceeds their mean portfolio return are not risk-adjusted and no corresponding RDs are calculated. The RD in (IV) checks for the control portfolios by subtracting the maximum of positive return increases from (I), (II), or (III). Example: The RD between the 60/40 XTF portfolio and HPT 3 is 6.43 percentage points without any subtraction since the RD between the 1/m, 1/n or 60/40 portfolio and the HPTs are negative.

Appendix D

Appendix D shows the corresponding Tables to the three robustness checks on portfolio replacements presented in chapter 5.3.3. The robustness tests check for (1) an increase in portfolio size, (2) replacing 50 percent (instead of 100 percent) of the each risky asset with the 60/40 benchmark XTF portfolio and (3) ratios of 25/75, 50/50, and 75/25 (instead of the 60/40) as asset class weights for the benchmark XTF portfolio. Robustness checks (1) and (2) are presented together in Table 39 to Table 42. Table 43 outlines the robustness check (3).

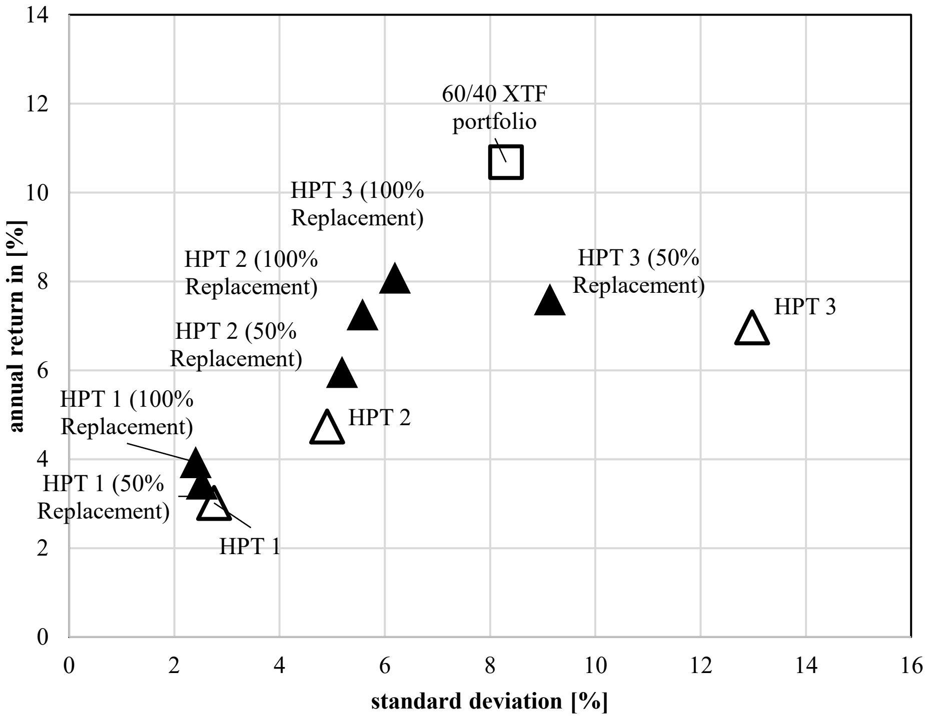
Table 39: Risk/return-changes of Portfolio Replacement (9 securities per HPT)



	Risk	Return	Portfolio Replacement (50% of risky assets)		Portfolio Replacement (100% of risky assets)	
60/40 XTF portfolio	8.30	10.68	Risk	Return	Risk	Return
HPT 1	3.00	3.07	2.63	3.50	2.40	3.95
			(-0.37)	*(0.43)*	*(-0.6)*	*(0.89)*
HPT 2	5.30	4.84	5.38	6.03	5.57	7.27
			(0.08)	*(1.19)*	*(0.27)*	*(2.43)*
HPT 3	14.40	6.97	9.75	7.64	6.19	8.09
			(-4.65)	*(0.67)*	*(-8.21)*	*(1.12)*

Notes: This table reveals the risk/return-positions of the HPTs (nine securities per HPT) with and without replacing 50 and 100 percent of each risky asset with the 60/40 XTF portfolio (delta in parenthesis). The replacement is performed at the beginning of the observation period in January 2014 and includes fixed and proportional transaction cost. Subsequently, a buy-and-hold strategy is presumed until December 2016.

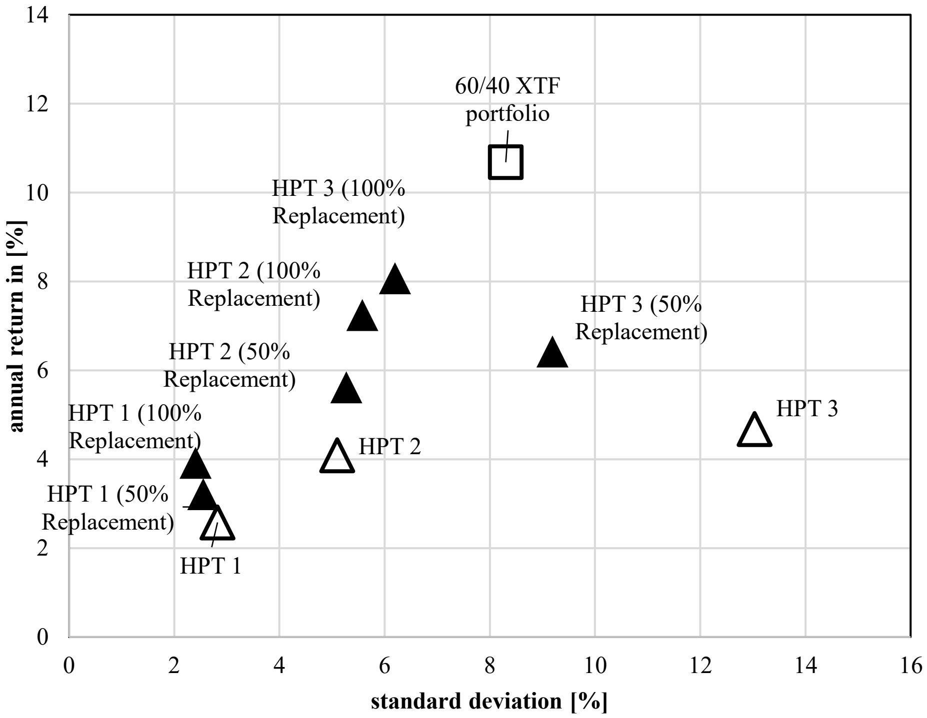
Table 40: Risk/return-changes of Portfolio Replacement (18 securities per HPT)



	Risk	Return	Portfolio Replacement (50% of risky assets)		Portfolio Replacement (100% of risky assets)	
60/40 XTF portfolio	8.30	10.68	Risk	Return	Risk	Return
HPT 1	2.75	3.02	2.52	3.45	2.40	3.94
			(-0.24)	*(0.43)*	*(-0.35)*	*(0.92)*
HPT 2	4.90	4.74	5.19	5.96	5.57	7.26
			(0.29)	*(1.22)*	*(0.67)*	*(2.52)*
HPT 3	12.98	6.97	9.13	7.59	6.19	8.08
			(-3.85)	*(0.63)*	*(-6.79)*	*(1.11)*

Notes: This table reveals the risk/return-positions of the HPTs (18 securities per HPT) with and without replacing 50 and 100 percent of each risky asset with the 60/40 XTF portfolio (delta in parenthesis). The replacement is performed at the beginning of the observation period in January 2014 and includes fixed and proportional transaction cost. Subsequently, a buy-and-hold strategy is presumed until December 2016.

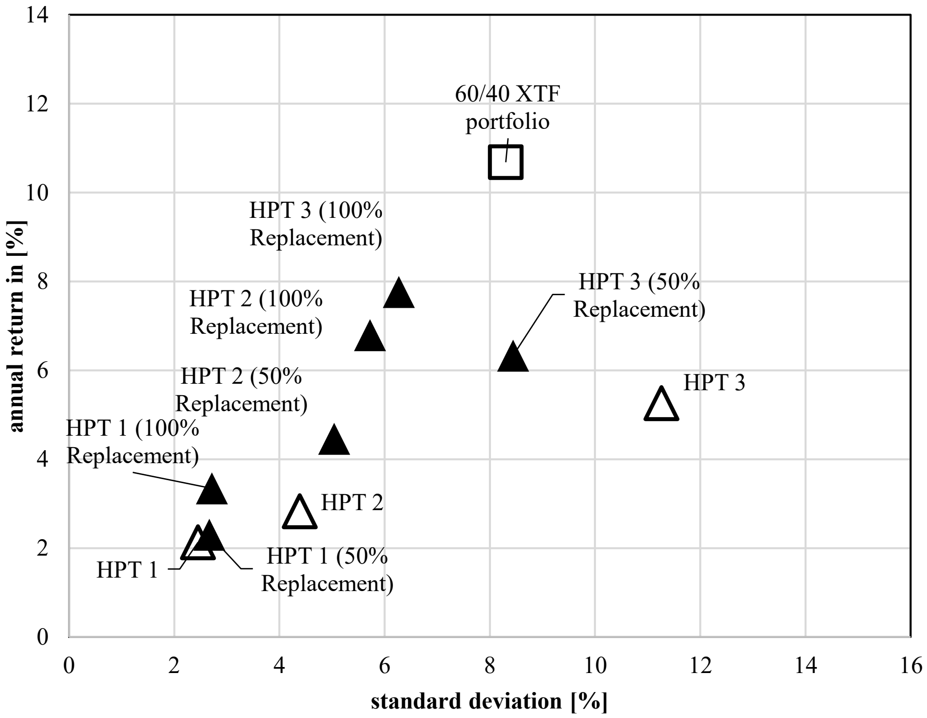
Table 41: Risk/return-changes of Portfolio Replacement (27 securities per HPT)



	Risk	Return	Portfolio Replacement (50% of risky assets)		Portfolio Replacement (100% of risky assets)	
60/40 XTF portfolio	8.30	10.68	Risk	Return	Risk	Return
HPT 1	2.82	2.58	2.55	3.21	2.41	3.92
			(-0.27)	*(0.63)*	*(-0.42)*	*(1.34)*
HPT 2	5.10	4.09	5.27	5.62	5.58	7.24
			(0.17)	*(1.53)*	*(0.48)*	*(3.16)*
HPT 3	13.03	4.68	9.19	6.42	6.19	8.07
			(-3.84)	*(1.75)*	*(-6.84)*	*(3.40)*

Notes: This table reveals the risk/return-positions of the HPTs (27 securities per HPT) with and without replacing 50 and 100 percent of each risky asset with the 60/40 XTF portfolio (delta in parenthesis). The replacement is performed at the beginning of the observation period in January 2014 and includes fixed and proportional transaction cost. Subsequently, a buy-and-hold strategy is presumed until December 2016.

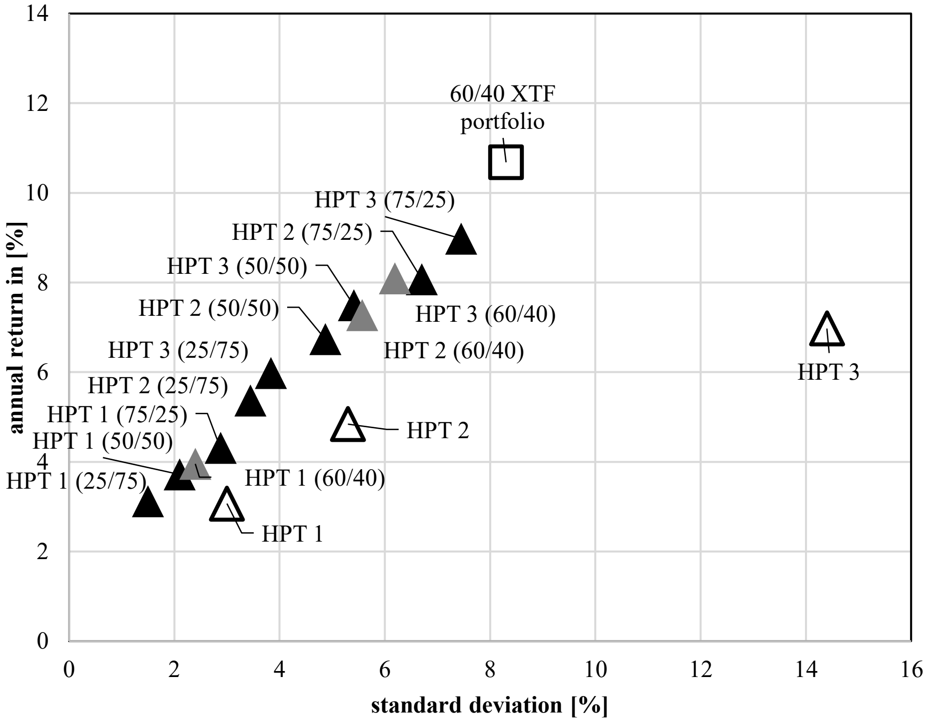
Table 42: Risk/return-changes of Portfolio Replacement (297 securities per HPT)



	Risk	Return	Portfolio Replacement (50% of risky assets)		Portfolio Replacement (100% of risky assets)	
60/40 XTF portfolio	8.30	10.68	Risk	Return	Risk	Return
HPT 1	2.45	2.13	2.67	2.30	2.72	3.34
			(0.21)	*(0.17)*	*(0.27)*	*(1.21)*
HPT 2	4.38	2.83	5.04	4.46	5.72	6.79
			(0.65)	*(1.63)*	*(1.34)*	*(3.96)*
HPT 3	11.26	5.26	8.44	6.33	6.27	7.76
			(-2.82)	*(1.07)*	*(-4.99)*	*(2.50)*

Notes: This table reveals the risk/return-positions of the HPTs (297 securities per HPT) with and without replacing 50 and 100 percent of each risky asset with the 60/40 XTF portfolio (delta in parenthesis). The replacement is performed at the beginning of the observation period in January 2014 and includes fixed and proportional transaction cost. Subsequently, a buy-and-hold strategy is presumed until December 2016.

Table 43: Portfolio Replacement using robustness benchmark XTF portfolios (nine securities per HPT) [Jan. 2014 – Dec. 2016]



	Risk	Return	25/75 XTF portfolio		50/50 XTF portfolio		75/25 XTF portfolio	
60/40 XTF portfolio	8.30	10.68	Risk	Return	Risk	Return	Risk	Return
HPT 1	3.00	3.07	1.50	3.12	2.10	3.72	2.88	4.31
			(-1.50)	*(0.05)*	*(-0.90)*	*(0.65)*	*(-0.12)*	*(1.24)*
HPT 2	5.30	4.84	3.45	5.37	4.87	6.74	6.70	8.07
			(-1.85)	*(0.53)*	*(-0.43)*	*(1.89)*	*(1.4)*	*(3.23)*
HPT 3	14.40	6.97	3.83	5.98	5.41	7.50	7.45	8.98
			(-10.57)	*(-0.99)*	*(-8.99)*	*(0.52)*	*(-6.95)*	*(2.00)*

Notes: This table reports the risk/return-positions of the initial HPTs (nine securities per HPT) with and without replacing the entire risk assets (100 percent of each risky asset) with the 60/40 (see grey triangles) and, as robustness, the 25/75, 50/50 and 75/25 XTF portfolio (delta in parenthesis). The replacement is performed at the beginning of the observation period in January 2014 and includes fixed and proportional transaction cost. Subsequently, a buy-and-hold strategy is presumed until December 2016.

Appendix E

Methodology

Table 44: Stock and bond indices used to categorize mixed funds

num.	Index category	Name	Ticker
1	Stock index	MSCI NORTH AMERICA E - PRICE INDEX	MSNAMRE
2	Stock index	MSCI EUROPE E - PRICE INDEX	MSEROPE
3	Stock index	MSCI AC ASIA PACIFIC E - PRICE INDEX	MSAAPFE
4	Stock index	MSCI EM E - PRICE INDEX	MSEMKFE
5	Stock index	MSCI AC WORLD :SM E - PRICE INDEX	MSZAWFE
6	Stock index	MSCI AC EUROPE :L E - PRICE INDEX	MSLERPE
7	Stock index	MSCI AC WORLD :L E - PRICE INDEX	MSLAWFE
8	Stock index	S&P 500/CITIGROUP PURE VALUE - PRICE INDEX	SP05PVA
9	Stock index	S&P 500/CITIGROUP PURE GROWTH - PRICE INDEX	SP05PGR
10	Stock index	S&P 500 DIVIDENDS ARISTOCRATS - PRICE INDEX	SP5DIAR
11	Stock index	DAX 30 PERFORMANCE - PRICE INDEX	DAXINDX
12	Stock index	EURO STOXX - PRICE INDEX	DJEURST
13	Stock index	MSCI AC WORLD E - PRICE INDEX	MSACWFE
14	Bond index	IBOXX EURO LIQUID CORPORATES - Gross Price Index - PRICE INDEX	IBELCAL
15	Bond index	IBOXX EURO CORPORATES - Gross Price Index - PRICE INDEX	IBCRPAL
16	Bond index	IBOXX EURO LIQUID SOVEREIGNS CAPPED 1.5 - 10.5 - Gross Price Index - PRICE INDEX	IBELSCB
17	Bond index	IBOXX EURO LIQUID SOVEREIGNS CAPPED 10.5+ - Gross Price Index - PRICE INDEX	IBELSCC
18	Bond index	IBOXX EURO OVERALL - Gross Price Index - PRICE INDEX	IBEURAL
19	Bond index	IBOXX EUR LIQUID HIGH YIELD INDEX - Gross Price Index - PRICE INDEX	IBEHYLQ

Notes: This table outlines details and tickers to the applied stock and bond indices which were used to calculate correlations with mixed funds and categorize the latter into stock and bond funds. Data source: Thomson Reuters Datastream.

Robustness Checks on Reinvestment Strategies: Portfolio size of 18 securities

Table 45: Descriptive statistics on benchmark XTF portfolios and portfolios of HPTs for a portfolio size of 18 securities [Jan. 2014 to June 2017]

	reinvestment-strategy	portfolio mean [%]	SD of portfolio means [%]	median [%]	skewness	kurtosis
HPT 1	replacement-strategy	0.2600	n.a.	0.1570	0.5708	0.9636
	XTF-strategy [av.]	0.1615	0.0569	0.0874	0.8246	1.3640
	default-strategy [av.]	0.1464	0.0578	0.0596	0.9000	1.4540
HPT 2	replacement-strategy	0.4410	n.a.	0.4600	0.0852	0.6693
	XTF-strategy [av.]	0.2182	0.0853	0.2073	0.4468	1.4198
	default-strategy [av.]	0.2192	0.0889	0.2137	0.4070	1.1690
HPT 3	replacement-strategy	0.6920	n.a.	0.4710	-0.0144	0.6486
	XTF-strategy [av.]	0.5409	0.2860	0.6163	0.0435	0.3033
	default-strategy [av.]	0.5265	0.2825	0.5816	0.0606	0.2441

Notes: This table shows descriptive statistics of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (18 risky securities per portfolio).

Table 46: Risk evaluation of benchmark XTF portfolios and portfolios of HPTs for a portfolio size of 18 securities [Jan. 2014 to June 2017]

	reinvestment-strategy	SD [%]	LPM0 [%]	LPM1 [%]	√LPM2 [%]	MDD [%]
HPT 1	replacement-strategy	0.9222	57.1429	0.3671	0.6245	3.6725
	XTF-strategy [av.]	0.8385	66.3381	0.4016	0.6187	3.5089
	default-strategy [av.]	0.8015	67.5381	0.4021	0.6022	3.3509
HPT 2	replacement-strategy	1.4467	52.3810	0.5688	1.0356	6.2396
	XTF-strategy [av.]	1.2024	65.4119	0.6049	0.9751	5.6244
	default-strategy [av.]	1.2260	64.8024	0.6168	0.9947	5.7532
HPT 3	replacement-strategy	2.4919	54.7619	1.0079	1.8277	9.7489
	XTF-strategy [av.]	3.0172	54.0333	1.3185	2.2874	13.5602
	default-strategy [av.]	2.9825	54.4000	1.3184	2.2673	13.4613

Notes: This table shows the risk evaluation according to the applied risk measures of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (18 risky securities per portfolio).

Table 47: Return Differences (RDs) for a portfolio size of 18 securities of HPT portfolios employing the XTF- and default-strategy [Jan. 2014 to June 2017]

	reinvestment-strategy	MV		M-LPM0		M-LPM1		M-LPM2		M-MDD
		RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD [%]
HPT 1	XTF-strategy [av.]	0.0752	0.0630	0.0772	0.1167	0.0837	0.1192	0.0865	0.1107	-0.1636
	default-strategy [av.]	0.0825	0.0575	0.0900	0.1296	0.0984	0.1330	0.0991	0.1285	-0.3216
	delta in RD: paired Wilcoxon-test (p)	*0.0073****	*-0.0054****	*0.0128****	*0.0129****	*0.0147****	*0.0139****	*0.0125****	*0.0179****	*-0.158****
HPT 2	XTF-strategy [av.]	0.1506	0.1509	0.2356	0.2526	0.2206	0.2423	0.1887	0.2008	-0.6152
	default-strategy [av.]	0.1549	0.1631	0.2339	0.2513	0.2218	0.2435	0.1918	0.2114	-0.4865
	delta in RD: paired Wilcoxon-test (p)	*0.0044****	*0.0122****	*-0.0017*	*-0.0013*	*0.0012***	*0.0011****	*0.0031****	*0.0106****	*0.1287****
HPT 3	XTF-strategy [av.]	0.2144	0.2341	0.1316	0.1251	0.2440	0.2434	0.2265	0.2318	3.8113
	default-strategy [av.]	0.2242	0.2409	0.1493	0.1426	0.2583	0.2542	0.2372	0.2394	3.7124
	delta in RD: paired Wilcoxon-test (p)	*0.0098****	*0.0068****	*0.0177****	*0.0175****	*0.0143****	*0.0108****	*0.0107****	*0.0076****	*-0.0989****

Notes: This table shows the RDs as average [av.] of 1,000 portfolios (18 risky securities per portfolio) following the XTF- and default-strategy for each of the applied risk-return-frameworks. RD_{HPT} denotes RDs that are based on the risk of the HPTs' portfolios. RD_{BM} denotes RDs that are based on the risk of a HPT's corresponding benchmark XTF portfolio. ***, **, and * indicate the one, five, and ten percent significance level of a paired, two-sided Wilcoxon test which was used to test statistical difference between the RDs according to the XTF- and default-strategy.

Table 48: Influence of transaction costs on investment outcomes for a portfolio size of 18 securities of HPT portfolios [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	sum of transaction costs [€]		cumulative VALUEpf until June 2017 [€]			cumulative return until June 2017 [%]		
			selling-/ purchase costs	accrued interest costs	including transaction costs	excluding transaction costs	difference in VALUEpf	including transaction costs	excluding transaction costs	difference in cumulative return
HPT 1	replacement-strategy	163,900	363	n.a.	182,507	182,942	435	11.35	11.62	0.27
	XTF-strategy [av.]		86	n.a.	175,185	175,282	97	6.89	6.94	0.06
	default-strategy [av.]		107	95	174,109	174,225	117	6.23	6.30	0.07
HPT 2	replacement-strategy	214,200	694	n.a.	256,599	257,462	863	19.79	20.20	0.40
	XTF-strategy [av.]		190	n.a.	234,157	234,349	192	9.32	9.41	0.09
	default-strategy [av.]		251	522	234,237	234,581	345	9.35	9.52	0.16
HPT 3	replacement-strategy	312,900	854	n.a.	412,774	413,969	1,195	31.92	32.30	0.38
	XTF-strategy [av.]		241	n.a.	387,873	388,150	277	23.96	24.05	0.09
	default-strategy [av.]		280	246	385,639	385,977	338	23.25	23.35	0.11

Notes: The left part of the table shows the initial VALUEpf by January 2014 and the sum of transaction costs that occur during the observation period (divided into selling-/purchase costs and accrued interest costs of BDs). Please note that selling-costs only occur in the replacement-strategy; accrued interest costs only emerge in the default-strategy, i.e., if a new BD is purchased. The middle part of the table reveals the cumulative VALUEpf at the end of the observation period in June 2017 (divided into VALUEpf including and excluding transaction costs as well as the difference between the latter). The right part of the table exhibits the characteristics of the middle part of the table in terms of returns. The values are presented for each HPT's benchmark XTF portfolio and as average [av.] of 1,000 HPT portfolios (18 risky securities per portfolio).

Table 49: Characteristics of reinvestments
for a portfolio size of 18 securities of HPT portfolios [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	January 2014 to June 2017			number of risky securities in June 2017
			number of transactions	sum of reinvested amounts [€]	in [%] of initial VALUEpf	
HPT 1	replacement-strategy	163,900	20.0	163,537	99.78	2.0
	XTF-strategy [av.]		5.9	10,608	6.47	15.1
	default-strategy [av.]		7.2	13,651	8.33	18.9
HPT 2	replacement-strategy	214,200	20.0	213,506	99.68	2.0
	XTF-strategy [av.]		9.3	38,856	18.14	15.1
	default-strategy [av.]		11.8	52,389	24.46	22.1
HPT 3	replacement-strategy	312,900	19.0	312,046	99.73	2.0
	XTF-strategy [av.]		14.3	38,792	12.40	15.1
	default-strategy [av.]		16.2	46,788	14.95	26.9

Notes: This table exhibits the initial VALUEpf by January 2014, the number of transactions, and the sum of reinvested amounts in Euro and in percent of the initial VALUEpf for each HPT's benchmark XTF portfolio and 1,000 HPT portfolios as average [av.] (18 risky securities per portfolio). The table also reveals the number of individual risky securities per portfolio at the end of the observation period.

Robustness Checks on Reinvestment Strategies: Portfolio size of 27 securities

Table 50: Descriptive statistics on benchmark XTF portfolios and portfolios of HPTs for a portfolio size of 27 securities [Jan. 2014 to June 2017]

	reinvestment-strategy	portfolio mean [%]	SD of portfolio means [%]	median [%]	skewness	kurtosis
HPT 1	replacement-strategy	0.2590	n.a.	0.1570	0.5747	0.9712
	XTF-strategy [av.]	0.1642	0.0575	0.0897	0.8680	1.4478
	default-strategy [av.]	0.1482	0.0594	0.0624	0.9528	1.5711
HPT 2	replacement-strategy	0.4410	n.a.	0.4600	0.0861	0.6704
	XTF-strategy [av.]	0.2236	0.1877	0.2079	0.4783	1.5423
	default-strategy [av.]	0.2230	0.1882	0.2144	0.4367	1.2947
HPT 3	replacement-strategy	0.6910	n.a.	0.4710	-0.0141	0.6476
	XTF-strategy [av.]	0.5571	0.2341	0.6206	0.0664	0.2798
	default-strategy [av.]	0.5441	0.2346	0.5937	0.0887	0.2284

Notes: This table shows descriptive statistics of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (27 risky securities per portfolio).

Table 51: Risk evaluation of benchmark XTF portfolios and portfolios of HPTs for a portfolio size of 27 securities [Jan. 2014 to June 2017]

	reinvestment-strategy	SD [%]	LPM0 [%]	LPM1 [%]	√LPM2 [%]	MDD [%]
HPT 1	replacement-strategy	0.9219	57.1429	0.3671	0.6245	3.6725
	XTF-strategy [av.]	0.8336	67.2333	0.3938	0.6093	3.4171
	default-strategy [av.]	0.7915	68.6214	0.3937	0.5903	3.2234
HPT 2	replacement-strategy	1.4466	52.3810	0.5688	1.0356	6.2396
	XTF-strategy [av.]	1.2088	65.8619	0.5913	0.9613	5.5546
	default-strategy [av.]	1.2278	65.5976	0.6022	0.9791	5.6199
HPT 3	replacement-strategy	2.4921	54.7619	1.0083	1.8280	9.7489
	XTF-strategy [av.]	2.8663	54.1048	1.2510	2.1682	12.2915
	default-strategy [av.]	2.8392	54.5976	1.2508	2.1497	12.1824

Notes: This table shows the risk evaluation according to the applied risk measures of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (27 risky securities per portfolio).

Table 52: Return Differences (RDs) for a portfolio size of 27 securities of HPT portfolios employing the XTF- and default-strategy [Jan. 2014 to June 2017]

	reinvestment-strategy	MV		M-LPM0		M-LPM1		M-LPM2		M-MDD
		RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD [%]
HPT 1	XTF-strategy [av.]	0.0680	0.0620	0.0717	0.1128	0.0826	0.1134	0.0807	0.1107	-0.2554
	default-strategy [av.]	0.0741	0.0634	0.0849	0.1272	0.0984	0.1292	0.0918	0.1263	-0.4491
	delta in RD: paired Wilcoxon-test (p)	*0.0061****	*0.0014****	*0.0132****	*0.0145****	*0.0158****	*0.0158****	*0.0111****	*0.0157****	*-0.1937****
HPT 2	XTF-strategy [av.]	0.1409	0.1651	0.2311	0.2494	0.2125	0.2381	0.1787	0.2054	-0.6850
	default-strategy [av.]	0.1458	0.1743	0.2314	0.2493	0.2154	0.2429	0.1834	0.2135	-0.6197
	delta in RD: paired Wilcoxon-test (p)	*0.0049****	*0.0092****	*0.0003**	*0*	*0.0029****	*0.0048****	*0.0047****	*0.0082****	*0.0653*
HPT 3	XTF-strategy [av.]	0.1777	0.1966	0.1156	0.1157	0.2054	0.2149	0.1884	0.1999	2.5426
	default-strategy [av.]	0.1867	0.2020	0.1332	0.1324	0.2181	0.2248	0.1977	0.2066	2.4335
	delta in RD: paired Wilcoxon-test (p)	*0.009****	*0.0053****	*0.0176****	*0.0167****	*0.0128****	*0.0099****	*0.0093****	*0.0067****	*-0.1091****

Notes: This table shows the RDs as average [av.] of 1,000 portfolios (27 risky securities per portfolio) following the XTF- and default-strategy for each of the applied risk-return-frameworks. RD_{HPT} denotes RDs that are based on the risk of the HPTs' portfolios. RD_{BM} denotes RDs that are based on the risk of a HPT's corresponding benchmark XTF portfolio. ***, **, and * indicate the one, five, and ten percent significance level of a paired, two-sided Wilcoxon test which was used to test statistical difference between the RDs according to the XTF- and default-strategy.

Table 53: Influence of transaction costs on investment outcomes for a portfolio size of 27 securities of HPT portfolios [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	sum of transaction costs [€]		cumulative VALUEpf until June 2017 [€]			cumulative return until June 2017 [%]		
			selling-/ purchase costs	accrued interest costs	including transaction costs	excluding transaction costs	difference in VALUEpf	including transaction costs	excluding transaction costs	difference in cumulative return
HPT 1	replacement-strategy	163,900	440	n.a.	182,423	182,942	519	11.30	11.62	0.32
	XTF-strategy [av.]		98	n.a.	175,312	175,422	110	6.96	7.03	0.07
	default-strategy [av.]		121	128	174,167	174,308	141	6.26	6.35	0.09
HPT 2	replacement-strategy	214,200	738	n.a.	256,546	257,462	916	19.77	20.20	0.43
	XTF-strategy [av.]		207	n.a.	234,163	234,371	209	9.32	9.42	0.10
	default-strategy [av.]		272	508	234,086	234,389	303	9.28	9.43	0.14
HPT 3	replacement-strategy	312,900	905	n.a.	412,707	413,969	1,262	31.90	32.30	0.40
	XTF-strategy [av.]		258	n.a.	390,261	390,557	297	24.72	24.82	0.09
	default-strategy [av.]		297	245	388,170	388,553	383	24.06	24.18	0.12

Notes: The left part of the table shows the initial VALUEpf by January 2014 and the sum of transaction costs that occur during the observation period (divided into selling-/purchase costs and accrued interest costs of BDs). Please note that selling-costs only occur in the replacement-strategy; accrued interest costs only emerge in the default-strategy, i.e., if a new BD is purchased. The middle part of the table reveals the cumulative VALUEpf at the end of the observation period in June 2017 (divided into VALUEpf including and excluding transaction costs as well as the difference between the latter). The right part of the table exhibits the characteristics of the middle part of the table in terms of returns. The values are presented for each HPT's benchmark XTF portfolio and as average [av.] of 1,000 HPT portfolios (27 risky securities per portfolio).

Table 54: Characteristics of reinvestments
for a portfolio size of 27 securities of HPT portfolios [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	January 2014 to June 2017			number of risky securities in June 2017
			number of transactions	sum of reinvested amounts [€]	in [%] of initial VALUEpf	
HPT 1	replacement-strategy	163,900	29.0	163,460	99.73	2.0
	XTF-strategy [av.]		7.1	10,683	6.52	21.7
	default-strategy [av.]		8.6	13,891	8.48	26.4
HPT 2	replacement-strategy	214,200	29.0	213,462	99.66	2.0
	XTF-strategy [av.]		10.9	39,038	18.23	21.7
	default-strategy [av.]		13.7	53,263	24.87	30.0
HPT 3	replacement-strategy	312,900	28.0	311,995	99.71	2.0
	XTF-strategy [av.]		16.2	38,222	12.22	21.7
	default-strategy [av.]		18.1	46,105	14.73	35.1

Notes: This table exhibits the initial VALUEpf by January 2014, the number of transactions, and the sum of reinvested amounts in Euro and in percent of the initial VALUEpf for each HPT's benchmark XTF portfolio and 1,000 HPT portfolios as average [av.] (27 risky securities per portfolio). The table also reveals the number of individual risky securities per portfolio at the end of the observation period.

Robustness Checks on Reinvestment Strategies: Portfolio size of 297 securities

Table 55: Descriptive statistics on benchmark XTF portfolios and portfolios of HPTs for a portfolio size of 297 securities [Jan. 2014 to June 2017]

	reinvestment-strategy	portfolio mean [%]	SD of portfolio means [%]	median [%]	skewness	kurtosis
HPT 1	replacement-strategy	0.2210	n.a.	0.1370	0.5700	0.7734
	XTF-strategy [av.]	0.1735	0.0142	0.0844	1.0351	1.9181
	default-strategy [av.]	0.1588	0.0609	0.0415	1.1873	2.1335
HPT 2	replacement-strategy	0.4110	n.a.	0.3650	0.1365	0.6136
	XTF-strategy [av.]	0.2204	0.0266	0.2104	0.5957	2.0281
	default-strategy [av.]	0.1933	1.0018	0.2268	0.5830	1.7883
HPT 3	replacement-strategy	0.6720	n.a.	0.4710	-0.0017	0.5789
	XTF-strategy [av.]	0.6590	0.0731	0.7884	0.0348	0.2815
	default-strategy [av.]	0.6465	0.0751	0.7581	0.0696	0.2009

Notes: This table shows descriptive statistics of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (297 risky securities per portfolio).

Table 56: Risk evaluation of benchmark XTF portfolios and portfolios of HPTs for a portfolio size of 297 securities [Jan. 2014 to June 2017]

	reinvestment-strategy	SD [%]	LPM0 [%]	LPM1 [%]	√LPM2 [%]	MDD [%]
HPT 1	replacement-strategy	0.9469	59.5238	0.4025	0.6653	3.6725
	XTF-strategy [av.]	0.7758	70.6405	0.3645	0.5550	2.9070
	default-strategy [av.]	0.7474	73.7714	0.3681	0.5384	2.6766
HPT 2	replacement-strategy	1.4535	54.7619	0.5936	1.0480	6.2396
	XTF-strategy [av.]	1.1540	67.9571	0.5593	0.9209	5.3262
	default-strategy [av.]	1.4277	70.0095	0.6062	1.1465	5.8555
HPT 3	replacement-strategy	2.5057	54.7619	1.0280	1.8481	9.7489
	XTF-strategy [av.]	2.3689	51.2786	1.0050	1.7756	8.1516
	default-strategy [av.]	2.2959	51.8738	0.9895	1.7250	7.7399

Notes: This table shows the risk evaluation according to the applied risk measures of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (297 risky securities per portfolio).

Table 57: Return Differences (RDs) for a portfolio size of 297 securities of HPT portfolios employing the XTF- and default-strategy [Jan. 2014 to June 2017]

	reinvestment-strategy	MV		M-LPM0		M-LPM1		M-LPM2		M-MDD
		RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD [%]
HPT 1	XTF-strategy [av.]	0.0096	n.a.	0.0165	0.0677	0.0277	0.0754	0.0123	0.0958	-0.7655
	default-strategy [av.]	0.0119	n.a.	0.0224	0.0843	0.0419	0.0890	0.0177	0.1111	-0.9959
	delta in RD: paired Wilcoxon-test (p)	*0.0022****	*n.a.*	*0.0059****	*0.0166****	*0.0143****	*0.0136****	*0.0054****	*0.0153****	*-0.2304****
HPT 2	XTF-strategy [av.]	0.0989	n.a.	0.1964	0.2244	0.1627	0.2196	0.1320	n.a.	-0.9134
	default-strategy [av.]	0.1320	0.2923	0.2244	0.2477	0.1964	0.1995	0.1665	0.2668	-0.3841
	delta in RD: paired Wilcoxon-test (p)	*0.033****	*n.a.*	*0.028****	*0.0233****	*0.0337****	*-0.0201****	*0.0344****	*n.a.*	*0.5293****
HPT 3	XTF-strategy [av.]	-0.0230	-0.0014	-0.0283	-0.0070	-0.0048	0.0075	-0.0137	0.0018	-1.5973
	default-strategy [av.]	-0.0284	0.0024	-0.0096	0.0099	-0.0007	0.0149	-0.0176	0.0059	-2.0090
	delta in RD: paired Wilcoxon-test (p)	*-0.0055****	*0.0039****	*0.0186****	*0.0169****	*0.0041****	*0.0074****	*-0.0039****	*0.004****	*-0.4117****

Notes: This table shows the RDs as average [av.] of 1,000 portfolios (297 risky securities per portfolio) following the XTF- and default-strategy for each of the applied risk-return-frameworks. RD_{HPT} denotes RDs that are based on the risk of the HPTs' portfolios. RD_{BM} denotes RDs that are based on the risk of a HPT's corresponding benchmark XTF portfolio. ***, **, and * indicate the one, five, and ten percent significance level of a paired, two-sided Wilcoxon test which was used to test statistical difference between the RDs according to the XTF- and default-strategy.

Table 58: Influence of transaction costs on investment outcomes for a portfolio size of 297 securities of HPT portfolios [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	sum of transaction costs [€]		cumulative VALUEpf until June 2017 [€]			cumulative return until June 2017 [%]		
			selling-/ purchase costs	accrued interest costs	including transaction costs	excluding transaction costs	difference in VALUEpf	including transaction costs	excluding transaction costs	difference in cumulative return
HPT 1	replacement-strategy	163,900	3,113	n.a.	179,460	182,942	3,482	9.49	11.62	2.12
	XTF-strategy [av.]		130	n.a.	176,060	176,203	143	7.42	7.51	0.09
	default-strategy [av.]		155	113	174,876	175,001	125	6.70	6.77	0.08
HPT 2	replacement-strategy	214,200	3,350	n.a.	253,429	257,462	4,033	18.31	20.20	1.88
	XTF-strategy [av.]		353	n.a.	234,191	234,545	353	9.33	9.50	0.16
	default-strategy [av.]		422	497	232,981	234,409	1,428	8.77	9.43	0.67
HPT 3	replacement-strategy	312,900	3,529	n.a.	409,260	413,969	4,709	30.80	32.30	1.50
	XTF-strategy [av.]		323	n.a.	407,818	408,188	369	30.34	30.45	0.12
	default-strategy [av.]		362	266	405,989	406,453	465	29.75	29.90	0.15

Notes: The left part of the table shows the initial VALUEpf by January 2014 and the sum of transaction costs that occur during the observation period (divided into selling-/purchase costs and accrued interest costs of BDs). Please note that selling-costs only occur in the replacement-strategy; accrued interest costs only emerge in the default-strategy, i.e., if a new BD is purchased. The middle part of the table reveals the cumulative VALUEpf at the end of the observation period in June 2017 (divided into VALUEpf including and excluding transaction costs as well as the difference between the latter). The right part of the table exhibits the characteristics of the middle part of the table in terms of returns. The values are presented for each HPT's benchmark XTF portfolio and as average [av.] of 1,000 HPT portfolios (297 risky securities per portfolio).

Table 59: Characteristics of reinvestments
for a portfolio size of 297 securities of HPT portfolios [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	January 2014 to June 2017			number of risky securities in June 2017
			number of transactions	sum of reinvested amounts [€]	in [%] of initial VALUEpf	
HPT 1	replacement-strategy	163,900	299.0	160,787	98.10	2.0
	XTF-strategy [av.]		10.0	11,879	7.25	217.2
	default-strategy [av.]		11.5	15,474	9.44	224.2
HPT 2	replacement-strategy	214,200	299.0	210,850	98.44	2.0
	XTF-strategy [av.]		24.7	42,217	19.71	217.2
	default-strategy [av.]		27.5	57,741	26.96	235.6
HPT 3	replacement-strategy	312,900	298.0	309,371	98.87	2.0
	XTF-strategy [av.]		22.0	40,589	12.97	217.2
	default-strategy [av.]		23.8	49,007	15.66	235.3

Notes: This table exhibits the initial VALUEpf by January 2014, the number of transactions, and the sum of reinvested amounts in Euro and in percent of the initial VALUEpf for each HPT's benchmark XTF portfolio and 1,000 HPT portfolios as average [av.] (297 risky securities per portfolio). The table also reveals the number of individual risky securities per portfolio at the end of the observation period.

Table 60: Descriptive statistics on benchmark XTF portfolios and portfolios of HPTs including an additional monthly reinvestment amount [Jan. 2014 to June 2017]

	reinvestment-strategy	portfolio mean [%]	SD of portfolio means [%]	median [%]	skewness	kurtosis
HPT 1	replacement-strategy	0.2640	n.a.	0.1520	0.5444	0.9514
	XTF-strategy [av.]	0.1838	0.2281	0.1125	0.6766	1.1125
	default-strategy [av.]	0.1511	0.2333	0.0666	0.7474	1.1486
HPT 2	replacement-strategy	0.4380	n.a.	0.4560	0.0819	0.6840
	XTF-strategy [av.]	0.2660	0.9746	0.2066	0.4186	1.2964
	default-strategy [av.]	0.2452	0.9841	0.1928	0.3718	1.0855
HPT 3	replacement-strategy	0.6920	n.a.	0.4710	-0.0167	0.6535
	XTF-strategy [av.]	0.5611	0.4181	0.6015	0.0744	0.3785
	default-strategy [av.]	0.5339	0.4233	0.5569	0.0904	0.3312

Notes: This table shows descriptive statistics of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (nine risky securities per portfolio; including a monthly fixed amount of 200 Euro for reinvestments).

Table 61: Risk evaluation of benchmark XTF portfolios and portfolios of HPTs including an additional monthly reinvestment amount [Jan. 2014 to June 2017]

	reinvestment-strategy	SD [%]	LPM0 [%]	LPM1 [%]	√LPM2 [%]	MDD [%]
HPT 1	replacement-strategy	0.9320	57.1429	0.3688	0.6311	3.7314
	XTF-strategy [av.]	0.9899	63.2595	0.4274	0.6970	4.0589
	default-strategy [av.]	0.9533	65.2310	0.4376	0.6906	4.0220
HPT 2	replacement-strategy	1.4437	52.3810	0.5687	1.0357	6.2409
	XTF-strategy [av.]	1.5044	64.5976	0.6402	1.0594	6.0509
	default-strategy [av.]	1.5507	64.3333	0.6729	1.1076	6.5368
HPT 3	replacement-strategy	2.4994	54.7619	1.0103	1.8334	9.7849
	XTF-strategy [av.]	3.4000	53.7524	1.4479	2.5181	15.5749
	default-strategy [av.]	3.3955	54.2571	1.4619	2.5220	15.6713

Notes: This table shows the risk evaluation according to the applied risk measures of each HPT's benchmark XTF portfolio and the HPTs' portfolios following the XTF- and default-strategy as average [av.] of 1,000 portfolios (nine risky securities per portfolio; including a monthly fixed amount of 200 Euro for reinvestments).

Table 62: Return Differences (RDs) of HPT portfolios employing the XTF- and default-strategy including an additional monthly reinvestment amount [Jan. 2014 to June 2017]

	reinvestment-strategy	MV		M-LPM0		M-LPM1		M-LPM2		M-MDD
		RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD_{HPT} [%]	RD_{BM} [%]	RD [%]
HPT 1	XTF-strategy [av.]	0.0526	0.0784	0.0631	0.1025	0.0578	0.1148	0.0596	0.1101	0.3275
	default-strategy [av.]	0.0771	0.0963	0.0934	0.1307	0.0877	0.1439	0.0910	0.1449	0.2906
	delta in RD: paired Wilcoxon-test (p)	*0.0246****	*0.0179****	*0.0303****	*0.0282****	*0.0299****	*0.0291****	*0.0314****	*0.0348****	*-0.0369****
HPT 2	XTF-strategy [av.]	0.1178	0.1629	0.1826	0.2061	0.1723	0.2276	0.1438	0.1901	-0.1900
	default-strategy [av.]	0.1459	0.1989	0.2031	0.2245	0.1989	0.2573	0.1729	0.2249	0.2959
	delta in RD: paired Wilcoxon-test (p)	*0.0281****	*0.036****	*0.0205****	*0.0184****	*0.0266****	*0.0296****	*0.0292****	*0.0348****	*0.4859****
HPT 3	XTF-strategy [av.]	0.2394	0.2604	0.1073	0.0833	0.2615	0.2470	0.2429	0.2385	5.7900
	default-strategy [av.]	0.2657	0.2793	0.1388	0.1130	0.2930	0.2699	0.2705	0.2596	5.8864
	delta in RD: paired Wilcoxon-test (p)	*0.0263****	*0.0189****	*0.0315****	*0.0298****	*0.0314****	*0.0228****	*0.0276****	*0.021****	*0.0964***

Notes: This table shows the RDs as average [av.] of 1,000 portfolios (nine risky securities per portfolio; including a monthly fixed amount of 200 Euro for reinvestments) following the XTF- and default-strategy for each of the applied risk-return-frameworks. RD_{HPT} denotes RDs that are based on the risk of the HPTs' portfolios. RD_{BM} denotes RDs that are based on the risk of a HPT's corresponding benchmark XTF portfolio. ***, **, and * indicate the one, five, and ten percent significance level of a paired, two-sided Wilcoxon test which was used to test statistical difference between the RDs according to the XTF- and default-strategy.

Table 63: Influence of transaction costs on investment outcomes
including an additional monthly reinvestment amount [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	sum of transaction costs [€]		cumulative VALUEpf until June 2017 [€]			cumulative return until June 2017 [%]		
			selling-/ purchase costs	accrued interest costs	including transaction costs	excluding transaction costs	difference in VALUEpf	including transaction costs	excluding transaction costs	difference in cumulative return
HPT 1	replacement-strategy	163,900	414	n.a.	191,441	191,928	487	11.68	11.98	0.30
	XTF-strategy [av.]		159	n.a.	184,704	184,882	178	7.57	7.68	0.11
	default-strategy [av.]		176	129	182,224	183,085	861	6.05	6.58	0.53
HPT 2	replacement-strategy	214,200	842	n.a.	265,160	266,184	1,024	19.87	20.35	0.48
	XTF-strategy [av.]		255	n.a.	243,232	243,492	261	9.63	9.75	0.12
	default-strategy [av.]		302	501	241,089	242,807	1,719	8.63	9.43	0.80
HPT 3	replacement-strategy	312,900	981	n.a.	422,105	423,448	1,343	32.22	32.65	0.43
	XTF-strategy [av.]		272	n.a.	399,753	400,066	313	25.07	25.17	0.10
	default-strategy [av.]		299	227	395,075	397,345	2,270	23.58	24.30	0.73

Notes: The left part of the table shows the initial VALUEpf by January 2014 and the sum of transaction costs that occur during the observation period (divided into selling-/purchase costs and accrued interest costs of BDs). Please note that selling-costs only occur in the replacement-strategy; accrued interest costs only emerge in the default-strategy, i.e., if a new BD is purchased. The middle part of the table reveals the cumulative VALUEpf at the end of the observation period in June 2017 (divided into VALUEpf including and excluding transaction costs as well as the difference between the latter). The right part of the table exhibits the characteristics of the middle part of the table in terms of returns. The values are presented for each HPT's benchmark XTF portfolio and as average [av.] of 1,000 HPT portfolios (nine risky securities per portfolio; including a monthly fixed amount of 200 Euro for reinvestments). Please note that while the monthly fixed amounts are included in cumulative VALUEpf, they are subtracted in cumulative returns (8,400 Euros on aggregate across the entire observation period). The subtraction does not affect the difference in cumulative returns.

Table 64: Characteristics of reinvestments including an additional monthly reinvestment amount [Jan. 2014 to June 2017]

	reinvestment-strategy	initial VALUEpf [€]	January 2014 to June 2017			number of risky securities in June 2017
			number of transactions	sum of reinvested amounts [€]	in [%] of initial VALUEpf	
HPT 1	replacement-strategy	163,900	19.0	171,604	104.70	2.0
	XTF-strategy [av.]		11.0	19,188	11.71	8.6
	default-strategy [av.]		11.9	22,501	13.73	16.5
HPT 2	replacement-strategy	214,200	19.0	221,476	103.40	2.0
	XTF-strategy [av.]		13.5	48,133	22.47	8.6
	default-strategy [av.]		14.8	60,715	28.34	18.2
HPT 3	replacement-strategy	312,900	18.0	320,038	102.28	2.0
	XTF-strategy [av.]		15.3	47,184	15.08	8.6
	default-strategy [av.]		16.3	54,002	17.26	20.6

Notes: This table exhibits the initial VALUEpf by January 2014, the number of transactions, and the sum of reinvested amounts in Euro and in percent of the initial VALUEpf for each HPT's benchmark XTF portfolio and 1,000 HPT portfolios as average [av.] (nine risky securities per portfolio; including a monthly fixed amount of 200 Euro for reinvestments). The table also reveals the number of individual risky securities per portfolio at the end of the observation period.