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Taring all Investors with the same Brush? Evidence for Heterogeneity in Individual Preferences from a Maximum Likelihood Approach

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Non-Technical Summary

Notable efforts have been made on the question of how individual investors in financial markets should handle their financial assets according to theory and how their trading actually differs from these models. The spectrum of implications drawn from theories on trading volume is vast and comprises extreme positions such as the famous No-Trade Theorem, according to which, in efficient markets and given a pool of homogeneous investors with rational expectations, investors cannot profit from trading as stocks offered for sale will not be bought by any counterparty. This contradicts the observation that individual investors engage in excessive trading and the empirical fact that bids are frequently matched with corresponding asks. Indeed, individual investors were found to be markedly heterogeneous in their personal and sociodemographic characteristics and, accordingly, in the formation of their subjective expectations which appears to be correlated with trading patterns such as the Disposition Effect and other trading strategies. However, heterogeneity in investors' expectations on market returns seems to add only partly to the overall question of why people trade in such huge amounts. Empirical evidence suggests that individual investors may not only differ with respect to their expectations but also in the structure of their risk preferences.

In order to shed some light on the questions of which preferences (in terms of microeconomic utility models) prevail in stock markets and by how much those preferences drive trading decisions of individual investors, we adopted, modified and applied a customized maximum likelihood approach on a randomly selected dataset of 656 private investors of a large German discount brokerage firm.

In concord with numerous studies on this topic, we find evidence that the majority of the investors in our dataset follow a trading pattern broadly reconcilable with Prospect Theory; but in contrast to those studies, we are not able to connect the utility-type classification to exogenous variables such as gender or age, thus concluding that the classification of a particular investor is independent. This implies that observable characteristics, used e.g. by financial advisors and serving as proxies for risk preferences, may not be the right instruments for this purpose.

Furthermore, we find some evidence that preferences seem to drive trading decisions by a moderate proportion although we fail to establish a link to most of the personal traits of the individual investors in our dataset.

TARING ALL INVESTORS WITH THE SAME BRUSH? EVIDENCE FOR HETEROGENEITY IN INDIVIDUAL PREFERENCES FROM A MAXIMUM LIKELIHOOD APPROACH

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Abstract. Microeconomic modeling of investors behavior in financial markets and its results crucially depends on assumptions about the mathematical shape of the underlying preference functions as well as their parameterizations. With the purpose to shed some light on the question, which preferences towards risky financial outcomes prevail in stock markets, we adopted and applied a maximum likelihood approach from the field of experimental economics on a randomly selected dataset of 656 private investors of a large German discount brokerage firm. According to our analysis we find evidence that the majority of these clients follow trading patterns in accordance with prospect theory (Kahneman and Tversky (1979)). We also find that observable sociodemographic and personal characteristics such as gender or age do not seem to correlate with specific preference types. Extended likelihood analysis indicates a moderate impact of preferences on trading decisions of individual investors, which increases if the underlying utility function is prospect theory. Regression analysis reveals that the impact of preferences on an investors' trading behavior is not connected to most personal characteristics, but seems to be related to round-trip length and the type of the utility function.

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1. Introduction

Notable efforts have been made to determine how individual investors in financial markets should handle their financial assets according to theory and how their trading actually differs from these models. The spectrum of implications drawn from theories on trading volume is vast and comprises extreme positions, such as the famous *no-trade theorem* (Aumann (1976), Milgrom and Stokey (1982), Tirole (1982)), according to which, in efficient markets and given a pool of homogeneous investors with rational expectations, investors cannot profit from trading because stocks offered for sale will not be bought by any counterparty. This argumentcontradicts the observation that individual investors engage in excessive trading (e.g., Odean (1999), Barber and Odean (2000)) and the fact that bids are frequently matched with corresponding asks. Karpoff (1987b) offered a solution by introducing heterogeneity at the investor level, leading to differences in opinion about the stock prices at which these investors are willing to commission purchase or sales orders, thus creating considerable trading volume (Wang (1994)). Indeed, besides high variations in expectations (Glaser and Weber (2007)), individual investors have been found to be markedly heterogeneous in their personal and sociodemographic characteristics, which appears to be correlated with trading patterns such as the disposition effect, the susceptibility to offload assets that gained in value while hesitating to sell assets whose value has recently depreciated (Shefrin and Statman (1985), Odean (1998), Grinblatt and Keloharju (2001b), Dhar and Zhu (2006), Kaustia (2010)). At the same time, individual investors show significant variability in their demand for positively skewed assets (Mitton and Vorkink (2007), Kumar and Goetzmann (2008), Kumar (2009b)), display high dispersion in the composition of their portfolios, usually tantamount to poor diversification (Kumar and Goetzmann (2008)), and reveal a significantly increased trading volume in bear markets as well as around price peaks (Cohen et al. (2002), Dhar and Kumar (2002), Hvidkjaer (2006)).

Heterogeneity in investors' expectations as proposed by Karpoff (1987b) seems to add only partly to the overall picture of why people trade in such huge amounts (DeBondt (1998)).[1] Empirical evidence suggests that individual investors may differ not only with respect to their expectations (e.g., Andreassen (1987), Patel et al. (1991), DeBondt (1993), DeBondt (1998)), but also in the structure of their risk preferences (e.g., Hey and Orme (1994), Harrison and Rutstrom (2009)) and risk aversion (for experimental evidence, see, e.g., Laury and Holt (2005); for evidence from financial markets, see, e.g., Ait-Sahalia and Lo (2000), Jackwerth (2000), Kliger and Levy (2002), Bliss and Panigirtzoglou (2004), Brunnermeier and Nagel (2008), Guiso and Paiella (2008), Chiappori and Paiella (2011)). Furthermore, from a theoretical perspective, attempts to reconcile observed high trading frequencies and extensive trading volumes with predictions from models on dynamic optimization using expected utility (EUT) have frequently failed (e.g., Bonaparte and Cooper (2010)). In contrast, replacing EUT in those dynamic models by alternative preferences—such as *rank-dependent utility* (RDU) (Quiggin (1982)), *prospect theory*, conceptualized by Kahneman and Tversky (1979), and *cumulative prospect theory* (CPT) as a refinement of the former (Tversky and Kahneman (1992))—theoretically unfolds considerable trading activity (Barberis and Xiong (2009), Barberis (2011), Ingersoll and Jin (2013)).

[1] Hirshleifer (2001) and Barber and Odean (2013) provided an overview of the ample evidence of the high trading volume of individual investors observed in experiments and empirical data.

With the purpose to shed light on which preferences (in terms of microeconomic utility models) prevail in stock markets and by how much those preferences drive the trading decisions of individual investors, we adopt, modify, and apply a customized maximum likelihood approach on a randomly selected dataset of 659 private investors from a large German discount brokerage firm. In concordance with numerous studies on this topic, we also find evidence that the majority of these investors follow a trading pattern broadly reconcilable with prospect theory (Kahneman and Tversky (1979)); however, in contrast to those studies, we are not able to connect the utility-type classification to exogenous variables such as gender and age, thus concluding that the classification of a particular investor is independent of personal and sociodemographic characteristics. Furthermore, we find evidence that preferences seem to drive trading decisions by a moderate proportion, but we also fail to establish a link to most of the personal traits of the individual investors in our dataset.

With respect to the structure of this paper, we briefly review the literature in Chapter 1 before presenting the econometric methodology in Chapter 2. Chapter 3 presents the results of a classification of 659 individual investors from a large German discount brokerage firm into various utility types, such as EUT (von Neumann and Morgenstern (1947)) and prospect theory (Kahneman and Tversky (1979), Tversky and Kahneman (1992)), and relates this classification to the investors' observable personal and sociodemographic characteristics. Chapter 4 addresses how much the trading behavior of these investors is governed by their preferences and how the impact of preferences is related to observable personal traits. We derive our conclusions in Chapter 5.

2. Investors' Preferences and Trading Behavior: Evidence from the Literature

Financial economists predominantly agree that individual investors' trading behavior differs from that of institutions, which are seen as informed and rational investors (Kaniel et al. (2008)). In contrast, individuals are often characterized as *noise traders* (Kyle (1985), Black (1986), DeLong et al. (1990), Campbell and Kyle (1993), Campbell et al. (1993), Llorente et al. (2002)), since individual investors have been found to trade on economically irrelevant factors (Kyle (1985), Black (1986)) such as past price patterns (Grinblatt and Keloharju (2001b), Garvey and Murphy (2004), Kaustia (2010)). Although noise trading has the potential to influence volatility (Andrade et al. (2008)), it requires correlation in trade directions to systematically affect market prices (Barber et al. (2009a), Lin and Hu (2010); see also Black (1986)) if the efficient market hypothesis holds. Research on individual investors has indicated that, besides noise, individual investors' trades contain systematic components (Kumar and Lee (2006), Dorn et al. (2008), Kaniel et al. (2008), Hvidkjaer (2008), Barber et al. (2009b)) such as similar preference structures within a group of investors, which, in turn, leads to the required correlated trading behavior.

Heterogeneity in individual preferences has been used to model trading volume (e.g., Berrada et al. (2007)) to investigate their role as potential causes of various observed trading patterns, such as individuals' reluctance to realize losses in contrast to gains, irrespective of portfolio adjustments and other plausible reasons (e.g., mean reversion) that could trigger a similar trade pattern (Shefrin and Statman (1985), Odean (1998), Grinblatt and Keloharju (2001b), Dhar and Zhu

(2006), Kaustia (2010)). Other studies find that individual investors systematically miss the merits of diversification (Kumar and Goetzmann (2008)), are attracted by stocks that can be characterized by low expected returns and highly positive skewness (Mitton and Vorkink (2007), Kumar and Goetzmann (2008), Kumar (2009b)), are drawn to more familiar investments (Barber and Odean (2008), Keloharju et al. (2012)), trade more after an increase in stock market prices (Cohen et al. (2002), Dhar and Kumar (2002), Hvidkjaer (2006)), and succumb to various cognitive traps that negatively affect their performance (e.g., DeBondt (1998), Barber and Odean (2000), Barber et al. (2009)). Empirical evidence suggests that these trading patterns, if emerging concurrently, have the potential to affect cross-sectional dependence in returns (for the impact of trading patterns, see, e.g., Grinblatt and Han (2005b), Han and Kumar (2010); for evidence on portfolio choice, see Kumar (2007)), variations in market volatility and prices (French (1980), Shiller (1981), Roll (1986), French and Roll (1986), Karpoff (1987a), Andreassen (1988), Gallant et al. (1992), Schwert (2002), Kumar and Lee (2006), Brandt et al. (2010), Foucault et al. (2011)), and even higher moments of the return distribution (Kraus and Litzenberger (1976), Mitton and Vorkink (2007), Barberis and Huang (2008)).

Early models on financial decision making, in which preferences are treated as a systematic and unobservable component, rely on EUT (von Neumann and Morgenstern (1947)), usually combined with the assumption of a homogeneous pool of investors. In particular, a classical (and still widely held) consensus is the notion that investors exhibit decreasing absolute risk aversion (DARA) and constant relative risk aversion (CRRA) as introduced by Arrow (1971).[2] This view seems to be supported by empirical studies (Gordon et al. (1972), Friend and Blume (1975), Blume and Friend (1975), Schlarbaum et al. (1975), Kroll et al. (1988), Landskroner (1988), Levy (1994), Brunnermeier and Nagel (2008), Guiso and Paiella (2008), Chiappori and Paiella (2011); for DARA, see Morin and Suarez (1983)), as well as the field of evolutionary finance, which conjectures that financial markets, if seen as coherent entities, should be characterized by a pool of homogeneous investors with logarithmic utility as a result of certain survival processes (Latane (1959), Blume and Easley (1992), Sinn (2003)). Accordingly, research on utility functions in finance and asset pricing focuses mostly on the risk aversion coefficient of a prespecified utility function (e.g., Ait-Sahalia and Lo (2000), Jackwerth (2000), Kliger and Levy (2002), Bliss and Panigirtzoglou (2004)) to recover risk aversion from observed asset prices (Cuoco and Zapatero (2000)), although the picture of a *representative* investor, characterized by a unique utility function, seems questionable (e.g., Wang (1994), Blackburn and Ukhov (2006), Bruhin et al. (2007), Harrison and Rutstrom (2009)).

[2]Arrow (1971), p. 96 mentioned that DARA emerges as a natural fact and seems to be supported by everyday observations. The author's preference for increasing relative risk aversion and the conclusion that relative risk aversion hovers around unity, though, is based on the required boundedness of the utility function and, thus, on purely theoretical grounds. It is worth noting that logarithmic utility, frequently assumed in financial studies (and championed by its proponents Latane (1959), Hakansson (1971), and Markowitz (1976)), is unbounded and serves as an approximation of $U(W)$ but implies CRRA. As far as we know, one of the earliest attempts to characterize the behavior of $U(W)$ with respect to changes in wealth was by Bernoulli (1954) argumentatively supporting a logarithmic form of $U(W)$. The author noted that *...any increase in wealth [...] will always result in an increase in utility that is inversely proportionate to the quantity of goods already possessed...* (Bernoulli (1954), §5), meaning $\partial U(W)/\partial W = W^{-1}$, which corresponds to $U(W) = log(W)$.

Another criticism is the fact that the literature came up quite early on with notable exceptions to the general notion according to which investors are generally risk averse (Friedman and Savage (1948), Markowitz (1952), Kahneman and Tversky (1979), Tversky and Kahneman (1992)) and act in accordance with axiomatic consistency (for early references, see Preston and Baratta (1948), Allais (1953), Edwards (1953), Edwards (1954)).[3] Subsequent studies that address various shortcomings of EUT theory in an attempt to reconcile empirical evidence with theoretical predictions prompted the development of generalized EUT theories (e.g., Edwards (1962), Karmarkar (1978), Karmarkar (1979), Quiggin (1982), Yaari (1987), Wakker (1994)), which involves modifications of the linearity feature of the expectations operator via transforming probability weights. Another direction of research modified the utility functional itself and led to the creation of *utility-of-income* models (Friedman and Savage (1948), Markowitz (1952), Yaari (1965), Kahneman and Tversky (1979), Hershey and Schoemaker (1980)) to explain simultaneous demand for gambling and insurance.[4] The fact that a modification of the utility function or the expectation operator alone cannot account for many empirical features led Kahneman and Tversky (1979) and Tversky and Kahneman (1992) to propose *prospect theory* as a descriptive non-EUT theory that combines both strands of research in a unified model. At the same time, this debate has been enriched by conclusions drawn from empirical evidence (e.g., Tversky and Kahneman (1991), Tversky and Kahneman (1992), Rabin (2000), Rabin and Thaler (2001)) indicating that individuals are more averse toward losses than they are apt to enjoy gains of equal magnitude (for a survey, see Wakker (2010)).

Alternative preferences and generalized EUT models have received some support from experimental studies (e.g., Lattimore et al. (1992), Hey and Orme (1994), Abdellaoui (2000)), with results mostly consistent with an inverse S-shaped probability weighting function (Wu and Gonzalez (1996), Wu and Gonzalez (1999), Abdellaoui (2000), Bleichrodt and Pinto (2000), Abdellaoui et al. (2005)) and, moreover, consistent with a concave value function in the domain of gains, backed in recent studies that deal with the best-fitting shape (for contradictory evidence, see, e.g., Blondel (2002), Stott (2006), Wakker (2008), Levy and Levy (2002); see also Wakker (2003)). The properties of diminishing sensitivity toward variations were confirmed by Wakker and Deneffe (1996), Fox and Tversky (1998), and Fennema and van Assen (1999). In finance, however, the facts are less clear, although alternative utility

[3]Furthermore, classical utility functions such as CRRA have been questioned lately at a different level of argumentation, particularly due to their inability to provide satisfying explanations for several puzzles regarding market risk premiums and stock market participation (for a discussion of theoretically justified risk aversion coefficients, see Kocherlakota (1996)). Mehra and Prescott (1985) argued that, if the equilibrium price in terms of returns on the stock market is calculated using the most simplistic model, as proposed by Lucas (1978), calibrated with historical US data, the historical average return in the US stock market appears to be too high to be compatible with common assumptions about risk aversion in finance (for a brief overview, see Gollier (2001)). Goetzman and Ibbotson (2005) and Mehra (2008) provided compressed reviews on the equity premium puzzle and more explanations. For instance, Mankiw and Zeldes (1991) addressed the extent of CRRA using a dynamic consumption approach and found $R(W)$ to be near 26. Even higher values were found by Blake (1996), using data drawn from the Financial Research Survey on households and their portfolio allocation decisions, assuming that households portfolio decisions are subject to a power function. The author's findings point to high coefficients of relative risk aversion, between eight and 47, with further evidence of DRRA. See also Rabin (2000) for a critical review on risk aversion parameterizations.

[4]Although there is ample experimental evidence that individuals do not treat probabilities linearly, Hakansson (1970) showed that the notion of risk aversion can be consistent with Friedman–Savage utility, even in the absence of decision weights, thus leaving the expectation operator unchanged.

models, such as prospect theory, that have been frequently proposed to explain various trading patterns—particularly as evidence for prospect theory from experimental economics—seems compelling (e.g., Currim and Sarin (1989), Camerer and Ho (1994), Hey and Orme (1994), Fennema and Wakker (1997), Loomes et al. (2002), Wu et al. (2005)), despite prospect theory being far from a definitive theory (Birnbaum et al. (1999), Starmer (2000)). For example, the theoretical and empirical literature hints at a relation between prospect theory and various phenomena such as portfolio choice behavior (Berkelaar et al. (2004), Gomes (2005), Polkovnichenko (2005), Jin and Zhou (2008), Bernard and Ghossoub (2010), He and Zhou (2011)) or particular trading patterns, among which perhaps the most intuitive but recently highly disputed link between prospect theory and trading patterns has been seen in the so-called *disposition effect*, initially coined by Shefrin and Statman (1985) and confirmed in countless empirical findings and numerous settings (Ferris et al. (1988), Odean (1998)).[5] The application of prospect theory in financial markets not only has implications for asset pricing (Benartzi and Thaler (1995), Barberis and Huang (2001), Barberis et al. (2001); for an overview, see Shefrin (2008)), but also sets the stage for explaining the presence of equity premium (Benartzi and Thaler (1995)), excess stock return volatility (Barberis et al. (2001)), overinsurance (Cutler and Zeckhauser (2004)), stock market momentum (Grinblatt and Han (2005b), Grinblatt and Han (2005a)), as well as its implications on market liquidity (Pasquariello (2008)), return forecasts (Barberis and Huang (2001)), the underperformance of initial public offerings (Green and Hwang (2011)), the observed low mean returns of lottery-like stocks (Polkovnichenko (2005), Kumar and Goetzmann (2008); notably, see Barberis and Huang (2008), Kumar (2009b)), and herding behavior in stock markets (Lin and Hu (2010)).

Traditional studies matching the best-fitting preference representation to observed aggregate behavior frequently draw upon the concept of a representative investor, ignoring that investors can vary in their preference functions and differ in their individual degree of risk aversion. Outside of the representative investor framework, heterogeneity in preferences is usually modeled as a distribution in risk aversion parameters given a particular class of utility function (e.g., Kliger and Levy (2002), Kliger and Levy (2009), von Gaudecker et al. (2009); for prospect theory, see Dimmock and Kouwenberg (2010) and Hwang and Satchell (2011)), although first attempts have been made to widen the spectrum to allow various kinds of different utility functions to coexist in the same market, as suggested by Bruhin et al. (2007), Harrison and Rutstrom (2009), Easley and Yang (2011), and Wahal and Yavuz (2013a), to capture evidence for heterogeneity in preferences (Hey and

[5]The suggestion that the disposition effect is engendered by differences in the values attached to potential gains and losses was introduced by Shefrin and Statman (1985) and has led subsequent studies to cite prospect theory as the main if not only driver of the disposition effect (Weber and Camerer (1998), Odean (1998), Garvey and Murphy (2004), Jordan and Diltz (2004), Lehenkari and Perttunen (2004), Frazzini (2006), Dhar and Zhu (2006), Kaustia (2010), Vlcek and Hens (2011)). If individual preferences follow the predictions of prospect theory, phenomena such as the disposition effect should also be observable in other environments. In fact, evidence of the disposition effect has been found among individual investors in the stock market (e.g., Schlarbaum et al. (1978a), Odean (1998), Odean (1999)), in the financial advice of stock brokers (Shapira and Venezia (2001)), in the behavior of future trades (Heisler (1994), Frino et al. (2004), Coval and Shumway (2005), Locke and Mann (2005)), in initial public offering trading volumes (Kaustia (2004a)), in real estate markets (Genesove and Mayer (2001)), in insurance contracts (e.g., Schoemaker and Kunreuther (1979), Camerer and Kunreuther (1989)), and in risk behavior observed in laboratory environments for stocks (Weber and Camerer (1998), Oehler et al. (2003), Lee et al. (2008)) and monetary endowments (for a comprehensive survey of the literature, see Chui (2001), Barberis (2013)).

Orme (1994), Barsky et al. (2002), Blackburn and Ukhov (2006), Choi et al. (2007), Chiappori et al. (2009)) and to understand the various different ways individual investors trade financial assets (Odean (1998)). Empirical studies on this subject seem to support this latest strand of literature, as they have found pronounced diversity in trading behavior and strategies at the individual level (Grinblatt and Keloharju (2001b), Shapira and Venezia (2001), Chui (2001), Garvey and Murphy (2004), Feng and Seasholes (2005), Dhar and Zhu (2006), Goetzmann and Massa (2008), Kumar (2009a), Wahal and Yavuz (2013b)). To calibrate such theoretical models that successfully incorporate utility function heterogeneity, the fraction of each utility type needs to be efficiently determined and estimated based on a relevant dataset, for which the model was designed. In the next section, we introduce such an estimation method and dataset for which we exemplarily unravel the underlying utility functions and try to answer some of the questions mentioned above.

3. How to Identify Individual Investors' Preferences

The empirical and theoretical studies presented in the previous section provide a multifaceted picture when it comes which utility functions prevail in financial markets. These articles are based on various methods and datasets and are thus difficult to compare directly and provide results that are virtually impossible to reconcile. Furthermore, most studies frequently simplify matters substantially by assuming the existence of a representative investor or a homogeneous pool of traders, although, due to its defect in allowing for heterogeneity, this assumption seems empirically questionable. For example, articles in the area of empirical asset pricing particularly favor EUT (e.g., Latane (1959), Hakansson (1971), Blume and Friend (1975), Friend and Blume (1975), Schlarbaum et al. (1975), Markowitz (1976), Morin and Suarez (1983), Landskroner (1988), Blume and Easley (1992), Ait-Sahalia and Lo (2000), Jackwerth (2000), Kliger and Levy (2002), Bliss and Panigirtzoglou (2004), Brunnermeier and Nagel (2008), Guiso and Paiella (2008), Chiappori and Paiella (2011)), probably due to its convenient technical properties and the inherent consistency of its results. Evidence based on trading data, in contrast, predominantly advocates alternative utility models such as prospect theory or regret aversion models, backed by conclusions frequently derived from argumentation based on intuition rather than from statistically valid investigation (e.g., Weber and Camerer (1998), Odean (1998), Garvey and Murphy (2004), Jordan and Diltz (2004), Lehenkari and Perttunen (2004), Frazzini (2006), Dhar and Zhu (2006)).

In the quest to understand the behavior of their participants, to distinguish systematic factors from random effects, and, finally, to circumvent dubious assumptions concerning homogeneity among individuals, experimental economists developed various discrete choice models and customized maximum likelihood methods, thus providing the econometric toolbox needed to answer the question of the best-fitting utility function (e.g., see Hey and Orme (1994) and particularly Orme (1995)). It is a natural conclusion to combine both strands of the literature for our purpose and to account for the specific particularities of datasets containing trading records similar to those used by Odean (1998), for example, generated by the way investors obtain estimates to approximate uncertain financial outcomes (Andreassen and Kraus (1990), Greenwood (2014)) and by tracking accrued returns through time. In this section, we sketch an adapted customized maximum likelihood approach similar to those proposed by Hey and Orme (1994), Harrison and Rutstrom (2008), and de Palma et al. (2008) where we explicate the adjustments made to deal with deficiencies of the likelihood function that could have an impact on utility model selection and which must be made before applying this customized maximum likelihood approach to financial data.

In financial markets, investment decisions are usually characterized by their sequential nature and the implicit option to revise previous decisions with time. These features permit decisions to be treated as a sequence of single decisions and the underlying investment process to be modeled as a dynamic optimization problem. For classical preference models such as EUT, this approach works fine, but it reaches its limits if one tries to find time-consistent solutions for alternative utility functions (Nielssen and Jaffray (2004), Barberis (2011), Ebert and Strack (2012); for surveys, see also Eckstein and Wolpin (1989), Rust (1994), Adda and Cooper (2003)). Despite this tendency to apply dynamic programming to identify optimal trading strategies, empirical evidence suggests that the observed trading behavior of individual investors seems more comparable with discrete (and myopic) decision processes (Rust (1992), Gneezy and Potters (1997), Thaler et al. (1997)), although notable exceptions exist (Normandin and St-Amour (2008)).

The myopic nature of the investor's decision process implies that an investor's decision to trade a stock is based on differences in utilities from the stock as a representation of a risky asset on a particular day t, denoted $V_{k,i}(W_{t,i}, R_{S,t}|\boldsymbol{\theta}_{k,i})$, and the utility from a risk-free asset, denoted $V_{k,i}(W_{t,i}, R_{f,t}|\boldsymbol{\theta}_{k,i})$, where the difference in utilities is denoted $\Delta_{t,i}(U_{k,i}|\boldsymbol{\theta_{k,i}})$, which is in line with recent studies (e.g., Kaustia (2004b), Kaustia (2010), Vlcek and Hens (2011). We drop the index i for simplicity whenever possible, keeping in mind that all calculations are performed at the investor level. Herein, the gross return of a risk-free investment is typically approximated by a money market account and denoted $R_{f,t}$, given a parameter set $\boldsymbol{\theta}_k$ to represent the utility-specific parameters of utility model type k and a wealth level W_t as evaluated on day t. In contrast, the utility resulting from the risky asset $V_k(W_t, R_{S,t}|\boldsymbol{\theta}_k)$, comprises a set of market parameters $R_{S,t}$ stemming from a risky asset, namely, a common stock, with S denoting the state of nature.[6] Since changes in preferences or market parameters embedded in the respective utility function contribute only partly to purchase or sales decisions, models of discrete choice usually contain an investor-specific, additively separable stochastic component ϵ_i to introduce a certain bluntness to the decision process (Train (1986), Train (2009), Rust (1994)). It is important to note that this component accounts for the fact that only a fraction of attributes for these decisions are observable and thus avoids the necessity to explicitly model other (potentially unobservable) variables or data imperfections (Cramer (1986), Rust (1994)), which allows a further decomposition $V_k(W_t, R_{S,t}|\boldsymbol{\theta}_k) = U_k(W_t, R_{S,t}|\boldsymbol{\theta}_k) + \epsilon_i$, where $U_k(W_t, R_{S,t}|\boldsymbol{\theta}_k)$ denotes the functional form of a utility model of type k.

To restrict the set of utility functions that specify $\Delta_t(U_k|\boldsymbol{\theta_k})$, we focus primarily on those preferences mentioned by the studies presented above, particularly EUT, as commonly found in texts on asset pricing (e.g., Duffie (2001), Gollier (2001), Back (2012), Munk (2013)) and in empirical studies (Morin and Suarez (1983), Landskroner (1988), Blume and Easley (1992), Levy (1994), Ait-Sahalia and Lo (2000), Jackwerth (2000), Kliger and Levy (2002), Bliss and Panigirtzoglou (2004),

[6] It should be noted that, although dynamic discrete choice models such as the multinomial probit model are difficult to estimate (Rust (1994)), methods such as the maximum simulated likelihood method (Train (1986), Train (2009)), certain approximations (Horowitz et al. (1982)), and alternative estimation methods (Magnac and Thesmar (2002)) have been proposed to circumvent evaluation of the multinomial probit function.

TABLE 1. Description of a Set of Preference Parameters $\boldsymbol{\theta_k}$

This table describes the parameter set $\boldsymbol{\theta_k}$. Expected utility models are denoted EUT and rank-dependent utility is denoted RDU. For simple prospect theory (Tversky and Kahneman (1992)) we use the notation SPT, whereas cumulative prospect theory (Tversky and Kahneman (1992)) is denoted CPT. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions (Saha (1993)). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals, where, in addition, $DHG0$ denotes value functionals as defined by DeGiorgi and Hens (2006).

$U_k(W_t, R_{S,t}\|\boldsymbol{\theta_k})$		Set $\boldsymbol{\theta_k}$	Interpretation	Key Reference
EUT	**CRRA**	α	Risk Aversion	Gollier (2001)
	EXPO	α	Risk Aversion	Saha (1993)
		ρ	Scaling Parameter	Saha et al. (1994)
RDU	**CRRA**	α	Risk Aversion	Quiggin (1982), Quiggin (1993)
		γ	Weighting Parameter	Quiggin (1982), Tversky and Kahneman (1992)
	EXPO	α	Risk Aversion	Saha (1993)
		ρ	Scaling Parameter	Saha et al. (1994)
		γ	Weighting Parameter	Quiggin (1982)
SPT	**CRRA**	α	Risk Sensitivity	Gomes (2005)
		λ	Loss Aversion	Kahneman and Tversky (1991)
		γ	Weighting Parameter	Quiggin (1982), Tversky and Kahneman (1992)
	POWR	α	Risk Sensitivity	Kahneman and Tversky (1979)
		λ	Loss Aversion	Kahneman and Tversky (1991)
		γ	Weighting Parameter	Quiggin (1982), Tversky and Kahneman (1992)
	DGH0	$\alpha^{\pm}$, $\lambda^{\pm}$	Scaling Parameter	DeGiorgi and Hens (2006)
		γ	Weighting Parameter	Quiggin (1982), Tversky and Kahneman (1992)
CPT	**CRRA**	α	Risk Sensitivity	Gomes (2005)
		λ	Loss Aversion	Kahneman and Tversky (1991)
		γ	Weighting Parameter	Quiggin (1982), Tversky and Kahneman (1992)
	POWR	α	Risk Sensitivity	Tversky and Kahneman (1992)
		λ	Loss Aversion	Kahneman and Tversky (1991)
		γ	Weighting Parameter	Quiggin (1982), Tversky and Kahneman (1992)
	DGH0	$\alpha^{\pm}$, $\lambda^{\pm}$	Scaling Parameters	DeGiorgi and Hens (2006)
		γ	Weighting Parameter	Quiggin (1982), Tversky and Kahneman (1992)

Brunnermeier and Nagel (2008), Guiso and Paiella (2008), Chiappori and Paiella (2011)). We also model $\Delta_t(U_k|\boldsymbol{\theta_k})$ using various versions of the generalization of EUT as proposed by Quiggin (1982), Quiggin (1993) and Wakker (1994) with combinations of selected features. To acknowledge the recent stream of literature on behavioral finance, we also capture models of alternative utility such as those of Kahneman and Tversky (1979) and Tversky and Kahneman (1992). We provide an overview of the parameter set $\boldsymbol{\theta_k}$ in Table 1 and enlist the various utility functions used in our analysis to populate $\Delta_t(U_k|\boldsymbol{\theta_k})$ in Table 2. For further details, see the appendix.

To specify the set of financial payoffs, we assume that a money market account approximates the riskless asset, which yields a known riskless gross return of $R_{f,t}$. Since it is common practice in experimental studies to model risky outcomes as lotteries, the stochastic price of the risky asset—essentially any stock traded by the investor over the respective period—is assumed to be characterized by a binomial process (Cox et al. (1979), Rendleman and Bartter (1979), Hull and White (1988)) in which two disjoint states S of the world can be identified, yielding a gross return of $R_{S,t}$. Arguments for the outcomes of the lotteries used for $\Delta_t(U_k|\boldsymbol{\theta_k})$ are estimated from this binomial process, where, in the upside state U, associated with some unknown physical probability $p_t > 0$ and where t indicates a particular day, the stock price rises and yields an upside return $R_{U,t} > 1$, whereas, in the downside state D with corresponding probability $1 - p_t$, the stock declines, generating a downside return $0 \leq R_{D,t} < 1$. The binomial model was originally constructed under the assumption of equally likely upward and downward movements in stock prices, which seems hardly justified for empirical time series of stocks. Empirical

TABLE 2. Utility Models Used as Arguments in the Likelihood Function $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$

This table lists the relevant utility models used in this study and explains their mathematical structure. Expected utility models are denoted *EUT* and rank-dependent utility is denoted *RDU*. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation *SPT*, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted *CPT*. Decision weights for weighting functions according to Quiggin (1982) are denoted *QU*82 and *KT*92 denotes decision weights as defined by Tversky and Kahneman (1992). For those utility models where no decision weights are applicable, we use the term *None* . Furthermore, we use the notation *CRRA* for utility functionals with constant relative risk aversion and *EXPO* to denote exponential power utility functions according to Saha (1993). For *SPT* and *CPT*, we use the notation *POWR* to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, *DHG*0 denotes a value functional as defined by DeGiorgi and Hens (2006). For *SPT* and *CPT*, we denote the reference points as W_{RP}.

			Utility Model Structure $U_k(W_t, R_{S,t}\|\boldsymbol{\theta}_k)$	**Utility/ Value Function** $u_k(W_t\|\boldsymbol{\theta}_k)$	**Weighting Function** $\omega(\hat{p}_{j,t}\|\boldsymbol{\theta}_k)$
EUT	**CRRA**	**None**	$= \sum_{j=1}^{t+1} \hat{p}_{j,t} u_{EUT}(W_t\|\boldsymbol{\theta}_{EUT})$	$= (W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1})^{1-\delta}(1-\delta)^{-1}$	not applicable
	EXPO	**None**		$= 1 - e^{-\rho (W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1})^{1-\delta}} \rho^{-1}$	not applicable
RDU	**CRRA**	**QU82**	$= \sum_{j=1}^{t+1} \pi_{j,t}(\Delta\omega(\hat{p}_{j,t}\|\boldsymbol{\theta}_{RDU})) u_{RDU}(W_t\|\boldsymbol{\theta}_{RDU})$	$= (W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1})^{1-\delta}(1-\delta)^{-1}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92	where		$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$
	EXPO	**QU82**	$\pi_{j,t} = \omega\left(\left(\sum_{k=j}^{t+1} \hat{p}_{k,t}\right) - \left(\sum_{k=j+1}^{t+1} \hat{p}_{k,t}\right)\right) \forall j$	$= 1 - e^{-\rho (W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1})^{1-\delta}} \rho^{-1}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92	$\pi_{j,t} = \omega\left(\hat{p}_{t+1,t}\right)$ if $j = t+1$		$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$
SPT	**CRRA**	**QU82**	$= \sum_{j=1}^{t+1} \pi_{j,t}(\omega(\hat{p}_{j,t}\|\boldsymbol{\theta}_{SPT})) u_{SPT}(W_t, W_{RP}\|\boldsymbol{\theta}_{SPT})$	$= (W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1} - W_{RP})^{1-\delta}(1-\delta)^{-1}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92			$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$
	POWR	**QU82**	where	$= \lambda^{I[\Delta W_t < 0]}(\|W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1} - W_{RP}\|)^{\alpha}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92	$\pi_{j,t} = \omega\left(\left(\sum_{k=j}^{t+1} \hat{p}_{k,t}\right)\right) - \omega\left(\left(\sum_{k=j+1}^{t+1} \hat{p}_{k,t}\right)\right) \forall j$		$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$
	DGH0	**QU82**		$= \mp\lambda^{\pm} e^{\mp\alpha(W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1} - W_{RP})} \pm \lambda^{\pm}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92			$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$
CPT	**CRRA**	**QU82**	$= \sum_{j=1}^{t+1} \pi_{j,t}(\Delta\omega(\hat{p}_{j,t}\|\boldsymbol{\theta}_{CPT})) u_{CPT}(W_t, W_{RP}\|\boldsymbol{\theta}_{CPT})$	$= (W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1})^{1-\delta}(1-\delta)^{-1}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92			$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$
	POWR	**QU82**	where for $\bar{j}$ denoting the break even node	$= \lambda^{I[\Delta W_t < 0]}(\|W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1} - W_{RP}\|)^{\alpha}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92	$\pi_{j,t} = \omega\left(\sum_{k=1}^{\bar{j}} \hat{p}_{k,t}\right) - \omega\left(\sum_{k=1}^{\bar{j}-1} \hat{p}_{k,t}\right) \forall j < \lfloor\bar{j}\rfloor$		$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$
	DGH0	**QU82**	$\pi_{j,t} = \omega\left(\hat{p}_{1,t}\right)$ if $j = 1$	$= \mp\lambda^{\pm} e^{\mp\alpha(W_t \hat{R}_{U,t}^{t-j+1} \hat{R}_{D,t}^{j-1} - W_{RP})} \pm \lambda^{\pm}$	$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-1}$
		KT92	$\pi_{j,t} = \omega\left(\sum_{k=\bar{j}}^{t+1} \hat{p}_{k,t}\right) - \omega\left(\sum_{k=\bar{j}+1}^{t+1} \hat{p}_{k,t}\right) \forall j > \lfloor\bar{j}\rfloor$ $\pi_{j,t} = \omega\left(\hat{p}_{t+1,t}\right)$ if $j = t+1$		$= \hat{p}_{j,t}^{\gamma}(\hat{p}_{j,t}^{\gamma} + (1-\hat{p}_{j,t})^{\gamma})^{-\frac{1}{\gamma}}$

studies on return characteristics provide ample evidence that the distributions of logarithmic returns are far from symmetric or approximately normally distributed, since persistent excess skewness has been detected (e.g., Kon (1984), Singleton and Wingender (1986), Aggarwal and Rao (1990), Turner and Weigel (1992), Harvey and Siddique (2000), Smith (2007)) that seems to relate positively with investor preferences for high but rare realizations of returns (Mitton and Vorkink (2007), Kumar and Goetzmann (2008), Kumar (2009b)). In the binomial process, this non-normality of log returns can be incorporated via a skewness parameter, denoted Γ_t, serving as an argument in the specification of p_t. To derive financial outcomes that enter $\Delta_t(U_k|\boldsymbol{\theta_k})$ as arguments, we assume that the stock prices evolve according to a binomial process for which we need to estimate the market parameters based upon the return for each security contained in the portfolio of each individual investor. Given the presentation of the time series of stock prices of the online brokerage firm, we use a rolling-window estimation for the time series of each stock given the brokers' default setting of the look-back horizon l to obtain estimates of the stocks' respective mean $\hat{\mu}_t$ and volatility $\hat{\sigma}_t$. From these time series, we furthermore infer the upside probabilities $\hat{p}_t$ and upside and downside returns, denoted $\hat{R}_{U,t}$ and $\hat{R}_{D,t}$, respectively, which are matched with the skewness of the respective stock, $\hat{\Gamma}_t$.[7] We provide further details of the estimation of the required market parameters in the appendix.

Given the stochastic properties of an investor-specific error term ϵ_i from which the respective conditional choice probabilities can be obtained, the required likelihood function of an investor i, denoted $L(\Delta_{t,i}(U_{k,i}|\boldsymbol{\theta_{k,i}}))$, can be derived.[8] For the remainder of this paper, we drop the index i for simplicity whenever possible (except for the error term itself) but need to keep in mind that all calculations are performed at the investor level. To specify the stochastic properties of the error term needed to construct $L(\Delta_t(U_k|\boldsymbol{\theta_k}))$, we follow Hey and Orme (1994) and Carbone and Hey (2000) and assume ϵ_i to be normally distributed, $\epsilon_i \sim N(0, \sigma_i^2)$, with a density $\phi(\epsilon_i) = (2\pi\sigma_i^2)^{-\frac{1}{2}} e^{-\frac{1}{2}(\epsilon_i/\sigma_i)^2}$, since those other components and factors that could drive the investment decisions of individual investors are assumed to be unsystematic with respect to utility $U_k(W_t, R_{S,t}|\boldsymbol{\theta}_k)$.[9] To customize the discrete choice model and to derive the respective choice probabilities given $\Delta_t(U_k|\boldsymbol{\theta_k})$, we introduce a buy-or-hold index $I_{k,t} := I[\Delta_t(U_k|\boldsymbol{\theta_k}) + \epsilon_i \geq 0]$ that is assumed to be one if the condition in brackets is met and zero otherwise. Therefore, the probability

[7] Note that another way to obtain $\hat{p}_t$ is to follow the study of Weber and Camerer (1998), in which individual investors infer $\hat{p}_t$ by averaging observed upticks and downticks, given the investors observe a change in prices, since the true probability p of the underlying binomial process is unknown.

[8] As a minor technicality, based on the predictability of $R_{f,t}$ and the fact that the utility of the risk-free money market account carries no uncertainty (at least in the short run), we assume that the investor-specific error is zero for payoffs generated by the risk-free asset. This avoids the necessity of evaluating all the elements of the covariance matrix of errors (Train (2009)).

[9] Other distributional assumptions can be made, such as those of Harless and Camerer (1994), Hey and Orme (1994), and Loomes and Sugden (1995); Booij et al. (2010) for lognormal distributed error terms; and Harrison and Rutstrom (2008) and Train (2009) for logistically distributed errors. We refer to Ballinger and Wilcox (1997) for a discussion of Cauchy and Laplace distributed errors. Note that different specifications of ϵ_i could affect the selection of the best-fitting utility model (e.g., see Wilcox (2008) for a discussion of the selection implications if ϵ_i is assumed to follow an extreme value distribution as sketched by Train (1986)).

of buying or holding the risky asset is defined as

$$\begin{aligned} p(\Delta_t(U_k|\boldsymbol{\theta_k}) \geq 0) &= \int_{-\infty}^{\infty} I[\Delta_t(U_k|\boldsymbol{\theta_k}) + \epsilon_i > 0]\phi(\epsilon_i)d\epsilon_i \\ &= \int_{-\infty}^{\frac{\Delta_t(U_k|\boldsymbol{\theta_k})}{\sigma_i}} \phi(\epsilon_i)d\epsilon_i \;=\; \Phi\left(\Delta_t(U_k|\boldsymbol{\theta_k})/\sigma_i\right). \end{aligned} \tag{3.1}$$

Thus, based on the normal distribution of ϵ_i, we denote the conditional choice probability of holding the stock as $\Phi\left(\Delta_t(U_k|\boldsymbol{\theta_k})/\sigma_i\right)$ and the probability of investing in the riskless asset as $1 - \Phi\left(\Delta_t(U_k|\boldsymbol{\theta_k})/\sigma_i\right) = \Phi\left(-\Delta_t(U_k|\boldsymbol{\theta_k})/\sigma_i\right)$, where Φ denotes the cumulative normal density function. For ease of handling these conditional choice probabilities, we aggregate both probabilities in a single variable, $p_{I_{k,t}}$. Note that the choice probabilities satisfy the conditions if stocks generate an infinite stream of utility (e.g., $\Delta_t(U_k|\boldsymbol{\theta_k}) \to \infty$), the choice probability of holding the stock converges to unity, implying that the investor almost surely favors holding the stock, and it approaches zero if $\Delta_t(U_k|\boldsymbol{\theta_k}) \to -\infty$ otherwise (Rust (1994)). Consequently, the binary choice feature of the discrete choice setting combined with the normal distribution of the error term allows us to construct a customized likelihood function $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ similar to that of Hey and Orme (1994), Harrison and Rutstrom (2008), and de Palma et al. (2008), representing a nonlinear probit model (Marschak (1960), Amemiya (1975), Amemiya (1981), Amemiya (1985), McFadden (1980), Train (1986), Train (2009), Ben-Akiva and Lerman (1985)). The overall logarithmized likelihood function of an investor i of utility type k can be accordingly expressed as

$$\log L(\Delta_t(U_k|\boldsymbol{\theta_k})) = \sum_{t \in T} \sum_{I \in I_{k,t}} I_{k,t} \log p_{I_{k,t}}(\Delta_t(U_k|\boldsymbol{\theta_k})), \tag{3.2}$$

in which $p_{I_{k,t}}(\Delta_t(U_k|\boldsymbol{\theta_k}))$ denotes the respective conditional probabilities as defined above.[10]

To identify the best-fitting underlying utility function of type k, we hark back to insights from likelihood theory, according to which the selection of the utility model that explains observed data the best should be based on the maximized likelihood value of each model k (Kullback (1968), Akaike (1973), Schwarz (1978), Amemiya (1980), Pawitan (2001), Burnham and Anderson (2002), Burnham and Anderson (2004)).[11] Application of the "pure" value of the maximized likelihood function $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ as a model selection criterion is usually not recommended, since the maximized likelihood function could be subject to overfitting, tendentially favoring multiparameter utility models (Carbone and Hey (1994), Carbone and Hey (1995), Hey and Orme (1994), Stott (2006)). Instead, the literature on model selection suggests sorting utility models according to the *Akaike information criterion* (AIC), which controls explicitly for varying numbers of parameters instead of using the maximized $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ (Akaike (1973), Akaike (1974), Bozdogan (2000), Pawitan (2001), Burnham and Anderson (2004)). The AIC is commonly expressed as

$$AIC = -\frac{2\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))}{nt} + \frac{2K_k}{nt}, \tag{3.3}$$

[10]Note that, given the binary choice assumption, the log-likelihood function can be explicitly written in a binomial form, as done by Harrison and Rutstrom (2008).

[11]Early studies such as those of Fisher (1922), Fisher (1956), and Kullback (1968) concluded that the maximized likelihood function $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ not only allows one to estimate the elements of $\hat{\boldsymbol{\theta}}_k$, but also reflects the information content of each model k and thus offers the opportunity to identify the best-fitting utility model among all k utility models.

according to Akaike (1974) in the representation of Amemiya (1980), where dividing by nt, the number of observations in terms of trading days t and traded stocks n, corrects for the different number of observations and where K_k denotes the rank of $\boldsymbol{\theta_k}$, the number of parameters to be estimated in utility model k. To take into account the varying sample size (particularly as our dataset contains portfolios with short trading histories and very few stocks) and the general finiteness of our dataset, we apply the *corrected AIC* (AICC), defined by

$$AICC = -\frac{2\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))}{nt} + \frac{2K_k}{nt} + \frac{2K_k(K_k+1)}{nt(nt-K_k-1)}, \tag{3.4}$$

as first proposed by Sugiura (1978) for ordinary least squares (OLS) regressions and suggested by Hurvich and Tsai (1989), McQuarrie and Tsai (1998), and Brockwell and Davis (2009) for time series model selection (for a discussion of the original version of the AIC and AICC as model selection criteria, see Burnham and Anderson (2002), Burnham and Anderson (2004)), which replaces the penalty term of the AIC by its exact term for bias adjustment, resulting in a greater penalty for models with additional parameters in comparison to the original AIC.

For the empirical analysis, we wrote a program using the statistical software *Stata* v. 10.1 in a maximum likelihood environment (Gould et al. (2006)), which provides a convenient way to implement and define customized likelihood functions (Harrison (2008)). Since the `ml model` command combined with the `maximize` option implicitly draws upon the underlying `optimize` functions embedded in Mata, it evokes and enables the selection of several numerical search algorithms. Based on various tests of our program, which were based on simulated trading data with known utility models and parameter settings and which we used to analyze the sensitivity of our results with respect to various numerical search algorithms, we decided to define these algorithms explicitly instead of relying on the default setting to prevent the numerical search algorithm from getting stuck or from generating unreliable results. Running the program in these tests revealed that the surface of $\log(L(\Delta_t(U_k|\boldsymbol{\theta_k})))$ seems to determine breakdowns in the search algorithm. For example, similar to previous studies on the efficiency of utility model selection (e.g., Carbone and Hey (1994)), we identified convex segments in the likelihood function causing the termination or hang-ups of the numerical search algorithm. These shortcomings could have an impact on utility model selection, since it cannot be ruled out that $\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}$ and thus the level of $\log(L(\Delta_t(U_k|\boldsymbol{\theta_k})))$ as a central ingredient for model selection are the result of a stopped numerical search due to local maxima or other deficiencies of $L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ (McCullough and Vinod (2003)).

To deal with problems in the numerical search algorithm and the termination in the iteration process due to flat or convex regions of the likelihood function $\log(L(\Delta_t(U_k|\boldsymbol{\theta_k})))$, we follow the relevant literature (Judge et al. (1985), Ruud (2000), Gould et al. (2006)) and systematically change the numerical algorithm: We use a mixed iteration procedure where we run a Newton–Raphson procedure for the first five steps and switch to the Davidon–Fletcher–Powell algorithm (Fletcher (1980)) for the next five iterations to push the estimates outside of the critical section of the likelihood function and then return to the former technique if no solution is obtained or the numerical algorithm fails to converge within five steps. To avoid being trapped at a local maximum, we decided to repeatedly use various starting values for the numerical algorithm (Liu and Mahmassani (2000)) and check whether the same ranking of utility models is obtained. In detail, we randomly altered the starting values of the vector $\boldsymbol{\theta_k}$ within the numerical search algorithm and reran the evaluation of $\log(L(\Delta_t(U_k|\boldsymbol{\theta_k})))$ for each of the individual investors under investigation. Among the different maximized likelihoods, we subsequently selected the highest of values for $\log(L(\Delta_t(U_k|\boldsymbol{\theta_k})))$.[12]

To capture errors in investor decision making (e.g., the preference reversals mentioned by Hey (1995), Hey and Carbone (1995),Carbone (1997), Loomes and Sugden (1995), Carbone and Hey (2000), Loomes et al. (2002)), to account for the presence of other trading factors that are independent of preferences (e.g., Grinblatt and Keloharju (2000), Grinblatt and Keloharju (2001b), Kaustia (2010)), and to deal with possible deficiencies in $\log(L(\Delta_t(U_k|\boldsymbol{\theta_k})))$, we implement an element of additional flexibility and estimate a nuisance parameter σ_i^2 along with the parameter set $\boldsymbol{\theta_k}$ as for Harrison and Rutstrom (2008) and Harrison (2008). Additionally, as suggested by Dhrymes (1971) and Cramer (1986), another purpose of $\hat{\sigma}_i^2$ is to absorb the impact of shortcomings in the likelihood function $L(\Delta_t(U_k|\boldsymbol{\theta_k}))$.[13] In the following Chapter, we present a dataset of trade histories and demographic characteristics at the investor level from a large German discount brokerage firm and discuss the results of the application of the likelihood approach presented.

4. The Distribution of Preferences among Individual Investors: Results from Discount Brokerage Data

To answer the questions in this paper, it is appropriate to conduct investigations and perform analyses at the individual level, since it has been advised and repeatedly applied in experimental economics (Hensher and Johnson (1981), Train (1986), Train (2009), Harrison and Rutstrom (2008)). A well-established way to investigate individual investors' behavior is to use trading data from discount brokers (e.g., Odean (1998), Odean (1999), Barber and Odean (1999), Barber and Odean (2000), Barber and Odean (2001b), Kumar and Goetzmann (2008), Kumar (2009a)). The structure of our dataset resembles those used by Odean (1999) and Barber and Odean (2000) and contains details of portfolio compositions at any point in time, as well as information on executed trades during the observation period, where single transactions can be uniquely attributed to each individual enlisted (for details, see Weber et al. (2014)).[14] This history of trades, usually dubbed the *trade file*, represents the actively stated decisions of a random selection of 5,000 individual investors. We consider this an advantage, since portfolio positions may not fully reflect risk preferences due to stale positions (Calvet et al. (2009), Bilias et al. (2010)), which may affect revealed risk preferences and thus could have an impact on the classification of the underlying utility functions. We admit that this comes at the cost of a certain loss of information (e.g., Carbone and Hey (1994)), since portfolio weights are not considered. Consequently, we refrain from presenting the results of the vector $\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}$, since a similar trade pattern can be generated by different values of $\boldsymbol{\theta_k}$ if the distribution of the error term σ_i is very small (the investor makes

[12]Note that, by generating random starting values, we intend to rule out systematic biases in $\log(L(\Delta_t(U_k|\boldsymbol{\theta_k})))$ due to local maxima in the likelihood function, since those local maxima were detected and found to be critical for utility model selection (Carbone and Hey (1994)).

[13]For the estimation of the standard deviation of the error term, we transform σ_i into an exponential function to ensure that the ascertained estimator is strictly positive (Rabe-Hersketh and Everitt (2004)) and recover the estimator for σ_i and the associated standard errors using the `nlcom` command in Stata.

[14]We emphasize that our analysis complements the study of Weber et al. (2014), who used the same dataset for their analysis of individual investors' trading behavior and the dependencies of various investment biases identified therein.

nearly no mistakes and makes decisions based on the difference in utilities).

Similar to empirical studies on the portfolio choice and trading behavior of individual investors such as those of Barber and Odean (2000), Barber and Odean (2001b), Barber et al. (2011), Graham and Kumar (2004), Mitton and Vorkink (2007), and Kumar and Goetzmann (2008), we focus exclusively on the trading records of stocks.[15] Our decision to discard trades in mutual funds, bonds, as well as options and other financial products with asymmetric payoffs is based on the fact that the time series of returns and the observed trading of these discarded financial products could be characterized by features and trading motives that differ from preferences and thus could bias our findings. For example, empirical studies indicate that performance data used to determine market parameters for each instrument could be driven by autocorrelation, as for mutual funds (Grinblatt and Titmann (1989), Grinblatt and Titmann (1993), Brown and Goetzmann (1995), Carhart (1997), Daniel et al. (1997), Chan et al. (2000), Wermers (2000), Coval and Moskowitz (2001), Kosowski et al. (2006)), generating trades that could imitate preference-based trading patterns (Murstein (2003)). Furthermore, the time series of other excluded financial products, such as bonds, may be governed by inherent mean reversion (pull-to-par effect), lacking market liquidity, as in the case of (corporate) fixed income instruments (causing stale price problems and delaying the execution of trade orders), or strategic pricing motives by market makers, as in the case of structured products (Baule and Tallau (2011)). These features not only appear inconsistent with the characteristics of the underlying binomial model that we apply in the case of returns, but also could result in strategies that interfere with the presumptions of Karpoff (1987b) and imitate those trading patterns that are possibly driven by preferences (Barberis and Xiong (2009)), such as the disposition effect (Odean (1998), Hung and Yu (2006), Kaustia (2010)). Moreover, studies by Ivcovich and Weisbrenner (2009), Chang et al. (2012), and Entrop et al. (2013) provide evidence that trading in stocks actually differs from trading in investment funds and retail structured products in terms of turnover, trade timing, and trade duration, which are essential ingredients for the likelihood approach applied.

To provide an empirically tractable discrete choice model, the results of a large number of empirical and theoretical studies need to be considered when it comes to individual investors' trading behavior. Empirical research provides some indication that individual investors treat different streams of income, such as dividends as well as cash flows resulting from corporate actions and other stocks (Shefrin and Statman (1984), Baker and Wurgler (2004)), in different mental accounts (Thaler (1985)). Furthermore, the tendency to evaluate risky lotteries separately, known as narrow framing (Barberis and Huang (2001), Barberis and Huang (2009) Barberis et al. (2001), Barberis et al. (2001), Berkelaar et al. (2004), Gomes (2005)), is in line with the results of Shefrin and Statman (1985), complementing recent studies on individual investors that examine the trading decisions for each stock separately (e.g., Odean (1998), Odean (1999), Barber and Odean (2000), Barber and Odean (2002), Barber and Odean (2008), Barberis and Huang (2001), Grinblatt and Keloharju (2001a), Grinblatt and Keloharju (2001b), Dhar and Kumar (2002), Hong

[15]Our restriction to trading in equities may naturally exclude the possibility of gaining insight into asset allocation decisions and the inherent preferences for skewness as described by Barberis and Huang (2001), Barberis and Huang (2008). Investing in securities with asymmetric payoffs could represent a trade-off in terms of utility from reduced portfolio variance due to diversification with benefits from increased portfolio skewness (Mitton and Vorkink (2007), Barberis and Huang (2008)). We do not consider an exclusion harmful to our analysis, since Weber et al. (2014) reported that investments in asymmetric products are quite uncommon in our dataset.

and Kumar (2002), Zhu (2002), Grinblatt and Han (2005b), Lim (2006), Frazzini (2006)). Narrow framing, in turn, allows us to define a finite and exhaustive set of alternatives satisfying the requirements for a discrete choice set (Amemiya (1980), Train (1986), Train (2009)). To derive this discrete choice set from the time series recorded in the trade file, Train (2009) noted that mutually exclusive options need to be defined.

The central task is therefore to translate complex trade patterns from brokerage data into a sequence of binary choices to specify the index $I_{k,t}$ in equation (3.2), since trading data usually contain discrete quantities (Schlarbaum et al. (1978a), Shefrin and Statman (1985), Odean (1998), Shapira and Venezia (2001)). For this purpose, we adopt common accounting principles such as the *first-in-first-out (FIFO)* or *last-in-first-out principle (LIFO)*, which allows us to decompose complex transactions into simple and self-contained trade components, known as *round trips*, as proposed by Schlarbaum et al. (1978b) and Schlarbaum et al. (1978a) and popularized by Shapira and Venezia (2001).[16] These round trips can be used to indicate whether an investor is invested in a stock, which meets the requirements of an exhaustive choice set and avoids inconsistencies in the likelihood function in the case of compounded order flows.[17] Due to tax treatments in Germany, we opt for an application of the FIFO principle throughout the dataset, assuming that the mental accounting of individual investors follows the current tax framework.

Confronted with the computational burden of evaluating all utility models and their associated likelihood functions numerically for each investor, we randomly select a subsample of 659 investors, which corresponds to a target confidence interval of 95%, given a binomial distribution of the utility function k and a conservative probability estimate of 50%. An inspection of the investors' time series leads to the exclusion of three investors, since, for our stock parameter estimates μ_t and σ_t, the variance–covariance matrix of the investors' portfolio holdings is not positive semidefinite and is, thus, internally inconsistent. Therefore, we are left with 656 individual investors covering $3,724$ distinct securities, for which we construct likelihood functions for each of the 18 utility models presented in Table 2. Given the trade history of the subsample, this theoretically sums to $309,359,880$ single likelihood functions, with an average of $37,872$ observations per investor. Due to the overlapping-window procedure in our estimation of the stock characteristics μ_t, σ_t, and Γ_t, this number of likelihood functions is reduced by those observations falling within the look-back period, which we assume to be 60 days. Consequently, we remove three investors and a total of 606 securities (equivalent to $2,130,138$ single

[16] Round-trip length and the application of accounting principles to stock trading as introduced by Lacey (1945) are commonly used to determine purchase prices or reference points to assess the profitability and determine the tax implications of trading strategies (e.g., Schlarbaum et al. (1978a), Silber (1984), Shefrin and Statman (1985), Odean (1998), Barber and Odean (2000), Shapira and Venezia (2001), Grinblatt and Keloharju (2004), Locke and Mann (2005), Brown et al. (2006), Kaustia (2010)). In our study, accounting principles determine round trips that result in unambiguous trading sequences, which are used as central arguments to determine the alternating sign of the arguments of the likelihood function via $I_{k,t}$.

[17] To exemplify the latter point, assume the sequence of a bid order over 70 stocks at time 1 followed by another bid over 120 stocks at time 2, an ask over 50 stocks at time 3, and a sale of the remaining 140 stocks at time 4 that could be decomposed into three round trips. For each observation between times 1 and 2 and times 3 and 4, the overall likelihood function contains three single likelihood functions $\log p_{I_{k,t}}(\Delta_t(U_k|\boldsymbol{\theta_k}))$ with opposite signs for $\Delta_t(U_k|\boldsymbol{\theta_k})$, resulting in ambiguous effects on $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$. In the above illustration, the application of the FIFO principle could solve this inconsistency, although we acknowledge that a different compounding of order flows may require a different accounting principle to address the problem adequately.

likelihood functions) from our analysis, since their time series spans fewer than 60 days. In the process of transferring these market parameters into the risk and return features of the respective stocks that can serve as arguments for the utility functions, we additionally filter for implausible binomial parameters (e.g., those that imply violations of non-arbitrage conditions or represent extreme outliers) such that the total number of $\log p_{I_{k,t}}(\Delta_t(U_k|\boldsymbol{\theta_k}))$ is further reduced to $307,077,930$ single likelihood functions.[18] After removing critical components in our market parameter time series, the remaining observations span $38,903$ round trips in our sample, conducted between January 1999 and November 2011 in equity instruments, with an average of approximately 107 and a median of 65 round trips per investor. Given this set of likelihood functions, we try to evaluate $46,200$ preference and nuisance parameters numerically and successfully estimate $27,959$ parameters, for a total of $6,415$ out of $11,754$ utility models.

The results from the model selection procedures strongly rely on the accuracy of the assessment of the respective models. Therefore, it is mandatory to examine whether all models under consideration face equal conditions to reflect their information content. We noted that running our program required constant monitoring and made manual interventions whenever necessary; due to deficiencies in $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ and of the underlying dataset, the numerical search algorithm got bogged down and execution stopped, indicating that the requirements of computational equality between the different utility models may not be met throughout the dataset. Consequently, the impossibility of evaluating and estimating $\boldsymbol{\theta_k}$ predetermines the baseline probability of the appearance of each utility model, which, in turn, forms the starting point for our analysis. If each model can be assessed properly and, thus, is equally likely to occur, the baseline probability of an individual investor being of utility type k is approximately 5.556%. Table 3 shows that not all models were evaluated equally successfully, such that the chances of observing a particular utility model vary and deviate from the baseline probability. Accordingly, although these problems occurred for all types of utility models under consideration, we found that predominantly non-EUT models, such as CPT, were affected.[19] However, we found that approximately 62.5% of all utility models, corresponding to an average of 11.2 (median of 12 with a maximum number of 17) utility models per investor, were evaluated successfully.

Further inspection of the percentage of utility models, where our program fails to provide values for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$, revealed that, for 5.393 utility models, the

[18]We sort the realized returns and remove the upper and lower 1%. Removing outliers prevents us from diluting the ranking of utility functions, since extreme returns could drive estimated market parameters, which affects the level of the likelihood function. Accompanying simulations have shown that the effects of extreme returns in the time series on the selection of utility functions is twofold: On one hand, large changes in market parameters due to extreme returns weaken the correlation between past returns and other parameters μ_t, σ_t and $_t$ that enter the utility functions as arguments, thus dampening potential multicollinearity problems stemming from the stock's risk and return parameters. On the other hand, if the amplitude of these changes is too high, the purchase or sale of the affected stock may be optimal under different utility models, say, model k and competing utility model m, causing ambiguity in model selection based on observed round trips, since the values of the maximized $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ are closer to $\log L(\Delta_t(U_m|\boldsymbol{\theta_m}))$. These likelihoods may no longer be significantly different, yielding high p-values of either a Vuong or likelihood ratio test if both likelihoods are tested against each other. Our pretests showed that, by removing outliers, the latter effect dominates, enhancing our utility model selection procedure.

[19]However, we noted that, under a value functional specified as by DeGiorgi and Hens (2006), problems in the evaluation of $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ were less frequent. We suspect that the mathematical shape of a negative exponential power functional seems to foster the evaluation of the likelihood function.

Table 3. Frequency of Appearance for Each Utility Model

This table captures the proportion of evaluated utility models to the total number of utility models evaluated (6.415 models in our dataset), denoted % *calc.*, as well as the proportion of utility models where the numerical seach algorithm was terminated to the total number of utility models where the search algorithm was terminated (5.393 models in our dataset), denoted %¬*calc*. Expected utility models are denoted EUT and rank-dependent utility is denoted RDU. Simple prospect theory (Kahneman and Tversky (1979)) uses the notation SPT, whereas cumulative prospect theory (Tversky and Kahneman (1992)) is denoted CPT. Decision weights in accordance with Quiggin (1982) are denoted $QU82$ and $KT92$ denotes decision weights in accordance with Tversky and Kahneman (1992). If no decision weights are applicable, we use the term *None*. Furthermore, we use the notation $CRRA$ for CRRA utility functionals and $EXPO$ to denote utility functions in accordance with Saha (1993). For SPT and CPT, we use the notation $POWR$ for models with kinked power functionals as for Kahneman and Tversky (1979) and $DHG0$ to denote value functionals as defined by DeGiorgi and Hens (2006).

		EUT		**RDU**		**SPT**		**CPT**	
		%calc.	**%¬calc.**	**%calc.**	**%¬calc.**	**%calc.**	**%¬calc.**	**%calc.**	**%¬calc.**
CRRA	**None**	6.14%	4.86%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	3.99%	7.42%	7.72%	2.99%	1.82%	9.99%
	KT92	0.00%	0.00%	5.30%	5.86%	6.86%	4.01%	5.02%	6.19%
EXPO	**None**	6.56%	4.36%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	5.33%	5.82%	0.00%	0.00%	0.00%	0.00%
	KT92	0.00%	0.00%	5.33%	5.82%	0.00%	0.00%	0.00%	0.00%
POWR	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	0.00%	5.02%	6.19%	0.73%	11.29%
	KT92	0.00%	0.00%	0.00%	0.00%	4.22%	7.14%	3.96%	7.45%
DGH0	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	0.00%	8.40%	2.17%	6.52%	4.41%
	KT92	0.00%	0.00%	0.00%	0.00%	8.71%	1.80%	8.36%	2.23%

numerical search algorithm suffers from several specific types of failure. While performing the evaluation of all utility models for all investors in our dataset, Stata reported that the iteration was terminated due to specialties in the surface of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$. In particular, the termination of the numerical search was frequently caused by local convexities and saddle points containing pronounced flat sections.[20] It turned out that termination of the search algorithm predominantly occurred in those iterations where the Newton–Raphson method was applied. This particular numerical search algorithm runs into problems if the Hessian matrix is degenerate, since the step size is determined by $-\boldsymbol{H}(\Delta_t(U_k|\boldsymbol{\theta}_{\boldsymbol{k}}))^{-1}$. Closer investigation of key elements of the numerical search algorithm revealed that, for plausible values of $\boldsymbol{\theta}_{\boldsymbol{k}}$, the determinant of the Hessian matrix $\mathbf{det}\,\boldsymbol{H}(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ is indeed fairly close to zero and contains both positive and negative eigenvalues. These results could be caused by flat sections (e.g., plateaus and saddle points) in the surface of the likelihood function, indicating that, besides a possible impact of $\Delta_t(U_k|\boldsymbol{\theta}_{\boldsymbol{k}})$ on $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$, a certain degree of multicollinearity in $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ (Griffiths et al. (1987)) or potential underidentification problems (Judge et al. (1985), Keele and Park (2006), Greene (2008); for utility models, see Carbone and Hey

[20]In these cases, the numerical search algorithm failed to converge within the 30 iteration steps by which we capped the maximum number of iterations, as recommended by Cramer (1986), thus yielding missing values for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$.

(1994)).[21] In other cases where Stata reports successful convergence and thus provides values for the likelihood function and assigns values to $\boldsymbol{\theta}_k$, associated standard errors were set to missing. In these cases, we found that, despite repeated execution of the evaluation of $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$, by using random starting values for the search algorithm to reduce the impact of local maxima, our program reported that the likelihood function is not concave in the last iteration step, setting standard errors to missing such that the values for the maximized $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ cannot be considered reliable (Gould et al. (2006)).

Problems at the surface of $\log L(\Delta_t(U_k|\boldsymbol{\theta_k}))$ due to convexities and insufficient steepness of the likelihood function can compromise our model selection. The literature on numerical methods offers several solutions, according to which these problems can be solved by applying a numerical search algorithm that does not directly rely on the Hessian matrix but uses an approximation of it (e.g., those of Berndt et al. (1974)) or by adding a positive term to the elements of the Hessian until it becomes invertible, such that $-\boldsymbol{H}(\Delta_t(U_k|\boldsymbol{\theta_k}))^{-1}$ exists (Marquardt (1963)). As for citeGriffithsHillPope1987, previous tests of our program using simulations have shown that many of the likelihood functions of those utility models where the Newton–Raphson algorithm failed can now be forced to converge to a solution, although a large sum of utility models still cannot be evaluated accurately. This is in line with Train (2009), since the (Berndt et al. (1974)) algorithm is an approximation of the Newton–Raphson algorithm. Consequently, for non-quadratic $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$, where the Newton–Raphson algorithm fails to proceed, the application of the Berndt–Hall–Hall–Hausman algorithm should not perform significantly better. In addition, the literature from experimental economics usually does not recommend the Berndt–Hall–Hall–Hausman method for the estimation of utility functions (Harrison and Rutstrom (2008), Harrison (2008)).[22]

Until now, our discussion has focused on the aspect that not every utility model under consideration was evaluated properly, but we did not provide further details on the information content of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$. In particular, it is not clear whether $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ is a result of pure coincidence, since trading decisions based on noise and irrelevant information could imitate the trading pattern of a particular utility model. Studies on noise trading, such as those of Black (1986), DeLong et al. (1990), Campbell and Kyle (1993), Campbell et al. (1993), and Llorente et al. (2002), indicate that individual investors indeed base their decisions on factors that neither provide economical value nor represent relevant information (e.g., past prices; see Grinblatt and Keloharju (2001b), Garvey and Murphy (2004), Kaustia (2010)). If an investor trading pattern is characterized by undirected fluctuations in portfolio positions as a consequence of randomly commissioning bid and ask orders (thus being independent of preference considerations), these underlying

[21] Under moderate multicollinearity, the step size of a search algorithm is reduced if entering flat segments of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$, since a flattening of the likelihood function could indicate that the maximum is close (Train (2009)). If $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ is characterized by a flat surface over a large range of plausible $\boldsymbol{\theta_k}$ values due to a sufficient degree of multicollinearity, the application of such an algorithm results in an increased number of iteration steps or termination of the search procedure given a cap on the maximum number of iteration steps such that the respective utility model is not evaluated adequately.

[22] Moreover, analyzing the iteration procedure and the surface of the likelihood function in our pretests revealed that a quadratic approximation of the maximized likelihood $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$, especially for non-EUT models, performs poorly, since a considerable number of iteration steps are required (Train (2009)). Note that a perfect quadratic approximation theoretically requires only one iteration to reach the maximum.

factors may be described by an error term $\epsilon^{Noise} \sim N(\mu_{Noise}, \sigma_{Noise})$. This noise is assumed to be unsystematic and therefore approximately normally distributed and hence orthogonal to preferences; in the style of Kyle (1985), we henceforth refer to such an investor as a *random trader*.[23] We hypothesize that, if an investor trades randomly, the associated likelihood $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ should be close to and statistically indistinct from the baseline log-likelihood $\log L(\Delta_t(\epsilon^{Noise}))$. Note that, irrespective of the utility model under investigation, all models for which we estimate $\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}$ should not contribute further information on the observed trading data of a random trader. Consequently, the utility classification of a random trader should be random if ranked according to the AICC. To address this suspicion, we proceed in three steps: First, we sort all utility models for which we obtained solutions $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ according to the AICC. In a second step, for each investor in our dataset, to whom we assign a list of ranked utility models, we construct a random trader counterpart by performing accompanying simulations using 120 repetitions provided by the observations of the investor under investigation to construct (artificial) trading histories of such a random trader counterpart. For each of these 120 draws, we generate trade signals by replacing the difference in utilities $\Delta_t(U_k|\boldsymbol{\theta}_{\boldsymbol{k}})$ by the stochastic element ϵ^{Noise}. Accordingly, the random trader has a positive exposure in the stock if the argument of ϵ^{Noise} yields a cumulative density $\Phi\left(\epsilon^{Noise}\right)$ above 50% and otherwise prefers to hold the riskless investment.[24] In the final step, we perform a test of the likelihood of each utility model of each individual investor with respect to the likelihood functions of their random trader counterpart. If our hypothesis, that these individual investors trade on noise in terms of ϵ^{Noise} rather than preferences, is correct, the likelihood ratio tests we applied should not indicate significant differences between the obtained values of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ and the baseline $\log L(\Delta_t(\epsilon^{Noise}))$.[25]

To perform the necessary tests for the difference between $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ and $\log L(\Delta_t(\epsilon^{Noise}))$, we performed $768,800$ likelihood ratio tests and aggregated the resulting p-values using Fisher's combination method (Fisher (1925), Fisher (1948),

[23] Admittedly, the decision to hold the respective stock could be correlated with other trading factors; consequently, we cannot exclude directional trading by mere coincidence (e.g., Barber et al. (2006)). However, in this paper, we implicitly assume that the effect of these factors on the likelihood is negligible, such that a utility model k does not contribute to the likelihood of a random trader so that its likelihood $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ should be largely independent of the utility model under consideration. Any effect on $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ could result from imitation of the respective trading behavior under utility model k and is suspected to be spurious. Consequently, we opt to use a normally distributed error term as described to imitate the trading behavior of an individual investor trading randomly.

[24] The values of μ_{Noise} and σ_{Noise} were determined using a grid search such that the resulting round-trip durations were comparable to the trade duration of the respective investor. For example, the trading sequences of a random trader matches (on average) to the trading sequences of an investor with an average trade duration of 41 days if we set $\mu_{Noise} = 1.0002$ and $\sigma_{Noise} = 0.50$. Note that (in this setting and in distinction from real investors) the random trader is invested 97% of the time in the same stock. The results are sensitive to changes in σ_{Noise} but rather robust with respect to modifications of μ_{Noise}.

[25] Concomitant with the fact that it is difficult to approximate the surface of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ using a second-order Taylor expansion around $\boldsymbol{\theta}_{\boldsymbol{k}}$, our likelihood ratio tests may be biased, since their applicability presupposes a sufficient quadratic approximation of the likelihood function (Pawitan (2001)). In our pretest, we found that, particularly for simple prospect theory (SPT) and CPT, a large number of iteration steps are necessary before a stable solution for $\boldsymbol{\theta}_{\boldsymbol{k}}$ is obtained, pointing to a surface of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ for which a second-order Taylor expansion performs poorly. We suspect that, for SPT and CPT, the underlying value functionals and decision weights probably impose convex sections in the likelihood function, driving our results with respect to $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$.

Van Zweet and Oosterhoff (1967)) to obtain the basis for the significance levels of Table 4.[26] From Table 4, it can be seen that the observed maximized likelihood values for all ranked utility models are significantly distinct from the respective baseline likelihood function of the random trader for the majority of our investors, such that we reject the hypothesis that both likelihood values are equal.[27] However, contrary to our hypothesis, according to which the assignment of first-ranked utility models to a random trader should be random, we find that SPT tends to achieve the first rank, whereby this phenomenon happens more frequently following an increase in the variance of ϵ^{Noise}, generating shorter round trips, although we note that, for all simulated round trips, SPT is statistically not distinct from the respective second-ranked utility models at the 10% level. However, there are several drawbacks with respect to Fisher's combination method, since it relies on the assumption of independent observations (Westberg (1985)) and treats small and large p-values differently (Rice (1990)). We find that whenever p-values indicate significance, although these values are positively related (as for Brown (1975)), the corresponding χ^2_{2K}-values are at least four-digit numbers, such that we expect little change, even if the positive correlation among p-values has been taken into account. However, we acknowledge that Fischer's combination method tends to reject the null hypothesis too frequently (Rice (1990)), such that, regarding the low significance of SPT as a first-ranked utility model in our comparison of first- to second-ranked utility models, this inherent drawback of Fisher's combination method supports the rejection of our hypothesis.[28] In light of these findings, an inspection of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ for the first-ranked utility models of our dataset furthermore reveals that variations of $\boldsymbol{\theta_k}$ result in significant changes of the likelihood values (reflected in the results of the likelihood ratio tests), further indicating that the contribution of the winning utility model to explain trading behavior may not be trivial.

Apart from deviations in the baseline likelihood, as shown in Table 3, sorting utility models according to (3.4) could affect model selection even if variations in the number of parameters between different utility models are explicitly considered (Sugiura (1978), Pawitan (2001), Burnham and Anderson (2002), Burnham and Anderson (2004)). Likelihood functions can be susceptible to overfitting problems in the rankings such that multiparameter utility models such as SPT may be preferred (Pawitan (2001)) if parameter corrections as in (3.4) are insufficient, explaining the high share of prospect theory models in our sample, although the results from Table 3 could point to a dominance of EUT in comparison to some versions of SPT. To identify possible overfitting issues, recall that we added a DeGiorgi and Hens (2006) ($DGH0$) functional to the different functional specifications of SPT and CPT. According to DeGiorgi and Hens (2006), the $DGH0$ value functional is defined

[26]In detail, aggregated p-values are calculated according to $-2\sum_{i=1}^{K}\ln(p_i) \sim \chi^2_{2K}$, based on the assumption that p_i follows a uniform distribution $U(0,1)$ (note that i indicates a summation index here and does not refer to an individual). Herein, K denotes the number of utility models of type k that achieved first rank and p_i denotes p-values from respective likelihood ratio tests of the respective utility model tested against the baseline log-likelihood $\log L(\Delta_t(\epsilon^{Noise}))$.

[27]Note that this result is in line with our finding of high steepness of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ among the majority of individual investors in our dataset, since, according to likelihood theory (e.g., Cramer (1986), Pawitan (2001), Train (2009)), the steepness of the likelihood surface indicates the relative fit of the respective utility model and thus its information content to the observations in our dataset.

[28]However, we also note that, if likelihood ratio tests are performed for first-ranked utility models only, the results are even more pronounced: The maximized likelihood of all first-ranked utility models are, without exception, statistically distinct from the likelihood of their respective random trader counterparts.

as a piecewise negative exponential value function and contains four different risk sensitivity parameters and one decision weight parameter (dependent on the version to be estimated), adding up to six parameters, including the nuisance parameter for the error term σ_i.[29] If the likelihood function $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ is prone to overfitting, then models containing a $DGH0$ functional should end up in higher ranks compared to SPT and CPT models with a power or CRRA value function. To determine whether our results suffer from overfitting, we check the average rank each utility model achieved in our dataset as reported in Table 4. Inspection of our results reveals that a $DGH0$ formulation of the value function obtained, on average, higher ranks within our subsample, but only in comparison to EUT and RDU, which are at most two- or three-parameter models, respectively. In contrast to SPT and CPT, as proposed by Kahneman and Tversky (1979), prospect theory models with a $DGH0$ functional obtain significantly lower ranks, particularly if compared to SPT given a CRRA value function (Wilcoxon signed-rank test p-value 0.022) and CPT under a power value function (Wilcoxon signed-rank test p-value 0.018), such that overfitting does not seem to drive our results.[30]

In the quest to identify the best-fitting utility model, recall that ranking competing models according to (3.4) is a widely accepted approach in experimental economics (e.g., Carbone and Hey (1994), Carbone and Hey (1995), Hey and Orme (1994), Stott (2006)), but further information regarding discrimination between two competing models can only be found in a few studies (e.g., Carbone and Hey (1995), Starmer (2000), Loomes et al. (2002), Conte et al. (2011)) and focuses predominantly on $\hat{\boldsymbol{\theta}}_{\boldsymbol{t}}$. Testing utility models of different rank against each other might be of some importance, since we find that first- and second-ranked utility models differ only by a small amount in their maximized likelihoods $L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$.[31] To provide a measure of reliability and to discriminate first- and second-ranked utility models, we supplement the results by appropriate significance tests between the first- and second-ranked utility models. In particular, whenever nested models are tested against each other, the usual likelihood ratio test is used (Rao (1973), Kent (1982)); in other cases, where we need to derive p-values for contrasting non-nested models such as CRRA and CPT, we apply a non-nested likelihood ratio test according to Vuong (1989).[32] We provide an overview of the tests used given the

[29]In addition to our procedure of randomly assigning values to the starting point of the parameter vector for the numerical search algorithm, similar to DeGiorgi and Hens (2006), we also run an estimation using a parameter vector for the numerical search algorithm where we determine its starting values such that they correspond to the parameter estimates of Tversky and Kahneman (1992). We find that this procedure generates inferior results and, on average, lower values for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ in comparison to the method of random starting values for $\boldsymbol{\theta}_{\boldsymbol{k}}$.

[30]Furthermore, where $DGH0$ models obtain the first rank, we test for the similarity of the likelihood to the likelihood of those utility models that obtained second rank according to a test for non-nested models (Vuong (1989)). We find that, for almost all cases, the likelihood of the $DGH0$ model is not significantly distinct from the second-ranked utility model, supporting our conclusion that overfitting does not appear to be much of a concern for utility model selection in our sample. Note that, similar to the findings of Hey and Orme (1994), we also find that utility models containing a Quiggin (1982) decision weight appear to obtain higher rankings compared to models with Tversky and Kahneman (1992) decision weights.

[31]We check the ranking of utility models and rerun the ranking according to the Schwartz information criterion (also known as the Bayes information criterion (Schwarz (1978))), as well as the original AIC, but find the same ranking of our results, irrespective of the criterion.

[32]Technically, the Vuong test specifies that, under the null hypothesis, the expectation of the logarithm of the likelihood ratio is symmetrically distributed around zero. In cases where this ratio is not close to a normal distribution, alternative non-nested model tests have been proposed (e.g., Clarke (2003), Clarke (2007)). According to Shapiro–Wilk and skewness tests (D'Agostino et al. (1990)), only a few likelihood functions in our dataset satisfy this normality assumption.

TABLE 4. Median Ranking and Log-Likelihood $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ by Utility Model

This table captures the median rankings for each utility model (denoted *Rank*) as well as the associated averaged values for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ per observation (denoted *log L.*). The *p*-values from the likelihood ratio tests of each utility model per investor with respect to the baseline log-likelihood $\log L(\Delta_t(\epsilon^{Noise}))$ from simulated random traders are calculated for each draw and then aggregated using Fisher's combination method (Fisher (1925), Fisher (1948), Van Zweet and Oosterhoff (1967)). Expected utility models are denoted EUT and rank-dependent utility is denoted RDU. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation SPT, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted CPT. Decision weights according to Quiggin (1982) are denoted $QU82$ and decision weights as defined by Tversky and Kahneman (1992) are denoted $KT92$. For those utility models where no decision weights are applicable, we use the term $None$. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions according to Saha (1993). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, $DHG0$ denotes a value functional as defined by DeGiorgi and Hens (2006). We use $***$, $**$, and $*$ to indicate significance at the 1%, 5%, and 10% levels, respectively. The test statistics of Fisher's combination method are not reported.

		EUT		**RDU**		**SPT**		**CPT**	
		Rank	**log L.**	**Rank**	**log L.**	**Rank**	**log L.**	**Rank**	**log L.**
CRRA	**None**	11.0	-0.675^{**}	0.0	0.0	0.0	0.0	0.0	0.0
	QU82	0.0	0.0	9.0	-0.590^{***}	2.0	-0.386^{***}	5.0	-0.532^{***}
	KT92	0.0	0.0	10.0	-0.645^{***}	3.0	-0.398^{***}	6.0	-0.504^{***}
EXPO	**None**	10.0	-0.653^{***}	0.0	0.0	0.0	0.0	0.0	0.0
	QU82	0.0	0.0	8.0	-0.583^{***}	0.0	0.0	0.0	0.0
	KT92	0.0	0.0	8.0	-0.590^{***}	0.0	0.0	0.0	0.0
POWR	**None**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	QU82	0.0	0.0	0.0	0.0	2.0	-0.351^{***}	7.0	-0.540^{***}
	KT92	0.0	0.0	0.0	0.0	2.0	-0.326^{***}	7.0	-0.511^{***}
DGH0	**None**	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	QU82	0.0	0.0	0.0	0.0	3.0	-0.427^{***}	7.0	-0.537^{***}
	KT92	0.0	0.0	0.0	0.0	5.0	-0.491^{***}	7.0	-0.538^{***}

Table 5. Utility Models: Nesting Structure and Statistical Tests

This table presents the nesting structure of the various models and the respective tests used to discriminate between two models. Expected utility models are denoted EUT and rank-dependent Utility is denoted RDU. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation SPT, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted CPT. Decision weights according to Quiggin (1982) are denoted $QU82$ and $KT92$ denotes decision weights as defined by Tversky and Kahneman (1992). For those utility models where no decision weights are applicable, we use the term $None$. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions according to Saha (1993). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, $DHG0$ denotes a value functional as defined by DeGiorgi and Hens (2006). For the entries, we use LR to denote likelihood ratio tests in the case of nested utility models and $V.$ to denote tests according to Vuong (1989) for non-nested utility models .

			EUT		RDU				SPT						CPT					
			CRRA	EXPO	CRRA		EXPO		CRRA		POWR		DGH0		CRRA		POWR		DGH0	
			None	None	QU82	KT92	QU82	KT92	QU82	KT92	QU82	KT92	QU82	KT92	QU82	KT92	QU82	KT92	QU82	KT92
EUT	CRRA	None	-	LR	LR	LR	LR	LR	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
	EXPO	None	LR	-	LR	LR	LR	LR	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
RDU	CRRA	QU82	LR	LR	-	V.	LR	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
		KT92	LR	LR	V.	-	V.	LR	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
	EXPO	QU82	LR	LR	LR	V.	-	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
		KT92	LR	LR	V.	LR	V.	-	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
SPT	CRRA	QU82	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
		KT92	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.
	POWR	QU82	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.	V.	V.	V.	V.	V.
		KT92	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.	V.	V.	V.	V.
	DGH0	QU82	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.	V.	V.	V.
		KT92	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.	V.	V.
CPT	CRRA	QU82	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.	V.
		KT92	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.	V.
	POWR	QU82	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.	V.
		KT92	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.	V.
	DGH0	QU82	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-	V.
		KT92	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	V.	-

Table 6. First-Ranked Utility Models to Second-Ranked Utility Models:
Summary Statistics Sorted by Significance

This table displays the proportion of first-ranked utility models that are statistically distinct from second-ranked models at the 10%-, 5%-, and 1% significance levels to the total number of first-ranked utility models that are statistically distinct from second-ranked models at the 10%, 5%, and 1% significance levels. The results for expected utility models are omitted, since no model is found to be significantly distinct from second-ranked models at the 10% level. Rank-dependent utility is denoted RDU. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation SPT, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted CPT. Decision weights for weighting functions according to Quiggin (1982) are denoted $QU82$ and decision weights as defined by Tversky and Kahneman (1992) are denoted $KT92$. For those utility models where no decision weights are applicable, we use the term $None$. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions according to Saha (1993). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, $DHG0$ denotes a value functional as defined by DeGiorgi and Hens (2006).

		RDU			**SPT**			**CPT**		
	p-values	< 10%	< 5%	< 1%	< 10%	< 5%	< 1%	< 10%	< 5%	< 1%
CRRA	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	22.18%	21.93%	21.52%	0.96%	0.80%	0.65%
	KT92	1.15%	1.01%	1.09%	17.59%	17.91%	17.83%	1.34%	1.21%	1.09%
EXPO	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	KT92	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
POWR	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	15.30%	14.69%	14.35%	0.19%	0.00%	0.00%
	KT92	0.00%	0.00%	0.00%	18.36%	18.71%	19.13%	1.34%	1.41%	1.09%
DGH0	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	16.83%	17.30%	17.83%	0.76%	0.80%	0.87%
	KT92	0.00%	0.00%	0.00%	1.91%	2.01%	2.17%	2.10%	2.21%	2.39%

structure of utility models in Table 5.[33]

Following Table 6, our dataset still displays a pronounced tendency to classify SPT as a winning utility model.[34] The question immediately arises whether our analysis is subject to a mechanical bias toward SPT apart from problems in the evaluation of some types of utility functions, as depicted in Table 3. By using the buy-or-hold index $I_{k,t} := I[\Delta_t(U_k|\boldsymbol{\theta_k}) + \epsilon_i \geq 0]$ within the likelihood function $L(\Delta_t(U_k|\boldsymbol{\theta_k}))$, we find the length of a trading sequence, or round trip, to be one

However, an application of Clarke's test reveals only small differences in comparison to Vuong's test, leaving our results unaltered.

[33]Further inspections of the estimates for $\boldsymbol{\theta_k}$ reveal marked imprecision. If nested models are modeled and tested alongside with nesting models, this imprecision favors nesting utility models such as expo-power utility (Saha (1993)) to nested ones such as CRRA, yielding estimates for $\boldsymbol{\theta_k}$ that are not statistically distinct from those constraining values under which the nested utility model coincides with a nesting one. We find that $\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}$ highly depends upon the characteristics of the investors' trading history, such that, due to the imprecision of $\boldsymbol{\theta_k}$, we obtain a ranking of utility models where nesting models prevail in the upper ranks, although the differences are not significant, as can be seen in Table 6.

[34]Note that after filtering for significant first-ranked utility models at the 10% level, our dataset comprises 523 investors (130 investors dropped out, since their first-ranked utility model was not statistically distinct from the second-ranked utility model at the 10% level). At the 5% level, only 497 investors remained in our dataset, whereas filtering at the 1% significance level left us with 460 investors in our dataset. In addition, our results from Table 6 correspond to our findings from Table 4, since we detect a tendency toward higher likelihoods for SPT utility models.

of the critical components that could drive our results for utility model selection. If round-trip duration is crucial for the classification of an individual investor in terms of utility models, then one way to (mechanically) generate different round-trip lengths is to change the underlying accounting rule from the *FIFO principle* to specifying the index $I_{k,t}$ in equation (3.2) under the *LIFO principle*. For instance, if application of the LIFO principle generates round trips with shorter durations (assuming the realized returns remain the same for complex trades, which may not necessarily be the case) and if shorter round trips are indicative of SPT, the application of the LIFO principle could bias our results toward SPT. For example, a link between round-trip length and SPT could be established based on the insights from our pretests of our program based on the simulations of random traders. Recall that we found that, contrary to our hypothesis, according to which first-ranked utility models are expected to be randomly assigned (given different levels of σ_{Noise}), SPT also tends to obtain the first rank, whereby this phenomenon is positively related to an increase in the variance of ϵ^{Noise}, which translates into shorter round trips.

A natural way to investigate whether a change from FIFO to LIFO affects our results is to completely rerun our analysis after changing the accounting rule and to compare the outcomes, which comes at a high computational burden. Alternatively, we could approximate the effect of a change of the accounting rule and determine the percentage of complex trades, since these are the round trips, that could be affected by a change of the accounting rule.[35] Although detecting the proportion of complex round trips is a preferable strategy, the outcomes of a switch to LIFO are less clear, since not only round-trip durations but also a trade timing component, namely, realized returns, are affected. Consequently, the timing of a particular trade and the accrued return makes the outcomes of a utility model selection process less predictable, since the selection of a specific utility model depends not only on round-trip length but also on other parameters, such as the realized return. Thus, given that realized returns are not affected by a different accounting rule, if round-trip length is comparable across utility types and statistically indistinct for various different utility models, then we would expect only moderate effects from a shortening of round trips on utility model selection if all trades are affected equally and simultaneously. Note that, even if shorter round trips correspond to trading decisions following SPT, recall that we defined $I_{k,t}$ under FIFO, which, according to our argumentation, should not facilitate the selection of SPT. On the other hand, the evidence of a few CRRA traders in our subsample might be an artifact of the FIFO principle if long round trips are tantamount to trading under an EUT regime. According to Table 6, no first-ranked EUT model is statistically distinct to its second-ranked successor, which might be another indication that EUT-type investors are an artifact of the application of FIFO. We inspected the ranking of utility models for the 653 trading histories of our simulated random traders and

[35]Furthermore, theoretical research on portfolio choice under prospect theory indicates that myopic optimization under CPT and SPT yields extreme portfolio positions and results in simple round trips (full sales of existing positions) if budget constraints are imposed. According to Jin and Zhou (2008), Bernard and Ghossoub (2010), and He and Zhou (2011), the portfolio choices of SPT- and CPT-type investors are predominantly characterized by corner solutions in the optimization process, yielding a pronounced stability of round-trip durations, irrespective of the application of FIFO or LIFO. Thus, the presence of simple round trips as detected in other studies on individual investors, such as that of Calvet et al. (2007), could also indicate the presence of prospect theory in our dataset and consequently strengthen our findings, according to which the majority of the individual investors in our dataset follow trading patterns consistent with SPT.

detected a similar tendency to select SPT as the winning utility model.[36] Note that these results are in line with those of Carbone and Hey (1994), who investigated the reliability of customized maximum likelihood methods to reveal the underlying utility function used to generate a simulated dataset of decisions. In particular, these authors used extensive simulations to test the reliability of maximum likelihood estimation techniques and found that the identification of the correct utility model is severely compromised if an additional error term ϵ^{Noise} is modeled along with the decision process.

Table 7. Average Trade Duration and Hazard Rates by Utility Model

This table presents the average round-trip duration in days as well as the hazard rates from a proportional hazard model (Cox (1972)) for first-ranked utility models. Expected utility models are denoted *EUT* and rank-dependent utility is denoted *RDU*. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation *SPT*, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted *CPT*. Decision weights for weighting functions according to Quiggin (1982) are denoted *QU*82 and decision weights as defined by Tversky and Kahneman (1992) are denoted *KT*92. For those utility models where no decision weights are applicable, we use the term *None*. Furthermore, we use the notation *CRRA* for utility functionals with constant relative risk aversion and *EXPO* to denote exponential power utility functions according to Saha (1993). For *SPT* and *CPT*, we use the notation *POWR* to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, *DHG*0 denotes a value functional as defined by DeGiorgi and Hens (2006). We denote round-trip durations in days by *Dur.* and use the term *Hazard* to indicate the hazard rates of a proportional hazard model (Cox (1972)). Log-rank tests reject the hypothesis that the hazard rates equal one, such that indicators for significance levels and standard errors are omitted.

		EUT		**RDU**		**SPT**		**CPT**	
		Dur.	**Hazard**	**Dur.**	**Hazard**	**Dur.**	**Hazard**	**Dur.**	**Hazard**
CRRA	**None**	73.55	1.44	0.00	0.00	0.00	0.00	0.00	0.00
	QU82	0.00	0.00	0.00	0.00	693.46	1.08	222.96	1.04
	KT92	0.00	0.00	164.18	1.60	507.97	1.01	181.76	1.17
EXPO	**None**	88.90	0.75	0.00	0.00	0.00	0.00	0.00	0.00
	QU82	0.00	0.00	83.72	0.69	0.00	0.00	0.00	0.00
	KT92	0.00	0.00	59.86	0.97	0.00	0.00	0.00	0.00
POWR	**None**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	QU82	0.00	0.00	0.00	0.00	793.82	0.82	27.36	1.45
	KT92	0.00	0.00	0.00	0.00	777.84	1.04	141.04	0.88
DGH0	**None**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	QU82	0.00	0.00	0.00	0.00	392.40	0.99	121.84	1.05
	KT92	0.00	0.00	0.00	0.00	136.51	0.89	177.08	0.70

If round-trip length but not the timing of a round trip (as is the case for a random trader) is crucial to the choice of the utility model, then accounting rules that shorten round trips could accidently favor the selection of SPT models. To analyze whether short-term round trips correspond to SPT, we simulated the trading behavior of an EUT-type and an SPT-type investor counterpart for each investor given his or her risk and return constellations as well as the number of observations to obtain the pure effects of these utility models on trading sequences and round-trip durations (*counterpart simulation*). In addition, we simulated the trading behavior of an EUT-type and an SPT-type investor for various risk and return

[36] To establish a connection to round-trip duration, recall that our simulated random trader is sensitive to changes in σ_{Noise}, which, in turn, drives the characteristics of ϵ^{Noise}, since an increase in σ_{Noise} reduces the average round-trip length.

constellations, for which we assumed a trade history of 1,260 trading days (corresponding to approximately five years) for the calculation of those artificial trading histories and, to reduce fluctuations from the simulations, we repeated these calculations 120 times (*artificial simulation*). In both simulations, we ran a behavioral trading model based on the assumption that differences in utility $\Delta_t(U_k|\boldsymbol{\theta_k})$ plus an error term ϵ_i (because the simulation σ_i was set close to zero (0.01)) as implied by equation (3.1) matter for the decision to hold/buy or sell the respective stock at the end of a particular day t. To fill in the necessary parameters for both simulations, we have chosen a prospect horizon of two weeks and a parameterization of the associated risk parameters as proposed by Tversky and Kahneman (1992) and Gollier (2001). Both of the simulated trading histories we obtained suggest that investors who decide according to SPT exhibit round trips with considerably longer durations (approximately 73.8 days, on average, for the counterpart simulation and 87.1 days, on average, for the artificial simulation) than random traders with σ_{Noise} set to 50% and are only comparable to random trading in our case if σ_i is larger than 32% for the artificial simulation. In comparison to an EUT-type investor with an average round-trip length of 63.3 days (counterpart simulation), the trading sequences of an SPT-type investor appear to be longer instead of shorter, contradicting our hypothesis, according to which SPT is associated with shorter round trips. However, statistical tests of the hazard ratios (Mantel (1966)) from a proportional hazard model (Cox (1972))[37] indicate that we cannot reject the hypothesis that the respective hazard rates of an EUT-type and an SPT-type investor are equal (p-value 0.221 for the counterpart simulation, p-value 0.374 for the artificial simulation). In light of this evidence, we would not expect substantial changes in the results from utility model selection if switching from FIFO to LIFO.[38] With regard to our dataset and despite the results from our simulations, however, Table 7 reveals that our dataset contains considerable variation and no clear pattern in average round-trip lengths, as measured in days as well as hazard rates across all utility models.[39] Based on the results of our simulations, we suspect that the selection of a particular utility model is driven not only by round-trip duration, but also by the timing of the trades, such that we expect only moderate effects on utility model selection from a change of the underlying accounting rule.

If our results are insensitive to round-trip length and thus accounting principles are unlikely to cause the vast overhang of SPT models in our dataset, then

[37]The proportional hazard model is widely used to analyze the trading patterns of individual investors (e.g., Ivcovic et al. (2005), Shumway and Wu (2006), Nolte (2012)), although the assumption of proportionality of the hazard rates implies a constant baseline hazard rate, which seems questionable, since Barber and Odean (2013) suspected considerable variability in the baseline hazard rate over time, given their results. Thus, since our results rely on the assumption that hazard rates are proportional, for which a log rank test is considered appropriate (Savage (1956), Mantel (1966)), its reliability could be subject to debate.

[38]Furthermore, recall that the difference in the likelihoods of random traders and the investors in our dataset is significant in all cases, such that the overhang of SPT is unlikely to be driven by round-trip length but, rather, by the timing of the trades, which we interpret as an indication of (at least partly) preference-driven trading.

[39]If hazard rates are estimated at an aggregate level, we also find variations in hazard rates across utility model classes: The hazard rate is 0.88 for EUT-type investors, 1.00 for RDU investors, 0.82 for CPT-type investors, and 1.02 for SPT-type investors in our dataset. If estimated per value functional class, we found a hazard rate of 1.09 for CRRA functions, whereas a utility functional, according to DeGiorgi and Hens (2006), yields a hazard rate of 0.96. Lower values are estimated for investors with a power functional (0.92) and exponential power functionals as those of Saha (1993) (0.78). Sorted by decision weight functionals, hazard rates range from 0.96 for Tversky and Kahneman (1992) decision weights to 0.88 for decision weights according to Quiggin (1982).

TABLE 8. Summary Statistics of Personal Characteristics by Utility Model

This table captures the sociodemographic and personal characteristics sorted by utility model. The demographics file contains information on marital status, gender, and age, as well as current reported financial wealth and income as prompted by the bank and reported in euros. Since our dataset information on portfolio volume was reported as ranges, we calculate them as mean wealth and income levels (Holt and Chaves (2001)) using mid-range values. Expected utility models are denoted EUT and rank-dependent utility is denoted RDU. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation SPT, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted CPT. Decision weights for weighting functions according to Quiggin (1982) are denoted $QU82$ and $KT92$ denotes decision weights as defined by Tversky and Kahneman (1992). For those utility models where no decision weights are applicable, we use the term $None$. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions according to Saha (1993). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, $DHG0$ denotes a value functional as defined by DeGiorgi and Hens (2006).

Utility Model			Gender			Age			Marital-Status			Income			Wealth			Risk-Class		
			Mean	**Std.Dev**	**N**	**Mean**	**Std.Dev**	**N**	**Mean**	**Std.Dev**	**N**	**Mean**	**Std.Dev**	**N**	**Mean**	**Std.Dev**	**N**	**Mean**	**Std.Dev**	**N**
EUT	**CRRA**	**None**	0.00%	0.00%	0	70.00	0.00	1	0.00%	0.00%	1	0	0	0	0	0	0	5.00	0.00	1
	EXPO	**None**	100.00%	0.00%	5	54.00	13.42	5	100.00%	0.00%	5	100,000	0	2	147,500	144,957	2	4.67	0.58	3
RDU	**CRRA**	**QU82**	0.00%	0.00%	0	0.00	0.00	0	0.00%	0.00%	0	0	0	0	0	0	0	0.00	0.00	0
		KT92	100.00%	0.00%	7	51.43	14.64	7	0.00%	0.00%	7	70,000	17,321	3	78,333	85,049	3	4.50	0.84	6
	EXPO	**QU82**	94.12%	24.25%	17	45.88	11.21	17	58.82%	50.73%	17	62,857	24,300	7	24,167	27,644	6	4.18	1.24	17
		KT92	88.89%	33.33%	9	52.22	14.81	9	77.78%	44.10%	9	70,000	17,321	3	25,000	17,321	3	4.50	0.93	8
SPT	**CRRA**	**QU82**	88.24%	32.34%	136	47.87	12.32	136	62.50%	62.50%	136	68,235	22,221	34	71,286	79,339	35	3.70	1.54	126
		KT92	91.43%	28.13%	105	47.17	12.17	106	56.60%	49.80%	106	58,750	26,232	40	55,526	63,222	38	3.68	1.36	97
	POWR	**QU82**	89.09%	31.32%	110	48.18	11.98	110	61.82%	48.81%	110	61,944	24,590	36	42,838	37,408	37	3.25	1.55	105
		KT92	90.99%	28.76%	111	47.93	13.08	111	63.06%	48.48%	111	60,909	22,497	44	49,500	50,062	40	3.48	1.36	97
	DGH0	**QU82**	92.78%	26.01%	97	48.76	12.01	97	64.95%	47.96%	97	58,500	23,810	40	53,382	62,882	34	4.01	1.33	91
		KT92	100.00%	0.00%	11	46.36	10.27	11	63.64%	50.45%	11	65,000	49,497	2	42,500	53,033	2	4.22	1.56	9
CPT	**CRRA**	**QU82**	80.00%	44.72%	5	44.00	8.94	5	60.00%	54.77%	5	40,000	14,142	2	47,500	45,962	2	3.80	1.64	5
		KT92	100.00%	0.00%	9	50.00	10.00	9	44.44%	52.70%	9	100,000	0	1	30,000	21,213	2	3.67	1.66	9
	POWR	**QU82**	100.00%	0.00%	1	40.00	0.00	1	100.00%	0.00%	1	50,000	0	1	45,000	0	1	5.00	0.00	1
		KT92	100.00%	0.00%	11	39.09	9.44	11	54.55%	52.22%	11	70,000	32,660	7	75,000	79,425	7	4.22	1.39	9
	DGH0	**QU82**	100.00%	0.00%	4	55.00	12.91	4	75.00%	50.00%	4	0	0	0	0	0	0	4.50	0.58	4
		KT92	92.31%	27.74%	13	43.85	11.93	13	46.15%	51.89%	13	60,000	35,590	4	30,000	32,404	5	4.38	1.26	13
	Total		90.95%	28.71%	652	47.86	12.26	653	60.95%	48.82%	653	62,257	24,436	226	53,894	60,034	217	3.71	1.44	601

the large proportion of SPT could be driven by the structure of our dataset, particularly if our dataset is biased toward exogenous variables that are correlated with specific utility models. The experimental economics literature suggests that personal and socioeconomic characteristics might correspond to different types of preferences if represented by their parameterization (e.g., Fennema and van Assen (1999), Donkers and van Soest (1999), Donkers et al. (2001), Gaechter et al. (2007), Croson and Gneezy (2009), Booij and Van de Kuilen (2009), Booij et al. (2010), Charness and Gneezy (2010), Charness and Gneezy (2012)), although we note that empirical evidence from field data with respect to the linkage between an investor's personal characteristics and utility classification is rather scarce (exceptions are Harrison et al. (2007) and Anderson et al. (2010)). Following Hosmer et al. (2013), we inspect a tabulation of these characteristics for the utility model as depicted in Table 8 for a selection of relevant exogenous variables such as gender (Barsky et al. (1997), Fehr-Duda et al. (2006), Bruhin et al. (2007), Gaechter et al. (2007), Booij and Van de Kuilen (2009), Croson and Gneezy (2009)), age (Harbaugh et al. (2002), Gaechter et al. (2007), Booij et al. (2010), von Gaudecker et al. (2009)), and wealth (Guiso and Paiella (2008), Brunnermeier and Nagel (2008)) and find differences with respect to the characteristics of the dataset used by Weber et al. (2014).[40]

According to Table 8, particular attention should be paid to fields where our dataset contains no entries, such as for reported wealth and income levels, as in the case for CPT given a $DGH0$ value functional. Zero entries may yield point estimates for the respective odd ratio that are either zero or infinitively large (Cox and Snell (1989), Collett (2002), Hirji (2005), Hosmer et al. (2013)) if conventional logistic regression methods are applied. For other utility models such as EUT, our dataset contains only a handful of observations, giving rise to concerns that maximum likelihood estimators from logistic regressions may be subject to small-sample bias (King and Zeng (2001)). In addition, Table 8 indicates that quasi-complete separation with respect to certain investor characteristics such as gender or marital status may drive our results (Anderson and Richardson (2002), McLachlan (1980), Schaefer (1983), Albert and Anderson (1984), Santner and Duffy (1986), Cordeiro and McCullagh (1991), Heinze (2006)). To address these shortcomings in the structure of our dataset, we follow King and Zeng (2001) and apply a penalized maximum likelihood logistic regression as proposed by Firth (1993)[41] to reduce possible biases due to rare events, as in the case of EUT. Heinze and Schemper (2002) furthermore showed in a simulation study that Firth's logistic adjustment can also solve quasi-complete separability problems, since running a conventional logistic regression yields infinite and thus inestimable estimates as, according to the authors, the affected estimates approach a boundary value.

[40]We detected some differences in the dataset of Weber et al. (2014), Table 1 in age and gender characteristics. The author reported that 84% of the investors in the dataset are male (90.6% in our dataset), with an average age of 51 years (47.8 years in our dataset), with smaller averages for the other characteristics in terms of percentage differences.

[41]Firth suggested a modification of the score equations to remedy the inherent bias in generalized linear models. For further details on the asymptotic properties of Firth's correction and a generalization for multinomial logistic regressions, see Bull et al. (2002). Technically, Firth proposed a modification that penalizes the log-likelihood function with one-half of the logarithm of the determinant of the information matrix (Firth (1993)). Although other methods exist to overcome perfect separation problems, such as exact logistic regression, where the outcomes are modeled as linear combinations of the covariates used (Hosmer et al. (2013)), we refrain from invoking the corresponding function `exactlogistic` due to its large memory requirements that make efficient estimation impossible. Firth's penalized maximum likelihood estimation can be accessed by the `firthlogit` command in Stata.

Table 9. Personal Characteristics and Utility-Type Classification: Results from a Penalized Maximum Likelihood Logistic Regression

item This table shows the results from a penalized maximum likelihood logistic regression as proposed by Firth (1993). Each cell contains coefficients where the dichotomous dependent variable is defined as an index taking the value of one if the respective utility model in the first row obtained the first rank and zero otherwise. Expected utility models are denoted EUT and rank-dependent utility is denoted RDU. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation SPT, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is as CPT. Decision weights for weighting functions according to Quiggin (1982) are denoted $QU82$ and $KT92$ denotes decision weights as defined by Tversky and Kahneman (1992) . For those utility models where no decision weights are applicable, we use the term *None*. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions according to Saha (1993). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, $DHG0$ denotes a value functional as defined by DeGiorgi and Hens (2006). We report the associated standard errors in parentheses and use $***$, $**$, and $*$ to indicate significance at the 1%, 5%, and 10% levels, respectively.

	EUT	RDU	SPT	CPT	CRRA	EXPO	POWR	DGH0	QU82	KT92
Gender	-1.593	-0.250	0.252	-0.580	-0.500	-0.755	0.084	1.077	-0.331	0.298
	(2.081)	(1.008)	(0.739)	(0.926)	(0.544)	(0.976)	(0.557)	(0.945)	(0.540)	(0.540)
Status	0.147	-1.039^{*}	0.184	0.534	-0.576^{***}	0.142	0.417	0.210	0.150	-0.191
	(1.648)	(0.641)	(0.444)	(0.612)	(0.323)	(0.696)	(0.327)	(0.405)	(0.310)	(0.310)
Age	0.029	0.058^{**}	-0.010	-0.038	-0.009	0.019	-0.004	0.016	0.000	-0.001
	(0.058)	(0.026)	(0.018)	(0.027)	(0.013)	(0.028)	(0.013)	(0.016)	(0.013)	(0.013)
R.class	0.135	0.364	-0.189	0.020	-0.083	0.417	-0.282^{**}	0.707^{***}	0.019	-0.027
	(0.645)	(0.369)	(0.190)	(0.221)	(0.119)	(0.367)	(0.117)	(0.238)	(0.114)	(0.114)
Income	3.153	0.676	-0.356	-0.302	0.156	0.711	-0.100	-0.350	0.073	-0.123
	(5.220)	(0.682)	(0.453)	(0.528)	(0.295)	(0.838)	(0.287)	(0.366)	(0.275)	(0.275)
Portf.	0.618	-0.393	0.030	0.148	0.168	-0.326	-0.016	-0.158	-0.065	0.032
	(0.842)	(0.317)	(0.200)	(0.145)	(0.145)	(0.328)	(0.143)	(0.191)	(0.138)	(0.138)
Const.	-46.255	-9.633	6.281	1.187	-2.432	-9.296	1.882	-0.963	0.107	0.862
	(53.930)	(7.987)	(5.086)	(5.646)	(3.301)	(9.449)	(3.225)	(4.022)	(3.082)	(3.086)
Obs.	210	210	210	210	210	210	210	210	210	210
$p > \chi^2_6$	0.825	0.141	0.914	0.878	0.311	0.682	0.224	0.070	0.989	0.981
LL	-5.393	-29.604	-70.256	-43.432	-120.903	-29.904	-123.519	-80.562	-131.220	-130.894

We report the corresponding results of our penalized maximum likelihood logistic regressions in Table 9. As can be seen, except for risk class, which represents self-stated risk aversion according to the German Securities Trading Act (WpHG), and marriage status, none of the personal characteristics chosen are statistically significant at the 1% significance level. This is contradistinctive to the results of studies by Fehr-Duda et al. (2006), Gaechter et al. (2007), Booij and Van de Kuilen (2009), Booij et al. (2010) and von Gaudecker et al. (2009), who find significant relations between personal characteristics such as age or gender and utility model parameterizations. In particular, the famous gender effect on risk taking seems to be non-existent in our dataset, in contrast to the findings of Fehr-Duda et al. (2006), who found in their experiments that female participants seem to predominantly follow decision patterns consistent with prospect theory, whereas male subjects appear to decide according to an EUT-type decision scheme. In light of our results, we conclude that the structure of our dataset seems to have barely any effect on the outcomes of our utility model selection.[42]

[42]Running a logit regression with reversed dependent variables, as suggested by Pennings and Smidts (2002), and comparing Nagelkerke's R^2 values shows no clear pattern of causality. However,

5. The Extent to Which Preferences Govern Trading Decisions

In accordance with, for example, Heath et al. (1999), Blackburn and Ukhov (2006), Barberis and Huang (2008), von Gaudecker et al. (2009), Kliger and Levy (2009), Dimmock and Kouwenberg (2010), and Hwang and Satchell (2011), who found indirect evidence for prospect theory, up to now we contributed to this stream of literature with the insight that the majority of individual investors in our dataset indeed seem to exhibit trading patterns that match prospect theory (Weber et al. (2014)). Regarding the proportion of utility models in stock markets, our findings support studies on phenomena widely seen as related to prospect theory, such as the disposition effect (e.g., Shefrin and Statman (1985), Odean (1998), Weber and Camerer (1998), Berkelaar et al. (2004), Grinblatt and Han (2005b), Gomes (2005), Dhar and Zhu (2006), Frazzini (2006), Kaustia (2010)), observed preferences for skewness in stocks' return distributions (Barberis and Huang (2008)), diversification behavior (Polkovnichenko (2005), Yao and Li (2013)), or trade clustering (Lim (2006), Egozcue and Wong (2010)). However, up to this point, it is not clear to what extent preferences drive the trading of individual investors, since other factors may foster such trade patterns.

By the implications of our decision model, the trading of individual investors is governed by utility considerations as well as other factors that are implicitly assumed to be independent of the respective preference structure. Binary choice models, such as our customized likelihood model, are designed to describe individual variation without the necessity of specifying neglected trading factors, since they can be captured by an error term (e.g., Train (1986), Train (2009), Cramer (1986)). If these other trading factors have a substantial impact, then the likelihood function $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ should reflect the information content of the respective utility model to observed data points (Kullback and Leibler (1951), Kullback (1968), Akaike (1973), Akaike (1974), Akaike (1981), Akaike (1983), Akaike (1992)). The suspicion that other factors might influence or even determine the trading decisions of individual investors as well is backed by empirical studies, such as that of Grinblatt and Keloharju (2001c), who pointed out that utility represents only a minor aspect in investors' decision making in stock markets. The authors indicated that other factors drive trade decisions, such as taxes (e.g., Branch (1977), Constantinides (1984), Lakonishok and Vermaelen (1986), Chan (1986), Lakonishok and Smidt (1986), Badrinath and Lewellen (1991), Poterba and Weisbrenner (2001), Grinblatt and Keloharju (2004), Barber and Odean (2004) and Ivcovich et al. (2009)), differences in opinion (Varian (1989), Wang (1994)), and overconfidence (Barber and Odean (1999), Barber and Odean (2001a), Statman et al. (2006), Glaser and Weber (2007), Chen et al. (2007), Grinblatt and Keloharju (2009)), in addition to other cognitive limitations unrelated to preferences (Barber and Odean (1999), Chang et al. (2012)).

To quantify the magnitude of the impact of preferences and other trading motives on trading behavior, we follow Burnham and Anderson (2002) and Burnham and Anderson (2004) and propose two measures based on the difference between the logarithm of the likelihood function $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ and a zero-information likelihood, denoted $\log L(\Delta_t(\epsilon_t^{\neg I}))$ and defined as $\log L(\Delta_t(\epsilon_t^{\neg I})) = nt\ln(0.5)$, where nt denotes the number of observations of a particular investor. Analogous to our

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it should be kept in mind that our dataset is not representative of the overall population of investors, since discount brokerage data might be prone to selection bias, with SPT-type investors potentially attracted to trades on online trading platforms.

Table 10. Summary Statistics: Shares of Preferences

This table presents the averaged relative distance of each utility model of first rank, measured in terms of $\Pi_{exp}(\epsilon_t^I)$ denoting the exponential proportion measure and $\Pi_{lin}(\epsilon_t^I)$ denoting the linear proportion measure, to zero-information likelihood $\log L(\Delta_t(\epsilon_t^{\neg I}))$. The entries are reported as percentages and can be interpreted as the relative shares of preferences to total trading, where 0% corresponds to the case where trading behavior is completely independent from preferences. Expected utility models are denoted EUT and rank-dependent utility is denoted RDU. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation SPT, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted CPT. Decision weights for weighting functions according to Quiggin (1982) are denoted $QU82$ and $KT92$ denotes decision weights as defined by Tversky and Kahneman (1992). For those utility models where no decision weights are applicable, we use the term $None$. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions according to Saha (1993). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, $DHG0$ denotes a value functional as defined by DeGiorgi and Hens (2006).

		EUT		**RDU**		**SPT**		**CPT**	
		$\Pi_{exp}(\epsilon_t^I)$	$\Pi_{lin}(\epsilon_t^I)$	$\Pi_{exp}(\epsilon_t^I)$	$\Pi_{lin}(\epsilon_t^I)$	$\Pi_{exp}(\epsilon_t^I)$	$\Pi_{lin}(\epsilon_t^I)$	$\Pi_{exp}(\epsilon_t^I)$	$\Pi_{lin}(\epsilon_t^I)$
CRRA	**None**	2.39%	1.74%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	0.00%	55.81%	48.70%	31.99%	26.06%
	KT92	0.00%	0.00%	41.03%	34.09%	47.60%	40.48%	41.50%	34.41%
EXPO	**None**	17.04%	13.11%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	30.36%	24.15%	0.00%	0.00%	0.00%	0.00%
	KT92	0.00%	0.00%	28.44%	23.05%	0.00%	0.00%	0.00%	0.00%
POWR	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	0.00%	64.22%	57.21%	46.55%	38.22%
	KT92	0.00%	0.00%	0.00%	0.00%	65.64%	58.61%	27.04%	21.16%
DGH0	**None**	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	QU82	0.00%	0.00%	0.00%	0.00%	36.04%	29.75%	13.79%	10.49%
	KT92	0.00%	0.00%	0.00%	0.00%	22.88%	17.74%	20.86%	16.38%

analysis of the trading pattern of a random trader, if the trading of an investor is independent from preferences, the inclusion of any utility model k should not improve $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$. Consequently, $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ should not be statistically distinct from $\log L(\Delta_t(\epsilon_t^{\neg I}))$, given the usual likelihood ratio tests. We borrow from Akaike (1981) and construct a first measure $\Pi_{exp}(\epsilon_t^I)$ that caters to the requirements of a measure that permits an interpretation as the share of preference in trading decisions. In detail, we propose a monotonic transformation of the difference between the two likelihood functions $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ and $\log L(\Delta_t(\epsilon_t^{\neg I}))$ using the exponential function and emphasize that it is imperative to divide $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ and $\log L(\Delta_t(\epsilon_t^{\neg I}))$ by the number of observations n_i for each investor i to ensure that $\Pi_{exp}(\epsilon_t^I)$ is insensitive to variations in the number of observations across individual investors. This allows us to rewrite $\Pi_{exp}(\epsilon_t^I)$ in the form of a cumulative exponential distribution, defined as $\Pi_{exp}(\epsilon_t^I) := 1 - e^{\kappa}$ and scaled up by the factor two, where $\kappa = \log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}})) - \log L(\Delta_t(\epsilon_t^{\neg I}))$, to calculate the extent to which investors' trading behavior is driven by preferences (for a related but mathematically distinct approach, see Burnham and Anderson (2002)).

By construction, measure $\Pi_{exp}(\epsilon_t^I)$ takes the value of zero if both log-likelihood functions are equal, which is tantamount to cases in which other factors completely determine an individual investor's trading behavior so that the preference share for this individual is zero. On the other hand, $\Pi_{exp}(\epsilon_t^I)$ converges to one the larger the distance between the two log-likelihood functions, although, even in the case of a perfect fit, our measure never reaches the hypothetical boundary of 100%.[43] Although in line with the literature, a major drawback in using cumulative exponential distributions instead of normalizing as Akaike (1981) did to determine the proportion of preferences in trading data, is the fact that, for all the values of $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ between the zero-information likelihood $\log L(\Delta_t(\epsilon_t^{\neg I}))$ and the case in which $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ hypothetically equals zero, our first measure $\Pi_{exp}(\epsilon_t^I)$ overestimates the impact of preferences on trading decisions.[44]

Consequently, we calculate a second measure $\Pi_{lin}(\epsilon_t^I)$, defined as a linear function $\Pi_{lin}(\epsilon_t^I) = 1 - \log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))(\log L(\Delta_t(\epsilon_t^{\neg I})))^{-1}$. Analogous to $\Pi_{exp}(\epsilon_t^I)$, this measure is zero if $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ equals $\log L(\Delta_t(\epsilon_t^{\neg I}))$ and is bounded at unity at the theoretical maximum of the logarithm of the likelihood function but allows a more intuitive interpretation of the values obtained for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ of the first-ranked utility model for any investor under investigation. We provide a summary of the results for $\Pi_{exp}(\epsilon_t^I)$ and $\Pi_{lin}(\epsilon_t^I)$ in Table 10. Note that all reported likelihoods are significantly different from the zero-information likelihood $\log L(\Delta_t(\epsilon_t^{\neg I}))$ at the 1% level according to accompanying likelihood ratio tests. For our dataset, the average share by which preferences seem to drive trading is 50.6% (median share 51.9%) for $\Pi_{exp}(\epsilon_t^I)$ and 43.9% (median share 43.3%) for $\Pi_{lin}(\epsilon_t^I)$. From Table 10, it can be seen that the average share of a utility model k for an investor trading to the zero-information likelihood $\log L(\Delta_t(\epsilon_t^{\neg I}))$ displays considerable variety across utility models, with larger values for SPT-type investors, which is in line with the results of Han and Kumar (2010), and only a moderate share for EUT-type investors. As the literature (Lakonishok and Smidt (1986), Grinblatt and Keloharju (2001c)) on the trading motives of individual investors suggests, the proportion by which trading behavior seems to be driven by preferences is rather moderate, even for individual investors classified as SPT investors, such that other trading motives seem to motivate the commissioning of trade orders in our dataset (see also Breuer et al. (2014) for the dependence of risk aversion results for a lottery-like questionnaire and the propensity to invest in stocks).

Investors in our dataset differ not only in the timing but also in the frequency at which they commission orders to the discount brokerage firm and the duration of their round trips. Triggered by Barber and Odean (2001b), who stated that knowledge of day trading is limited but its importance might be significant, the natural focus of studies on discount brokerage data in particular turned to short-term trades and, in its most extreme version, *(intra)day trading.* (Intra)day trades are typically characterized by their trade patterns, which are quite distinct from the large bulk

[43] Note that, unlike Akaike (1981), our intention is to derive an interpretation with respect to the zero-information likelihood $\log L(\Delta_t(\epsilon_t^{\neg I}))$, since we do not strive for a relative comparison to the utility model m with the lowest value for $\log L(\Delta_t(U_m|\hat{\boldsymbol{\theta}}_{\boldsymbol{m}}))$. Consequently, normalization by the sum of transformed differences to the smallest maximum likelihood value, which constitutes Akaike weights, is not expedient (Burnham and Anderson (2004)). Furthermore, we suspect that, in addition, Akaike weights might be sensitive to the number of models evaluated, which differs among the individual investors under consideration. An increase in the utility models evaluated increases the number of transformed likelihood functions added to the sum in the denominator, thus decreasing the Akaike weight for utility model k. Therefore, according to our interpretation, an increased number of models evaluated would falsely indicate a decreased proportion of preferences in terms of utility model k in an investor's trading decision.

[44] To illustrate this, note that, for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}})) = \frac{1}{2} n \ln(0.5)$, the measure $\Pi_{exp}(\epsilon_t^I)$ that follows a cumulative exponential distribution returns the value 0.586 or 58.6%, respectively, whereas one would expect $\Pi_{exp}(\epsilon_t^I)$ to reflect the 50% share of preferences, thus overstating the proportion by which a particular utility model drives the trading pattern of this individual investor.

Table 11. Share of Trading Behavior Preferences by Round-Trip Duration

This table displays the average proportion of preferences $\Pi_{lin}(\epsilon_t^I)$ and $\Pi_{exp}(\epsilon_t^I)$, as well as the average of the log-likelihood values per-observation *Log.LL* for various duration groups, where the baseline log-likelihood is -0.693. The average duration in days is denoted *Ave.dur.* and the number of observations is denoted *Obs.* The values of the measures for the minimum and maximum are denoted *min* and *max*, respectively.

Duration	< 10 days	< 20 days	< 60 days	< 126 days	< 252 days	< 504 days
log. LL	-.243	-.330	-.463	-.518	-.531	-.506
min	-.337	-.490	-.656	-.683	-.683	-.683
max	-.100	-.100	-.100	-.100	-.100	-.100
$\Pi_{exp}(\epsilon_t^I)$	72.04%	60.18%	40.05%	31.03%	29.14%	33.37%
min	59.87%	36.64%	7.17%	2.07%	2.07%	2.07%
min	89.48%	89.48%	89.48%	89.48%	89.48%	89.48%
$\Pi_{lin}(\epsilon_t^I)$	64.92%	52.36%	40.05%	25.15%	23.37%	17.83%
min	51.32%	29.19%	7.17%	1.50%	1.50%	1.50%
max	85.57%	85.57%	85.57%	85.57%	85.57%	85.57%
Ave. dur.	7.59	11.73	36.53	64.15	114.78	214.75
Obs.	5	13	64	122	213	347
Duration	≥ 10 days	≥ 20 days	≥ 60 days	≥ 126 days	≥ 252 days	≥ 504 days
log. LL	-.390	-.390	-.381	-.359	-.320	-.256
min	-.683	-.683	-.683	-.677	-.652	-.597
max	-.083	-.083	-.083	-.083	-.083	-.083
$\Pi_{exp}(\epsilon_t^I)$	50.49%	50.47%	51.82%	55.17%	61.08%	70.26%
min	2.07%	2.07%	2.07%	3.24%	8.06%	18.33%
min	91.38%	91.38%	91.38%	91.38%	91.38%	91.38%
$\Pi_{lin}(\epsilon_t^I)$	43.76%	43.75%	45.10%	48.24%	53.87%	63.07%
min	1.50%	1.50%	1.50%	2.36%	5.94%	13.87%
max	88.07%	88.07%	88.07%	88.07%	88.07%	88.07%
Ave. dur.	574.58	581.58	628.24	686.52	790.73	973.36
Obs.	648	640	589	531	440	306

of trades, since the average round trips of day traders are found to be rather short (e.g., Harris and Schultz (1998), Garvey and Murphy (2002), Feng and Seasholes (2005)), resulting in a higher trading frequency (e.g., Seasholes and Wu (2004)), remarkable sensitivity to market changes such as past price patterns (Grinblatt and Keloharju (2001b), Garvey and Murphy (2004), Kaustia (2010)) or price peaks (Cohen et al. (2002), Dhar and Kumar (2002), Hvidkjaer (2006)), and higher portfolio turnover (Garvey and Murphy (2002), Jordan and Diltz (2003), Jordan and Diltz (2004), Barber et al. (2004), Linnainmaa (2005)), and display significant erosion in their performance, which, in the majority of studies, is found to be closely connected to round-trip duration and turnover (e.g., Barber and Odean (2000), Barber and Odean (2001b), Garvey and Murphy (2002), Barber et al. (2004), Linnainmaa (2005)). Due to the pronouncedly short durations of the round trips, (intra)day trading is considered more associated with noise trading (Barber and Odean (2001b), Barber et al. (2009b)) than with preferences.

If the assertion holds that investors with short round trips are more likely to trade on noise than preferences, then we expect to observe lower values for $\Pi_{lin}(\epsilon_t^I)$ and $\Pi_{exp}(\epsilon_t^I)$ as well as the log-likelihood values $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ per observation for those investors who engage in short-term trading, since their trading is driven by changes in stock prices and, to a lesser extent, by preference considerations. Recall that, in Chapter 3, we simulated random trader counterparts for all investors in our dataset and found that log-likelihood values $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ are close to the baseline log-likelihood $\log L(\Delta_t(\epsilon^{Noise}))$. In contrast to these results, we find that, for simulated EUT-type and SPT-type investors, the respective log-likelihoods $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ reveal a remarkable steepness according to their score vectors and broadly display values for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ that are significantly distinct from the respective baseline likelihood. If $\log L(\Delta_t(\epsilon^{Noise}))$ serves as a proxy for $\log L(\Delta_t(\epsilon_t^{\neg I}))$, implying that our construction of a random trader approximates the trading behavior of a noise trader in the sense of Kyle (1985) and Black (1986), and if a shorter round trip indicates trading on noise, then we would expect to observe $\Pi_{lin}(\epsilon_t^I)$ and $\Pi_{exp}(\epsilon_t^I)$ decrease in round-trip duration across all individual investors in our dataset.

A first indication of whether our results are in line with our hypothesis can be seen in Table 11, where we find some consensus with our hypothesis, according to which investors with shorter round trips display smaller values for $\log L(\Delta_t(U_k|\hat{\boldsymbol{\theta}}_{\boldsymbol{k}}))$ per observation and thus for both measures $\Pi_{exp}(\epsilon_t^I)$ and $\Pi_{lin}(\epsilon_t^I)$. However, a first inspection of our results is not indicative, since we also note that, for round-trip lengths under 20 trading days (or approximately one month), this effect reverses, which we attribute to small-sample effects. In addition, our definition of short round trips does not coincide with (intra)day trading, since we calculate the average duration per investor, in contrast to empirical studies such as that of Linnainmaa (2005), who defined an investor as a day trader if at least one (intra)day round trip in the investor's trade record can be identified. To test our hypothesis and to control for the effects of personal and sociodemographic characteristics on trade duration, we estimate a proportional hazard model (Cox (1972) in which we investigate the relation between hazard rates and $\Pi_{exp}(\epsilon_t^I)$ and $\Pi_{lin}(\epsilon_t^I)$. Our results indicate, that the share of preferences increases with round-trip duration: For $\Pi_{exp}(\epsilon_t^I)$, we find that hazard rates increase by 7.4% and 8.1% in the case of $\Pi_{exp}(\epsilon_t^I)$, both values being statistically significant at 1%, even after controlling for personal characteristics. These hazard rates provide evidence that, particularly for investors with short round trips, other trading factors besides preferences seem to dominate (Barber and Odean (2001b), Grinblatt and Keloharju (2001b), Cohen et al. (2002), Dhar and Kumar (2002), Garvey and Murphy (2004), Hvidkjaer (2006), Glaser and Weber (2007), Zhang and Swanson (2010)), which is also in line with the literature on noise trading (Barber and Odean (2000), Barber and Odean (2001b), Garvey and Murphy (2002), Barber et al. (2004), Linnainmaa (2005) Barber et al. (2009b)).

To the best of our knowledge, the literature on preferences in financial markets provides no direct evidence (Holt and Chaves (2001), Guiso and Paiella (2008)) or, at best, mixed results for the question of the extent to which preferences are connected to personal characteristics and govern the trading decisions of individual investors (Barsky et al. (1997), Foucault et al. (2011)). However, studies in experimental economics indicate that personal traits such as age and gender could be connected to the tendency to hold stocks (Dohmen et al. (2009)). To investigate the magnitude of the impact of personal characteristics on the commissioning of sales or purchase orders, we run an OLS regression to establish the connections between observable variables and the share by which preferences seem to explain trading behavior in our dataset. Since only two investors with EUT-type preferences provided further information on their wealth and income, we decided to drop these from our analysis. The results of this regression are obtained for groups of preferences and presented in Table 12. Our results are robust with respect to round-trip length. Similar to our results in Table 9, we only find a notable significant connection between the variable *RiskClass* and the proportion of preferences, which indicates that personal and sociodemographic characteristics are weak indicators

Table 12. Personal Characteristics and Shares of Preferences: Results from an OLS Regression

This table reports the results from an OLS regression where the shares of preference $\Pi_{exp}(\epsilon_t^I)$ and $\Pi_{lin}(\epsilon_t^I)$ are used as the dependent variable for each utility classification (utility type, functional type, and decision weight type) of our dataset. Expected utility models are denoted EUT and rank-dependent utility is denoted RDU. For simple prospect theory according to Kahneman and Tversky (1979), we use the notation SPT, whereas cumulative prospect theory according to Tversky and Kahneman (1992) is denoted CPT. Decision weights for weighting functions according to Quiggin (1982) are denoted $QU82$ and $KT92$ denotes decision weights as defined by Tversky and Kahneman (1992). For those utility models where no decision weights are applicable, we use the term *None*. Furthermore, we use the notation $CRRA$ for utility functionals with constant relative risk aversion and $EXPO$ to denote exponential power utility functions according to Saha (1993). For SPT and CPT, we use the notation $POWR$ to indicate models with kinked power functionals as proposed by Kahneman and Tversky (1979), where, in addition, $DHG0$ denotes a value functional as defined by DeGiorgi and Hens (2006). The results for EUT are omitted due to the small number of observations for this utility model that match certain investor characteristics (see also the results from Table 8). We report the associated standard errors in parentheses and use $***$, $**$, and $*$ to indicate significance at the 1%, 5%, and 10% levels, respectively.

	RDU	**SPT**	**CPT**	**CRRA**	**EXPO**	**POWR**	**DGH0**	**QU82**	**KT92**
				Results for Exponential Proportion Measure $\Pi_{exp}(\epsilon_t^I)$					
Gender	-0.066	-0.051	0.204	0.067	-0.044	-0.111	-0.198	0.073	-0.208^{**}
	(0.103)	(0.063)	(0.150)	(0.082)	(0.122)	(0.092)	(0.248)	(0.082)	(0.088)
Status	-0.140^{*}	-0.013	0.074	-0.033	-0.078	-0.024	0.050	0.015	-0.014
	(0.053)	(0.037)	(0.062)	(0.052)	(0.164)	(0.054)	(0.067)	(0.051)	(0.045)
Age	0.006^{**}	-0.001	-0.005	-0.002	0.001	0.001	-0.002	-0.001	-0.002
	(0.002)	(0.002)	(0.005)	(0.002)	(0.009)	(0.002)	(0.003)	(0.002)	(0.002)
R.class	0.075	-0.051^{***}	0.003	-0.015	0.033	-0.050^{***}	-0.006	-0.056^{***}	-0.036^{**}
	(0.039)	(0.013)	(0.120)	(0.018)	(0.083)	(0.019)	(0.041)	(0.017)	(0.019)
Income	0.067	-0.007	-0.122	0.000	0.071	-0.022	0.001	0.019	-0.060
	(0.080)	(0.031)	(0.085)	(0.048)	(0.118)	(0.044)	(0.082)	(0.047)	(0.039)
Portf.	0.013	0.034^{**}	-0.040	0.038	-0.047	0.035	-0.021	0.023	0.040^{*}
	(0.030)	(0.016)	(0.055)	(0.024)	(0.066)	(0.023)	(0.034)	(0.022)	(0.021)
Const.	-1.171	0.523	1.952^{**}	0.188	-0.221	0.705	0.847	0.216	1.143^{**}
	(0.928)	(0.354)	(0.600)	(0.517)	(1.394)	(0.519)	(0.815)	(0.521)	(0.451)
Obs.	11	182	15	77	10	84	39	110	98
R^2	0.827	0.111	0.693	0.066	0.582	0.152	0.056	0.113	0.162
adj.R^2	0.567	0.081	0.464	-0.014	-0.253	0.086	-0.121	0.062	0.107
				Results for Linear Proportion Measure $\Pi_{lin}(\epsilon_t^I)$					
Gender	-0.053	-0.049	0.165	0.059	-0.035	-0.113	-0.165	0.068	-0.202^{**}
	(0.082)	(0.061)	(0.129)	(0.078)	(0.095)	(0.091)	(0.222)	(0.078)	(0.086)
Status	-0.114^{*}	-0.012	0.061	-0.031	-0.061	-0.023	0.044	0.013	-0.013
	(0.043)	(0.036)	(0.053)	(0.050)	(0.128)	(0.054)	(0.060)	(0.049)	(0.044)
Age	0.005^{**}	-0.001	-0.004	-0.002	0.000	0.001	-0.002	-0.001	-0.001
	(0.002)	(0.001)	(0.004)	(0.002)	(0.007)	(0.002)	(0.003)	(0.002)	(0.002)
R.class	0.062	-0.051^{***}	0.003	-0.014	0.026	-0.052^{***}	-0.007	-0.055^{***}	-0.038^{**}
	(0.031)	(0.013)	(0.021)	(0.017)	(0.065)	(0.019)	(0.037)	(0.016)	(0.019)
Income	0.052	-0.008	-0.101	0.004	0.056	-0.025	-0.003	0.014	-0.054
	(0.064)	(0.030)	(0.073)	(0.046)	(0.092)	(0.044)	(0.073)	(0.045)	(0.038)
Portf.	0.014	0.034^{**}	-0.033	0.037	-0.038	0.036	-0.018	0.024	0.038^{*}
	(0.024)	(0.015)	(0.047)	(0.023)	(0.051)	(0.023)	(0.030)	(0.021)	(0.020)
Const.	-0.971	0.470	1.601^{**}	0.073	-0.176	0.679	0.764	0.198	1.019^{**}
	(0.742)	(0.343)	(0.516)	(0.495)	(1.086)	(0.513)	(0.727)	(0.497)	(0.438)
Obs.	11	182	15	77	10	84	39	110	98
R^2	0.839	0.118	0.672	0.066	0.590	0.162	0.058	0.118	0.165
adj.R^2	0.597	0.088	0.425	-0.015	-0.232	0.097	-0.119	0.067	0.110

for individual preferences in general (for a similar conclusion, see Hoffmann et al. (2010)). We suspect that more preference-driven investors put greater emphasis on risk and select a higher value for their risk classification according to the German Securities Act since risk also enters their utility function and thus seems to play a crucial role in their decision of whether to buy a stock or not. Thus, it appears that the trading of individuals is governed by factors other than preferences, which is in line with Grinblatt and Keloharju (2009), although the extent to which preferences govern trading decisions may differ for buying and selling orders (Barber and Odean (2008)).

6. Conclusion

The microeconomic modeling of investor behavior in financial markets and its results crucially depend on assumptions about the mathematical shape of the underlying preference functions, as well as their parameterization. With the purpose of shedding light on the question of which preferences toward risky financial outcomes prevail in stock markets, we adopted and applied a maximum likelihood approach from the field of experimental economics on a randomly selected dataset of 656 private investors of a large German discount brokerage firm. According to our analysis, we found evidence that the majority of these clients follow trading patterns in accordance with prospect theory (Kahneman and Tversky (1979)). We also found that observable sociodemographic and personal characteristics, such as gender or age, do not seem to be correlated with specific preference types. With respect to the overall impact of preferences on trading behavior, we find a moderate impact for individual investors. A classification of investors according to various utility types reveals that the strength of the impact of preferences on an investor's trading behavior is unconnected to most personal characteristics but seems to be related with round-trip length.

Appendix A. Notes on the estimation of stocks market parameters

In this paper, we use the the first two moments of the observed return distribution to estimate values for the required upside and downside returns $\hat{R}_{U,t}$ and $\hat{R}_{D,t}$. In particular, we calculate stock-specific values for $\hat{R}_{S,t}$ using the fact that we can assign values for $\hat{R}_{D,t}$ and $\hat{R}_{U,t}$ by calculating from $\hat{\mu}_t$ and $\hat{\sigma}_t$ at time t for differing formation periods with $\hat{R}_{U,t} = e^{\frac{\hat{\mu}_t}{l}+\sqrt{\frac{1-\hat{p}_t}{\hat{p}_t}\frac{\hat{\sigma}_t^2}{l}}}$ and $\hat{R}_{D,t} = e^{\frac{\hat{\mu}_t}{l}-\sqrt{\frac{\hat{p}_t}{1-\hat{p}_t}\frac{\hat{\sigma}_t^2}{l}}}$, respectively. This is a standard procedure (Ingersoll (1987)) and is widely applied as similar expressions can be found in Johnson et al. (1997) for non-standardized skewness, Barberis and Xiong (2009), Ebert and Strack (2009) and Johnson et al. (2012). The corresponding upside probabilities $\hat{p}_t$ are derived from our estimates of $\hat{\Gamma}_t$, where we use $\hat{p}_t$ as the remaining degree of freedom to implement the connection to the skewness of the return distribution, such that $\hat{p}_t = \frac{(4+l\hat{\Gamma}_t^2 \pm \sqrt{l\hat{\Gamma}_t^4+4l\hat{\Gamma}_t^2})}{(8+2l\hat{\Gamma}_t^2)}$, where $+$ if $\hat{\Gamma}_t < 0$ and $-$ if $\hat{\Gamma}_t > 0$, which implies that $\hat{p}_t = 0.5$ if $\hat{\Gamma}_t = 0$. Ebert and Strack (2009) states for $l = 1$ that this expression is strictly positive and unique such that the requirements of Kolmogoroff are satisfied. Furthermore, we use the 3-Month Euribor as retrieved from Thompson Reuters Datastream on 02.12.2012 as a proxy for the riskfree return $R_{f,t}$.

Appendix B. Notes on the set of utility functions used

To restrict the set of utility functions, we focus primarily on those preferences mentioned by the studies presented above, partly due to missing empirical evidence as utility functions left out are of rather pedagogically than empirically relevant or as some forms may arise computational difficulties the econometric approach applied here simply cannot cope with. In asset pricing, theories of rational decision making play an important role, reflected by the fact that expected utility paradigm is still widely applied. Consequently, we model preferences as in Landskroner (1988), Morin and Suarez (1983), Blume and Easley (1992), Levy (1994), Ait-Sahalia and Lo (2000), Jackwerth (2000), Kliger and Levy (2002), Bliss and Panigirtzoglou (2004), Brunnermeier and Nagel (2008), Guiso and Paiella (2008) as well as Chiappori and Paiella (2011) and define the utility of an *expected utility*-type investor (EUT) according to

$$U_{EUT}(W_t|\boldsymbol{\theta}_{EUT}) = \sum_{j=1}^{t+1} \hat{p}_{j,t} u_{EUT}(W_t|\boldsymbol{\theta}_{EUT}), \tag{B.1}$$

where $\hat{p}_{j,t}$ denotes the respective probabilities associated with the respective state. In particular, we denote the utility functional as u_{EUT} given the flexible expo-power specification as used in Saha (1993), where $\boldsymbol{\theta_{EUT}}$ incorporates parameters of relative and absolute risk aversion such that (dependent on the respective constellation of its parameterization (e.g. Saha et al. (1994))), utility function $u_{EUT}(W_t|\boldsymbol{\theta}_{EUT})$ principally reflects properties of $DARA$, $CRRA$ and IARA as well as $DRRA$ or $IRRA$. Moreover, to benchmark the case where $u_{EUT}(W_t|\boldsymbol{\theta}_{EUT})$ converges to $CRRA$ utility we additionally model $CRRA$-utility according to the form used in Gollier (2001), simultaneously covering mean–variance preferences (see Back (2012).

There is some evidence that generalized expected utility theories such as rank-dependent utility (Polkovnichenko (2005) and Prigent (2010)) might be relevant in financial markets. Thus we consider an investor with *rank-dependent utility* (RDU) according to Quiggin (1982), Quiggin (1993) and Wakker (1994), where the utility drawn from a stock is written as

$$U_{RDU}(W_t|\boldsymbol{\theta}_{RDU}) = \sum_{j=1}^{t+1} \pi_{j,t}(\Delta\omega(\hat{p}_{j,t}|\boldsymbol{\theta}_{RDU}))u_{RDU}(W_t|\boldsymbol{\theta}_{RDU}). \tag{B.2}$$

In comparison to expected utility (EUT) as presented above, RDU may lead to first-order risk aversion due to its application of cumulative decision weights (Yaari (1965)), leaving the utility functionals unaltered. These decision weights, denoted as $\pi_{j,t}(\omega(\hat{p}_{j,t}|\boldsymbol{\theta}_{RDU}))$ are defined as decumulative probability transformation functions according to Abdellaoui (2000) in the following process, although alternative formulations exist such as in the original version of RDU (see Quiggin (1982) and Quiggin (1993)).[45] To grasp the particular structure of the decision weighting functional $\omega(\hat{p}_{j,t}|\boldsymbol{\theta}_{RDU})$, we adopted the frequently used form of Karmarkar (1979), Karmarkar (1978) and Quiggin (1982), according to which the decision weights if added up across all states of nature equals unity (Abdellaoui (2000)). Contrasting this, studies explicitly dealing with the implications of nonlinear probability treatments caused by decision weights can be found more often lately in the context of asset pricing (e.g.(Barberis and Huang (2008) and Barberis (2011)) so that, in order to cater this stream of literature, we implemented a subadditive weighting function as proposed by Kahneman and Tversky (1979), Tversky and Kahneman (1992) and used in Wu and Gonzalez (1996).

We also acknowledge the recognition of alternative utility functions such as Prospect Theory (Kahneman and Tversky (1979)) and its refinement, cumulative prospect theory (Tversky and Kahneman (1992)) in studies dealing with asset pricing, portfolio choice and trading behavior (Berkelaar et al. (2004), Gomes (2005), Polkovnichenko (2005), Barberis and Xiong (2009), Barberis (2011), Jin and Zhou (2008), Bernard and Ghossoub (2010), He and Zhou (2011) and Ingersoll and Jin (2013)). Reflecting this trend, we model preferences for both versions of Prospect Theory, namely *simple prospect theory* (SPT) and *cumulative prospect theory* (CPT), and define utility functionals $u_{SPT}(W_t, W_{RP}|\boldsymbol{\theta}_{SPT})$ where gains and losses form the support of this functional. These gains and losses are assumed to be marked against a static reference point W_{RP}, which is usually based on an initial wealth level or purchase price (also see Grinblatt and Keloharju (2001b), Garvey and Murphy (2004), for dynamic reference points Meng (2010)) such that in general, both versions of Prospect Theory can be expressed as

$$U_{SPT}(W_t, W_{RP}|\boldsymbol{\theta}_{SPT}) = \sum_{j=1}^{t+1} \pi_{j,t}(\omega(\hat{p}_{j,t}|\boldsymbol{\theta}_{SPT}))u_{SPT}(W_t, W_{RP}|\boldsymbol{\theta}_{SPT}). \tag{B.3}$$

The original formulation of Kahneman and Tversky (1979) with respect to the utility functional has been adapted in countless studies on various issues in asset pricing (Berkelaar et al. (2004), Berkelaar and Kouwenberg (2009), Kliger and Levy (2009) and others) such that we model $u_{SPT}(W_t, W_{RP}|\boldsymbol{\theta}_{SPT})$ accordingly as a kinked power-function as elaborated in the appendix of Kahneman and Tversky (1979), although some studies model the demand of SPT-type investors according to a different form of the value functional and apply a mathematical construct similar to $CRRA$ utility (e.g. Barberis et al. (2001), Gomes (2005) or Barberis and

[45] A preliminary dry-run of our program as a test of the econometric procedure used evinced that the original formulation of the decision weights has virtually no effect on the outcomes. Based on these simulations, we are confident enough to omit an explicit application of the original formulation of RDU.

Huang (2008)).[46] For *cumulative prospect theory* (CPT), we calculate the utility of the financial prospects according to Tversky and Kahneman (1992) as

$$U_{CPT}(W_t, W_{RP}|\boldsymbol{\theta}_{CPT}) = \sum_{j=1}^{t+1} \pi_{j,t}(\Delta\omega(\hat{p}_{j,t}|\boldsymbol{\theta}_{CPT}))u_{CPT}(W_t, W_{RP}|\boldsymbol{\theta}_{CPT}), \quad \text{(B.4)}$$

where as the distinguishing feature, differences in decision weights across states, ranked according to their associated prospects and denoted as $\pi_{j,t}(\Delta\omega(\hat{p}_{j,t}|\boldsymbol{\theta}_{CPT}))$ represent the central constituent of CPT (see Tversky and Kahneman (1992) and Fennema and Wakker (1997) for details). Note that this contrasts SPT, in which a specific decision weight $\pi_{j,t}(\omega(\hat{p}_{j,t}|\boldsymbol{\theta}_{SPT}))$ is assigned to each state of nature as elaborated above. Furthermore, it appears noteworthy to say that for CPT, we use the same specifications with respect to $u_{CPT}(W_t, W_{RP}|\boldsymbol{\theta}_{CPT})$ as for the original version of Prospect Theory.

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[46] Its worthwhile to mention that in Barberis et al. (2001) and Barberis and Huang (2008), state specific changes in consumption instead of changes in wealth enter the functional $u_{SPT}(W_t, W_{RP}|\boldsymbol{\theta}_{SPT})$ (also Barberis and Xiong (2009)) such that a direct comparison of the results drawn in those papers to implications of equation(B.3) is necessarily flawed to some extend.

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