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The Behavioural Implications of Passive Robo-Advising on Personal Savings - Evidence from Kron AS

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Abstract

The political shift and technological development since the 2008 financial crisis have shaped a new era, taking financial wealth management to robo-advisory (RA). This thesis studies the behavioural implications of a Norwegian passive robo-advisor (RAr) that constructs tailored saving plans for retail investors. These implications are investigated on individual and stereotype saving behaviour. Main results show, that changes to invested capital and expected investment horizon are the most relevant factors for diverse successes in passive robo-advising. Investors providing supplementary capital at later points in time acquire a 3.4% higher Assets under management (AUM) than investors who keep their invested capital constant. Those who withdraw funds from the RAr marginally decrease their AUM. This adjustment behaviour is different for distinct investor groups. Trend-chasing does not explain this difference. Deviations from intended saving behaviour in the robo-advisor are greater for stereotypes around age, gender, and residence, where age was the main driver. Differences between stereotypes were reduced over time, however individual differences in behaviour were not. To be beneficial for personal savings, passive robo-advising has to be extended from pure portfolio advice to counsel on adjusting invested capital. Identified possible solutions are to incorporate individuality in the advisor's customer assessment and notifying on potential pitfalls concerning adjustments to invested capital.

Keywords - *Robo-Advisory, FinTech, Behavioural Finance, Personal Traits, Stereotypes, Decision-making, Investment Behaviour*

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Abbreviations

Table I Overview of Abbreviations

Abbreviation	Explanation
Accd	Account age in days
Act	Activity in Kron's tool
AUM	Assets under management
AumDelta	Change in the AUM
BIS	Basel Commit
CEO	Chief Executive Officer
EBA	European Banking Authority
ETFs	Exchange traded funds
FinTech	Financial technology
Fl	Financial literacy
Flowscat	Transaction flows
FOR	Combination of investor demographics: Female-Older-Rural
FOU	Combination of investor demographics: Female-Older-Urban
FSB	Financial Stability Board
FYR	Combination of investor demographics: Female-Younger-Rural
FYU	Combination of investor demographics: Female-Younger-Urban
Horiz	Investment horizon
IMF	International Monetary Fund
Inv_Incr	Invested if return increased
Log_Mob	Log-ins to Kron's mobile application
Log_Web	Log-ins to Kron's web application
MOR	Combination of investor demographics: Male-Older-Rural
MOU	Combination of investor demographics: Male-Older-Urban
Mpf	Model portfolio
MYR	Combination of investor demographics: Male-Younger-Rural
MYU	Combination of investor demographics: Male-Younger-Urban
Netret	Net return on invested funds
OECD	Organization for Economic Co-operation and Development
Pref	Preferred investment sector
RA	Robo-advisory
RAr(s)	Robo-advisor(s)
Ret	Return
Retlag	Lagged return

Risk	Risk level
SumDelta	Change in the total sum of transactions
Trans	Transactions

Definitions

Table II Overview of Definitions

Terms	Definition
Assets under management (AUM)	The total market value of the investment entity RA manages on behalf of clients. AUM includes deposits, mutual funds and cash. Investors often assign authority to the company to trade on their behalf under discretionary management ("Journal of asset management," 2000).
Credit squeeze/crunch	Credit squeeze/crunch is a situation that occurs when there is a sudden shortage of funds, leading to a decline in lending activity by financial institutions. This makes it harder for companies and consumers to borrow due to leaders' fear of defaults and bankruptcy (Bernanke, Lown, & Friedman, 1991).
Digital natives	"Refers to those consumers who grew up with digital technologies" (Frost, 2020, p. 8).
Noncognitive abilities	Is generally defined as any skill that is not cognitive (e.g. attention, thinking, skills etc.), and rather includes skills such as emotional maturity, empathy and interpersonal skills (Borghans, Duckworth, Heckman, & Weel, 2008).
Older generation	Includes 'Baby Boomers' (born between the 1940s and 1960s) and 'Generation X' (born between the mid 1960s and early 1980s) (Frost, 2020, p. 8).
Onboarding	Is the process of the client opening an account with Kron AS.
Personal traits	Include all consumer characteristics related to patterns of behaviour, thoughts, and feelings (Roberts, 2009).
Retail investor	Is also known as an individual investor. It is a non-professional investor who buys and sells exchange traded funds (ETFs), mutual funds as securities through traditional or online brokerage firms, or other types of investment accounts (O'Hare, 2007).
Robo-advisory	Is "an automated investment platform that uses quantitative algorithms to provide financial advice and manage investors' portfolios, while being accessible to clients online" (Beketov, Lehmann, & Wittke, 2018; Fisch, Labouré, & Turner, 2018; Sironi, 2016).

	In this study, it is exclusively used in the context of financial investment advisory; where robo-advisory increasingly replaces the classic retail financial advisory process (e.g. human advisory). It is not used in the generic concept of robo-advisory, which can be transferred to other domains such as the real estate industry or health care (Jung, Dorner, Glaser, & Morana, 2018; Sironi, 2016).
Saving behaviour	Is defined as the pattern of the investor's actions related to their personal finances (Martin, 2000).
Savings	Is the amount the consumer is left with after all personal expenditures are subtracted from the amount of disposable income earned in a given period; not to be confused with saving money by buying a cheaper product. Here, savings is a reference to the generated amount the investor has saved with Kron's tool (Martin, 2000).
Stereotype Threats	Is a social psychology term. "[..] in which there is a negative stereotype about a person's group, and he or she is concerned about being judged or treated negatively on the basis of this stereotype" (Steven J Spencer, Logel, & Davies, 2016, p. 416).
The tool	Kron's saving robo-advisor.
Younger generation	Includes 'Millennials' (born between the early 1980s and mid 1990s) and 'Generation Z' (born between the late 1990s and late 2000s) (Frost, 2020, p. 8).
Trend-chasing	It is a common bias to buy assets that have high past returns and sell assets that have low past returns, by trying to capitalize on a market movement that is already under way. It is particularly common among individual and inexperienced investors (Fong, 2014)

1.0 Introduction

The capital market offers a vast and multi-faceted range of financial products and services for investments and savings. These create endless opportunities for investors, though possibly convoluting the appropriate financial decision. Making decisions about personal wealth, and carrying the associated risk, is a difficult challenge for many retail investors[1] without any professional advice. Consequently, individuals are generally sceptic about participating in capital markets, especially following the effects of the 2008 financial crisis (Agarwal, Chomsisengphet, & Lim, 2017; Jung, Glaser, & Köpplin, 2019). Nonetheless, individuals had to reconsider their personal savings and investments after the crisis. The low-interest-rate policy made benefits from capital markets more evident for individuals. Further, the technology evolution in the last two decades has led to numerous innovations in financial services (Bachmann, De Giorgi, & Hens, 2018b). Robo-advisory (RA) provides financial advice and manages investors' portfolios online (Beketov et al., 2018; Fisch et al., 2018; Sironi, 2016). The term RA covers a wide range of digital (semi-) automatic investment services and platforms.

A passive robo-advisor (RAr) is almost entirely automated, and the investor remains passive in decision-making about portfolio management. This study focused on two central aspects around passive RA. Firstly, how individual investors behave and make financial decisions in RA and secondly, what implications RA has on investors' savings. The research object was the passive RAr developed by a Norwegian company, Kron AS. The underlying theory of the study is behavioural economics, which incorporates elements from other social sciences. We divided the thesis into four topics. The research objective was firstly, to investigate the relationship between invested capital and generated savings. Results from the topic 'Measuring Investment Behaviour in Passive Robo-Advising' showed, that adjustments to invested capital and investment horizon are the significant determinants of diverse successes in savings. Secondly, the study investigated deviations from 'rational' investment behaviour among users. The topic 'Responses to Market Movements' established whether adjustments to invested capital are explained by market movements.

[1] Retail investor: also known as an individual investor. It is a non-professional investor who buys and sells exchange traded funds (ETFs), mutual funds as securities through traditional or online brokerage firms, or other types of investment accounts (O'Hare, 2007).

We found that returns hardly predict transactions of individual users or stereotypes of investors. Personality traits, however, showed to explain a greater part of the variation in these transactions and have a greater influence on saving behaviour. Thereafter, the focus was to identify differences in the capital adjustment behaviour, by segmentation of the demographics gender, age and residence. The analysis performed under topic 'Differences in Saving Behaviour' led to a segmentation of investors with different saving behaviour, identifiable by their demographic traits. Lastly, the study investigated whether the effect of personal traits and stereotyping is diminished over time. The topic 'Differences in Saving Patterns over Time' showed that while differences between segments were reduced over time, the variety of individual saving patterns increased.

Overall, our research shows, that Kron's RAr provides an additional benefit for its investors, by reducing the effect of stereotyping in their saving behaviour. Further effects of real individuality were not reduced. However, we find that gender and age are the main drivers for the difference between investors' saving behaviour, where age is the denominator for these differences. The magnitude of benefits from capital markets is highly dependent on the investors' willingness to stay invested. Withdrawing funds interrupts the original saving plan and shows differences in saving behaviour through passive robo-advising. We conclude that the benefit for retail investors from easier access to capital markets is dependent on their consistency around saving behaviour. Considering inconsistencies in the intended saving behaviour, the RAr should extend its core function to advise on adjusting invested capital. This would increase value from robo-advising for retail investors.

In this thesis, Chapter 2 contains the literature review of research on RA and behavioural economics, where the key take-aways are summarised in 2.4. The research object, Kron's RAr, the company Kron AS, and the specific investment process in this RAr are described in chapter 3. Next, Chapter 4 contains the methodology for this study, with the hypotheses outlined in 4.1. Chapter 5 contains all empirical results, where the most relevant findings are presented in Table 3 at the beginning of the chapter. All analysis of empirical findings is presented in Chapter 6, where each section contains an interim conclusion. Chapter 7 presents our final conclusion.

1.1 Background

The aftermath of the 2008 financial crisis left the world with long-term consequences. These include volatile financial markets, higher unemployment rates, low interest-rate policies, and generally high financial uncertainty for the majority of individuals (Campello, Graham, & Harvey, 2010; Mishkin, 1990; Reinhart & Rogoff, 2009). Inevitably, the global market growth prognosis was downgraded to its lowest since then, by both the International Monetary Fund[2] (IMF) and the Organization for Economic Co-operation and Development (OECD) (Lea, 2019; Leiva-Leon, Pérez-Quirós, & Rots, 2020; OECD, 1993). Paradoxically, the capital market growth has been incredibly high since 2008, compared to the real economy. Majority of retail investors did not invest and benefit from this upturn, due to high financial uncertainty. Barriers of high wealth requirements and knowledge thresholds add to this ("Money and Happiness," 2019).

The last decade saw multiple discussions on what universal action should be in terms of stimulating the global real economy. A key factor in these discussions is the distrust consumers have in the financial system regarding their personal savings. These savings are a vital part of stimulating the global market by affecting the disposable market capital (Liu & Woo, 1994; Tesar, 1991). Governments have gone through a political shift since 2008. They started advocating for a new responsible approach to personal finance, encouraging individuals to take more charge of their financial security for future needs (Brounen, Koedijk, & Pownall, 2016; Jensrud, 2019). Nonetheless, the financial markets still excluded 2.5 billion adults from the formal financial system in 2015. Individuals are often discriminated due to high wealth requirements and limited accessibility (Adams, 1978; Chishti, 2016). Consumers still had to reconsider their household savings and investments after 2008. The consequential credit squeeze[3] made alternative sources of finance more attractive to consumers (Brunnermeier, 2009; Davis & Schumm, 1987; Mackenzie, 2015; Tesar, 1991). A technology boom enabled digitalisation and automation of originally human-driven processes.

2 IMF: An organization of 189 countries, working to foster global monetary cooperation, facilitate international trade, secure financial stability, promote high employment and sustainable economic growth, and reduce poverty around the world ("The IMF at a Glance," 2020).

3 Credit squeeze/crunch: is a situation that occurs when there is a sudden shortage of funds, leading to a decline in lending activity by financial institutions. This makes it harder for companies and consumers to borrow due to leaders' fear of defaults and bankruptcy (Bernanke et al., 1991).

Industry players within financial technology (FinTech) incorporated this automation, and thereby disrupted the financial markets. Customers appreciate value-creating features such as lower cost structures, more available information, ability to compare products and overall simpler languages between themselves and the provider. This led to an increased level of transparency, better accessibility, and lower transaction costs for savings and payments (Chishti, 2016). In recent years, FinTechs have proven the ability to enable access to the financial system by lowering the knowledge and wealth-requirement thresholds (Demirguc-Kunt, Klapper, Singer, Ansar, & Hess, 2018; Ludden, Thompson, & Mohsin, 2015).

These companies continuously capture larger market shares and captivate more aspects of our daily lives (Chiu, 2017; Perez, 2010). The World Bank operates the most comprehensive data set on how adults save, borrow, make payments, and manage risk. With an analysis of universal financial inclusion, the World Bank reports the many potential market development benefits through digital financial services (Demirguc-Kunt et al., 2018). These arguments build upon Schumpeter's hypothesis that technological innovation can be a key driver for economic growth (Kogan, Papanikolaou, Seru, & Stoffman, 2017; Nelson, 2000; Scherer, 1986). The large industry players agree with the World Bank on the possibilities that FinTechs create for consumers worldwide. The CEO of Lending Club, Scott Sanborn was quoted saying:

> With fintech it's the first time we have financial innovation that's not about taking more risk or finding loopholes in regulations but rather about using technology to lower the costs and pass on the cost savings to customers (Mackenzie, 2015, p. 51).

One of the fastest-growing markets in the FinTech industry is RA, due to its increasing popularity within equity investments. It takes on the well-known traits from traditional human advisory and combines it with a simple, digital and sophisticated interface. These tools incorporate features that are designed to ease financial decision-making on accurate risk-measurement, portfolio selection and rebalancing (Jung et al., 2019). This facilitates the entry to capital markets for consumers, without the fear of being schemed with high fees and loss of wealth (Bachmann, De Giorgi, & Hens, 2018a; Chishti, 2016).

1.2 Relevance

Even with the global emphasis on individual savings, and on financial security for consumers, limited research has been conducted about the effect of personality traits in personal savings (Brounen et al., 2016). Whilst RA reduces the difficulty of choosing an appropriate investment strategy and portfolio rebalancing, individual investors tend to make less rational decisions than professionals (De Bondt, 1998). One of the reasons behind this is that investors' personal traits naturally influence how they make financial decisions. Recent studies have considered these traits when analysing different variables in economic decision-making (Carr & Steele, 2010; Steven J Spencer et al., 2016; Walton & Cohen, 2003). Previous papers have focused on providing a basic understanding for RA's elements, and how it compares to traditional advisory (Brown & Taylor, 2014; Browning & Lusardi, 1996; Kausel, Hansen, & Tapia, 2016). Others have identified the behavioural implications from the use of RA as a further research area (Jung, Dorner, Glaser, et al., 2018). "This area has seen relatively little research (e.g., Tufano 1989) […] Less work on FinTech is aimed at the stock market investing decisions of households" (D'Acunto, Prabhala, & Rossi, 2019, p. 1988). This study mainly contributes to the work of Campbell (2006) on savings, as well as different studies on the functionality and implications of robo-advisors.

1.3 Research Question

This paper aims to identify value-creating effects for more individuals from using passive robo-advisory (RA). The objective is to analyse whether RA can incentivise investors to dedicate to financial stability and savings regardless of their personal disposition. We want to examine, if Kron's robo-advisor (RAr) enables all its investors to benefit from capital markets on equal terms, regardless of their demographics. We pose our research question:

> *"From a behavioural perspective: Does Kron's robo-advisor incentivise similar saving patterns across different investors, and thus create benefit from capital markets for more individuals, due to the elimination of personal traits in investment behaviour?"*

2.0 Literature Review

The literature review will address three areas of research on robo-advisory (RA), investment behaviour, and saving behaviour, as presented in Figure 1 below. The first section contains studies on the development and conceptualization of RA. In the second section, there will be a discussion on the implications of personal traits and stereotypes on investment behaviour. Finally, the third section will focus on the role of personal saving behaviour in traditional savings, and in RA. Further, the last section contains a summary of the key takeaways for this thesis.

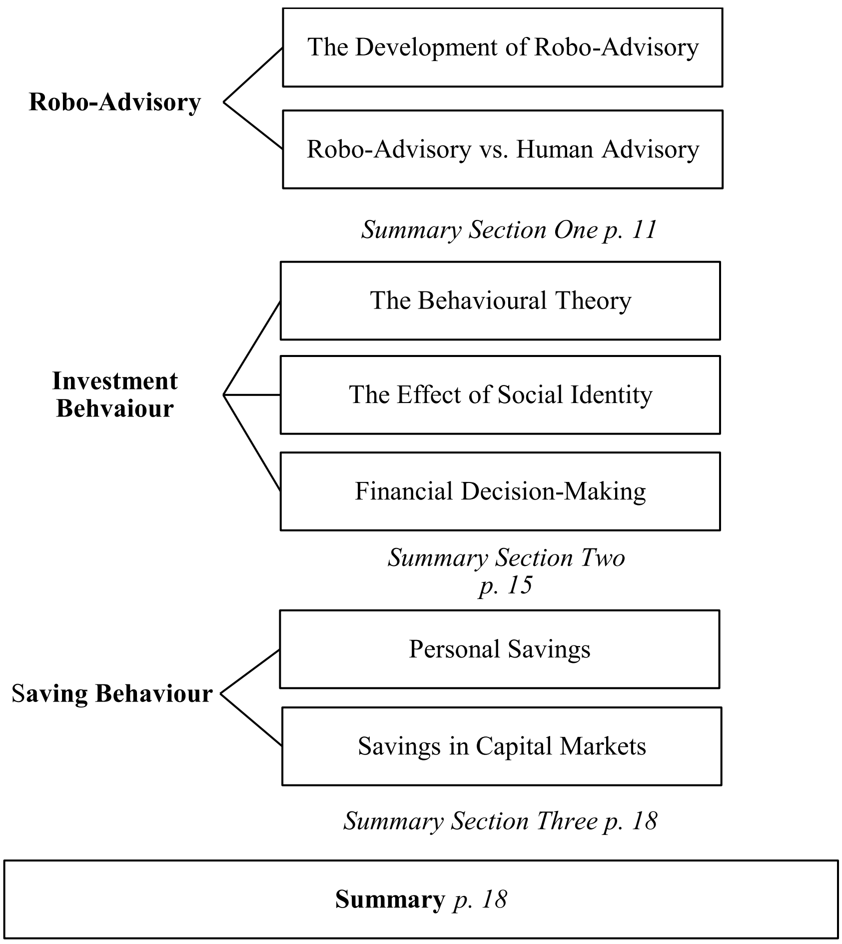

Figure 1: Overview of The Literature Review

The process of collecting relevant literature started among well-established journals. The string of keywords used was ‘robo-advisory’, ‘fintech’, ‘behavioural finance’, ‘investment behaviour’, ‘personal traits’, ‘stereotypes’ and ‘decision making’. The focus has been on publications from 1990-2020, and peer-reviewed journals were utilized to ensure the quality of the articles (Saunders, 2016).

2.1 Robo-Advisory

2.1.1 The Development of Robo-Advisory

The digital revolution has moved the financial sector into a large and mostly untouched area, with fast changes and high potential. Bill Gates was famously quoted back in 1994 saying: "Banking is necessary, Banks are not" (Jung, Dorner, Glaser, et al., 2018, p. 1). As time passes, research has backed Gates' statement. Researchers have defined two waves of digitalization, the first wave changed many aspects of everyday life, and with that challenged the existing business models (Alt & Puschmann, 2016; Jung, Dorner, Glaser, et al., 2018). The second wave has taken a step further and shifted the focus towards a smart service, based on algorithms and intelligent software to increase automation. This shift led to the development of FinTechs in digital money services and RA (Jung, Dorner, Weinhardt, & Pusmaz, 2018). RA is a part of the fast-growing evolution within technological innovations in the financial service industry. It can be defined as "an automated investment platform that uses quantitative algorithms to provide financial advice and manage investors' portfolios, while being accessible to clients online" (Beketov et al., 2018; Fisch et al., 2018; Sironi, 2016).

Studies have classified RA into four generations. The 1st and 2nd generation RA is comprised of online questionnaires and proposals to clients. It merely provided a combination of advice and online access to traditional "manual" asset management services. Following this, the evolution to 3rd and 4th generation included the use of quantitative algorithms to construct and rebalance portfolios. This provided a more "truly" automated portfolio management performance. The only difference between the two generations is the increasing level of automation and methodological advance for details. Both still cover the entire investment management process; from investor analysis to the selection of the available instrument universe, periodic portfolio rebalancing and choosing an appropriate performance measure for reporting (Beketov et al., 2018; Deloitte, 2016). The interest for financial advisory increased because of more available information, resulting in higher transparency and accessibility to financial markets.

Researchers at Oxford University describe the financial markets as "a fascinating example of 'complexity in action': a real-world complex system whose evaluation is dictated by the decision of a crowd of traders who continually try to win the vast global game" (Johnson, Jefferies, & Hui, 2003, p. 1). Understanding the complexity of this system and making appropriate capital market investing decisions is challenging for professionals. Less-educated individuals within the field will thus have even greater difficulty. The continuous increase in available securities adds to these complexities. With more available opportunities, investors have more saving prospects through investments, though this can also lead to higher risk exposure and more difficulty regarding the appropriate investment choice. While the digital revolution has increased the supply for financial products in the market, it has also increased the consumers' power through more accessibility to information (Labrecque, vor dem Esche, Mathwick, Novak, & Hofacker, 2013). This, in turn, broadened the awareness for the importance of assessment and transparency in financial decision-making. Studies show that robo-advisors (RAr(s)) can deliver an optimal solution for higher levels of assessment and transparency. Limitations from studies indicate room for research confirming that RArs offers a potential solution to capital market investing problems among individuals (Chishti, 2016).

2.1.2 Robo-Advisory vs. Traditional Human Advisory

Automated financial advisors are less vulnerable to potential conflicts of interest, whereas traditional human financial advisors are often prone to misguiding incentive-based compensation schemes. Empirical research has established that there is a large segment of unmaintained consumers, who are discriminated from using traditional advisory (Fisch et al., 2018; Nussbaumer, Matter, à Porta, & Schwabe, 2012). RA targets these retail investors regardless of their wealth, due to its transparent and low-cost structure from using inexpensive Exchange Traded Funds (ETFs), and automation (Bhatnagar, 2016). It differs from traditional investment advisors, due to two conceptual levels of customer assessment and portfolio management. Researchers have synthesized the traditional human advisory's six phases of service into the following three phases of RA Configuration, Matching and Customization, and Maintenance (Kilic, Heinrich, & Schwabe, 2015; Nussbaumer, Matter, & Schwabe, 2012).

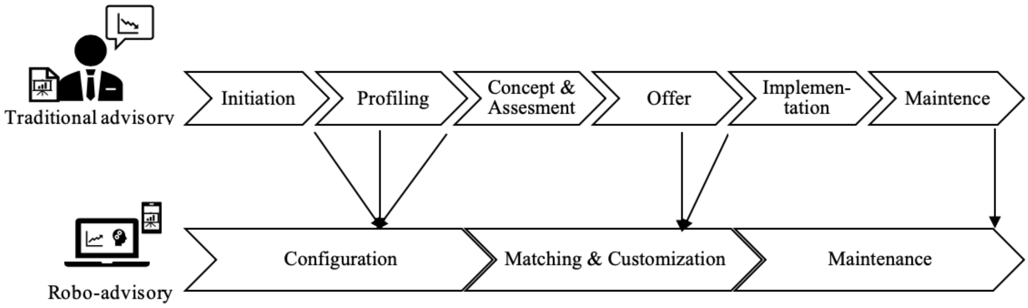

Figure 2: The Synthesis of Human Advisory into Robo-Advisory

2.1.2.1 Customer Assessment: Phase 1 - Configuration

RA aims to transform the complete traditional human-to-human advisory process into a human-to-computer (i.e. digital) advisory process. Where traditional investment profiling is conducted during in-person interviews, RA profiles its investors through online questionnaires and self-reporting processes (Jung, Dorner, Glaser, et al., 2018). A study found that the majority of investors can accurately indicate their risk aversion, and other information (Grable, Roszkowski, Joo, O'Neill, & Lytton, 2009). Though, the precision of the RAr’s customer assessment is dependent on the amount of collected data on the investor’s demographics, goals, risk level, time horizon and expectations for returns. These are then quantified by algorithms and automatically processed on the digital platform (Jung, Dorner, Glaser, et al., 2018). By this, asymmetric information is reduced between client and advisor (Kilic et al., 2015). Due to automated customer assessment, cost structures are lowered, and affordability of investment advice increases (Jung et al., 2019).

2.1.2.2 Portfolio Management: Phase 2 - Matching & Customization

The next step is customer portfolio management, which can be defined as “the management of portfolios including one or more financial products, by mandates given by clients on a discretionary client-by-client basis” (Jung, Dorner, Glaser, et al., 2018, p. 82). This allows RA to manage clients’ portfolios optimally. Moreover, the client receives recommendations based on gathered information through appropriate algorithms. Compared to traditional portfolio management, RA is predominantly based on financial products, such as ETFs, which require less active portfolio management. This also results in lower cost structures and is easier to communicate to a wider range of consumers (Gastineau, 2010; Jung, Dorner, Glaser, et al., 2018).

2.1.2.3 Portfolio Management: Phase 3 - Maintenance

Within 'Maintenance' active and passive portfolio management are distinct. In passive portfolio management rebalancing is fully quantified. The RAr will automatically choose from a set of pre-determined assets according to the client's preferences in the configuration phase. On the other hand, if the client receives rebalancing suggestions and decides actual execution self-directedly, the RAr is conducting active portfolio management (Browne, 2000; Jung, Dorner, Glaser, et al., 2018; Malkiel, 2003). Additionally, the portfolio construction and investment strategy approach can be either static or dynamic. When the initial adjustment to a client's profile directs the portfolio construction and is never adjusted after, it can be classified as static RA. Dynamic RArs allow clients to adjust the overall strategy in a discretionary way during the investment horizon (Jung, Dorner, Glaser, et al., 2018; Lam, 2016).

2.1.3 Benefits & Potential Downsides

There are many potential benefits from RA such as push notifications on market developments, opportunity and risk alerts, lower fees and periodic portfolio reviews. These components, and the simplicity and transparency of RA, enable less financially literate individuals to receive investment advice. Studies have found that consumers are getting more informed, involved, and engaged in their investment decisions and contractual relationships (Jung, Dorner, Glaser, et al., 2018; Ludden et al., 2015). The European Banking Authority (EBA), the Financial Stability Board (FSB), and the Basel Committee (BIS) all agree on the benefits FinTech has for a functioning financial market, through more efficiency and competition. However, the FinTech sector is growing rapidly, while regulation processes are slow. Thus, global regulators work to establish a framework for regulating the growing risk exposure for consumers from the unchartered area within the financial sector (e.g. cyber-risk, operational risk and strategic risk) (Jensrud, 2019). The extent of the downsides, however, is dependent on the RA itself, as quality in algorithms, business models and client assessments vary (Cocca, 2016; Tertilt & Scholz, 2018). Moreover, RA has faced criticism about the increasing problem of promising 'low fee' or 'zero-fee' transactions. Users still bear the transaction costs, advisory fees and the cost of brokerage (Fein, 2015; Jung et al., 2019).

2.1.4 Interim Summary

Today's 4th generation robo-advisors (RAr(s)) are fully automated. In passive robo-advisory (RA), portfolio selection, diversification and rebalancing are managed by algorithms. Therefore, they are not drivers of differences in performance among individuals. Literature has identified potential drivers to be: i) the client's interaction with the RA, ii) client's investing behaviour and iii) the accuracy of the client's self-assessed indications on investment preferences. Biases can arise during the clients' interaction with RArs, and in their investing behaviour (Baker & Ricciardi, 2014). A remaining question is whether RA can mitigate the biases from personal traits and stereotypes (Agarwal et al., 2017; Jung, Dorner, Glaser, et al., 2018; Jung et al., 2019).

2.2 Investment Behaviour

2.2.1 The Behavioural Theory

Traditional economic models assume that consumers are rational human beings, or '*homines economici'* (Campbell, 2006). These models have a strict framework, with fewer opportunities for interpretations. Recent research has a wider view of consumer behaviour and financial decision-making, which are not always rational (Kausel et al., 2016). "In the economics of the human brain lies a potential explanation for why people are not, cannot be – and would not want to be – as rational as so many economics assume" (McKenzie, 2010). These theories trace back to Adam Smith who identified three terms to describe how human beings act and think: Overconfidence, Loss aversion, and Self-Control (Smith, 1937; Richard H. Thaler, 2009). The nature of human beings' decision-making is surrounded by biases according to different influences. Kahneman describes his system one thinking: fast, instinct-driven and emotional (Kahneman, 2011). These theories imply that economic models tailored to one type of agent are not accurate, but rather, that different types of agents make different decisions according to said influences or biases. Richer Thaler researched the benefits of the behavioural theory: "[..] for empirical work, the behaviour approach offers the opportunity to develop better models of economy behaviour by incorporating insight from other social science disciplines" (Richard H Thaler, 2016, p. 1).

2.2.2 The Effect of Social Identity

Studies found evidence that the performance of individuals depends on their social identity. All individuals identify with some social group based on their personal traits, stereotypes, or a combination of the two (Carr & Steele, 2010; Steele, 1997; Steele, Spencer, & Aronson, 2002). Previous studies have used the classification of demographics for the segmentation of consumers and markets. Demographics are easier to measure than other segmentation variables and provide a fundamental profile of the target sample (Stafford, 1996). These can then be complemented with less measurable factors such as behavioural and psychographic traits. Moreover, social identity based on the investors' demographics can be a key factor in explaining the complexity around investment decisions (Agarwal, Driscoll, Gabaix, & Laibson, 2007; Anderson et al., 2005).

The gender discussion is widely covered in literature and there is evidence of a social stigma around women's "poorer" ability to solve quantitative problems and to make financial decisions, and "slow" adaptation to technology (Carr & Steele, 2010; Margaret, Todd, & Nalini, 1999; Steven J. Spencer, Steele, & Quinn, 1999). Atkinson et al. (2003) examined the performance and investment behaviour of female and male fixed-income mutual fund managers. The study found no significant difference in terms of performance, risk, and other fundamental characteristics. Rather, the difference in investment behaviour often attributed to gender was related to investment knowledge and wealth constraints.

Moreover, there is evidence of social stigmas around *age*. Older generations[4] compared to younger generations[5] are less likely to access the internet and adopt new technology, such as FinTech applications (Carlin, Olafsson, & Pagel, 2017). Hansman and Schutjens (1993) proposed their "rational assumption" that age is a strong predictor of an individual change in attributes and behaviour (Stafford, 1996). Furthermore, a global survey designed to map out the age of digitally active users revealed: only 9% were 75 and older, while 48% were between 25 and 34 years old (Frost, 2020).

[4] Older generation: includes 'Baby Boomers' (born between the 1940s and 1960s) and 'Generation X' (born between the mid 1960s and early 1980s) (Frost, 2020, p. 8).
[5] Younger generation: includes 'Millennials' (born between the early 1980s and mid 1990s) and 'Generation Z' (born between the late 1990s and late 2000s) (Frost, 2020, p. 8).

Additionally, other studies identify a connection to financial literacy. Older generations who have more experience with economic hardship are more likely to save for later. Hence, they should have higher financial literacy, compared to the younger generation that does not value financial planning and security as much (Bencivenga & Smith, 1991; Brounen et al., 2016). On the other hand, research also shows that older individuals have problems performing a simple interest-rate calculation, which indicates lower financial literacy (Lusardi & Mitchell, 2007; Mitchell & Lusardi, 2011). There is limited research on whether personal traits affect individual saving behaviour. This lack of research is unexpected since a central part of theories on why people save is linked to psychological motives (Brown & Taylor, 2014; Browning & Lusardi, 1996; Kausel et al., 2016).

2.2.2.1 Personal Traits

The research published during the past decade signals a growing interest regarding the role of personal traits in economic outcomes (Almlund, Duckworth, Heckman, & Kautz, 2011). Roberts (2009) defines personal traits as*:* "the relatively enduring patterns of thoughts, feelings, and behaviour that reflect the tendency to respond in certain ways under certain circumstances" (p. 140). Prior research provides evidence that personal traits can predict a variety of variables ranging from earnings and occupational attainment (Heckman, Stixrud, & Urzua, 2006), to experimental game decisions (Kagel & McGee, 2014).

The majority of research investigating the connection between people's personal traits and their saving behaviour has used The Big Five Model (Five-Factor Model) (Becker, Deckers, Dohmen, Falk, & Kosse, 2011; Brown & Taylor, 2014; Kagel & McGee, 2014). It is a world-renowned taxonomy of personal traits. It originates from Allport & Osbert´s (1936) 'lexical hypotheses' (Borghans et al., 2008). It captures personality traits at the broadest level of abstraction (Becker, Deckers, Dohmen, Falk, & Kosse, 2012). The model provides a solid framework on how different elements of individuals' personal traits can affect their general behaviour, and therefore their investment behaviour (Becker et al., 2011; Ferguson, Heckman, & Corr, 2011). Nonetheless, this model does not account for the stereotypical perspective that both society and individuals themselves impose on individuals' social position and abilities.

2.2.2.2 Stereotypes & Stereotype Threat

In a situation where the individual might be surrounded by a social stigma regarding their identity, they could experience what is known as stereotype threat[6]. However, the target individual does not need to believe that their stereotype is negatively affected. What rather results in the emergence of stereotype threat, is the knowledge that a stereotype exists, and the explicit articulation that a particular task is diagnostic of ability (Kray, Galinsky, & Thompson, 2002; Steele, 1997). Studies concerning stereotypes show evidence that "extra pressure" can undermine the targeted group's performance, compared to less stereotyped individuals in their position (Major & O'brien, 2005; Steele, 1997; Steele et al., 2002). This can explain much of the underperformance phenomenon, where one's performance is negatively affected in diverse conditions, such as negotiations (Kray et al., 2002) and financial decision-making (Carr & Steele, 2010). Researchers within the field of the "underperformance phenomenon" find that people sharing a given social identity underperform (Major & O'brien, 2005; Steele et al., 2002).

2.2.3 Financial Decision-Making

Newer studies have looked into how stereotyping and the devaluation of one's identity affects financial decision-making (Carr & Steele, 2010). In literature, decision-making is often understood as the product of stable cognitive processes, hence driven by cognitive representations of utility (Kahneman & Tversky, 1979). Others attributed decision-making to innate factors such as demographics (Apicella et al., 2008; Grasmick, Hagan, Blackwell, & Arneklev, 1996), as well as more situation-sensitive factors such as emotions (Lerner & Keltner, 2000; Loewenstein, Weber, Hsee, & Welch, 2001). As in Kahneman's (2011) example, decision-making can be divided into two systems. The first is driven by deliberative processing, and the second by intuition and effect (Evans, 2003). Moreover, research shows that people behave away from normative rationality, while not fully engaging with the deliberative system (Evans, 2003; Kahneman & Frederick, 2002; Loewenstein et al., 2001).

6 Stereotype threat: is a social psychology term "[..] in which there is a negative stereotype about a person's group, and he or she is concerned about being judged or treated negatively on the basis of this stereotype" (Steven J Spencer et al., 2016, p. 416).

A factor found to affect decision-making is ego depletion. This term explains that a target of stereotyping experiences depletion of self-control when exposed to a situation where the target tries to suppress thoughts of negative stereotypes (Inzlicht & Kang, 2010). It interferes with the deliberative system of a person, so that the individual depends more on the intuitive system, and thus makes more impulsive decisions (Masicampo & Baumeister, 2008; Vohs, 2006). Impulsive actions can have costly effects on consumers when making financial decisions. Research on household finance finds evidence of the causal effect of noncognitive abilities and financial distress. Parise and Pejnenburg (2019), find emotional stability and conscientiousness to be the two most relevant factors in economic decision-making. Their study reveals, that people in the lower quintile of noncognitive abilities are ten times more likely to find themselves in financial distress, than those in the higher quintiles. Poor financial decisions have a material impact on households' 'lifetime welfare'(Parise & Peijnenburg, 2019).

2.2.4 Interim Summary

Research within behavioural economics has established that biases arise in financial decision-making. Detecting these biases with an appropriate and valid measure is part of the complexity in explaining differences in investment behaviours. Stafford (1996) used the classification of demographics for the segmentation of consumers. Social stigmas around gender and age are specifically relevant for explaining differences in decision-making. However, the study by Atkinson et al. (2003) delivers evidence, that mainly gender divergence is visible in investment behaviour. According to Hansman and Schutjens (1993), it is rational to assume that age is the strongest predictor of an individual change in behavioural traits. Personal traits can be defined as patterns in individual responses to certain circumstances (Roberts, 2009). This definition can be extended on to the patterns in responses of individual investors to market movements. Carr and Steele (2010) provide evidence that stereotyping in financial decision-making results in the underperformance phenomenon. Generally, stereotyping can affect financial decision-making and investment behaviour. Overall, the most influential factors for differences in investment behaviour are deviations from normative rationality.

2.3 Saving Behaviour

2.3.1 Personal Savings

The link between individual behaviour and individual savings was the research objective for Brounen et al. (2016). They found evidence that saving behaviour varies across generations, gender, and levels of financial literacy. The individual's propensity to save decreases with age, and it is highest among the financially literate. Their research underlines the importance of accounting for individual behaviour when investigating personal savings.

Ramsey (1928) and Fisher (1930) were the first to address the choices households and individuals make regarding savings for future needs. They offered a new standard for economics by accounting for the intertemporal allocation of time, effort, and money (Brounen et al., 2016). Campbell (2006) took this research further, and compared established rational models to how households actually make financial decisions. He argued that many find adequate solutions to complex investment problems, whereas others find less optimal solutions. Campbell's (2006) research confirms the importance of financial education and stricter consumer regulations, to avoid financial mistakes. The importance of financial literacy in financial decisions was first documented by Bernheim (1995, 1998). Recent studies have looked into the effect of low financial literacy in social groups such as those with low education. These groups fail to plan and save for their retirement and increase the risk of running short later in life (Brounen et al., 2016; Mitchell & Lusardi, 2011). The notion that some household financial decisions are inferior to others, can potentially have important aggregate implications (Agarwal et al., 2017; Bhatnagar, 2016; Gabaix & Laibson, 2018). With a two-period model for consumptions and savings, Bowman et al. (1999) focused on the prediction of differences in saving behaviour. Another study used this methodology and found out that asymmetry arises in response to positive and negative shocks to permanent income (P. J. Fisher & Montalto, 2011). Similarly, a study by Kumar et al. (2006) used individual investor's trades to measure changes in their sentiment. They detected the asymmetries by analysing the individual response to market movements.

2.3.2 Savings in Capital Markets

Multiple studies argue that most individual investors could benefit from capital market participation. These benefits, however, depend highly on the investors' ability to hold appropriately diversified portfolios (Campbell, 2006; Campbell & Viceira, 2002). However, studies find that investors rarely diversify in practice (Badarinza, Campbell, & Ramadorai, 2016). A solution to mitigate the under-diversification problem has previously been to use human financial advisors. These advisors help investors to select portfolios with higher diversification. However, besides the individual investors, human financial advisors themselves are prone to behavioural biases and display cognitive limitations (Foerster, Linnainmaa, Melzer, & Previtero, 2017). This indicates, that advisors without behavioural biases could potentially lead to more benefits from capital market participation.

Bhattacharya et al. (2012) studied the effect unbiased financial advice has on retail investor portfolio efficiency. The study concluded that the availability of unbiased advice is necessary. However, it is not a sufficient condition to increase the individual investor's benefits from capital markets. They found, that investors who needed the advice most were least likely to obtain it. Controversially to Bhattacharya et al. (2012), D'Acunto et al. (2019) found that active RA can reduce prominent behavioural biases, such as trend-chasing[7] (Fong, 2014), the disposition effect, and the rank effect. The study from D'Acunto et al. (2019) distinguished between well-diversified investors and non-diversified investors. They find that the adaptation of the tool's effect varies across investors based on the investor's portfolio diversification before take-up of the tool. Under-diversified investors experience an increase in the number of stocks held, and in market-adjusted volatility, and therefore higher returns. Secondly, they find no change in diversification nor performance for the well-diversified investors. Even though they traded on a higher frequency. Their study, however, was conducted on an active RA. Less research is aimed at passive robo-advising, where the measure of investor performance within RA cannot be diversification of portfolios.

[7] Trend-chasing: is a common bias to buy assets that have high past returns and sell assets that have low past returns, by trying to capitalize on a market movement that is already under way. It is particularly common among individual and inexperienced investors (Fong, 2014)

2.3.3 Interim Summary

Kumar et al. (2006) researched the retail investors' sentiment on market changes. The study provides a base to investigate individual investor behaviour when using passive robo-advisory (RA). Moreover, Brounen et al. (2016) investigated the link between how individual behaviour affects personal savings. They found evidence that saving behaviour generally varies across generations, gender, and financial literacy. Their research highlighted the importance of accounting for individual behaviour when investigating personal saving. Bhattacharya et al. (2012) conclude that, generally, unbiased financial advice does not improve portfolio efficiency of retail investors much. On the other hand, D'Acunto et al. (2019) estimate that RA increases the benefit from capital markets. The study found that active robo-advisors (RAr(s)) can mitigate under-diversification and trend-chasing.

2.4 Summary of Literature Review

The chapter presented a literature overview of: i) the relevant facts on robo-advisory, ii) factors influencing investment behaviour and iii) factors influencing saving behaviour. Furthermore, the last section includes research on the benefits of robo-advisory for savings in capital markets. To give optimal and unbiased advice, a passive RA is mainly dependent on the accuracy of users' information provision, as well as their response to market movements. Moreover, users of a passive RA do not influence portfolio management, or the overall investment strategy[8]. Hence, these investors will mainly be subjected to trend-chasing. Therefore, this study explores the differences in user responses to changes in their portfolio. The objective is to differentiate among investor demographics, as well as investor stereotypes. The combined literature suggests considering the following elements when working on the identification of this relationship: i) investor demographics, ii) stereotypes among investors, iii) market movements as drivers for user responses and iv) individual trades as measuring for different investor behaviour. Thereafter, the current study will investigate the possible elimination of personal predisposition. The aim is to reveal new dynamics regarding savings and capital market participation.

[8] See section 2.1.2.3, for the features of passive robo-advisory

3.0 Research Object - Kron AS

The Norwegian FinTech Kron developed a RAr that specializes in savings through equity investments. It provides investment opportunities in stock markets through ETFs and passive portfolio management. Kron has all necessary permits from the Norwegian Financial authorities and takes the security of their clients seriously. The company keeps its clients' and their assets separate. In the event of financial distress, the clients will not be liable. All client information is strictly confidential and data processing follows privacy laws ("Kron," 2019). The company is backed by its parent company Formuesforvaltning AS, the largest privately-owned asset manager in Norway. They have over 19 years of experience in asset management ("Formuesforvaltning," 2020; "Kron," 2019).

Kron constructs personalized saving plans clients, by following the customer assessment (i.e. configuration) and customer portfolio management (i.e. matching, customization, and maintenance) presented Figure 3. Kron profiles its clients with a simple, yet comprehensive, 5-step questionnaire. Investors can indicate their level of proficiency in investments. They must state whether their expected goal for savings is based on long-term, medium-term or short-term needs. The investors' risk aversion is preliminarily detected by asking them about concern for market movements. The investors are also asked to indicate a preferred investment sector, from Kron's range of sectors: Index, Gender Equality, Technology, Sustainability, Real Estate, and the Norwegian Oil Fund. The default option indicates no preference and Kron will consequently allocate stocks from multiple sectors to the portfolio ("Kron," 2019). After this, Kron's algorithm profiles the individual clients based on the given information and allocates an appropriate model portfolio. These model portfolios follow the Markowitz mean-variance optimization to account for the investor's expected risk and return (Beketov et al., 2018). Kron's model portfolios are always constructed as a combination of the allocated investor's risk aversion, and the indicated preferred investment sector. This combination determines the share of risky and non-risky assets in the portfolio. Hence, Kron's algorithm fully manages the diversification of investors' portfolios. Clients simply sign up, indicate their investment experience, preferences concerning investment horizon and risk, and the investment sector. In the last step, the investor decides how much money to invest, either as a lump sum, in monthly intervals, or both.

Then the tool generates a scenario analysis for the investor that shows the potential return over a short-term, mid-term, and long-term investment horizon. Finally, when the saving plan is set, the investor has easy access through the web and mobile application, to check the current portfolio value and make changes to his/her transactions. Kron's tool is a passive RAr. This means that the clients cannot actively participate in portfolio rebalancing or change any factors concerning the overall investment strategy. Nonetheless, clients have constant access to their accounts and receive push notifications on updates regarding market movements. Therefore, clients only influence their saving performance through the amount and timing of each transaction. Additionally, customers influence factors of portfolio construction during the customer assessment process, subject to their provided information being accurate. Overall, Kron provides a tool that makes saving easy and capital markets more accessible for all individuals, regardless of their personal disposition ("Kron," 2019).

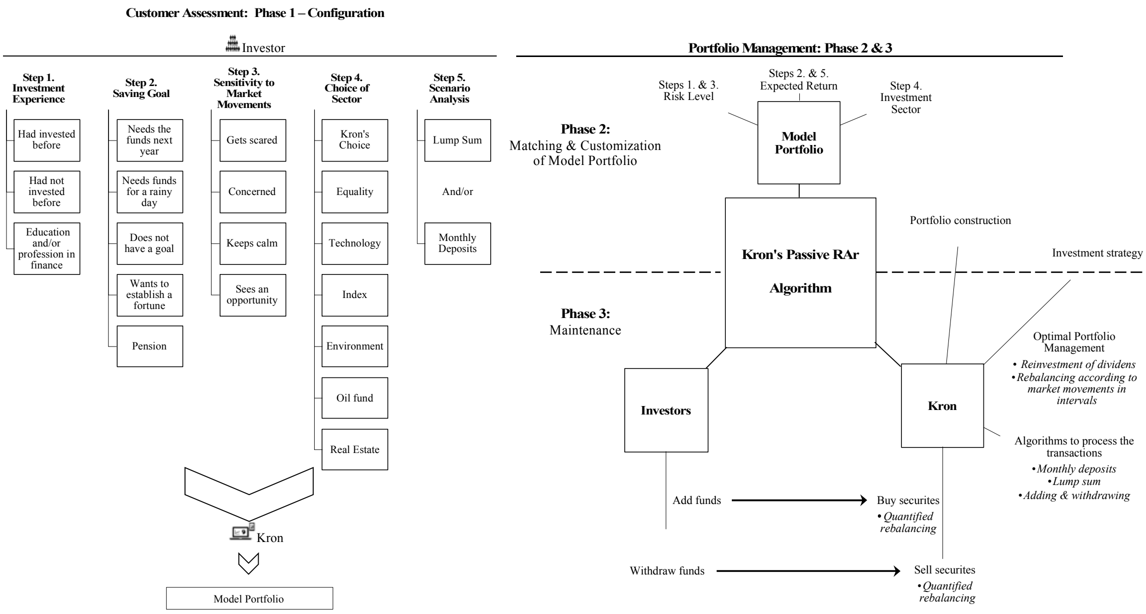

Figure 3: The Interaction between Investors and Kron's Algorithm

This figure illustrates the interaction between the investor and Kron over the entire investment process. On the left-hand side, all steps of investor information provision are shown, which constitute the first phase of robo-advising: Configuration. This phase leads to Kron's construction of the model portfolio, based on the investor's indicated preferences. The construction of the model portfolio is shown on the top right-hand side, for phase 2. Steps 1 and 3 from phase 1 indicate the investor's risk aversion. Steps 2 and 5 give indications on the investor's expected return. Step 4 determines the investment sector. The bottom right-hand side of the figure shows phase 3 in the investment process: Maintenance. This aspect shows the interaction between investors and the robo-advisor concerning portfolio management. It outlines how the investor's transactions affect the maintenance of the model portfolios, and the actions executed by the algorithm for optimal management.

4.0 Methodology

The purpose of our research was to identify whether more individuals can benefit from capital markets on equal terms when using a passive robo-advisor (RAr). Therefore, we investigated the relationship between personal saving behaviours and the use of Kron's tool. We restate our **research question** *"From a behavioural perspective: Does Kron's robo-advisor incentivise similar saving patterns across different investors, and thus create benefit from capital markets for more individuals, due to the elimination of personal traits in investment behaviour?"*

To answer this, we established four main hypotheses on the following central areas from literature findings: i) measuring investment behaviour in passive robo-advisory, ii) investor behaviour and responses to market movements, iii) differences in saving behaviour and iv) saving patterns over time. We conducted a quantitative study using the primary data collected from Kron. The models under each hypothesis were estimated using different assumptions collected from literature and econometric theory. Overall, we estimated eight models.

4.1 Hypotheses

4.1.1 Hypothesis One: Measuring Investment Behaviour in Passive Robo-Advising

Kumar et al. (2006) used individual trades as a measure for investor behaviour. Similarly, we hypothesized whether Kron's users' transactions could be used as the relevant measure for differences in user performance. We thus studied the impact of invested capital on generated savings per investor. We used investors' AUMs as proxy for their generated savings. In broad terms, the sum of the entire invested capital per investor, and the rate of return an investor acquires on this capital. It, therefore, seems arbitrary or redundant to hypothesize whether transactions affect this measure. Due to limited literature on passive RA, we deemed it necessary to test how the effects of net invested capital relate to Kron's client base. Following the prediction by Brounen et al. (2016), we therefore also theorised whether the investors' generated savings and invested capital vary across generations, gender, areas of residence, and levels of financial literacy.

H_1: *Total invested capital by each investor is the main driver for differences in individual saving performance.*

> **$H_{1,1}$:** *Increasing net invested capital over time has a marginally increasing effect on the investor's AUM.*
>
> **$H_{1,2}$:** *Different demographic groups generate different AUMs.*
>
> **$H_{1,3}$:** *The investment behaviour in terms of total invested capital differs across demographic groups.*

4.1.2 Hypothesis Two: Responses to Market Movements

Secondly, we hypothesized market movements to be drivers for investor behaviour, as also suggested by Kumar et al. (2006). We used the returns from Kron's model portfolios as a proxy for these market movements. The responses were measured in each investor's transactions, when and if investors execute them. We tested the effect of timing regarding two central aspects of retail investor behaviour: i) whether individuals or specific groups chase market trends and ii) whether market volatility affects the number of transactions executed. Under this hypothesis, we aimed to reveal additional effects of social identity on investor behaviour.

Trend-chasing[9] is a common behavioural bias among retail investors (Baker & Ricciardi, 2014; Fong, 2014). Following the literature on passive RA, we assumed that trend-chasing is one of the more significant biases in passive RA. Therefore, we investigated the investors' responses to the returns of Kron's model portfolios. Here, we tested whether they are significant in estimating transactions of individuals, and types of investors.

H_2: *Investors respond to portfolio returns by adjusting their monthly net invested capital.*

> **$H_{2,1}$:** *Investors who observe an increase in portfolio returns add funds and withdraw invested capital when returns went down.*
>
> **$H_{2,2}$:** *Investors adjust their amount of monthly net invested capital according to market movements.*

[9] Trend-chasing is a common bias to buy assets that have high past returns and sell assets that have low past returns, by trying to capitalize on a market movement that is already under way. It is particularly common among individual and inexperienced investors (Fong, 2014)

4.1.3 Hypothesis Three: Differences in Saving Behaviour

The differences in saving behaviour constitute another focal aspect of this research. Therefore, we hypothesized whether different investors have significantly different saving behaviours with respect to their transactions. According to the literature on social identity, these differences were explored between average transactions of individuals and types of investors. Overall, we wanted to conclude, whether investors perform differently and whether they do so differently individually, or in groups.

H_3: *Investors' dedication to saving is dependent on the effects of personal traits and stereotypes.*

> **$H_{3,1}$:** *Individual investors adjust their monthly net invested capital differently.*
>
> **$H_{3,2}$:** *The average monthly net invested capital differs between types of investors.*

4.1.4 Hypothesis Four: Differences in Saving Patterns over Time

Similar to the study by D'Acunto et al. (2019), we wanted to analyse whether Kron's passive RA diminishes irrational behaviour in savings. Therefore, we investigated whether investors' responses are less affected by market returns over time. If so, investors adjust their saving behaviour to benefit from using Kron's tool for saving.

H_4: *Over time, marginal differences between investors' saving patterns are reduced.*

4.2 Research Approach

Utilizing our measures and variables for analysis, we take a quantitative approach to our study, without any subjective interpretations of the data (Bell, Bryman, & Harley, 2018). We used quantitative methods with a simulation approach to build our own models to represent the behaviour of the process over time (Kothari, 2004). We aim to make inferences on the significance of variables and simultaneously reveal potential fixed or random effects, as well as within and between information (D'Acunto et al., 2019). We used Stata to conduct all analyses.

4.3 Data

The data was provided by Kron in February 2020 and was gathered for this purpose. It was a comprehensive data set containing only relevant information on a sample of 3,964 of Kron's private retail investors during the time horizon of June 2017 (launching of Kron) and February 2020. All observations were first sorted according to a given client identifier.

The data contained the following baseline demographics of clients:

i) Gender

ii) Age

iii) Area name of the investor's residence (origin)

iv) Investment experience indicated optionally during sign-up

We flagged international accounts (residence located outside Norway), to get more homogeneous data. Additionally, not all investors indicated their investment experience. This led to missing observations under these two demographics. We further classified observations into groups. For our study, the target market is the Kron's clients, and as Stafford (1996), we chose to focus on age and gender. Instead of household income, we chose the client's residence and level of financial literacy. By binomially combining Kron's client base under the demographics age, gender, and residence, we created a total of eight investor types (see Figure 4: Average Monthly Transactions by Investor). The demographic of investor experience were excluded from this combination, as we encountered multiple missing observations (Saunders, 2016). The creation of these types allowed us to identify if there were differences between stereotypes and not only between individuals.

Table 1: Investor Types

Abbreviation	Combination	Abbreviation	Combination
FOR	Female-Older-Urban	MOU	Male-Older-Urban
FOU	Female-Older-Rural	MOR	Male-Older-Rural
FYR	Female-Younger-Rural	MYR	Male-Younger-Rural
FYU	Female-Younger-Urban	MYU	Male-Younger-Urban

The data set additionally included observations on all clients concerning:

v) Account factors: average log-ins to web and mobile applications, account age, starting and end date of the client's account

vi) The client's choice on personalised portfolio factors: saving horizon, optional chosen investment sector of interest

vii) The by Kron allocated risk level per investor

viii) The by Kron allocated model portfolio per investor

The data also included investors' assets under management (AUMs)[10] per 01.07.19, and per 13.02.20, as well as information on each client's transactions (date of every transaction, the amount, and the type of transaction made). We sorted and modified the transaction data:

ix) All transactions during the client's participation in Kron were summed up to that client's total sum of net transactions. Added funds were added to the sum, withdraws were deducted.

x) All transactions per client were sorted according to the date of the transaction. Then we summed up each client's monthly transactions. Added funds per month were added to the sum, withdraws were deducted. This gave us the monthly net transactions per client. If a client had not onboarded yet or had closed the account already, the observation is missing. If the client did not execute any transaction in a certain month, this observation contains a zero for that month.

Furthermore, all clients who did not have any transaction data were classified as inactive clients. Those with transactions only in the period from 01.07.19 to 13.02.20 were classified as semi-active. Clients with a minimum of one transaction over the entire period were marked as active clients. The time-weighted monthly returns of each model portfolio were originally displayed in a separate data set. These were observed over a period from June 2017 to January 2020. The portfolio returns were sorted to the specific client identifier, subject to each investor's model portfolio and participation (time of onboarding and time of closing account). In each month, where the client hadn't onboarded Kron yet, that client's return contains a missing observation (Saunders, 2016).

[10] AUM: The total market value of the investment entity RA manages on behalf of clients. AUM includes deposits, mutual funds and cash. Investors often assign authority to the company to trade on their behalf under discretionary management ("Journal of asset management," 2000).

The data can be viewed as dependable with the limitation that Kron is a newly established company and not all their collected data is quantified. Since the data was collected for this purpose from a competitive industry player in the RA sector, it was exclusive for this research. It thereby provided real-life insight into how investors interact with RA and what RA does for investors (Beketov et al., 2018; D'Acunto et al., 2019; Hohenberger, Lee, & Coughlin, 2019).

4.4 Model Estimation

The data contained various cross-sectional factors to analyse the effects on generated savings. Thus, to test our first hypothesis, we used a cross-sectional, multiple regression model (see section 4.4.1). These models, however, can comprise the issues of: i) multicollinearity, ii) heteroskedasticity, iii) unobserved endogeneity, and iv) omitted variable biases. Issues i) and ii) are observable and solvable under cross-sectional models. Regarding multicollinearity, we analysed the correlation between all variables, excluded variables that were too highly correlated, and substituted these with other controlling variables. To ensure robustness in models I-IV (see section 4.4.1), we ran a Breusch-Pagan/Cook-Weisberg test in Stata to detect heteroskedasticity. For all models, the null was rejected, indicating heteroskedasticity. We proceeded with robust standard errors in model I, II, III, and IV. Observing specific heterogeneities in cross-sectional data is limited. Therefore, we used panel data analysis for hypotheses two through four, and to provide a possible solution to mitigate issues iii) and iv) (Chenhall & Moers, 2007; Park, 2011). Though our data set is unbalanced (Wooldridge, 2010), it enabled us to explore these heterogeneities concerning investors' saving behaviour. Additionally, we could control for unobserved endogeneity, and reduce the probability of an omitted variable bias.

Concerning panel analysis, estimation methods differ in execution and interpretation, as well as resulting model robustness. The selected model must reflect the nature of our data and our research purpose appropriately (Schunck, 2013). Panel data estimators can easily become biased, inefficient, or inconsistent if not fitted correctly to the data. For most of our panel models, an F-test determined whether we could use OLS estimators or should use fixed effects estimators.

A Breusch-Pagan LM test assessed OLS against random effects estimators. For all our panel models, both null hypotheses from the F-test and the Breusch-Pagan test were rejected, and we conducted a Hausman test. This determined whether we should apply fixed or random effects. Under the alternative hypothesis, fixed effects estimators are consistent, and at least as efficient as random effects.

With a short panel and 3,964 cross-sectional observations, we needed to be aware of clustering. In our data set, multiple investors have the same model portfolio, and thus often acquire similar returns. This resulted in clusters among observations around these portfolios. Conclusively, standard errors were clustered and not robust when estimating the significance of a relationship between transactions and returns. A drawback in the Hausman test is that it does not account for clusters. Therefore, we ran a test for overidentifying restrictions with the *xtoverid* command in Stata (Schaffer & Stillman, 2006). We applied fixed effects when we had rejected the null hypothesis. A disadvantage of fixed effects estimation is that between variation is not observable in these models (Baltagi, Bresson, & Pirotte, 2003; Hsiao, 2003; Wooldridge, 2010). Between estimation in panel analysis disregards the within variation of cross-sectional time-varying observations. However, it delivered a valuable means to test for differences *across* investors in the current study (Baltagi et al., 2003; Hsiao, 2003; Wooldridge, 2010). Therefore, we used between estimators in models VII and VIII, where it was appropriate.

Following the literature on personal saving behaviour and stereotypes, we had several expectations. Our main assumptions concerning the saving behaviour of investors were: i) females save differently than males, ii) younger generations save less than older generations, iii) younger generations adapt faster to the RA than the older generations, iv) people located in urban areas save more than those located in rural areas, and v) people located in urban areas use FinTech applications more than those located in rural areas. For our model estimation we also assumed: i) investors are biased to trend-chasing if returns are significant in explaining the variation of transactions and ii) variation across investors is random. Finally, a vital assumption for our panel model estimation was that the first three months ex 2017 represent the pre-tool savings of each investor. This way we could model differences in savings, and control for the investor's personal savings before using the tool.

4.4.1 Models I - IV: Measuring Investment Behaviour in Passive Robo-Advising

Firstly, we tested whether transactions are the significant measure for saving behaviour. Transactions show the investor's deposits, as well as adjustments to invested capital. With models I and II we investigated the relationship between the utilization of the tool, and the savings generated per investor. Under the first hypothesis we disregarded time-varying factors, and thus used a stock observation of each investor's assets under management (AUM) as a proxy for their generated savings. The main independent variable was the total sum of the investor's net transactions. To control for active choices the investor makes, we included variables for the investor's indicated preferences. Secondly, in models III and IV, we tested the demographic trends with respect to generated savings (AUM) and the total sum of net transactions.

$$\mathrm{AUM_i} = \alpha + \mathrm{Account\ Age_i} + \mathrm{Log-ins_i} + \mathrm{Investment\ Activity_i} + \mathrm{Investment\ Horizon_i} + \mathrm{Investment\ Sector_i} + \mathrm{Sum\ of\ Transactions_i} \tag{I}$$

$$\Delta\mathrm{AUM_i} = \alpha + \mathrm{Account\ Age_i} + \mathrm{Log-ins_i} + \mathrm{Investment\ Activity_i} + \mathrm{Investment\ Horizon_i} + \mathrm{Investment\ Sector_i} + \Delta\mathrm{Sum\ of\ Transactions_i} \tag{II}$$

$$\mathrm{AUM_i} = \alpha + \mathrm{Gender_i} + \mathrm{Age_i} + \mathrm{Tax\ Residence_i} + \mathrm{Financial\ Literacy_i} \tag{III}$$

$$\mathrm{Sum\ of\ Transactions_i} = \alpha + \mathrm{Gender_i} + \mathrm{Age_i} + \mathrm{Tax\ Residence_i} + \mathrm{Financial\ Literacy_i} \tag{IV}$$

4.4.2 Model V & VI: Responses to Market Movements

In these models, we analysed monthly transactions to see if investors chase returns, or if their transactions were driven by other factors. The data on returns are time-weighted monthly averages. We, therefore, analysed both previous and current returns, because investors could respond after observing them in the same month, or the following. Finally, we differentiated between the effects of returns on individual and grouped investors.

We assumed that variation across investors is random, and that differences in responses across investors have some influence on their transactions. Firstly, in model V, we tested whether previous returns affect inflows and outflows to and from the investor's account. A random effects-model for the first test allows for individual coefficients per observation, which results in heterogeneous effects across the data set. If the effects would not differ much, fixed effects will give better precision. A general benefit of random-effects estimation is, that you can include time-invariant variables (Baltagi et al., 2003; Hsiao, 2003; Wooldridge, 2010). We thus introduced additional controlling variables: i) investor type, ii) investment horizon and iii) whether an investor has selected an investment sector or not. The investor types proxy social identity (see Table 2: Overview of Variables). By including these controlling factors, we were able to determine whether they affect the relationship between flows of transactions and previous returns. Additionally, we tested demographics as controlling variables in the model.

In the next model, VI, we regressed individual monthly transactions (monthly sum of net transactions) on returns from the same month. The Hausman was again adjusted for clustering, and we used the *xtoverid* command to test fixed against random effects with clustering. Both tests resulted in suggesting a fixed effects estimation. In this model, we also included time dummies in the second regression to account for all financial, and macro-economic effects equal for all investors. In the third and fourth regression under this model, we set our panel grouping variable to investor *types*. This allowed us to account for time-invariant social identity traits in a fixed effects model, where one cannot include time-invariant variables. Therefore, we regressed monthly transactions of investor types on returns of these types in the same month, first excluding (third regression), and finally including time effects (fourth regression). This model predicted the marginal change of individual and type specific transactions, following an increase in current returns.

$$\mathrm{Flows}_{i,t} = \alpha + \mathrm{Returns}_{i,t-1} + (\mathrm{Dummy\ Month}_t) \qquad \text{(Random Effects)} \qquad \text{(V)}$$

$$\mathrm{Transactions}_{i,t} = \alpha + \mathrm{Returns}_{i,t} + (\mathrm{Dummy\ Month}_t) \qquad \text{(Fixed Effects)} \qquad \text{(VI)}$$

4.4.3 Model VII & Multiple Mean Comparison: Differences in Saving Behaviour

Under hypothesis three we tested for a significant difference between transactions executed by individual investors, and by investor types. To establish whether individuals have significantly different saving behaviours, we used a between estimation of the effect of between variation in returns on between variation in individual transactions. This is estimated in model VII.

$$\text{Transactions}_{i,t} = \alpha + \text{Returns}_{i,t} \qquad \text{(Between Estimation 1)} \qquad \text{(VII)}$$

To test the difference of average transactions executed by certain types of investors, we used a *one-way* ANOVA. This analysis can only confirm whether or not there are differences between groups. Therefore, we had to perform post hoc tests, to establish which combinations of investor type average transactions were significantly different. Post hoc testing is performed with independent t-tests. These t-tests, however, underly an increased risk of type-I errors, due to the increased number of groups. We consequently used the Bonferroni correction and confirmed results with a similar correction from Scheffe (Bonferroni, 1935; Homack, 2001; Weisstein, 2004). Furthermore, we applied a mixed model parametric analysis of variance in the individual type specific effects (Kackar & Harville, 1984). The delta-method was used with Taylor approximation for expansion around the variables' mean. Then we estimated the variance of this expansion (Oehlert, 1992; Savin, 1980).

4.4.4 Model VIII: Differences in Saving Patterns over Time

In our last model, we wanted to observe whether these potential differences in saving behaviour are diminished over time by the use of passive RAr. Therefore, we included a time trend variable in our between estimation model. Similar to model VII, a between model revealed the information we were interested in; whether the differences between returns leads to a significant difference between individual transactions, and whether this effect is reduced over time.

$$\text{Transactions}_{i,t} = \alpha + \text{Returns}_{i,t} + \text{Time Trend} \qquad \text{(Between Estimation 2)} \qquad \text{(VIII)}$$

4.5 Variables

Table 2: Overview of Variables

Variable	Demographics
Female	takes on the value 1 if the investor's gender is female
Fl	takes on the value 1 if the investor has indicated that he has investment experience; this variable serves as proxy for financial literacy
Type	is a categorical variable that indicates the type of investor according to Table 1
Urban	takes on the value 1 if the investor's residence is in an urban area, and 0 if it is outside of an urban area ('rural')
Younger	takes on the value 1 if the investor's age is under 37 at the time of data collection, and 0 otherwise
	Account
Accd	indicates the account age in days
Act	is a categorical variable that takes on the value 2 if the investor has made transactions in his/her entire period of using the tool, 1 if he/she made transactions only in a later period, and 0 if the investor has not made any transactions during the period of using the tool
Log_Mob	indicates the overall average monthly log-ins on the mobile application per investor
Log_Web	indicates the overall average monthly log-ins on the web application per investor
	Portfolio
Choice	takes on the value 1 if the investor has indicated a specific investment sector, and 0 if he/she chose Kron's default option
Horiz	is a categorical variable that takes on the value 1 if the savings horizon of the investor is short term, 2 if it is medium term, and 3 if it is long term; it indicates the user's goal for saving
Mpf	is a categorical variable indicating the investor's model portfolio allocated to him/her by Kron
Pref	is a categorical variable which indicates the preferred investment sector
Risk	is Kron's identification of a comparable risk level based on the clients' answers in the investor questionnaire
	Transactions
Flowscat*	is a categorical variable which takes on the value 1 if the investor has added funds to his account in a specific month, 0 if no transaction occurred, and -1 if the investor withdrew funds
Inv_Incr*	takes on the value 1 if the investor added funds to his account when the return in the previous month had increased
Sum19	indicates the total sum of transactions made by each investor per 01.07.2019
Sum20	indicates the total sum of transactions made by each investor per 13.02.2020
SumDelta	is the change in the total sum of transactions per investor between 01.07.2019 and 13.02.2020

Trans*	is the transaction amount per investor per month; the value 0 indicates that in a certain month the investor has not executed any transactions, and if the value if missing, the investor had either not started using the tool, are had quit using before that month.
	Returns
Aum19	is the total AUM per investor per 01.07.2019
Aum20	is the total AUM per investor per 13.02.2020
AumDelta	is the change in the generated AUM per investor between 01.07.2019 and 13.02.2020
Netret19	is the net return per 01.07.2019 of the invested amount per investor considering his/her AUM
Netret20	is the net return per 13.02.2020 of the invested amount per investor considering his/her AUM
Ret*	contains the investor's return from the given model portfolio in a certain month
Retlag*	is the variable for lagged returns (at lag 1)

*These variables vary cross-sectionally and in time.

4.6 Limitations of the Study

The data set only contains information regarding Kron's Norwegian private clients. The scope of research was limited to the research area within the robo-advisor of the Norwegian company Kron. The data was therefore not compared to: i) client information prior to onboarding and ii) secondary data. Moreover, we limited our research to the four categories of baseline demographics of investors. We also do not look into details about fee structure and tax structure when compared to traditional human-advisory.

Further, we did not account for: i) specific market movements, ii) the market notifications Kron provides to its clients and iii) net rate of returns on invested capital. Additionally, we were missing observations to investigate investors' level of financial literacy and its impact. We also lacked variables that are observed over time, to further control the relationship between transactions and returns. Lastly, we note that our panel was very short, as it only contained observations over 32 months. This might result in faults concerning model precision. We will though state, that the data collected is more than comprehensive for our research purpose and provides relevant insights.

5.0 Empirical Results

Our research objective is to identify empirical evidence suggesting a relationship between personal saving behaviour and the use of Kron's robo-advisor (RAr). The empirical results include an inferential interpretation and are addressed in four major sections. Section 5.1 contains descriptive statistics for both the cross-sectional and panel descriptive analysis. Section 5.2 presents regression results on different measures for saving behaviour under hypothesis one. Results of models I to IV are linked to answering sub-hypothesis one to four, respectively. In section 5.3 we reveal findings related to hypothesis two, aiming to answer whether investors chase returns. Models V and VI provide results to test drivers of saving behaviours. Following this, section 5.4 revolves around results for testing differences in performance across demographics under hypothesis three. Lastly, section 5.5 contains model estimates regarding hypothesis four and investigates a time trend in potential differences.

The tables in the following sections contain the relevant findings for our analysis. The complete regression and non-parametric analyses outputs can be found in the appendices. Individual table descriptions will refer to the correct appendix subdivision. Moreover, the relevance of the main findings will be analysed and discussed in Chapter 6.0.

Table 3: Overview of Main Empirical Results

Section	**Findings**
	Cross-Sectional Data
Table 1: Summary Statistics for Cross-Section	**Demographic trend balanced:** - Males accounted for two-thirds of the data - Equal share of younger and older generations in the sample - 78.7% of users were from an urban area - Observations on previous investment experience (*FI*) were missing
Table 5: Summary Statistics of Total Transactions & AUM per Demographic	Suggested differences in average transactions and AUMs in the cross-section of all demographics.
	Panel Data
Table 6: Panel Summary Statistics - Main Variables	**The within variation for individuals is:** ***Greater for****:* i) The transaction flows (Flowscat) ii) The transaction amounts (Trans) ***Smaller for:*** i) Current returns (*Ret*) ii) Previous returns (*Retlag*)
Figure 4: Average Monthly Transactions by Investor Types	The bar-chart for average monthly transactions across types illustrated differences between them.
	Measuring Investment Behaviour in Passive Robo-Advising
Models I & II: Transactions	**Found to be significant (minimum 90% confidence level):** i) The total invested capital (*Sum*) explaining the variation in the AUM in both 2019, and 2020, and the investment horizon (*Horiz*) ii) The change total invested capital (*SumDelta*) resulted in a positive, higher change in the AUM over the period between 01.07.19 and 13.02.20
Models III & IV: Differences across Demographics	**Found to be significant (minimum 90% confidence level):** i) The differences among the demographics gender and age with respect to acquired AUMs ii) The interaction term between the two **Significant gaps in total net invested capital:** iii) The difference among demographics gender and age with respect to total invested capital iv) The interaction term between the two
	Responses to Market Movements
Model V: Transaction Flows & Previous Returns	**Found to have an effect on variation in inflows and outflows (minimum 90% confidence level):** i) Previous returns (*Retlag*) only with time effects, and no other controlling variables ii) Demographics gender (*Female*) and age (*Younger*) iii) Investor types (*Types*) and investment horizon (*Horiz*)
Model VI: Transaction Amounts & Current Returns	**Found to have an effect on variation in transaction amounts (minimum 90% confidence level):** i) Current returns for individual transactions only without time effects ii) Current returns for transactions grouped by types only without time effects
	Differences in Saving Behaviour
One-Way ANOVA, Post Hoc Bonferroni	Significantly (minimum 90% confidence level) different average transactions between: **FYU** & **MOU,** and **MOU & MY***
Delta-Method	Significantly (minimum 90% confidence level) different random effects between: * **FYU & FOU, MYU & FOU, MOR & FYU, MOU & FYU, MYU & MOR & MY & MOU***
	Differences in Saving Patterns over Time
Model VIII Differences in Saving Patterns over Time	**Differences in saving patterns between:** ***Investor types:*** i) Reduced over time ***Individuals***: ii) Not reduced over time

*Notation: *F- female, M-male, Y-younger, O-older, U-urban and R-Rural*

5.1 Descriptive Statistics

5.1.1 Correlation of Variables

We investigated the correlation between all independent and dependent variables (see Table 4: Pearson Correlation for Cross-Section). Reading the matrix horizontally, we first identified that the demographics are not strongly correlated with any variables such as total invested capital (*Sum19 & Sum 20*), AUM (*Aum19 & Aum20*), the investment sector indicators preference (*Pref*) and active sector choice (*Choice*), nor the investment horizon (*Horiz*). Moreover, when studying the transaction and return variables, we found that *Sum20* and *Choice* have a correlation of almost zero (r = 0.0003). *Aum19* and *Sum19* are highly positively correlated, while *Aum20* and *Sum20* were slightly negatively correlated. We additionally found a high correlation with a coefficient of r =0.936 between *Pref* and *Mpf*, as well as between *Horiz* and *Risk* (r = 0.950).

Table 4: Pearson Correlation for Cross-Section

Pearson Correlation Matrix: Cross-Section

	Female	Younger	Urban	Fl	Choice	Horiz	Pref	Risk	Mpf	Start	End	Accd	Act	Log_Web	Log_Mob	Sum19	Aum19	Sum20	Aum20	SumDelta	AumDelta
Female	1.000																				
Younger	-0.017	1.000																			
Urban	0.112	0.068	1.000																		
Fl	-0.168	-0.127	-0.061	1.000																	
Choice	-0.170	0.018	-0.042	-0.078	1.000																
Horiz	-0.016	0.060	0.145	0.197	-0.143	1.000															
Pref	0.034	0.054	-0.001	0.003	0.142	0.175	1.000														
Risk	-0.012	0.049	0.119	0.159	-0.140	0.956*	0.203	1.000													
Mpf	-0.037	0.051	-0.014	-0.018	0.484	0.203	0.926*	0.233	1.000												
Start	-0.236	0.070	0.004	-0.017	0.151	-0.085	0.066	-0.096	0.098	1.000											
End	0.161	-0.052	-0.005	-0.014	-0.144	0.036	-0.051	0.047	-0.087	-0.706	1.000										
Accd	0.236	-0.070	-0.004	0.017	-0.151	0.085	-0.066	0.096	-0.098	-1.000	0.706	1.000									
Act	0.041	-0.078	-0.056	-0.070	-0.058	-0.089	-0.168	-0.100	-0.176	-0.006	0.052	0.006	1.000								
Log_Web	0.073	-0.014	-0.066	-0.063	-0.065	0.033	0.021	0.050	-0.003	-0.170	0.165	0.170	-0.005	1.000							
Log_Mob	0.021	-0.168	0.036	-0.053	-0.208	0.002	-0.020	0.030	-0.093	-0.275	0.234	0.275	0.007	0.224	1.000						
Sum19	-0.049	-0.211	-0.082	0.082	0.004	0.016	0.114	0.015	0.100	-0.232	0.156	0.232	0.031	0.283	0.270	1.000					
Aum19	-0.053	-0.192	-0.107	0.062	0.049	0.025	0.138	0.033	0.141	-0.233	0.144	0.233	0.032	0.315	0.262	0.953*	1.000				
Sum20	0.016	-0.051	0.102	0.041	-0.014	-0.016	-0.108	-0.059	-0.110	-0.081	0.049	0.081	-0.011	-0.181	0.260	0.233	0.161	1.000			
Aum20	0.037	-0.072	-0.002	-0.017	0.108	-0.176	0.046	-0.178	0.060	-0.255	0.250	0.255	0.026	0.060	0.160	0.235	0.241	-0.060	1.000		
SumDelta	0.055	0.201	0.115	-0.071	-0.008	-0.022	-0.149	-0.033	-0.136	0.214	-0.145	-0.214	-0.035	-0.345	-0.198	-0.955**	-0.929**	0.066	-0.260	1.000	
AumDelta	0.053	0.192	0.107	-0.062	-0.049	-0.025	-0.138	-0.033	-0.141	0.233	-0.144	-0.233	-0.032	-0.315	-0.262	-0.953**	-1.000	-0.161	-0.240	0.929*	1.000

This table presents the Pearson correlation matrix for correlation coefficients between all cross-sectional independent and dependent variables. Relevant positive and negative coefficients are marked with *, and **, respectively. See Appendix Table A4: Pearson Correlation Matrix for all Variables for the Pearson correlation matrix of all variables.

5.1.2 Cross-Sectional Data

The summary statistics of the cross-sectional data set are displayed in Table 5: Cross-Sectional Summary Statistics. We found that females accounted for 29.6% of the sample. There was a balance in the share of younger and older users, where 55.1% are younger than 37 years old. The majority (78.7%) of the investors had residences located in an urban area.

Only 2,235 of the investors indicated their previous investing experience, and on average 58.5% of those investors had previous experience when signing up. On average, investors acquired an AUM of NOK 114,606.00 per 01.07.19, and a lower average AUM of NOK 85,720.52 in the period between launch and 13.02.20. The maximum amount invested by users was NOK 7,590,771.00 over the entire period. Of all users, 69.3% chose a specific investment sector, the remaining chose Kron's default selection option. Investors indicated an average saving horizon between medium-term and long-term. The mean account age for all users was 238.35 days, and investors used the mobile application almost 36 times a month, whereas they logged in to the web application only 1.68 times a month. Almost all investors were on average active in the entire sample period (mean of *Act* = 1.98).

Table 5: Cross-Sectional Summary Statistics

Cross-Sectional Summary Statistics

Variable	Obs	Mean	Std.Dev	Min	Max
Female	3,964	0.296	0.457	-	1.000
Younger	3,964	0.551	0.497	-	1.000
Urban	3,841	0.787	0.410	-	1.000
FI	2,235	0.585	0.493	-	1.000
Choice	3,964	0.693	0.461	-	1.000
Horiz	3,964	2.564	0.630	1.000	3.000
Pref	3,964	3.514	1.830	1.000	7.000
Risk	3,964	4.875	1.436	1.000	7.000
Accd	3,964	238.354	219.697	1.000	1,004.000
Act	3,964	1.984	0.139	-	2.000
Log_Mob	3,963	35.082	68.012	-	1,933.000
Log_Web	3,963	1.675	5.623	-	145.000
Sum19	1,556	98,777.450	319,144.100	- 77,678.000	7,590,771.000
Sum20	3,955	68,326.340	231,485.000	- 129,500.000	7,590,771.000
Aum19	1,610	114,606.000	530,682.600	-	18,500,000.000
Aum20	3,964	85,720.520	414,940.400	-	21,600,000.000

This table presents the summary statistics for all variables in the cross-section, except for *AumDelta,* and *SumDelta*. It includes the number of observations, mean, standard deviation, and the minimum and maximum for each variable.

From Panel A and Panel B in Table 6: Summary Statistics of Total Transactions & AUM per Demographic, we could observe that females on average invested a lower 'total amount' than males in the entire period. The acquired AUMs of males were approximately three times the amount of the females' AUMs. In Panels C and D, we observed the same trend for younger and older investors, where younger investors added fewer funds to their accounts, and had considerably smaller AUMs, on average. Panels E and F show that the same transaction trend held for users from urban and rural areas. Here, both groups acquired approximately the same AUM in 2019, but investors from urban areas acquired a higher average AUM in 2020.

Table 6: Summary Statistics of Total Transactions & AUM per Demographic

Net Invested Capital & AUM per Demographic										
Variable	PANEL A: FEMALE					PANEL B: MALE				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Sum19	368.000	68,271.070	158,315.300	- 14,890.000	1,668,838.000	1,188.000	108,227.200	353,981.300	- 77,678.000	7,590,771.000
Sum20	1,169.000	48,667.730	138,921.200	- 23,303.000	2,820,000.000	2,786.000	76,575.060	260,295.100	-129,500.000	7,590,771.000
Aum19	383.000	79,924.300	174,402.100	-	1,315,442.000	1,227.000	125,431.600	599,693.800	-	18,500,000.000
Aum20	1,173.000	60,200.210	170,873.600	-	2,927,372.000	2,791.000	96,446.180	481,569.600	-	21,600,000.000
Variable	PANEL C: YOUNGER GENERATION					PANEL D: OLDER GENERATION				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Sum19	766.000	52,499.740	117,267.400	- 77,678.000	1,324,500.000	790.000	143,649.300	428,145.100	- 41,865.000	7,590,771.000
Sum20	2,182.000	38,615.760	94,472.800	- 82,612.000	2,000,000.000	1,773.000	104,890.600	325,820.800	-129,500.000	7,590,771.000
Aum19	792.000	57,928.360	130,018.500	-	1,463,862.000	818.000	169,482.100	729,475.400	-	18,500,000.000
Aum20	2,183.000	45,511.530	112,048.700	-	2,149,346.000	1,781.000	135,005.300	602,933.600	-	21,600,000.000
Variable	PANEL E: URBAN RESIDENCE					PANEL F: RURAL RESIDENCE				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Sum19	1,222.000	95,127.760	320,310.800	- 41,865.000	7,590,771.000	281.000	107,764.900	321,600.700	- 77,678.000	4,300,000.000
Sum20	3,016.000	67,603.100	236,427.100	-129,500.000	7,590,771.000	818.000	64,684.240	206,021.800	- 77,678.000	3,500,000.000
Aum19	1,265.000	113,098.000	574,152.600	-	18,500,000.000	290.000	116,216.100	331,649.800	-	4,460,087.000
Aum20	3,022.000	86,377.930	454,828.700	-	21,600,000.000	819.000	77,193.750	237,851.900	-	4,154,031.000

The table presents the summary statistics for a number of observations, mean, standard deviation, min and max of the variables *Sum19, Sum20, Aum19,* and *Aum20,* by demographic groups. Panel A contains the summary statistics for each variable observed in the demographic group 'Female'. Panel B contains the summary statistics for each variable observed in the demographic group 'Male'. Panel C contains the summary statistics for each variable observed in the demographic group 'Younger generation'. Panel D contains the summary statistics for each variable observed in the demographic group 'Older generation'. Panel E contains the summary statistics for each variable observed in the demographic group 'Urban residence'. Panel F contains the summary statistics for each variable observed in the demographic group 'Rural residence'.

Ultimately, the demographic trend in the data set was not always balanced. Males accounted for two-thirds of the data, and 78.7% of users were from an urban area. There was a balance in the trend for demographics age (*Younger*) and financial literacy (*Fl*), though observations on *Fl* were often missing. Findings in Table 5 suggested differences in average transactions and AUMs in the cross-section of all demographics.

5.1.3 Panel Data

The summary statistics for the panel is presented in Table 7: Panel Summary Statistics - Main Variables. It contains the main variables of interest for the panel analysis. For a complete list of the panel summary statistics, see Appendix A: Table A5. For all the variables, we observed higher within than between variation. Both *Ret* and *Retlag* indicated a low between variation, due to multiple investors holding the same portfolio. Furthermore, *Flowscat* showed an overall mean of 0.162, indicating that the frequency of inflows was higher than the frequency of outflows. *Trans* had an overall mean of 8,396.142. The between variation for *Trans* was 66,878.55, and the within variation was higher, at 92,964.19. Additionally, this showed that the differences in transactions over time for each investor were higher than the differences in transactions across the sample. The variable *Inv_Incr* indicates (without causality) whether an investor added funds after a previous return had increased. For this variable, we observed very low between variation, and significantly higher within variation. This showed, that the differences in investors' reactions between all investors were minor. However, the differences between one individual investor's response to an increase in returns varied more over time.

Table 7: Panel Summary Statistics - Main Variables

Panel Summary Statistics - Main Variables

Variable		Mean	Std. Dev.	Min	Max	Observations		
Ret	Overall	0.013	0.021	- 0.058	0.053	N	=	29,725
	Between		0.007	- 0.041	0.041	n	=	3,744
	Within		0.020	- 0.059	0.057	Tbar	=	8
Retlag	Overall	0.013	0.021	- 0.058	0.053	N	=	29,724
	Between		0.007	- 0.041	0.041	n	=	3,828
	Within		0.020	- 0.059	0.056	Tbar	=	8
Flowscat	Overall	0.162	0.379	- 1.000	1.000	N	=	126,848
	Between		0.219	- 0.375	0.969	n	=	3,964
	Within		0.309	- 1.744	1.537	T	=	32
Trans	Overall	8,396.142	97,385.750	-8,850,000.000	6,600,000.000	N	=	30,352
	Between		60,878.550	- 25,558.630	2,900,000.000	n	=	3,754
	Within		92,964.190	-8,849,289.000	6,600,711.000	Tbar	=	8
Inv_Incr	Overall	0.061	0.239	-	1.000	N	=	126,848
	Between		0.072	-	0.375	n	=	3,964
	Within		0.227	- 0.314	1.029	T	=	32

The table presents the summary statistics of panel variables *Ret, Retlag, Flowscat, Trans,* and *Inv_Incr*. It includes the overall mean, number of all observations over time (N), number of cross-sectional observations (n), and average observed time period (T/Tbar). Further, it shows the overall, between, and within the standard deviation, and the overall, between, and within minimum and maximum. See Appendix A: Table A5 for summary statistics of the entire panel data.

Figure 4 illustrates the average transactions executed per month per investor *type*. We observed an overall difference between females and males, where women executed fewer net transactions per month. Moreover, we looked at the average transactions for older men from urban areas and those from rural areas, and none of the other group averages reached similarly high values. Within the types of women, older women generally transacted more money than younger women, for both rural and urban female groups.

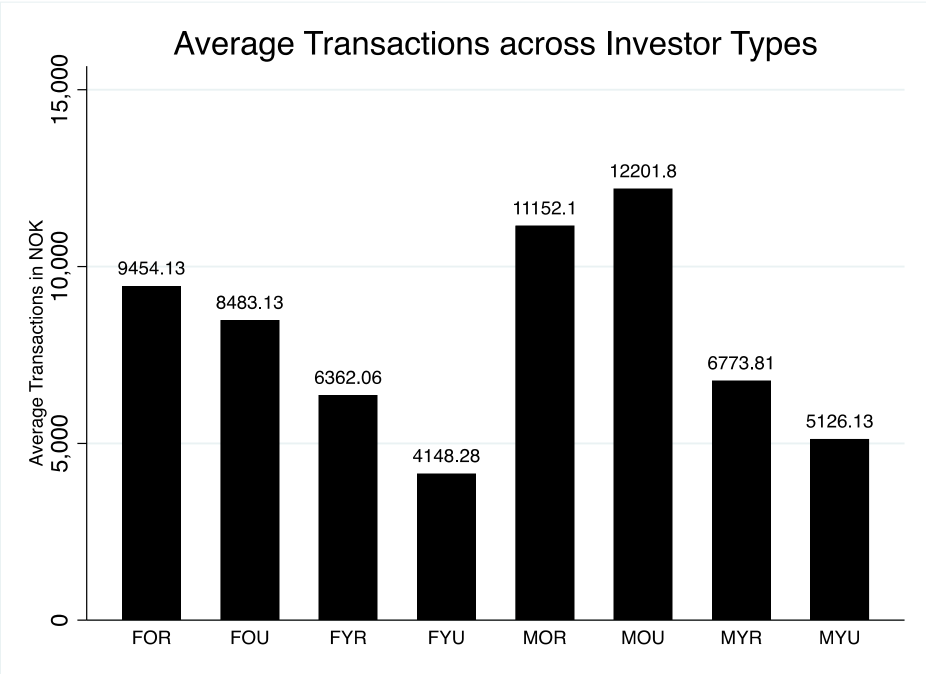

Figure 4: Average Monthly Transactions by Investor Types

This figure illustrates the average transactions each investor stereotype executes per month in a bar-chart. The y-axis shows the monthly average transactions measured in Norwegian Kroner. The x-axis shows the stereotype names (F- female, M-male, Y-younger, O-older, U-urban and R-Rural) for the corresponding bars in alphabetical order and contains all investor types as also shown in Table 1: Investor Types. The NOK value of each investor type's average monthly transactions is presented on top of each bar.

Overall, we noticed that the within variation for individuals is greater for the transaction flows (*Flowscat*) and transactions (*Trans*), while smaller for *Ret* and *Retlag*. Finally, the bar-chart for average transactions across *types* also illustrated differences between them.

5.2 Measuring Investment Behaviour in Passive Robo-Advising: Model I - IV

5.2.1 Invested Capital: Models I & II

The regression outputs from Model I and II are displayed in Table 8: Regression Output Model I & Model II. Under Model I, we tested the relationship between the AUM and the sum of transaction in the years 2019 and 2020. In both regressions, the coefficient for the sum of transactions (*Sum19* and *Sum20*) was positive and statistically significant at the 1% level. Among the controlling variables, only the investment horizon coefficient (*Horiz*) was significant at the 10% level in regression 1.1, and at the 5% level in regression 1.2. Under Model II we were interested in the effect of changes. We detected a high significance in the positive coefficient for *SumDelta,* estimated at 1.034 in regression 2.1. The coefficient for *AumDelta* in regression 2.2 was also significant at the 1% level.

Table 8: Regression Output Model I & Model II

Model I		
Variables	1.1: AUM19	1.2: AUM20
Accd	- 74.648	- 41.652
	(75.999)	(64.100)
Log_Web	- 1,638.020	- 1,140.930
	(1,625.497)	(1,197.726)
Log_Mob	- 176.527	- 30.333
	(195.057)	(34.383)
Act	5,267.625	4,026.728
	(20,685.410)	(8,819.006)
Pref	5,685.114	4,280.074
	(5,066.762)	(3,690.006)
Horiz	28,595.080 *	13,116.590 **
	(15,295.670)	(6,267.613)
Sum19	1.532 ***	
	(0.349)	
Sum20		1.605 ***
		(0.359)
Constant	-102,129.700	-68,384.030 *
	(71,175.950)	(40,452.030)
R-squared	0.8145	0.794

Model II		
Variables	2.1: Δ in AUM	2.2: Δ in SUM
Accd	48.871 ***	- 20.748 *
	(9.983)	(11.710)
Log_Web	734.280 **	- 203.365
	(309.168)	(339.971)
Log_Mob	58.125	27.358
	(51.248)	(50.548)
Act	662.109	1,996.863
	(6,968.111)	(4,077.688)
Pref	589.756	- 992.318
	(5,066.762)	(1,286.226)
Horiz	2,896.404	- 3,382.888
	(1,761.759)	(3,368.342)
SumDelta	1.034 ***	
	(0.029)	
AumDelta		0.568 ***
		(0.205)
Constant	- 16,682.720	13,840.670
	(20,903.170)	(15,118.020)
R-squared	0.595	0.590

This table presents the respective outputs for regressions 1.1 and 1.2 under Model I, and regressions 2.1 and 2.2 under Model II. The corresponding regression number and the dependent variable is listed in the first row under the model name. Both outputs contain the list of independent variables in the first column, and the coefficient estimates for all variables, the intercept coefficient, and the corresponding robust standard errors (.) below the coefficients, in columns 2 and 3, respectively. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. The last row contains the R-squared measure for each regression. See Appendix B: Table B1 and Table B2 for the complete regression output.

5.2.2 Differences across Demographics: Models III & IV

Regression outputs for models III and IV are displayed in Table 9: Regression Output Model III & Model IV. In regressions 3.1 and 3.2, we tested for a significant difference in AUMs across demographics. We used the AUM in 2020 (*Aum20*) as the outcome variable in both regressions. From the results, we only observed significant (1%) differences within gender (*Female*) and age (*Younger*), and within financial literacy (*Fl*) at a 10% significance level. Furthermore, the overall gender gap was estimated at negative 37,516.67. The overall age gap was negative for users under 37 with a coefficient of 98,764.87 for the variable *Younger*. To further estimate the gender gap between young females and males, we investigated the interaction between gender and age with respect to the generated AUMs in regression 3.2. Our results indicated a difference in the interaction term as significant at the 1% level, as well as the individual effects of differences in gender and age. In Model IV we explored the differences between and across demographics regarding the sum of transactions (*Sum20*). In regression 4.1, we found that merely the coefficients for *Female* and *Younger* are strongly significant at the 1% level, whereas coefficients for neither *Urban* nor *Fl* indicated any statistical significance. Finally, in regression 4.2, we used the interaction of *Female* and *Younger* and found that the coefficients for all three variables and the intercept were significant at 1%.

Table 9: Regression Output Model III & Model IV

Model III				
Variables	3.1: AUM20		3.2: AUM20	
Female	- 37,516.760	***	- 74,693.230	***
	(11,132.310)		(22,561.370)	
Younger	- 98,764.870	***	-110,357.400	***
	(12,103.300)		(20,798.140)	
Urban	16,002.330			
	(12,924.830)			
Fl	19,638.850	*		
	(10,695.360)			
Interactions				
*Female*Younger*			62,997.130	***
			(23,090.18)	
Constant	141,860.600	***	159,078.300	***
	(16,197.470)		(20,587.99)	
R-squared	0.040		0.015	

Model IV				
Variables	4.1: SUM20		4.2: SUM20	
Female	- 33,646.370	***	- 53,753.920	***
	(9,583.404)		(13,240.700)	
Younger	- 83,010.970	***	- 80,250.870	***
	(10,562.120)		(11,082.520)	
Urban	11,580.850			
	(11,458.950)			
Fl	6,808.256			
	(9,659.818)			
Interactions				
*Female*Younger*			41,582.760	***
			(13,780.920)	
Constant	125,493.700	***	122,202.300	***
	(14,664.110)		(10,780.620)	
R-squared	0.036		0.026	

This table presents the respective outputs for regressions 3.1 and 3.2 under Model III, and regressions 4.1 and 4.2 under model IV. The corresponding regression number, and dependent variable, is listed in the first row under the model name. Both outputs contain the list of independent and interaction variables in the first column, the coefficient estimates for all variables, the intercept coefficient, and the corresponding robust standard errors (.) below the coefficients, in columns 2 and 3, respectively. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. The last row contains the R-squared measure for each regression. See Appendix B: Table B3 and Table B4 for complete regression output.

Summing up, under Models I and II, the sum of transactions was significant in explaining the variation in the AUM in both 2019, and 2020. Furthermore, the change in the sum of transactions was significant and resulted in a positive change in the AUM. The change in the AUM as an independent variable was also significant and resulted in a positive, yet lower change in transactions. In Models III & IV the differences among the demographics gender and age with respect to acquired AUMs were significant, as well as an interaction term between the two. Females and males also showed a significantly different total transaction amount. This held for younger and older users, as well as the same interaction of *Female* and *Younger*.

5.3 Responses to Market Movements: Model V & VI

5.3.1 Transaction Flows & Previous Returns: Model V

With Model V we investigated the effect of previous returns (*Retlag*) on the variable *Flowscat*, which indicates whether an investor added, withdrew, or not transacted funds. Our results are displayed in Table 10: Regression Output Model V. The Hausman test and the test for overidentifying restrictions for regressions 5.1 through 5.4 resulted in a high p-value, and we thus used random effects. The results of regression 5.1 indicated an insignificant coefficient for *Retlag*. We also observed that *rho* (fraction of variance due to individual error term μ_i) was estimated at 0.502. After including time dummies, the coefficient for *Retlag* was negative and significant at 5%. Furthermore, *rho* was estimated lower at 0.492 (compared to regression 5.1).

Following this, regression 5.3 included additional controlling variables, next to time effects. The results indicated that after controlling for investor preferences and types, the coefficient for previous returns was not significant anymore. Moreover, coefficients for *Type* and *Horiz* were significant at 1%, where *Type* had a coefficient estimate of 0.007 and *Horiz* of negative 0.044. *Rho* was here at 0.490. Finally, in regression 5.4, we observed a significant (5%) negative coefficient for *Female* and a significant (1%) positive coefficient for *Younger*. *Rho* was here estimated at 0.416. All in all, previous returns were only significant in regression with time effects and no other controlling variables.

Table 10: Regression Output Model V

Model V: Flowscat - Random Effects								
Variables	5.1		5.2		5.3		5.4	
Retlag	0.027		-0.473	**	-0.284		-0.279	
	(0.046)		(0.232)		-0.215		(0.316)	
Type					0.007	***		
					(0.002)			
Horiz					-0.044	***		
					(0.010)			
Choice					0.009			
					(0.009)			
Female							-0.021	**
							(0.010)	
Younger							0.051	***
							(0.008)	
Urban							0.010	
							(0.010)	
Fl							0.012	
							(0.012)	
Constant	0.148	***	0.165	***	0.229	***	0.089	***
	(0.007)		(0.012)		(0.032)		(0.017)	
Time Effects	No		Yes		Yes		Yes	
Sigma_u	0.252		0.247		0.247		0.209	
Sigma_e	0.251		0.251		0.252		0.247	
Rho	0.502		0.492		0.490		0.416	
R-sq:								
Within	0.0000		0.0009		0.0009		0.0011	
Between	0.0001		0.0210		0.0147		0.0223	
Overall	0.0000		0.0024		0.0070		0.0049	
Obs. per group								
Min	1.000		1.000		1.000		1.000	
Avg.	7.800		7.800		7.700		9.700	
Max	32.000		32.000		32.000		30.000	
Number of obs.	29,701.000		29,701.000		29,701.000		29,701.000	
Number of groups (ID):	3,828.000		3,828.000		3,828.000		3,828.000	

This table shows the regression outputs for regressions 5.1 to 5.4 from a random-effects model, V, with *Flowscat* as the dependent variable. The first row contains the model name, the dependent variable estimated, and the estimation method. The corresponding regression number is listed in the row under the model name. The table contains the list of independent variables used in each regression (column 1), the coefficient estimates for all variables and the intercept according to each regression number, and the corresponding (.) robust standard errors below the coefficients (column 2-5). Note that all (.) standard errors are adjusted for clusters in the model portfolios. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. For each regression, this table shows whether time effects were included. The error term components sigma_u and sigma_e are presented below the indication for time effects, as well as the fraction *rho* of individual fixed effects variance μ_i. The table further contains the R-squared measures for between, within, and overall variation of all regressions. The last two rows contain the number of time periods observed per group, the total number of observations, and the number of groups (grouping variable ID). See Appendix C: Regressions – Random Effects Model for the complete regression outputs.

5.3.2 Transaction Amounts & Current Returns: Model VI

Under Model VI we investigated the effect of returns (*Ret*) on the transaction amounts (*Trans*) executed in the same month, by individual investors and investor types. Table 11: Regression Output Model VI, shows the results. The Hausman test for regressions 6.1 through 6.4 resulted in a p-value lower than 10%, and we thus used fixed effects. In regression 6.1 we investigated the effect of returns from model portfolios on individual transactions in the same month. The regression estimated a significant (5%) coefficient for *Ret,* estimated at negative 73,408.88. *Rho* for regression 6.1 was estimated at 0.266. The coefficient for the intercept is estimated at 9,682.509, and significant at 1%.

Moreover, in regression 6.2, we included time effects with dummies and no longer observed any statistical significance for individuals' returns. *Rho* was here estimated at 0.272. The coefficient of the intercept, however, remained significant at 1%, with an estimated value of 35,497.88. Following this, in regression 6.3, we grouped the observations according to our investor types (*Type*). We could observe that *Ret*'s coefficient was statistically significant again at the 5% level and estimated at negative 56,390.920. The coefficient of the intercept remained statistically significantly different from zero at the 1% level. In the last regression, we again included time effects. The results for 6.4 showed neither significance for the coefficient of returns, nor the coefficient of the constant.

Summing up, we saw that current returns have a significant effect on the variation of transactions of individual investors. When accounting for time effects, however, current returns are not significant under neither individual nor type-grouped observations.

Table 11: Regression Output Model VI

Model VI: Trans - Fixed Effects

Variables	6.1	6.2	6.3	6.4
Ret	- 73,408.880 **	- 5,314.354	-56,390.920 **	-88,130.630
	(34,167.140)	(97,208.420)	(28,173.760)	(95,180.270)
Constant	9,682.509 ***	35,497.880 ***	9,298.261 ***	12,895.340
	(440.357)	(2,070.540)	(693.880)	(98,961.810)
Time Effects	No	Yes	No	Yes
Investor Type Effects	No	No	Yes	Yes
Grouping Variable	ID	ID	Type	Type
Sigma_u	61,080.086	61,699.879	2,845.883	2,418.421
Sigma_e	101,486.860	100,979.350	99,202.949	98,950.159
Rho	0.266	0.272	0.001	0.001
R-sq:				
Within	0.0002	0.0114	0.0001	0.0063
Between	0.0089	0.0056	0.4398	0.6274
Overall	0.0001	0.0056	0.0002	0.0066
Obs. per group				
Min	1.000	1.000	517.000	517.000
Avg.	7.800	7.800	3,519.200	3,519.200
Max	32.000	32.000	8,597.000	8,597.000
Number of obs.	29,126.000	29,126.000	28,154.000	28,154.000
Number of groups:				
ID	3,739.000	3,739.000		
Investor types			8.000	8.000

This table shows the regression outputs for regressions 6.1 to 6.4 from fixed effects Model VI, with *Trans* as the dependent variable. The first row contains the model name, the dependent variable estimated, and the estimation method. The corresponding regression number is listed in the row under the model name. The table contains the list of independent variables used in each regression (column 1), the coefficient estimates for all variables and the intercept according to each regression number, and the corresponding (.) robust standard errors below the coefficients (column 2-5). Standard errors (.) in 6.1 and 6.2 are adjusted for clusters in the model portfolios. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. For each regression, this table shows whether time effects and stereo-type effects were included. In the row below, the table indicates the regression grouping variable for the panel. The error term components sigma_u and sigma_e are indicated, as well as the fraction *rho* of individual fixed effects variance μ_i. The table further contains the R-squared measures for between, within, and overall variation for all regressions. The last rows contain the number of time periods observed per group, the total number of observations, and the number of groups (by grouping variable ID and type). See Appendix D: Regressions – Fixed Effects Model for the complete regression outputs.

5.4 Differences in Saving Behaviour: Model VII, ANOVA, & Delta-Method

5.4.1 Model VII

With Model VII we wanted to investigate the between variation among individual investors. The regression output for a between estimation of *Trans* with respect to individual returns is presented in Table 12: Regression Output Model VII. The results showed that the coefficient for *Ret* is statistically significantly different from zero at 1%. Furthermore, this coefficient was estimated to be positive, with a value of 809,566.100.

Table 12: Regression Output Model VII

Model VII: Trans - Between Estimation		
Variables	7.0	
Ret	809,566.100	***
	(139,611.000)	
Constant	- 745.370	
	(2,421.171)	
R-sq:		
Within	0.0002	
Between	0.0089	
Overall	0.0001	
Obs. per group		
Min	1.000	
Avg.	7.800	
Max	32.000	
Number of obs.	*29,148.000*	
Number of groups (ID)	*3,740.000*	

This table shows the regression output for between estimation Model VII, with *Trans* as the dependent variable. The first row contains the model name, the dependent variable estimated, and the estimation method. The corresponding regression number is listed in the row under the model name. The table contains the coefficient estimate for the independent variable *Ret,* and the intercept, as well as the corresponding (.) standard errors below the coefficients, in column 2. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. The table also indicates the R-squared measures for between, within, and overall variation of the regression. The last rows contain the number of observed time periods per group, the total number of observations, and the number of groups (grouping variable ID). See Appendix E: Table E1: Complete Regression Output 7.0 for the complete regression output.

5.4.2 One-Way ANOVA, Post Hoc Bonferroni

In this section, we performed an analysis of variance (ANOVA) for the different investor types, with a post hoc Bonferroni test. Results are presented in Table 13: One-way Comparison of Average Transactions by Type, Bonferroni. The leading ANOVA table for this comparison can be found in Appendix E: Table E2: ANOVA by Investor Types. The ANOVA resulted in an F-statistic of 0.000, indicating significant differences in the population means. The post estimation with Bonferroni correction indicated, that only means between *MOU* and *FYU,* and between *MOU* and *MY* were significantly different. Both differences in means were significant at the 1% level. Between *MYU* and *MOU* there was a negative difference for the average transactions. The same held for *FYU* and *MOU*, where *FYU* had a significantly lower average of transactions. Another one-way multiple mean comparison after a Scheffe correction was performed to confirm our results (see Appendix E: Table E3: One-way Comparison of Average Transactions by Type, Scheffe). We found the same results of significance with this post estimation.

Table 13: One-way Comparison of Average Transactions by Type, Bonferroni

Comparison of Average Trans by Type							
Bonferroni							
Row Mean - Col Mean							
	FOR	FOU	FYR	FYU	MOR	MOU	MYR
FOU	-971.000						
	1.000						
FYR	-3,092.070	-2,121.070					
	1.000	1.000					
FYU	-5,305.850	-4,334.850	-2,213.780				
	1.000	1.000	1.000				
MOR	1,697.950	2,668.950	4,790.020	7,003.810			
	1.000	1.000	1.000	0.322			
MOU	2,747.650	3,718.650	5,839.720	8,053.500	1,049.700		
	1.000	1.000	1.000	0.003***	1.000		
MYR	-2,680.320	-1,709.320	411.750	2,625.540	-4,378.270	-5,427.970	
	1.000	1.000	1.000	1.000	1.000	0.761	
MYU	-4,328.000	-3,357.000	-1,235.930	977.850	-6,025.950	-7,075.650	-1,647.680
	1.000	1.000	1.000	1.000	0.295	0.000***	1.000

This table shows the output for the multiple-mean comparison after the Bonferroni correction. The third row shows how the differences computed. The investor types are listed in the first column, and the fourth row, constituting the matrix. Values on the top within the matrix indicate the difference between a mean of a type (row) and another type (column). The value below indicates the p-value for rejection of the null for no difference in means. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. A description of the types can be found in Table 1: Investor Types, where the initials stand for F- female, M-male, Y-younger, O-older, U-urban and R-Rural.

5.4.3 Delta-Method

We ran a parametric test to compare the residual effects of transactions between different investor types. The necessary regression output for obtaining the variances in the residuals per type can be found in Appendix E: Table E 4.1 Mixed Model Regression Output. The results from the delta-method comparison are presented in Table 14: Delta-Method for Mixed Model Residual Comparison, Bonferroni. From this we observed that the variation between the following investor types was significant: *FYU* and *FOU, MYU* and *FOU, MOR* and *FYU, MOU* and *FYU, MYU* and *MOR, MYU* and *MOU*. All differences showed a minimum of 90% confidence. Appendix E: Individual & Stereotype Differences

Table 14: Delta-Method for Mixed Model Residual Comparison, Bonferroni

Delta-Method Bonferroni							
Type							
			Contrast	Std. Err.	z	P>z	
FOU	vs	FOR	- 931.836	3,192.504	-0.290	1.000	
FYR	vs	FOR	-2,918.369	3,638.948	-0.800	1.000	
FYU	vs	FOR	-5,306.163	3,104.326	-1.710	1.000	
MOR	vs	FOR	1,846.388	3,670.824	0.500	1.000	
MOU	vs	FOR	2,924.431	3,545.552	0.820	1.000	
MYR	vs	FOR	-2,384.164	3,249.474	-0.730	1.000	
MYU	vs	FOR	-4,187.622	3,103.606	-1.350	1.000	
FYR	vs	FOU	-1,986.533	2,111.592	-0.940	1.000	
FYU	vs	FOU	-4,374.327	923.955	-4.730	0.000	***
MOR	vs	FOU	2,778.224	2,166.049	1.280	1.000	
MOU	vs	FOU	3,856.267	1,946.217	1.980	1.000	
MYR	vs	FOU	-1,452.328	1,332.655	-1.090	1.000	
MYU	vs	FOU	-3,255.786	921.534	-3.530	0.012	**
FYU	vs	FYR	-2,387.794	1,975.677	-1.210	1.000	
MOR	vs	FYR	4,764.757	2,782.398	1.710	1.000	
MOU	vs	FYR	5,842.800	2,614.912	2.230	0.713	
MYR	vs	FYR	534.205	2,196.600	0.240	1.000	
MYU	vs	FYR	-1,269.253	1,974.531	-0.640	1.000	
MOR	vs	FYU	7,152.551	2,033.858	3.520	0.012	**
MOU	vs	FYU	8,230.594	1,797.940	4.580	0.000	***
MYR	vs	FYU	2,921.999	1,104.702	2.650	0.229	
MYU	vs	FYU	1,118.541	542.068	2.060	1.000	
MOU	vs	MOR	1,078.043	2,659.063	0.410	1.000	
MYR	vs	MOR	-4,230.552	2,249.200	-1.880	1.000	
MYU	vs	MOR	-6,034.010	2,032.761	-2.970	0.084	*
MYR	vs	MOU	-5,308.595	2,038.366	-2.600	0.258	
MYU	vs	MOU	-7,112.053	1,796.699	-3.960	0.002	***
MYU	vs	MYR	-1,803.458	1,102.645	-1.640	1.000	

This table shows the approximated differences in fixed effects error term components between all eight investor types. In total, the table lists 28 differences. The first column indicates which two types are compared. The second column contains the approximated difference from the delta-method, where the value indicates the difference between the first type compared to the second in column one. Columns three, four, and five contain the standard error, z test score, and p-value for the rejection rule. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. A description of the types can be found in Table 1: Investor Types, where: F- female, M-male, Y-younger, O-older, U-urban and R-Rural.

The between estimation under Model VII indicated a significant difference in the effect of current returns on transactions per individual. The non-parametric tests for the multiple mean comparison showed significantly higher averages for older male users from urban areas, compared to other younger males, and also compared to younger females. Finally, significant differences were visible between younger females with an urban residence and other male investors with different demographics. According to these findings, the only significant difference among female users was between younger and older females, both from urban areas.

5.5 Differences in Saving Patterns over Time: Model VIII

In our last model, we investigated the effect of differences between individual investors and investor types on the deviation of average transactions over time. Outputs for regressions 8.1 to 8.4 are presented in Table 15: Regression Output Model VIII. This model was estimated with between estimation. Regressions 8.1 and 8.2 inspected the between variation of individual transactions (*Trans*) with respect to current returns (*Ret*) and a time trend (t). Thereafter, regressions 8.3 and 8.4 estimated the between variation of transactions grouped by type, with respect to returns and a time trend.

Results for 8.1 showed statistical significance for the positive coefficient of the between variation of *Ret* at 1%. This effect was estimated at 649,465.600. The coefficient for the time trend variable t was positive, with a value of 598.495, and significantly different from zero at the 5% level. The coefficient for the intercept was significant at 1%. Under 8.2, *Trans* was regressed solely on the time trend (t). We observed a significant (1%) positive coefficient for this variable, as well as for the coefficient of the intercept (1%). Regression output 8.3 reports the coefficients for the intercept, returns and the trend variable, and we observed that none of the above was statistically significant for explaining the between variation of transactions per investor type. Under regression 8.4 however, we disregarded between variation of returns by type and regressed solely on the trend variable. Grouped by types, this regression estimated a negative coefficient for the trend variable, with a significance at a 5% level. The coefficient for the intercept was significant at 1%.

Table 15: Regression Output Model VIII

Model VIII: Trans - Between Estimation								
Variables	8.1		8.2		8.3		8.4	
Ret	649,465.600	***			- 307,164.100			
	(160,594.300)				(2,427,391.000)			
t	598.4905	**	1,263.666	***	-1504.748		- 1,694.314	**
	(297.070)		(256.8654)		(1,540.963)		(610.609)	
Constant	-426,861.200	**	-892,969.300	***	1,085,863.000		1,216,766.000	**
	(211,522.900)		(183,936.300)		(1,071,329)		(435,637.800)	
Investor Types	No		No		Yes		Yes	
Grouping Variable	ID		ID		Type		Type	
R-sq:								
Within	0.0011		0.0072		0.0017		0.0020	
Between	0.0100		0.0064		0.5296		0.5620	
Overall	0.0006		0.0024		0.0019		0.0023	
Obs. per group								
Min	1.000		1.000		517.000		543.000	
Avg.	7.800		8.100		3,519.200		3,663.500	
Max	32.000		32.000		8,597.000		8,850.000	
Number of obs.	29,148.000		30,352.000		28,154.000		29,308.000	
Number of groups:								
ID	3,740.000		3,754.000					
Investor types					8.000		8.000	

This table shows the regression outputs for regressions 8.1 to 8.4 from a between estimation Model, VIII, with *Trans* as the dependent variable. The corresponding regression number is listed in the first row under the model name. It contains the list of independent variables used in each regression, the coefficient estimates for all variables and the intercept, and the corresponding (.) standard errors below the coefficients. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. For each regression, this table shows whether stereo-type effects were included, and the corresponding grouping variable for the panel. The table further contains the R-squared measures for between, within, and overall variation for all regressions. The last rows contain the number of observations made per group over time, the total number of observations for each regression, and the number of groups (by grouping variable ID and type). See Appendix F: Regressions – Second Between Estimation for the complete regression outputs.

According to results from Model VIII, we observed that between variation in returns and a time trend variable was significant for explaining between variation of individuals' transactions. For between variation of investor types, this explanatory significance was only observable when regressing solely on a time trend. Grouped by type, returns and a time trend together indicated no statistically significant explanatory power for variation of transactions across types.

6.0 Discussion

In this chapter, we discuss the causal and economic interpretation of our findings from Chapter 5. We thereby aim to answer our **research question**: *"From a behavioural perspective: Does Kron's robo-advisor incentivize similar saving patterns across different investors, and thus create benefit from capital markets for more individuals, due to the elimination of personal traits in investment behaviour?"* The objective of our research is to firstly establish whether transactions are the relevant measure for differences in saving behaviour. Secondly, we will study if the investors' personal traits and stereotypes affect their investment behaviour when utilizing Kron's passive robo-advisor (RAr). Then we examine whether this effect is equal for all investors or investor types. Finally, we will analyse our findings on whether the effect of the investors' personal dispositions is diminished over time in Kron's passive RAr.

6.1 Analysis of Descriptive Statistics

We used a Pearson correlation matrix (see Table 4: Pearson Correlation) to preliminarily investigate the relationship between our variables. Overall, the demographics are not correlated with any other independent or controlling variables. Concerning Pearson correlation though, the interpretation of correlations between categorical and continuous variables is overall not conclusive. The same holds for *Sum20* and *Choice,* which indicated a correlation close to zero between them. Between continuous variables, we found a high positive correlation between *Aum19* and *Sum19*. Originally, we had expected the sum of transactions to be highly correlated to the AUM. However, a slightly negative correlation between *Aum20* and *Sum20* was unexpected. With descriptive statistics alone, we could not estimate the direction of the causation in this coefficient. Nevertheless, the absolute value of this correlation should have been higher according to our expectations. A Pearson correlation coefficient is faulty, such as being strongly influenced by outliers. We identified a few outliers in the variables for the sum of transactions (*Sum19* and *Sum20*), as well as in the variables for AUMs (*Aum19* and *Aum20*). These could have had a strong influence on the correlation coefficients. Additionally, the Pearson coefficient is dependent on an assumption of homoskedasticity, which we observed for our Models I, II, III and IV.

We detected a high correlation between preference (*Pref)* and model portfolio (*Mpf*), and between investment horizon (*Horiz)* and risk level (*Risk)*. This indicated that the investment horizon is highly related to the investor's allocated risk level. Further, *Horiz* can mostly account for risk in the user's performance. Preference is thereby also highly related to the model portfolio and can account for the allocations the tool made. As a consequence, and to avoid issues of multicollinearity, we excluded one variable of each in the regressions with these controlling factors. Between *Pref* and *Mpf,* we chose *Pref* as more appropriate control, as this variable depicts a subjective choice of the investor. The investor's model portfolio is allocated by Kron's algorithm and does therefore not represent this investor's own choices as accurately. We applied the same logic when choosing between *Horiz* and *Risk*. We chose *Horiz* for all models since we used controlling variables for investor preferences and indications. Due to the drawbacks in the Pearson correlation coefficient with our data, we did not rely on the accuracy of other correlation findings.

Furthermore, the findings from the cross-sectional summary statistics are partly in line with our original expectations (see Table 5: Cross-Sectional Summary Statistics). We found that one-third of the sample consists of females and that they invest three times less than the male counterpart (Carr & Steele, 2010; Margaret et al., 1999). We also found an approximately equal share of younger and older individuals in the sample. This comes from the fact that the original mean of all investor's age was around 37 years old. For our dichotomous variable *Younger*, this was a natural split between younger and older generations. This split in generations was found to be relevant in previous literature (Frost, 2020). The descriptive analysis also confirmed that younger generations invested less capital in total, compared to the older generations (Bencivenga & Smith, 1991; Brounen et al., 2016). Moreover, our expectation regarding the investors' residence was confirmed, where 78.7% of the investors resided in an urban area, and they acquired a higher average AUM in 2020. Due to inconclusive data regarding users' previous investment experience, we could only account for 2,235 investors' indications. Of these, 58,5% indicated higher financial literacy due to experience (Deuflhard, Georgarakos, & Inderst, 2019). Our findings also suggested that on average investors acquired a lower AUM per 13.02.2020, than per 01.07.19.

Other observations include investors' individual preferences. A total of 69.3% made an active choice and specified a preferred investment sector. The summary statistics also suggested that the majority of investors indicated a savings horizon between medium-term and long-term (Campbell & Viceira, 2002). However, we did not rely strongly on the variable account age, since we cannot predict how long investors will hold their accounts. Finally, the investors used their mobile application approximately 36 times a month, and the web application only 1.675 times a month. We assumed, that this high average for the mobile log-ins illustrates a shift towards digital finance (Carlin et al., 2017). Based on this summary, we got the impression that users want simpler interfaces through mobile services and more online accessibility. Further, we assumed that the high averages for investment sector choice (*Choice*), savings horizon (*Horiz*), and investment activity (*Act*) arose due to a growing interest for responsibility in personal savings. Overall, Kron's clients seem to follow the global trend for more security through long-term investments (Brounen et al., 2016; Jensrud, 2019).

The panel summary statistics (see Table 7: Panel Summary Statistics - Main Variables) for *Inv_Incr* showed, that the differences in investors' reactions between all investors were minor. However, the differences between one individual investor's response to an increase in previous returns varied more over time. Originally, we hypothesized using individual transactions as a measure for the investment behaviour (Kumar & Lee, 2006). For the main transaction variable (*Trans*), we found the within variation to be considerably higher, and differences across individuals to be lower. This suggests that the gap in saving behaviour (measured by *Trans*) for each individual is wider over time. This could however also be the result of other differences in saving behaviour between some individuals that are not as strong as between others. Therefore, this confirms the importance of examining individuals and stereotypes in the data set. We not only wanted to observe heterogeneities among individuals, but also the differences of heterogeneities between specific groups. This introductory analysis of panel data was extended with Figure 4. Here, we could see that there were differences between investor types, yet not all differences were as great. We moved on to investigate the significance of these differences in average transactions under hypothesis three.

6.2 Measuring Investment Behaviour in Passive Robo-Advising

When establishing an appropriate measure for Kron’s investors’ behaviour, we looked into the study from Kumar et al. (2006). It suggested using individual trades as outcome variable when estimating differences in investor behaviour. This was not appropriate for our study, as Kron’s tool is a passive robo-advisor (RAr), and therefore the algorithm executes the investors’ trades. It was hence crucial to establish a similar and relevant measure for behaviour.

Model I (Table 8: Regression Output Model I & Model II) showed, that the total amount of transactions (*Sum19* & *Sum20*) executed by individuals was continuously significant. Among our controlling variables (*Accd, Log_Web, Log_Mob, Act, Pref,* and *Horiz*) for account factors and investor information provision, only the indicated investment horizon was significant in both regressions (Campbell & Viceira, 2002). As mentioned above, account age was not reliable as an explanatory variable. Our original intuition was further, that log-ins to Kron’s tool should help explaining differences in generated savings because investors use technology in financial services differently (Carlin et al., 2017). Unexpectedly, this was not a significant controlling variable. We concluded, that mere online accessibility is necessary to add funds to your accounts, but it is not sufficient to explain saving performance in passive RA ("Money and Happiness," 2019).

This was confirmed by the insignificance of *Act* in both regressions. It tells us that users who provided funds continuously the entire period of using, do not result in having significantly different saving performances. Rather, it confirmed that the performance is mainly dependent on the amount each user *adds* to his account (Campbell & Viceira, 2002). The results also led us to conclude, that in passive RA it is irrelevant which investment sector the investor chooses. Following findings from correlation analysis, we extend this conclusion: There are therefore no sectors within Kron’s selection which stand out in leading to better performances in AUM. Controversially to findings from the literature, we thus conclude that accuracy in user’s information provision is not as relevant as expected. The only provided information that should indeed be accurate, is the investor’s saving horizon (i.e. individual expected holding period) (Jung et al., 2019).

We further explain the significance of the investment horizon with the fact that individuals who take long-term future stability more seriously, perform better (Bencivenga & Smith, 1991; Brounen et al., 2016; Parise & Peijnenburg, 2019). Another explanation is linked to the allocated risk level per investor. To recall, Kron's RA allocates model portfolios which follow the Markowitz mean-variance optimization (Beketov et al., 2018; Jung et al., 2019). These portfolios are constructed according to each investor's risk level, as well as his preferred investment sector.

Since the investment sector does not drive variation in generated AUMs, we assume that this variation comes from the volatility in the portfolio. As seen in correlation findings, the variable for investment horizon contains observations commoving on a high level with the investor's risk factor. A reason for this could be that the algorithm detects long-term holding periods and allocates portfolios which allow higher anti-proportional covariances (Beketov et al., 2018). These can decompress the diversification performance of the portfolio over a longer period. Thus, volatility and returns of portfolios will be higher if the holding period is longer. This could explain that users who indicate long-term saving preferences will thus most likely be allocated a higher risk level, receive a higher return, and generate more savings. This is in line with traditional financial theory, where higher volatility leads to higher returns or higher losses (Beketov et al., 2018).

Summing up, we find only two relevant factors for passive investors and their saving performance in terms of AUMs. Firstly, users should be continuously dedicated to their future finances by planning to save for longer. Secondly, users should dedicate the highest possible fraction of their disposable income to their savings in RA, without withdrawing funds from their accounts.

Model I alone is not sufficient for fully clarifying the direction of the causation between Kron's investors' total invested capital, and their generated AUMs. Previously, we could only deny or confirm the relationship between these two variables. We wanted to examine, whether increasing the invested capital has an effect. If not, investors who invest a one-time lump sum should reach a similar saving performance than investors who invest over time.

Therefore, we looked at the response of investors' savings, following a change to their invested funds in model II (see Table 8: Regression Output Model I & Model II). In a second regression, we estimated the opposite effect. As we used this model to corroborate our findings, we added the same controlling variables from Model I. Although the investor's account age was now significant in both regressions under Model II, we disregarded it as an explanatory variable. As previously established, account age was not an accurate measure for us. It did, however, control the relationship between transactions and AUMs.

According to our results, Kron investors who increased their total added funds by NOK 1 between 01.07.19 and 13.02.20, will gain an estimated NOK 0.034 higher AUM, than the original investment amount would have earned. Increasing the entire invested funds can, therefore, lead to 3.4% higher generated savings than investors who kept their invested capital constant during the investment period. Similarly, withdrawing funds will have the opposite effect, and will result in an estimated lower AUM. Our findings suggest firstly, that there is an absolute effect of invested funds on generated savings. Secondly, the relationship between the two is proportional. Investors can increase their generated savings by adding funds later and will negatively affect their savings by withdrawing (Campbell & Viceira, 2002).

The second regression showed that following an increase of NOK 1 in generated AUM, the corresponding total transactions per investor will increase by NOK 0.568. This estimate suggested that investors will increase their provided funds when their AUM goes up. Yet, they will increase their funds by a smaller amount than the observed increase in their generated savings. The effect of change in transactions on AUMs was higher. Without fully guaranteeing causality, we concluded that an increase in AUM does therefore not drive whether users add more funds to their accounts. Rather, the users' generated savings will be higher, if they further invest capital at later points in time. This finally showed that investing a one-time lump sum is not as beneficial. Users of passive RA should rather invest supplementary capital later (Campbell, 2006; Campbell & Viceira, 2002; Campbell & Yogo, 2006; Campello et al., 2010).

After having established the effect of transactions on savings, we wanted to account for variation in savings caused by the individuality of all Kron investors. Traditional economic models assume that individuals are rational (Campbell, 2006). The economists Adam Smith, Daniel Kahneman, and Richer Thaler, however all argue that economic models tailored to one type of agent cannot be considered accurate. Rather, different types of agents make independent decisions according to their influences or biases. The behavioural theory offers opportunities to develop better models of economic behaviour (Smith, 1937; Richard H. Thaler, 2009; Richard H Thaler, 2016).

We first had to establish an appropriate measurable profile for the client base. In Stafford's (1996) study, the author states that demographics continue to be one of the most popular and well-accepted bases to segment customers. She highlights the importance of identifying the key demographics of one's target market to create a measurable profile. Therefore, we tested for significant demographic trends in acquired savings, and in total added funds.

Model III (see Table 9: Regression Output Model III & Model IV) was used to test whether there is a gap in generated savings among demographics. Our results revealed that the generated AUM differs most significantly among demographics gender and age. Additionally, we found that a gap in financial literacy was only significant in the first regression. One reason for its relatively lower level of significance could be missing observations within financial literacy (*Fl)* (see Table 5: Cross-Sectional Summary Statistics). Another explanation is that passive RA reduces the individual's difficulty in choosing an appropriate investment strategy and rebalancing. This would make the need for previous investment experience for savings in capital markets almost redundant (Jung, Dorner, Glaser, et al., 2018).

Individuals still tend to make different financial decisions (Carr & Steele, 2010; Steven J Spencer et al., 2016). We, therefore, used the significance of differences in financial literacy as supporting evidence but did not consider it fully conclusive. For those who reported investing experience, on average, the generated AUM was higher by NOK 19,638.85.

The investor's level of financial literacy is still a source of differences in performance when saving in capital markets (Agarwal et al., 2007). In our sample, the difference in financial literacy is not as great as the differences in gender and age. There is high significance in the overall gender gap. The estimated average AUM for women was NOK 37,516.67 lower than for men. Controversially to Atkinson et al. (2003), we found a difference in performance between males and females. The authors argue that women's and men's investment performance is not different, though their investment behaviour is.

In that study, this difference in behaviour is mainly attributable to differences in investment knowledge. However, as Atkinson et al.'s (2003) study is placed in a different setting, this comparison is not counterfactual. We can therefore only conclude that there is, in fact, a significant gender gap regarding personal savings in Kron's RAr. The regression results confirmed that women, on average, acquired fewer savings than men. Moreover, keeping all other factors constant, our model estimated an average AUM of NOK 141,860.60 for financially experienced males above the age of 37, that live outside cities. This was among the highest values for average AUMs (Agarwal et al., 2007). However, the coefficient for the variable indicating the investors' residence (*Urban*), was insignificant in this first model. The differences in generated savings were not dependent on the location of the user. Secondly, the overall age gap indicated that the average AUM for younger users was lower by NOK 98,764.87, compared to users older than 37. This is in line with our expectations based on age and generations in savings, as well as predictions from Model I; those over 37 (older generations) will have a longer savings horizon, due to factors like family planning in progressed adulthood, and save more (Bencivenga & Smith, 1991; Brounen et al., 2016; Stafford, 1996).

Subsequently, we investigated the difference between younger and older males and females (interaction between gender and age) with respect to the generated AUMs. We estimated the gender gap between young females and males, which resulted in an estimated NOK 11,696.1 lower AUM for young females than for young males. Then, we estimated the gender gap between older women and men, and this resulted in a gap of negative NOK 74,693.23 for older women.

Considering both generations in the gender gap, the variation between older men and women was therefore considerably higher, by NOK 62,997.13. This leads us to conclude that among Kron's users, the differences in gender among older generations are considerably higher than in gender among younger generations. The studies from Carr & Steele (2010) and Margaret et al. (1999) provided evidence on social stigma around women's "poorer" ability to solve quantitative problems, making financial decisions, and adopting technology. We can confirm the notion of social stigmas and stereotyping in savings, as our results find that women saved significantly less, and made up only 30% of the sample. The lower participation of women saving in the RAr could also explain the variance with respect to performance.

Further, the decreasing impact of social stigma around gender over the decades between the 1940s and 2000s can be a possible explanation for the difference in gender gaps between older and younger generations. The societal impact of progression regarding equality between men and women, and the following shifts in society construction for men's and women's position in society, would be an explanation for this decreasing effect (Stafford, 1996; Steele, 1997). However, we reached a limit of investigating these heterogeneities in our cross-section and tested these effects in later models. Differences in generated savings under Model III could only tell us about the final performance. These diverse successes could, however, come from different factors (e.g. different investment horizons and returns). To link our findings from Model III to the established driver 'transactions', we explored these differences regarding the total amount of invested funds per demographic (see Table 9: Regression Output Model III & Model IV). Here, we found that merely *Female* and *Younger* are strongly significant (Agarwal et al., 2007; Anderson et al., 2005).

Moreover, we found the gender gap to be NOK 33,646.370 less for females, than the total transactions executed by males. Concerning the age gap, our results showed that the younger generation reached an average total sum of transactions that was NOK 83,010.970 lower than older generations. This again confirms our expectations regarding differences in saving patterns among different age groups (Badarinza et al., 2016; Bencivenga & Smith, 1991; Stafford, 1996).

With an interaction term between *Female* and *Younger,* we could then observe that the gender gap had widened and that the age gap was reduced. We estimated the average total sum of transactions of older females to be NOK 53,753.92 lower than older males. Additionally, we estimated the gender gap between younger men and women, which resulted in NOK 12,171.16 lower average transactions for younger women than younger men. We saw that also this gap was significantly lower than the gender gap between older women and men.

6.2.1 Interim Conclusion

As a result, of the discussion above, we confirm sub-hypotheses $H_{1,1}$[11]. We found that online accessibility is not sufficient to explain saving performance in passive RA, even though it is necessary to adjust invested capital ("Money and Happiness," 2019). We confirm that the tool's performance is mainly dependent on the amount each user adds over time to the account. An increase in transactions leads to a 3.4% higher AUM than keeping capital constant. Evidently, users who withdraw funds will perform worse. The savings an individual generates in passive robo-advisory (RA) are therefore almost solely dependent on increasing invested capital (Campbell & Viceira, 2002). Investors' different goals for savings also explain the diverse successes. Users that showed to be more dedicated to long-term financial stability, invested more capital over time and acquired higher savings. It is further irrelevant which investment sector Kron's user selected. Regarding sub-hypothesis $H_{1,2}$[12] and $H_{1,3}$[13], we found that the AUM and total invested capital indeed differs among different demographics, where the differences between gender and age were most significant (Stafford, 1996). Men acquired both higher AUMs as well as invest more than females overall, and users of older generations obtained higher savings for both gender groups. We believe this difference to come from a natural progression in adulthood. The literature shows that individuals at a certain age tend to take personal finances more seriously. Lastly, we confirm our first hypothesis[14], H_1, that invested capital is the main driver for differences in individual performance (Almlund, Duckworth, Heckman, & Kautz, 2011).

[11] $H_{1.1}$: *Increasing total invested capital over time has a marginally increasing effect on the investor's AUM.*
[12] $H_{1.2}$: *Different demographic groups generate different AUMs.*
[13] $H_{1.3}$: *The investment behaviour in terms of total invested capital differs across demographic groups.*
[14] H_1: *Total invested capital by each investor is the main driver for differences in individual saving performance.*

6.3 Responses to Market Movements

As we had established transactions as an appropriate measure for investment behaviour in passive RA, we needed to confirm the intuition that Kron's users behave away from intended investment behaviour (Campbell & Viceira, 2002; Kahneman, 2011). We tested the effect of returns on users' executed transactions per month. Combining findings from literature, we assumed trend-chasing to be the most descriptive behavioural bias for identifying deviations from rationality. According to the study by Kumar et al. (2006), returns trigger these deviations. Based on this we were interested in analysing if there was a trend between and among individual investors and types of investors, and whether they chase the returns (D'Acunto et al., 2019).

Our findings showed that previous returns were insignificant in explaining variation regarding inflows and outflows of individual transactions. This indicates that investors do not respond to previous market movements by adding or withdrawing funds to their accounts (D'Acunto et al., 2019). We used random effects in this model, as we believed the variation across individual investors to be uncorrelated with previous returns. In other words, time-invariant individuality is not related to previous returns. Additionally, we assumed that the differences across investors in the data set have an effect on their flows of transactions (Richard H. Thaler, 2009).

The estimated fraction of the error term allocated to time-invariant fixed effects of individuality was at 50.2%. This means, half of the noise around predictions of transaction flows is attributed to individuality, and the other half is time-variant other idiosyncratic. Examples of this noise are changes to an individual's experience over time, or individual changes to salary, among others (Richard H Thaler, 2016). Having regressed solely on previous returns, we observed that our p-value for a model Chi-squared test was very high.

Additionally, the overall R-squared was very low. We therefore concluded, that this model was not sufficiently or incorrectly specified, and ran additional regressions. Regression 5.2 through 5.4 resulted in significant Chi-square results and increased overall R-squared measures. After accounting for time effects, we detected significance in the negative coefficient for previous returns. This showed, that with time effects, the additional change in responses to previous returns is attributable to each investor's personal disposition. In other words, when accounting for macro-economic effects in passive RA, investors themselves are affecting transactions, and react differently to returns. This results in different saving behaviour across individuals. Further, it confirms the intuition that other factors may also predict differences in behaviour and not only exogenous factors that are equal for all investors, such as overall market volatility or income shocks (Campbell & Yogo, 2006; D'Acunto et al., 2019). Following these results, an investor would stop providing additional capital, or even withdraw from the account. Even though the fraction of the error term attributed to time-invariant factors had decreased, this change was not sufficiently indicative for our model. Individual time-variant factors, such as changes in income for one investor, could still impact the variation in transactions.

We were specifically interested in the impact of personal traits on rational behaviour in passive RA, and thus included time-invariant variables in our next regressions. After controlling for investor preferences, and types, the coefficient for previous returns was not significant anymore. Rather, the investor stereotypes and the investment horizon explain why the clients' monthly transactions differ. In this regression, the fraction of the error term attributed to individual fixed effects was at 49%. This indicated, that less than half of the variation captured by the error term was attributed to individual fixed effects. We concluded, that changes to monthly transactions are better explained with differences in stereotypes and their different saving horizons. This confirms our results under hypothesis one. Moreover, investors' transactions are not dependent on account factors, nor portfolio factors. Stereotyping mainly explains how investors use the tool differently in terms of their transactions (Carr & Steele, 2010; Margaret et al., 1999; Steele et al., 2002). Additionally, this regression revealed the highest overall R-squared.

Accounting for stereotypes and the investment horizon, we found the best-fitted model for estimating differences in investors' transactions.The last regression, however, included the individual demographics and showed a slightly lower overall R-squared. This result could stem from the fact that the regression only included individual demographics, next to previous returns, and no other controlling variables. Returns were still insignificant. We further observed that the coefficient *rho* had decreased again to 0.416. This was lowest for all regressions under model V and indicated a reduction in the individual time-invariant effect in the error term. Here, *Female* and *Younger* showed to be significant again, whereas *Urban* and *Fl* were not (Agarwal et al., 2007; Anderson et al., 2005).

We confirm: The fact that monthly transactions differ is mainly explained by differences in gender and age. Whether individuals add or withdraw funds, is not sufficiently explained by previous market movements. We could not observe a bias for trend-chasing under this model. Yet, because Kron's investors withdraw funds, we can confirm that they deviate from intended saving behaviour. Users could decide to withdraw invested capital for different reasons. For one, they could still have limited trust in capital markets and therefore would not like to see their gains be lost. Here, they withdraw either gains or their original invested capital and keep remaining capital to be reinvested. Another explanation is that funds are too accessible in Kron's RA. Users observe a higher increase in their savings than when depositing in a bank account. They would, therefore, think that withdrawing only a fraction of their invested capital still leaves them with a higher net return on their savings. Finally, it could be that consumers simply withdraw because they need funds in a particular month. Overall, individual investors seem to use their accounts in Kron's RA as a checking account. They take out invested capital when they need it, without considering their overall saving goal.

As we observed differences in their capital adjustment behaviour regardless of returns from the previous month, we wanted to examine if returns in the current month affected transactions. To estimate model VI, we used a fixed effects estimation. For our analysis, this meant that estimators were now time demeaned, and we had a common coefficient on the regressors. The intercept varied for both individuals and investor types.

In the first regression, we had regressed transactions only on individuals' returns from the same month. We observed significance in the negative coefficient for those returns and the intercept. Investors would, therefore, adjust the amount of monthly invested capital, given a one-unit increase in returns. This adjustment could occur because investors withdraw funds, or because they do not invest as much in a particular month. They observe an increase in their portfolio value and change their monthly net invested capital. This confirms our original expectations, that investors are subject to influences of irrationality. They do not, however, act on a trend-chasing bias. This would only occur when investors observe market movements, and then invest proportionally to these, rather than the opposite (D'Acunto et al., 2019; "Money and Happiness," 2019).

Negative adjustments to invested capital though, lead to a bad outcome in generated savings and represent deviations from intended saving behaviour. A passive RAr is beneficial when funds are added over time (as established under hypothesis one). Even though the net invested monthly capital could be positive, investors should not withdraw any funds. If so, the algorithm has to rebalance the portfolio by selling securities, to provide the funds requested for withdrawal. Investors would thus miss any future opportunities from the original portfolio held. Further, the significance in the coefficient for the intercept showed that fixed effects, following individuality of investors, could also explain differences in transaction behaviour. Naturally, transactions are therefore influenced by time-invariant, unobserved investor factors, such as gender. In a fixed effects model, all time-invariant factors are already accounted for, thereby avoiding omitted variable biases.

To explain the notion of investors adjusting monthly invested capital, we included time effects in our next regression. This accounted for shocks to the real economy, such as housing prices, inflation, and employment in Norway, as well as other time-variant effects. After controlling for these, returns did no longer explain the individual investor's variation in transactions. Therefore, we concluded, that investors do not make changes to their invested capital as response to market movements. The coefficient for the intercept was still highly significant.

This suggested, that within one investor's total monthly transactions, changes are attributable to time-invariant factors, such as social identity.

Following this, to account for stereotyping in saving behaviour, we investigated stereo type effects in the next regression. In this setting, our panel was not clustered around the model portfolios, as observations were more dispersed across our grouping variable *Type*. We, therefore, did not use adjusted standard errors in the regressions with stereo type effects. The first regression including these effects indicated, that changes in returns again predicted changes to transactions of *Types*. The coefficient for returns grouped by investor type was again negative, resulting in an expected negative adjustment. The conclusion on investor behaviour remains; types of investors respond to market movement, yet not as expected. According to this model, all types of investors would withdraw, or invest less capital corresponding to an increase in returns. The intercept was significant and showed that there are nonetheless differences due to other factors influencing transactions. These could include effects of education, and income, if they did not vary for investors over the sample period. Other factors could also include effects we did not account for (Carr & Steele, 2010; D'Acunto et al., 2019; "Money and Happiness," 2019).

We applied the same logic as in regressions with individual investors and included time effects. The results were similar for investor stereotypes, as returns were not significant after including these. There is no commonality in stereotypes of investors responding to market movements in a certain way. The changes to each stereotype's invested capital must therefore have a different driver, which we believe to be effects of social identity. Additionally, we observed insignificance in the coefficient for the intercept. This showed, that not even time-invariant effects are explaining why stereotypes adjust their monthly net invested capital.

That said, we reflected on the fact that we grouped our observations in the panel and concluded that the model estimation here is not as accurate as we would like it to be. In previous regressions under model VI, we had already accounted for unobserved heterogeneity. By grouping investors into types, there might be more unobserved attributes of investor types that we did not account for, and which influenced our results. We therefore mainly used model estimation for individuals to answer our second sub-hypothesis. Generally, fixed effects are unobservable if they are not constant across the sample.

For our analysis this would mean, that the effect of returns was equal for all of Kron's investors, as well as effects of time-invariant factors. This is controversial to our expectations, as we had believed to find differences between individuals' and stereotypes' responses. Random effects models, however, assume that the size of each effect is an estimate of their *own true* effect size. The estimator represents a weighted average of within and between information. Variance in the observations is here attributable to both sampling error, and real between variance. To observe heterogeneities with respect to investors' individuality, this model was therefore more appropriate for an overall conclusion regarding responses to market movements in passive RA (Bhattacharya et al., 2012; D'Acunto et al., 2019; "Money and Happiness," 2019).

6.3.1 Interim Conclusion

When investigating responses to previous returns, we found that there is no relationship between these and monthly invested capital. Considering macro-economic trends and demographics, we identified the effect of individuality to be relevant. This is further reinforced with the indicated saving horizon. We confirm, that investors behave differently, though this is not driven by market movements (Baker & Ricciardi, 2014; Heckman et al., 2006). Whether investors withdraw or add funds is more dependent on their personal traits, stereo type, and dedication to long-term savings (Campbell & Viceira, 2002). This corroborates our conclusion under hypothesis one, while we cannot confirm $H_{2,1}$[15]. Further, volatility in current returns did not explain differences in transaction behaviour either. Therefore, we can also not confirm $H_{2,2}$[16], as returns are significant in explaining the within variation of transactions in some settings, but these effects are not overweighing other fixed effects. Individual investors do not adjust the amount of monthly invested capital to changes in their portfolio value. We further found no trend for responses to market movements in stereotypes. Overall, we cannot confirm H_2[17]. Considering all relevant effects in this model, investors did not respond to portfolio returns by adjusting their monthly net invested capital.

[15] $H_{2.1}$*: Investors who observe an increase in portfolio returns add funds and withdraw invested capital when returns went down.*
[16] $H_{2.2}$*: Investors adjust their amount of monthly net invested capital according to market movements.*
[17] H_2: *Investors respond to portfolio returns by adjusting their monthly net invested capital.*

6.4 Differences in Saving Behaviour

We continued examining the effect of personal traits and stereotypes on Kron's investors' behaviour. The studies by Agarwal et al. (2007) and Anderson et al. (2005) underline the importance of investors' demographics as key factor in explaining the complexity around investment decisions. We therefore used our previously constructed grouping variable (*Type*) as proxy for stereotyping under this hypothesis.

We tested for significant differences between individual average invested capital. If the divergence of investors' returns increases, the expected difference between their monthly invested capital is estimated at NOK 809,566.10. In other words, individuals respond differently to an increase in returns, and add or withdraw funds from their account contrarily. The investors can also simply keep their invested capital constant. We believe these differences arise due to distinct effects of personal traits in financial decision making (Apicella et al., 2008; Grasmick et al., 1996; Lerner & Keltner, 2000). We get the impression that Kron's investors are not incentivised to save in the same way. An explanation could be that individuality was not considered previously in the algorithm. We conclude that passive RA must adjust its core function, advice, to account for some investor individuality.

With a between estimation method we could only confirm that there is a difference in performance, but not direct it to specific investors' personal attributes. We then tested average transactions between types of investors under sub-hypothesis $H_{3,2}$[18]. Between older men from urban areas, and younger females from urban areas, the average transactions of men were NOK 8,053.50 higher than for the younger female counterpart. This indicated that in the same area (urban and rural), older males save significantly more than younger females. Considering our expectations that there is a difference in savings between males and females, as well as between older and younger users, we cannot estimate whether it is gender or age that mainly drives this difference. We expected to get a more causal interpretation by analysing the other significant differences in means.

[18] $H_{3,2}$: *The average monthly net invested capital differs between types of investors.*

The difference between younger and older males from urban areas is estimated at NOK -7,075.65, indicating that the average for younger males is lower by this amount. This is in line with our expectations. We assumed older users to save more, due to different influential factors; users above a certain age have possibly higher incomes than younger users and find themselves in more need for savings due to family planning and advancing retirement (Masicampo & Baumeister, 2008; Vohs, 2006). This indicates that it is mainly the age difference that drives different saving behaviour (Agarwal et al., 2007; Foerster et al., 2017). Nonetheless, we needed to consider that ANOVA's validity is dependent on multiple assumptions. With our data, and specifically our observations on transactions, we cannot confirm with high certainty: i) that observations are independent from one another, as we might find a relationship between observations of transactions in each type and ii) that transactions are approximately normally distributed across types.

We therefore analysed the output of the parametric delta-method. With a mixed model we obtained the residuals from regressing transactions on returns and grouped these residuals by type. The delta method helped to approximate the marginal difference in these residuals. We could thereby analyse whether different investor types have significantly different fixed effect error term components. We adjusted our significance level with a Bonferroni correction. From this test we observed that there are more significant differences between investor types, than the one-way ANOVA indicated. We detected significance between the following investor types: *MYU* and *MOU, MOU* and *FYU, MYU* and *FOU, MOR* and *FYU, MYU* and *MOR, FYU* and *FOU* (recall, each type's initials stand for the demographics in the combination, see Table 2). The first two significant differences confirmed the results from the ANOVA. We had previously established that mainly age directs this deviation. Under parametric analysis however, we could analyse additional components.

The difference between *MYU* and *FOU* showed, that age is not the only relevant and rational factor to account for. According to our findings, also gender affects saving behaviour. Here, we had estimated the effect of younger males' net invested capital to be NOK 3,255.79 higher than older females.

This can be explained with societal insight. Literature suggests, that there is a stigma around women underperforming in financial decision making (Carr & Steele, 2010; Steele, 1997). Investors from different origins (urban or rural) also showed individual effects regarding their transactions. *MOR's* results are higher compared to both *FYU*, and *MYU*. This showed that the investor's residence can be of relevance for explaining dissimilarities in behaviour. One reason for this could be that more awareness for savings is created in greater urban surroundings, due to effects of advertising, higher costs, and others. Another reason could be that older generations simply prefer living in rural areas. In turn, the main drivers of differences would still be gender and age (Agarwal et al., 2007; Anderson et al., 2005; Stafford, 1996). We recall, that on a bar-chart of average monthly transactions across stereotypes, older males from rural areas invested by far the most capital per month. The age difference holds for both genders. *FYU* and *FOU* behaved very differently, as did *MYU* and *MOR*.

We identified that women have on average fewer net transactions per month compared to men. There are two potential reasons for this: i) they do not add as much additional funds, or ii) because they withdrew more funds from their accounts (Atkinson et al., 2003). We also found that within the types of women, generally older women transacted more money than younger women, for both rural and urban female groups. These results confirm another aspect of our expectations: older individuals save more, as they might have higher disposable incomes. Nonetheless, this is not coherent with our expectation that the older generation would use the tool less, and therefore also save less (Brounen et al., 2016; Carlin et al., 2017). They might use the tool less as a technology, yet invest higher net capital, and save more rationally. Users of older generation have higher net transactions, indicating at least that they add more funds over time, instead of withdrawing invested capital from their portfolio (Brounen et al., 2016; Carlin et al., 2017; Frost, 2020). We therefore support Hansman's and Schutjens' (1993) proposed "rational assumption", that age is a strong predictor of an individual change in behaviour (Stafford, 1996). We extend this to the saving behaviour of individuals.

6.4.1 Interim Conclusion

We found evidence that individuals respond differently to an increase in returns by either keeping funds constant, adding or withdrawing funds. We confirm our sub-hypothesis $H_{3,1}$[19], that individual investors adjust their monthly net invested capital differently. Returns, however, do not accurately determine when and if investors make adjustments to their average monthly invested capital (Campbell, 2006; Campbell & Viceira, 2002). We observed this from models V and VI (see Table 10 and Table 11). Examining investor stereotypes was more conclusive than the between estimation of individuals. Age and gender continue to be the main drivers of gaps in demographic groups (Stafford, 1996). The fact that the investor belonged to the older generation seems to be the main driver for differences between investor types. Older men transacted by far more than both younger females and males and younger females transacted less than older females. The age gap holds for investors from both urban and rural areas. We confirm $H_{3,2}$[20], because we found six substantial differences between different investor stereotypes (Carr & Steele, 2010). Overall, we conclude that investors' dedication to saving is dependent on effects of social identity, where personal traits caused by gender and age have the strongest effect [21] (Agarwal et al., 2017; Steele, 1997; Steele et al., 2002).

6.5 Differences in Saving Patterns over Time

Analysis under hypothesis three showed, that within variation is not the most important information for answering our research question. Rather, we wanted to observe differences in investor behaviour. Random effects revealed a combination of within and between information. Under our last hypothesis, however, we were solely interested in differences *between* investors, and how they change over time (see Table 15: Regression Output Model VIII). We analysed the between variation in individual transactions with respect to returns and a time trend. Although returns were found to be irrelevant for explaining why and when investors adjust their invested capital, we still tested them as our independent variable. As we believed, in between estimation they would still reveal differences in saving patterns.

[19] $H_{3.1}$: *Individual investors adjust their monthly net invested capital differently.*
[20] $H_{3.2}$: *The average monthly net invested capital differs between types of investors.*
[21] H_3: *Investors' dedication to saving is dependent on the effects of personal traits and stereotypes.*

If the gap between individual investors' returns increases, the difference between their monthly saving pattern will expand by NOK 649,465.600, on average. The time trend (*t*) was significant and estimated at 598.495. This means, that the difference between investors saving patterns increases over time. This effect is small compared to other coefficient estimates. If we observe investors one month longer, while returns are constant between investors, we will only find a small difference of NOK 598.495 between them, on average. Conversely, if returns are increasingly different over time between individuals, the gap in their saving behaviour will be higher every month.

Moreover, the second regression included only a time trend. The results showed now, that the time trend was higher, at NOK 1,263.666. This implies that the difference between individual saving patterns is larger if we observe one investor in a later month, compared to another investor. Therefore, we conclude, that holding the account longer will increase the average monthly net invested capital by investors, and thus the difference between them. This could mean that individuals observe the benefit of adding funds to their accounts over time, as suggested under hypothesis one. They, therefore, invest supplementary funds later. Still, we could not conclude whether the investor really *adds* funds, or whether the individual simply does not withdraw as much as in previous months. The notion that clients do not withdraw as much or keep monthly net capital constant is not as beneficial as adding invested capital. Nevertheless, this still means improved performance. To second our results, we additionally investigated the between variation of transactions grouped by type. In the first regression, we found that no coefficients were significant. As stated previously though, we found later that returns do not distinguish type-specific investor behaviour. We, therefore, excluded returns in the last regression and regressed transactions of stereotypes only on a time trend. Our analysis then showed a significant negative coefficient for the trend variable. This tells us that when disregarding any other factors, the between variation in transactions among investor types decreases over time. In other words, if one stereotype holds accounts for longer, the difference to other stereotypes will be NOK 1,694.314 less every month. We explain this result with the fact that grouped as types, other differences due to individuality were averaged out, and the average effect of stereotyping was diminished over time.

6.5.1 Interim Conclusion

When observing individuals, the gap between their saving patterns was increased over time. This indicated that the difference between individual adjustments was higher, the longer investors use the tool. From this we could not confirm our hypothesis[22]. When investigating differences between stereotypes however, we found that the difference between their average transactions was lower when observed over time. We close by saying that differences between individual saving patterns were not diminished. This could have many explanations, but foremost we believe this to be effects that were not included in our measures for idiosyncratic factors. One example are influences due to individual shocks, such as individual changes to employment and other individual exogenous factors. Nonetheless, previously established dissimilarities of stereotype saving behaviour were diminished. We can confirm hypothesis four, that marginal differences in saving patterns attributed to social identity were reduced. This indicates a general benefit of robo-advising, that effects of investors' dispositions, that originally might have limited in benefitting from robo-advising, were reduced over time. This is a strong indications for benefits of investing through robo-advising (Bhattacharya et al., 2012; D'Acunto et al., 2019; "Money and Happiness," 2019).

[22] H_4: *Over time, marginal differences between investors' saving patterns are reduced.*

7.0 Conclusion

We partly confirm our research question and conclude that passive robo-advising does deliver benefits from capital markets to more individuals, by reducing personal traits. These traits were not fully eliminated in the investors' behaviour within Kron's RAr. Further, to increase these benefits, passive robo-advisory (RA) has to be extended from pure investment advice to counsel on adjusting invested capital. In our research, we saw that robo-advisory and behavioural finance are naturally linked in the growing FinTech industry. Innovations of financial services ease consumers' decision-making and reduce knowledge and wealth requirement thresholds. After the 2008 financial crisis, consumers appreciated higher levels of transparency, reduced costs, and more understandable and accessible financial services. Additionally, faster contact with clients through push notifications enhances the value (Jung et al., 2019). Market movements are brought to the investor's attention faster and adjustments can be implemented instantly online (D'Acunto et al., 2019). Generally, the main reasons for picking robo-advisors (RAr(s)) are convenience, and not being schemed with products customers think they do not need ("Money and Happiness," 2019). Moreover, the benefits of using RA go further than advantages of product delivery, lower costs, and execution. D'Acunto et al. (2019) found a reducing effect of RA on behavioural biases.

Contrarily, we found that within Kron's RAr, investors hardly show signs of a prominent behavioural bias, trend-chasing. We used the transactions of Kron's clients to estimate adjustments to invested capital. These showed deviations from intended saving behaviour. Neither time-weighted previous nor current market movements explain these transactions. Conversely, effects of personal traits on adjustments to invested capital were greater. We add, that these effects are subject to additional factors, such as macro-economic shocks, and personal changes to the individual trade-off between consumption and saving. Investors add, but also withdraw funds which could be partly explained by effects of social identity. Further, these effects turned out to be stronger for some types of investors, than for others. Younger generations from rural and urban areas made more adjustments to their invested capital, and their monthly transactions were considerably lower than transactions executed by older users.

This could be based on purely economic explanations, where younger people simply have less capital disposable. However, another explanation could be that older generations take future financial stability more seriously (Campbell, 2006). If this were the case, younger generations should be constrained from withdrawing their invested capital from RArs. The same holds for men and women, where women transacted by far fewer funds than men and seemed to make more adjustments to their invested capital. In literature, the main reason for explaining this phenomenon is based on a social stigma around women's poorer ability concerning quantitative thinking, and financial decision-making (Carr & Steele, 2010; Steven J. Spencer et al., 1999). In our opinion, passive robo-advisory does not sufficiently provide individual investors with the appropriate advice to yield maximum benefits from capital markets.

To connect all elements of our research, we can confirm H_1, H_3, and H_4, while we fail to confirm H_2. Our results showed that investors behave differently when adjusting their invested capital. This is not driven by market movements, but rather individual factors, which include personality and stereotyping. The fact that investors withdraw or add funds is to an extent dependent on their personal traits, stereotype, and dedication to long-term savings. Although we were able to confirm H_3 by our methodology, our results are not conclusive enough to tell us the magnitude of the effect. We would assume it is dependent on various other exogenous factors. What we though can confirm is H_4, that over time the differences between the investor types' saving patterns are reduced. Overall, this helps us to support our research question that Kron's RA does incentivise similar saving patterns. We explain this with the fact that clients must observe the benefit of using Kron's tool before their saving behaviours starts to align. This effect did not occur when looking into individuals, rather than stereotypes. Various other effects influence individuals in their savings, which are *not* reduced by using the tool over time. Kron's RA is beneficial for its client base. Although, the magnitude of the benefit is dependent on the individual investor keeping the account for the set investment period. We did not find evidence of a difference between investing a lump sum of invested capital and monthly invested capital within the same time frame (see Figure 3: The Interaction between Investors and Kron's Algorithm). Naturally, economics would assume a benefit from cost-averaging.

The notion that investors experience this effect is not supported by Kron's data. The analysis, however, showed two factors that substantially influence saving performance. First, investing additional capital at later points in time leads to a marginal increase in savings, no matter the frequency. Secondly, long-term savers perform relatively better. This also implies that withdrawing invested capital leads to a marginal decrease in generated savings. It seems as Kron's investors withdraw money randomly. The question is why people would use RA if they do not commit to future financial stability long-term. There can be many reasons for this, such as the easy accessibility, changes to investors' personal situations, or simply placing funds in a traditional bank account due to lack of trust in capital markets. Another explanation for the occurrence of withdrawals within Kron's RAr is the innate nature of each country's market and its participants. Norway is a very costly country to live in, and the social structure lets more people benefit from stable national pension planning. Norwegian users of Kron might have a bigger utility by trading off their long-term savings for acute consumption. However, fully identifying why users withdraw is outside the scope of this paper.

Kron's RAr reduces personal traits, though it still has problems accounting for clients' deviations from intended saving behaviour regarding holding invested capital. Bhattacharya et al. (2012) conclude, that RA is a necessary condition to increase access to capital markets for more individuals, yet it is not sufficient to distribute benefits from capital markets to more retail investors. Even though these authors analysed diversification, which we did not, this conclusion poses a parallel to ours. Passive RA by the advice on portfolio construction is a necessary condition for benefits from digitalised and automated financial advice. However, to really generate value for the customer from a long-term perspective, a passive RAr should consider, that individuals behave extremely differently in personal savings. It would be profitable for both Kron and its clients to provide an extension of the algorithm. This extension will then have to limit the client's accessibility to withdraw funds and thereby results in a more successful investment over a set period. Considering that users of RA invest in capital markets, and do not deposit in banks, restricting the withdrawal of their own money is not an option. The client still bears the main risk, and returns cannot be guaranteed. Yet it is a difficult discipline for many individuals to leave the capital invested long-term.

A possible solution could be incorporating the user's individuality in the customer assessment and analysing previous account activity within the tool. If users would be able to announce that they are planning on withdrawing, the algorithm could analyse the scenario if the withdrawal is made. This could show the investor a scenario analysis if he/she withdraws funds, and outline downsides. By this, less financially literate could be made more aware of the implications of negatively adjusting their invested capital. To make passive RA more valuable for personal savings, the algorithm should recommend when it is most sensible for investors to withdraw, as well as notify when it is best to add invested capital. When investors indicate a specific saving horizon and put in a request for withdrawal before the end of the investment period, the algorithm should account for this, and extend its advice. One downside of this solution is, that the advice from passive robo-advising will go further than risk assessment and portfolio management, and therefore potentially be more costly for individuals. Overall, we support Campbell's (2006) research on the importance of stricter consumer regulations, to avoid financial mistakes. There are surely many legal aspects to consider, yet we would propose extending the core function of passive RA – advice – to assist individuals in using the benefits they would get if they were advised better on leaving the capital in the tool.

7.1 Model Improvement

Our models were constructed solely to investigate the relationship between Kron's passive RA and the clients' saving patterns within the tool. The models will, therefore, require some improvements for use in further research, subject to extended data. The cross-sectional models may appear to contain redundant elements of estimation, such as the intuitive relationship between invested capital and AUM. These are elements that further research can take as given and investigate the rate of return to investors from using robo-advisory, and whether they differ when invested capital is constant. Concerning panel estimation methods, we consider that other models could deliver better insight to the heterogeneities in question. A GMM model or difference-in-differences strategies could reveal other effects and possibly be estimated more precisely.

7.2 Future Research

We identified three specific fields for future research, based on literature and our research within Kron's passive RA. The first is comparing the results from this paper to another passive RAr, as well as passive robo-advising in other countries. This would show whether our identified measures are reliable and replicable for research in passive RA. Additionally, this could reveal whether comparable methodologies reach similar or opposite conclusions. Studying these effects in other countries could show the impact of different consumption and investment cultures. Our study can also be compared to papers focusing on active RA, as we took parallels from the authors D'Acunto et al. (2019). Though passive and active RA are contractually different in the interaction with investors, they both have to consider the investors' individuality and irrationality. In passive RA this is directed almost exclusively on invested capital, whereas active RA research will be able to extend this onto portfolio theory and relative effects on capital market dynamics.

Secondly, we investigated the effect of RA on savings in capital markets considering baseline demographics by segmentation. The conclusion shows the overall effect of personal traits and stereotyping. Future research in behavioural economics, however, could be dedicated to finding which less measurable factors such as behavioural and psychographic traits complement this segmentation. This could lead to better marketing insight for RArs generally. To add to this, new studies could further test if limited accessibility to withdraw funds instantly, has a practical effect on individual saving performance. This could be extended on to research within household finance. Finally, comparing our findings to secondary data, either for this same sample, or a new sample, will reveal more information on the entire topic of savings. Examples of secondary data include simultaneous observations on users' bank accounts, marital status, health insurance, and overall household debt status. Further, the same analysis would be interesting to observe during the 2020 Corona crisis. We want to encourage research that expands the question of benefits from capital markets in passive RA to the financial system. Important industry players, non-profit organizations, and academics all see the benefits FinTech innovation has on universal financial inclusion. A society shift becomes more evident through the rising of automated FinTech. Can financial technology generate societal value? We leave it in the hands of future research to answer this question.

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Appendices

Appendix A: Descriptive Statistics

Appendix A1: Observations for Demographics & Investor Indications

Table A1: Demographics & Investor Indications

Factors for Robo-Advisor

DEMOGRAPHICS

	Freq,	Percent
Male	2,791	70.410
Female	1,173	29.590
Older	1,781	44.930
Younger	2,183	55.070
Rural	819	21.320
Urban	3,022	78.680
Not fl (Financial literacy)	928	41.520
fl (Financial literacy)	1,307	58.480

	Freq,	Percent	Cum.
Type			
FOR	155	4.040	4.040
FOU	407	10.600	14.630
FYR	108	2.810	17.440
FYU	466	12.130	29.580
MOR	248	6.460	36.030
MOU	923	24.030	60.060
MYR	308	8.020	68.080
MYU	1,226	31.920	100.000

PORTFOLIO

	Freq.	Percent	Cum.
Active choice			
No	1,215	30.650	30.650
Yes	2,749	69.350	100.000
Time horizon			
Short-term	298	7.520	7.520
Mid-term	1,133	28.580	36.100
Long-term	2,533	63.900	100.000
Preference			
Equality	48	1.210	1.210
Index	1,519	38.320	39.530
Kron's Chosen	1,215	30.650	70.180
Oil fund	178	4.490	74.670
Real Estate	73	1.840	76.510
Sustainability	394	9.940	86.450
Tech	537	13.550	100.000
Risk level			
1	171	4.310	4.310
2	127	3.200	7.520
3	317	8.000	15.510
4	816	20.590	36.100
5	640	16.150	52.250
6	1,767	44.580	96.820
7	126	3.180	100.000

This table presents the tabulated frequencies and percentages of the dichotomous variables *Female, Younger, Urban,* and *Fl.* It further shows the tabulated frequencies, percentages, and cumulative percentages of the categorical variables *Type, Choice, Horiz, Pref,* and *Risk.*

Appendix A2: Factors per Demographic

Table A2.1: Account Factors per Demographic

Account Factors per Demographic

Variable	PANEL A: FEMALE					PANEL B: MALE				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Log_Web	1,173.000	1.174	4.596	-	61.000	2,790.000	1.885	5.990	-	145.000
Log_Mob	1,173.000	32.950	71.291	-	1,850.000	2,790.000	35.978	66.577	-	1,933.000
Accd	1,173.000	214.504	209.617	1.000	925.000	2,790.000	248.378	223.075	1.000	1,004.000
Act	1,173.000	1.984	0.145	-	2.000	2,790.000	1.985	0.137	-	2.000
Variable	PANEL C: YOUNGER GENERATION					PANEL D: OLDER GENERATION				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Log_Web	2,183.000	1.455	4.944	-	91.000	1,780.000	1.944	6.349	-	145.000
Log_Mob	2,183.000	36.936	65.500	-	1,850.000	1,780.000	32.808	70.923	-	1,933.000
Accd	2,183.000	211.446	190.836	1.000	942.000	1,780.000	271.336	246.662	2.000	1,004.000
Act	2,183.000	1.982	0.153	-	2.000	1,780.000	1.988	0.120	-	2.000
Variable	PANEL E: URBAN RESIDENCE					PANEL F: RURAL RESIDENCE				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Log_Web	3,022.000	1.544	4.950	-	91.000	819.000	2.020	7.340	-	145.000
Log_Mob	3,022.000	35.730	72.114	-	1,933.000	819.000	33.520	53.773	-	713.000
Accd	3,022.000	243.589	223.124	1.000	1,004.000	819.000	215.121	203.880	2.000	931.000
Act	3,022.000	1.987	0.117	-	2.000	819.000	1.976	0.202	-	2.000

This table presents the summary statistics number of observations, mean, standard deviation, min and max of the account factor variables *Log_Web, Log_Mob, Accd,* and *Act,* by demographic groups. Panel A contains the summary statistics for each variable observed in the demographic group ‘Female’. Panel B contains the summary statistics for each variable observed in the demographic group ‘Male’. Panel C contains the summary statistics for each variable observed in the demographic group Younger generation’. Panel D contains the summary statistics for each variable observed in the demographic group ‘Older generation’. Panel E contains the summary statistics for each variable observed in the demographic group ‘Urban residence’. Panel F contains the summary statistics for each variable observed in the demographic group ‘Rural residence’.

Table A2.2: Portfolio Factors per Demographic

Portfolio Factors per Demographic

Variable	PANEL A: FEMALE					PANEL B: MALE				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Choice	1,173.000	0.645	0.479	-	1.000	2,791.000	0.714	0.452	-	1.000
Horiz	1,173.000	2.506	0.639	1.000	3.000	2,791.000	2.588	0.624	1.000	3.000
Pref	1,173.000	3.456	1.765	1.000	7.000	2,791.000	3.539	1.856	1.000	7.000
Risk	1,173.000	4.739	1.433	1.000	7.000	2,791.000	4.932	1.433	1.000	7.000
Variable	PANEL C: YOUNGER GENERATION					PANEL D: OLDER GENERATION				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Choice	2,183.000	0.694	0.461	-	1.000	1,780.000	0.693	0.461	-	1.000
Horiz	2,183.000	2.513	0.662	1.000	3.000	1,780.000	2.626	0.581	1.000	3.000
Pref	2,183.000	3.607	1.870	1.000	7.000	1,780.000	3.400	1.773	1.000	7.000
Risk	2,183.000	4.753	1.523	1.000	7.000	1,780.000	5.024	1.306	1.000	7.000
Variable	PANEL E: URBAN RESIDENCE					PANEL F: RURAL RESIDENCE				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Choice	3,022.000	0.693	0.461	-	1.000	819.000	0.691	0.462	-	1.000
Horiz	3,022.000	2.568	0.628	1.000	3.000	819.000	2.552	0.640	1.000	3.000
Pref	3,022.000	3.561	1.850	1.000	7.000	819.000	3.368	1.756	1.000	7.000
Risk	3,022.000	4.891	1.438	1.000	7.000	819.000	4.818	1.437	1.000	7.000

This table presents the summary statistics number of observations, mean, standard deviation, min and max of the portfolio factor variables *Choice, Horiz, Pref,* and *Risk,* by demographic groups. Panel A contains the summary statistics for each variable observed in the demographic group ‘Female’. Panel B contains the summary statistics for each variable observed in the demographic group ‘Male’. Panel C contains the summary statistics for each variable observed in the demographic group Younger generation’. Panel D contains the summary statistics for each variable observed in the demographic group ‘Older generation’. Panel E contains the summary statistics for each variable observed in the demographic group ‘Urban residence’. Panel F contains the summary statistics for each variable observed in the demographic group ‘Rural residence’.

Appendix A3: Financial Literacy

Table A3: Accounts Indicating Financial Literacy

Accounts indicating Financial Literacy

Variable	PANEL A: FINANCIAL LITERACY					PANEL B: NO FINANCIAL LITERACY				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Log_Web	1,307.000	2.310	5.793	-	84.000	928.000	2.642	7.037	-	91.000
Log_Mob	1,307.000	24.661	41.676	-	713.000	928.000	31.555	52.887	-	862.000
Accd	1,307.000	318.718	218.767	1.000	906.000	928.000	261.306	185.392	1.000	906.000
Act	1,307.000	1.986	0.123	-	2.000	928.000	1.980	0.163	-	2.000
Sum19	849.000	97,853.180	243,028.800	- 77,678.000	2,859,747.000	500.000	73,579.510	235,326.700	- 14,890.000	2,800,000.000
Sum20	1,302.000	99,264.880	247,711.500	-129,500.000	3,500,000.000	927.000	74,775.330	216,984.100	- 76,676.000	2,820,000.000
Aum19	879.000	111,074.400	272,723.700	-	3,036,009.000	519.000	72,835.970	210,769.700	-	2,020,554.000
Aum20	1,307.000	124,151.600	302,784.700	-	3,730,607.000	928.000	84,266.560	228,541.400	-	2,927,372.000

This table presents the summary statistics number of observations, mean, standard deviation, min and max of the variables *Log_Web, Log_Mob, Accd, Act, Sum19, Sum20, Aum19,* and *Aum20* by indication of financial literacy. Panel A contains the summary statistics for each variable observed in accounts that had indicated previous investing experience. Panel B contains the summary statistics for each variable observed in accounts that had indicated no investing experience.

Appendix A4: Correlation

Table A4: Pearson Correlation Matrix for all Variables

Pearson Correlation Matrix: All Variables

	Female	Younger	Urban	Type	Fl	Choice	Pref	Risk	Mpf	Horiz	Start	End	Act	Accd	Log_Web	Log_Mob	Sum19	Sum20	Aum19	Aum20	Ret	Retlag	Flowscat	Trans	Inv_Incr
Female	1.000																								
Younger	0.029	1.000																							
Urban	0.127	-0.120	1.000																						
Type	-0.780	0.555	0.065	1.000																					
Fl	-0.142**	-0.170*	-0.049	0.002	1.000																				
Choice	-0.137	-0.097	-0.058	0.041	0.085	1.000																			
Pref	0.065	-0.008	-0.121	-0.088	0.103	0.158	1.000																		
Risk	-0.066	0.106	-0.004	0.119	0.144	-0.054	0.229	1.000																	
Mpf	0.001*	-0.033**	-0.127**	-0.052**	0.129*	0.482*	0.936*	0.272*	1.000																
Horiz	-0.075	0.112	0.025	0.136	0.138	-0.056	0.165	0.950*	0.211	1.000															
Start	-0.329	-0.149	-0.063	0.167	0.046	0.160	0.090	-0.060	0.128	-0.063	1.000														
End	0.238	0.045	0.031	-0.163	-0.011	-0.126	-0.034	-0.010	-0.074	-0.024	-0.717	1.000													
Act	0.009	0.023	0.003	0.007	-0.011	-0.002	-0.005	-0.022	-0.007	-0.016	-0.054	0.066	1.000												
Accd	0.329	0.149	0.063	-0.167	-0.046	-0.160	-0.090	0.060	-0.128	0.063	-1.000	0.717	0.054	1.000											
Log_Web	0.117	0.023	-0.104	-0.108	-0.142	-0.106	-0.073	-0.005	-0.101	-0.033	-0.196	0.209	0.018	0.196	1.000										
Log_Mob	0.044	-0.188	0.116	-0.122	-0.138	-0.202	-0.057	-0.025	-0.123	-0.017	-0.292	0.239	0.012	0.292	0.289	1.000									
Sum19	-0.085	-0.153	0.001	-0.023	0.064	0.028	-0.009	0.067	0.008	0.083	-0.234	0.138	0.043	0.234	0.286	0.285	1.000								
Sum20	0.007	-0.169	0.163	-0.069	0.011	0.0003*	-0.040	-0.077	-0.042	-0.006	-0.156	0.099	0.009	0.156	-0.123	0.391	0.373	1.000							
Aum19	-0.096	-0.133	-0.042	-0.012	0.069	0.061	-0.009	0.097	0.023	0.106	-0.213	0.114	0.042	0.213	0.290*	0.281*	0.972*	0.311	1.000						
Aum20	-0.052	-0.078	0.026	0.002	0.025	0.117	-0.088	-0.297	-0.062	-0.256	-0.220	0.217	0.022	0.220	0.057	0.160	0.084	-0.024**	0.079	1.000					
Ret	0.037*	0.052*	0.019*	0.006*	0.019*	-0.071	0.010	0.093	-0.007**	0.095	-0.085	0.051	-0.026	0.085	0.018	0.021	0.006	0.043	-0.001**	-0.021	1.000				
Retlag	0.010	0.034	0.004	0.013	-0.012	-0.055	0.017	0.084	0.004	0.079	-0.069	0.040	-0.049	0.069	0.019	0.019	0.019	0.048	0.010	-0.016	-0.209	1.000			
Flowscat	-0.018	-0.020	0.049	0.015	0.001	-0.001	0.143	0.056	0.127	0.032	0.020	0.022	-0.025	-0.020	-0.011	-0.198	-0.084	-0.090	-0.097	-0.029	0.039	0.036	1.000		
Trans	0.033*	0.022*	0.036*	-0.005**	0.009*	-0.010	-0.036	0.015	-0.034	0.020	-0.037	0.023	-0.015	0.037	-0.010	-0.026	-0.096	0.031	-0.089	-0.037	-0.005	-0.057	-0.007	1.000	
Inv_Incr	0.031	0.021	0.019	-0.009	0.008	-0.132	-0.031	-0.023	-0.076	-0.022	-0.045	0.039	-0.057	0.045	0.028	0.038	-0.009	0.034	-0.024	-0.003	-0.121	0.594	0.014	-0.018	1.000

This table presents the Pearson correlation matrix for all dependent and independent variables in the study. Relevant positive and negative coefficients are marked with *, and **, respectively

Appendix A5: Panel Summary Statistics

Table A5: Summary Statistics of Panel Data

Panel Summary Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
t	Overall	704.500	9.233	689.000	720.000	N = 126,848
	Between		-	704.500	704.500	n = 3,964
	Within		9.233	689.000	720.000	T = 32
ID	Overall	1,982.500	1,144.313	1.000	3,964.000	N = 126,848
	Between		1,144.453	1.000	3,964.000	n = 3,964
	Within		-	1,982.500	1,982.500	T = 32
Female	Overall	0.296	0.456	-	1.000	N = 126,848
	Between		0.457	-	1.000	n = 3,964
	Within		-	0.296	0.296	T = 32
Younger	Overall	0.551	0.497	-	1.000	N = 126,848
	Between		0.497	-	1.000	n = 3,964
	Within		-	0.551	0.551	T = 32
Urban	Overall	0.787	0.410	-	1.000	N = 122,912
	Between		0.410	-	1.000	n = 3,841
	Within		-	0.787	0.787	T = 32
Type	Overall	5.701	2.185	1.000	8.000	N = 122,912
	Between		2.185	1.000	8.000	n = 3,841
	Within		-	5.701	5.701	T = 32
Fl	Overall	0.585	0.493	-	1.000	N = 71,520
	Between		0.493	-	1.000	n = 2,235
	Within		-	0.585	0.585	T = 32
Choice	Overall	0.693	0.461	-	1.000	N = 126,848
	Between		0.461	-	1.000	n = 3,964
	Within		-	0.693	0.693	T = 32
Pref	Overall	3.514	1.830	1.000	7.000	N = 126,848
	Between		1.830	1.000	7.000	n = 3,964
	Within		-	3.514	3.514	T = 32
Risk	Overall	4.875	1.436	1.000	7.000	N = 126,848
	Between		1.436	1.000	7.000	n = 3,964
	Within		-	4.875	4.875	T = 32
Mpf	Overall	18.356	15.306	1.000	49.000	N = 126,816
	Between		15.308	1.000	49.000	n = 3,963
	Within		-	18.356	18.356	T = 32
Horiz	Overall	2.564	0.630	1.000	3.000	N = 126,848
	Between		0.630	1.000	3.000	n = 3,964
	Within		-	2.564	2.564	T = 32
Start	Overall	21,719.600	219.680	20,954.000	21,957.000	N = 126,816
	Between		219.707	20,954.000	21,957.000	n = 3,963
	Within		-	21,719.600	21,719.600	T = 32
End	Overall	21,808.430	114.433	21,124.000	21,958.000	N = 11,840
	Between		114.582	21,124.000	21,958.000	n = 370
	Within		0.480	21,792.930	21,823.930	T = 32
Transtot	Overall	8,188,437.000	6,047,578.000	-5,365,572.000	26,900,000.000	N = 126,848
	Between		189,315.100	7,602,599.000	8,612,368.000	n = 3,964
	Within		6,044,615.000	-5,621,360.000	27,300,000.000	T = 32
Ret	Overall	0.013	0.021	- 0.058	0.053	N = 29,725
	Between		0.007	- 0.041	0.041	n = 3,744
	Within		0.020	- 0.059	0.057	bar = 8
Retlag	Overall	0.013	0.021	- 0.058	0.053	N = 29,724
	Between		0.007	- 0.041	0.041	n = 3,828
	Within		0.020	- 0.059	0.056	bar = 8
Flowscat	Overall	0.162	0.379	- 1.000	1.000	N = 126,848
	Between		0.219	- 0.375	0.969	n = 3,964
	Within		0.309	- 1.744	1.537	T = 32
Trans	Overall	8,396.142	97,385.750	-8,850,000.000	6,600,000.000	N = 30,352
	Between		60,878.550	- 25,558.630	2,900,000.000	n = 3,754
	Within		92,964.190	-8,849,289.000	6,600,711.000	bar = 8
Inv_Incr	Overall	0.061	0.239	-	1.000	N = 126,848
	Between		0.072	-	0.375	n = 3,964
	Within		0.227	- 0.314	1.029	T = 32
Trans2	Overall	2,009.016	47,771.210	-8,850,000.000	6,600,000.000	N = 126,848
	Between		6,962.572	- 4,046.875	237,211.600	n = 3,964
	Within		47,261.220	-8,850,393.000	6,599,607.000	T = 32

The table presents the summary statistics of all variables in the panel data setting. It includes the overall mean, number of all observations over time (N), number of cross-sectional observations (n), and average observed time period (T/bar). Further, it shows the overall, between, and within standard deviation, and the overall, between, and within minimum and maximum, for each variable.

Appendix B: Regressions – Cross-Sectional Models

Appendix B1: Model I

Table B1: Complete Regression Output Model I

Regression 1.1 - Aum19						
Number of obs.	*1,555.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Accd	- 74.648	27.202	- 2.740	0.006	- 128.005	- 21.290
Log_web	- 1,638.020	1,095.766	- 1.490	0.135	- 3,787.363	511.323
Log_mob	- 176.527	172.086	- 1.030	0.305	- 514.073	161.020
Act	5,267.625	52,252.940	0.100	0.920	- 97,226.440	107,761.700
Pref	5,685.114	3,123.384	1.820	0.069	- 441.400	11,811.630
Horiz	28,595.080	10,094.550	2.830	0.005	8,794.639	48,395.520
Sum19	1.532	0.019	81.320	-	1.495	1.569
Constant	-102,129.700	108,351.600	- 0.940	0.346	-314,661.300	110,401.800
R-squared	0.815					
F(7, 1547)	26.200					
Prob > F	-					
Root MSE	230,000.000					

Regression 1.2 - Aum20						
Number of obs.	*3,954.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Accd	- 41.652	64.100	-0.650	0.516	- 167.325	84.020
Log_web	- 1,140.930	1,197.726	-0.950	0.341	- 3,489.150	1,207.290
Log_mob	- 30.333	34.383	-0.880	0.378	- 97.743	37.076
Act	4,026.728	8,819.006	0.460	0.648	- 13,263.510	21,316.970
Pref	4,280.074	3,690.006	1.160	0.246	- 2,954.424	11,514.570
Horiz	13,116.590	6,267.613	2.090	0.036	828.524	25,404.650
Sum20	1.605	0.359	4.480	-	0.902	2.308
Constant	- 68,384.030	40,452.030	-1.690	0.091	-147,692.900	10,924.830
R-squared	0.794					
F(7, 3946)	91.720					
Prob > F	-					
Root MSE	190,000.000					

This table presents the entire outputs for regressions 1.1 and 1.2 under model II, with dependent variables *Aum19* and *Aum20,* respectively. The corresponding regression number, and dependent variable are listed in the first row. Both outputs contain the number of observations (row 2), and the independent variables, listed in column 1, used in each regression. The second column contains the coefficient estimates for all variables and the intercept, the third column contains the corresponding robust standard errors, and the resulting t test statistics are presented in the fourth column. The last three columns show the p-value and 95% confidence interval for rejection rule of the respective coefficient. The last rows contain the R-squared measure, the F test statistic for the regression, the corresponding p-value for joint coefficient testing, as well as the root mean squared error for the model, for both regressions.

Appendix B2: Model II

Table B2: Complete Regression Output Model II

Regression 2.1 - Change in AUM (AumDelta)						
Number of obs.	*1,555.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Accd	48.871	9.983	4.900	-	29.289	68.453
Log_web	734.280	309.168	2.380	0.018	127.848	1,340.711
Log_mob	58.125	51.248	1.130	0.257	- 42.399	158.649
Act	662.109	6,968.111	0.100	0.924	-13,005.830	14,330.050
Pref	589.756	1,761.759	0.330	0.738	- 2,865.932	4,045.443
Horiz	2,896.404	1,971.753	1.470	0.142	- 971.188	6,763.995
SumDelta	1.034	0.029	36.160	-	0.978	1.090
Constant	-16,682.720	20,903.170	- 0.800	0.425	-57,684.250	24,318.820
R-squared	0.595					
F(7, 1547)	232.200					
Prob > F	-					
Root MSE	90,089.000					

Regression 2.2 - Change in Sum (SumDelta)						
Number of obs.	*1,555.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Accd	- 20.748	11.710	-1.770	0.077	- 43.717	2.222
Log_web	- 203.365	339.971	-0.600	0.550	- 870.219	463.488
Log_mob	27.358	50.548	0.540	0.588	- 71.793	126.508
Act	1,996.863	4,077.688	0.490	0.624	- 6,001.516	9,995.242
Pref	- 992.318	1,286.226	-0.770	0.441	- 3,515.249	1,530.613
Horiz	- 3,382.888	3,368.342	-1.000	0.315	- 9,989.885	3,224.110
AumDelta	0.568	0.205	2.770	0.006	0.166	0.970
Constant	13,840.670	15,118.020	0.920	0.360	-15,813.300	43,494.640
R-squared	0.590					
F(7, 1547)	14.250					
Prob > F	-					
Root MSE	66,789.000					

This table presents the entire outputs for regressions 2.1 and 2.2 under model II, with dependent variables *AumDelta* and *SumDelta,* respectively. The corresponding regression number, and dependent variable are listed in the first row. Both outputs contain the number of observations (row 2), and the independent variables, listed in column 1, used in each regression. The second column contains the coefficient estimates for all variables and the intercept, the third column contains the corresponding robust standard errors, and the resulting t test statistics are presented in the fourth column. The last three columns show the p-value and 95% confidence interval for rejection rule of the respective coefficient. The last rows in each output contain the R-squared measure, the F test statistic for the regression, the corresponding p-value for joint coefficient testing, as well as the root mean squared error for the model.

Appendix B3: Model III

Table B3: Complete Regression Output Model III

Regression 3.1 - Aum20						
Number of obs.	*2,162.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Female	- 37,516.760	11,132.310	-3.370	0.001	- 59,347.930	- 15,685.590
Younger	- 98,764.870	12,103.300	-8.160	-	-122,500.200	- 75,029.530
Urban	16,002.330	12,924.830	1.240	0.216	- 9,344.087	41,348.750
Fl	19,638.850	10,695.360	1.840	0.066	- 1,335.440	40,613.150
Constant	141,860.600	16,197.470	8.760	-	110,096.300	173,624.900
R-squared	0.040					
F(4, 2157)	18.830					
Prob > F	-					
Root MSE	2.70E+05					

Regression 3.2 - Aum20						
Number of obs.	*3,964.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Female	- 74,693.230	22,561.370	- 3.310	0.001	-118,926.200	- 30,460.240
Younger	-110,357.400	20,798.140	- 5.310	-	-151,133.500	- 69,581.350
Female*Younger	62,997.130	23,090.180	2.730	0.006	17,727.370	108,266.900
Constant	159,078.300	20,587.990	7.730	-	118,714.200	199,442.300
R-squared	0.015					
F(3, 3960)	17.500					
Prob > F	-					
Root MSE	4.10E+05					

This table presents the entire outputs for regressions 3.1 and 3.2 under model III, with dependent variable *Aum20* for both regressions. The corresponding regression number, and dependent variable are listed in the first row. Both outputs contain the number of observations (row 2), and the independent variables, listed in column 1, used in each regression. The second column contains the coefficient estimates for all variables and the intercept, the third column contains the corresponding robust standard errors, and the resulting t test statistics are presented in the fourth column. The last three columns show the p-value and 95% confidence interval for rejection rule of the respective coefficient. The last rows in each output contain the R-squared measure, the F test statistic for the regression, the corresponding p-value for joint coefficient testing, as well as the root mean squared error for the model.

Appendix B4: Model IV

Table B4: Complete Regression Output Model IV

Regression 4.1 - Sum 20						
Number of obs.	*2,157.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Female	- 33,646.370	9,583.404	-3.510	-	- 52,440.070	- 14,852.670
Younger	- 83,010.970	10,562.120	-7.860	-	-103,724.000	- 62,297.940
Urban	11,580.850	11,458.950	1.010	0.312	- 10,890.920	34,052.620
Fl	6,808.256	9,659.818	0.700	0.481	- 12,135.290	25,751.810
Constant	125,493.700	14,664.110	8.560	-	96,736.380	154,251.000
R-squared	0.036					
F(4, 2152)	17.440					
Prob > F	-					
Root MSE	2.30E+05					

Regression 4.2 - Sum 20						
Number of obs.	*3,955.000*					
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Female	- 53,753.920	13,240.700	- 4.060	-	- 79,713.160	- 27,794.670
Younger	- 80,250.870	11,082.520	- 7.240	-	-101,978.900	- 58,522.860
Female*Younger	41,582.760	13,780.920	3.020	0.003	14,564.370	68,601.140
Constant	122,202.300	10,780.620	11.340	-	101,066.200	143,338.400
R-squared	0.026					
F(3, 3951)	28.440					
Prob > F	-					
Root MSE	2.30E+05					

This table presents the entire outputs for regressions 4.1 and 4.2 under model IV, with dependent variable *Sum20* for both regressions. The corresponding regression number, and dependent variable are listed in the first row. Both outputs contain the number of observations (row 2), and the independent variables, listed in column 1, used in each regression. The second column contains the coefficient estimates for all variables and the intercept, the third column contains the corresponding robust standard errors, and the resulting t test statistics are presented in the fourth column. The last three columns show the p-value and 95% confidence interval for rejection rule of the respective coefficient. The last rows in each output contain the R-squared measure, the F test statistic for the regression, the corresponding p-value for joint coefficient testing, as well as the root mean squared error for the model.

Appendix C: Regressions – Random Effects Model

Appendix C1: Model V

Table C1: Complete Regression Output 5.1

Regression 5.1 - Flowscat - Random Effects						
Number of obs.		*29,701.000*				
Number of groups (ID)		*3,828.000*				
	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Retlag	0.027	0.046	0.580	0.559	- 0.063	0.116
Constant	0.148	0.007	20.350	-	0.134	0.163
Sigma_u	0.252					
Sigma_e	0.251					
Rho**	0.502					
R-sq:						
Within	0.000					
Between	0.000					
Overall	0.000					
Obs. per group						
Min	1.000					
Avg.	7.800					
Max	32.000					
		Wald chi2(1)		3.40E-01		
Corr(u_i, X) = 0 (assumed)		Prob > chi2		0.559		
		Theta	----------	--------		
Min	5 %	Median	95 %	Max		
0.294	0.294	0.593	0.808	0.827		

This table shows the entire regression output for regression 5.1 under random effects model V, with *Flowscat* as the dependent variable. The corresponding regression number, the dependent variable, and estimation method is listed in the first row. The table shows the number of total observations under this variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for independent variable *Retlag* and the intercept, the corresponding robust standard errors, z test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that all standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented in column 2 below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. Rows 14, 15, and 16 contain the number of time periods observed per group. Under the main regression output, the table contains the Wald Chi Squared test statistic, and corresponding p-value for model fitness testing, as well as the assumed correlation of zero in random effects models between the fixed effect error term component and the regressors. Lastly it shows the min, 5th percentile, median, 95th percentile, and max estimated random effect Theta.

Table C2: Complete Regression Output 5.2

Regression 5.2 - Flowscat - Random Effects						
Number of obs.		*29,701.000*				
Number of groups (ID)		*3,828.000*				
	Coef.	Std. Err.	z	P>z	[95% Conf.Interval]	
Retlag	-0.473	0.232	-2.040	0.042	-0.928	-0.018
t						
690	-0.177	0.006	-30.340	-	-0.189	-0.166
691	-0.103	0.037	-2.810	0.005	-0.175	-0.031
692	-0.007	0.033	-0.230	0.822	-0.071	0.056
693	-0.020	0.022	-0.890	0.372	-0.063	0.024
694	0.014	0.017	0.800	0.424	-0.020	0.048
695	-0.018	0.016	-1.100	0.273	-0.049	0.014
696	-0.023	0.016	-1.510	0.132	-0.054	0.007
697	-0.029	0.014	-2.090	0.037	-0.056	-0.002
698	-0.033	0.015	-2.220	0.026	-0.062	-0.004
699	-0.048	0.018	-2.670	0.008	-0.084	-0.013
700	-0.001	0.015	-0.060	0.952	-0.031	0.029
701	-0.008	0.013	-0.630	0.529	-0.034	0.017
702	-0.027	0.015	-1.790	0.074	-0.057	0.003
703	-0.020	0.013	-1.510	0.130	-0.045	0.006
704	-0.017	0.015	-1.110	0.268	-0.046	0.013
705	-0.033	0.017	-1.930	0.054	-0.066	0.001
706	-0.064	0.020	-3.140	0.002	-0.104	-0.024
707	-0.012	0.007	-1.650	0.098	-0.027	0.002
708	-0.043	0.017	-2.570	0.010	-0.075	-0.010
709	0.008	0.010	0.790	0.429	-0.012	0.028
710	-0.003	0.007	-0.370	0.714	-0.017	0.012
711	0.007	0.010	0.690	0.489	-0.012	0.026
712	-0.009	0.007	-1.200	0.230	-0.023	0.006
713	-0.029	0.018	-1.650	0.100	-0.065	0.006
714	-0.005	0.006	-0.730	0.465	-0.017	0.008
715	0.002	0.006	0.250	0.806	-0.011	0.014
716	-0.019	0.009	-2.230	0.026	-0.036	-0.002
717	-0.019	0.010	-1.870	0.061	-0.039	0.001
718	-0.009	0.005	-1.810	0.070	-0.020	0.001
719	-0.006	0.006	-0.920	0.359	-0.018	0.006
720	-0.013	0.009	-1.460	0.145	-0.032	0.005
Constant	0.165	0.012	13.250	-	0.141	0.189
Sigma_u	0.247					
Sigma_e	0.251					
Rho	0.492					
R-sq:						
Within	0.0009					
Between	0.0210					
Overall	0.0024					
Obs. per group						
Min	1.000					
Avg.	7.800					
Max	32.000					

		Wald chi2(32)	6,400,000.000
Corr(u_i, X) = 0 (assumed)		Prob > chi2	0.000

		Theta	----------	--------
Min	5 %	Median	95 %	Max
0.287	0.287	0.586	0.805	0.823

This table shows the entire regression output for regression 5.2 under random effects model V, with *Flowscat* as the dependent variable. The corresponding regression number, the dependent variable, and estimation method is listed in the first row. The table shows the number of total observations under the dependent variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for independent variable *Retlag,* the time dummy variables and the intercept, the corresponding robust standard errors, z test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that all standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of time periods observed per group. Under the main regression output, the table contains the Wald Chi Squared test statistic, and corresponding p-value for model fitness testing, as well as the assumed correlation of zero in random effects models between the fixed effect error term component and the regressors. Lastly it shows the min, 5th percentile, median, 95th percentile, and max estimated random effect Theta.

Table C3: Complete Regression Output 5.3

Regression 5.3 - Flowscat - Random Effects						
Number of obs.		*28,696.000*				
Number of groups (ID)		*3,707.000*				
	Coef.	Std.Err.	z	P>z	[95% Conf.Interval]	
Retlag	-0.284	0.215	-1.320	0.187	-0.705	0.137
Type	0.007	0.002	3.040	0.002	0.002	0.011
Horiz	-0.043	0.010	-4.390	-	-0.063	-0.024
Choice	0.009	0.009	0.970	0.331	-0.009	0.027
t						
690	-0.174	0.006	-30.500	-	-0.185	-0.163
691	-0.095	0.036	-2.630	0.008	-0.166	-0.024
692	-0.001	0.033	-0.030	0.976	-0.066	0.064
693	-0.021	0.022	-0.930	0.355	-0.065	0.023
694	0.013	0.018	0.750	0.456	-0.022	0.048
695	-0.015	0.017	-0.890	0.373	-0.048	0.018
696	-0.018	0.016	-1.130	0.259	-0.050	0.013
697	-0.022	0.013	-1.640	0.101	-0.049	0.004
698	-0.025	0.015	-1.700	0.088	-0.055	0.004
699	-0.039	0.019	-2.020	0.043	-0.076	-0.001
700	0.001	0.016	0.040	0.969	-0.030	0.031
701	-0.004	0.014	-0.270	0.786	-0.030	0.023
702	-0.020	0.015	-1.280	0.200	-0.050	0.010
703	-0.019	0.014	-1.380	0.169	-0.045	0.008
704	-0.017	0.016	-1.070	0.284	-0.048	0.014
705	-0.024	0.017	-1.420	0.155	-0.057	0.009
706	-0.052	0.020	-2.660	0.008	-0.090	-0.014
707	-0.011	0.007	-1.470	0.142	-0.025	0.004
708	-0.031	0.016	-1.970	0.048	-0.061	-0.000
709	0.007	0.010	0.760	0.449	-0.012	0.026
710	-0.003	0.007	-0.340	0.731	-0.017	0.012
711	0.009	0.010	0.920	0.358	-0.010	0.029
712	-0.011	0.008	-1.420	0.155	-0.027	0.004
713	-0.018	0.017	-1.070	0.285	-0.051	0.015
714	-0.006	0.006	-1.040	0.297	-0.018	0.005
715	-0.001	0.007	-0.110	0.914	-0.014	0.013
716	-0.014	0.008	-1.690	0.092	-0.029	0.002
717	-0.018	0.010	-1.790	0.073	-0.038	0.002
718	-0.010	0.005	-2.020	0.044	-0.020	-0.000
719	-0.005	0.007	-0.720	0.470	-0.018	0.008
720	-0.010	0.009	-1.040	0.297	-0.028	0.009
Constant	0.229	0.032	7.110	-	0.166	0.292
Sigma_u	0.247					
Sigma_e	0.252					
Rho	0.490					
R-sq:						
Within	0.0009					
Between	0.0147					
Overall	0.0070					
Obs. per group						
Min	1.000					
Avg.	7.700					
Max	32.000					

		Wald chi2(35)	23,500,000.000	
Corr(u_i, X) = 0 (assumed)		Prob > chi2	0.000	
		Theta	----------	--------
Min	5 %	Median	95 %	Max
0.286	0.286	0.585	0.804	0.823

This table shows the entire regression output for regression 5.3 under random effects model V, with *Flowscat* as the dependent variable. The corresponding regression number, the dependent variable, and estimation method is listed in the first row. The table shows the number of total observations under the dependent variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for independent variables *Retlag, Type, Horiz,* and *Choice,* the time dummy variables and the intercept, the corresponding robust standard errors, z test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that all standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of time periods observed per group. Under the main regression output, the table contains the Wald Chi Squared test statistic, and corresponding p-value for model fitness testing, as well as the assumed correlation of zero in random effects models between the fixed effect error term component and the regressors. Lastly it shows the min, 5th percentile, median, 95th percentile, and max estimated random effect Theta.

Table C4: Complete Regression Output 5.4

Regression 5.4 - Flowscat - Random Effects						
Number of obs.		*20,633.000*				
Number of groups (ID)		*2,123.000*				
	Coef.	Std.Err.	z	P>z	[95% Conf.Interval]	
Retlag	-0.279	0.316	0.880	0.378	-0.898	0.340
Female	-0.021	0.010	2.150	0.032	-0.040	-0.002
Younger	0.051	0.008	6.160	-	0.035	0.067
Urban	0.010	0.010	1.070	0.286	-0.009	0.029
Fl	0.012	0.012	0.940	0.346	-0.013	0.036
t						
692	0.023	0.024	0.940	0.346	-0.025	0.070
693	0.023	0.023	0.990	0.324	-0.023	0.069
694	0.030	0.023	1.270	0.206	-0.016	0.076
695	0.003	0.016	0.160	0.872	-0.029	0.034
696	-0.010	0.027	0.350	0.726	-0.063	0.044
697	-0.012	0.019	0.630	0.527	-0.049	0.025
698	-0.015	0.019	0.810	0.417	-0.052	0.022
699	-0.034	0.023	1.470	0.141	-0.078	0.011
700	0.023	0.023	1.030	0.301	-0.021	0.067
701	0.016	0.014	1.130	0.259	-0.011	0.043
702	0.008	0.019	0.430	0.670	-0.030	0.046
703	0.001	0.014	0.040	0.965	-0.028	0.029
704	-0.009	0.020	0.440	0.659	-0.047	0.030
705	-0.016	0.024	0.690	0.489	-0.063	0.030
706	-0.034	0.025	1.360	0.173	-0.083	0.015
707	0.003	0.009	0.330	0.740	-0.015	0.021
708	-0.014	0.024	0.580	0.559	-0.061	0.033
709	0.025	0.012	2.060	0.039	0.001	0.049
710	0.007	0.009	0.800	0.426	-0.010	0.025
711	0.022	0.009	2.330	0.020	0.003	0.040
712	0.000	0.008	0.060	0.953	-0.015	0.015
713	-0.005	0.022	0.230	0.820	-0.048	0.038
714	0.011	0.008	1.370	0.171	-0.005	0.026
715	0.015	0.007	2.040	0.041	0.001	0.029
716	0.002	0.011	0.170	0.868	-0.020	0.024
717	-0.010	0.011	0.900	0.369	-0.030	0.011
718	0.000	0.007	0.060	0.952	-0.013	0.014
719	-0.001	0.008	0.060	0.950	-0.016	0.015
720	-0.001	0.012	0.040	0.967	-0.025	0.024
Constant	0.089	0.017	5.260	-	0.056	0.122
Sigma_u	0.209					
Sigma_e	0.247					
Rho	0.416					
R-sq:						
Within	0.0011					
Between	0.0223					
Overall	0.0049					
Obs. per group						
Min	1.000					
Avg.	9.700					
Max	30.000					

		Wald chi2(34)	1031.34	
Corr(u_i, X) = 0 (assumed)		Prob > chi2	0.000	
		Theta	----------	--------
Min	5 %	Median	95 %	Max
0.236	0.236	0.614	0.774	0.789

This table shows the entire regression output for regression 5.4 under random effects model V, with *Flowscat* as the dependent variable. The corresponding regression number, the dependent variable, and estimation method is listed in the first row. The table shows the number of total observations under the dependent variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for independent variables *Retlag, Female, Younger, Urban, Fl,* the time dummy variables and the intercept, the corresponding robust standard errors, z test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that all standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of time periods observed per group. Under the main regression output, the table contains the Wald Chi Squared test statistic, and corresponding p-value for model fitness testing, as well as the assumed correlation of zero in random effects models between the fixed effect error term component and the regressors. Lastly it shows the min, 5th percentile, median, 95th percentile, and max estimated random effect Theta.

Appendix D: Regressions – Fixed Effects Model

Appendix D1: Model VI

Table D1: Complete Regression Output 6.1

Regression 6.1 - Trans - Fixed Effects - By Individual						
Number of obs.		*29,126.000*				
Number of groups (ID)		*3,739.000*				
	Coef.	Std.Err.	t	P>t	[95% Conf.Interval]	
Ret	- 73,408.880	34,167.140	- 2.150	0.037	- 142,106.500	- 4,711.253
Constant	9,682.509	440.357	21.990	-	8,797.112	10,567.910
Sigma_u	61,080.086					
Sigma_e	101,486.860					
Rho	0.266					
R-sq:						
Within	0.0002					
Between	0.0089					
Overall	0.0001					
Obs. per group						
Min	1.000					
Avg.	7.800					
Max	32.000					
			F(1,48)	4.6200		
Corr(u_i, Xb)	- 0.0135		Prob > F	0.0367		

This table shows the entire regression output for regression 6.1 under fixed effects model VI, with *Trans* as the dependent variable, estimated by individuals. The regression number, the dependent variable, estimation method, and grouping method of the panel are listed in the first row. The table shows the number of total observations under the dependent variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for the independent variable *Ret* and the intercept, the corresponding robust standard errors, t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of time periods observed per group. Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the correlation between the error term component μ_i and the regressors.

Table D2: Complete Regression Output 6.2

Regression 6.2 - Trans - Fixed Effects - By Individual						
Number of obs.		*29,126.000*				
Number of groups (ID)		*3,739.000*				
	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Ret	-5,314.354	97,208.420	-0.050	0.957	-200,765.000	190,136.300
t						
690	6,730.538	5,435.755	1.240	0.222	-4,198.780	17,659.860
691	19,965.400	11,151.050	1.790	0.080	-2,455.288	42,386.090
692	11,364.020	17,124.720	0.660	0.510	-23,067.540	45,795.580
693	20,535.370	7,871.689	2.610	0.012	4,708.284	36,362.470
694	11,722.160	14,555.260	0.810	0.425	-17,543.150	40,987.480
695	11,057.940	11,729.590	0.940	0.351	-12,525.970	34,641.860
696	44,114.720	21,586.280	2.040	0.046	712.604	87,516.840
697	-1,259.083	6,178.192	-0.200	0.839	-13,681.170	11,163.000
698	3,559.319	11,494.300	0.310	0.758	-19,551.520	26,670.160
699	-12,420.900	2,927.505	-4.240	-	-18,307.040	-6,534.753
700	-13,504.480	3,867.910	-3.490	0.001	-21,281.430	-5,727.524
701	-12,030.980	8,096.718	-1.490	0.144	-28,310.530	4,248.559
702	-40,982.320	21,856.540	-1.880	0.067	-84,927.830	2,963.201
703	-14,580.770	5,740.213	-2.540	0.014	-26,122.240	-3,039.294
704	-12,734.650	3,955.402	-3.220	0.002	-20,687.520	-4,781.786
705	-21,290.290	6,332.434	-3.360	0.002	-34,022.500	-8,558.073
706	-17,402.490	3,981.676	-4.370	-	-25,408.180	-9,396.789
707	-18,588.200	6,358.115	-2.920	0.005	-31,372.050	-5,804.353
708	-17,733.180	2,629.427	-6.740	-	-23,019.990	-12,446.360
709	-18,911.830	3,251.279	-5.820	-	-25,448.960	-12,374.690
710	-22,800.960	2,305.666	-9.890	-	-27,436.820	-18,165.110
711	-24,175.080	2,342.476	-10.320	-	-28,884.940	-19,465.210
712	-26,676.840	5,412.045	-4.930	-	-37,558.480	-15,795.190
713	-26,979.860	2,554.585	-10.560	-	-32,116.190	-21,843.520
714	-29,927.600	2,465.773	-12.140	-	-34,885.370	-24,969.830
715	-32,352.000	2,320.532	-13.940	-	-37,017.740	-27,686.260
716	-33,207.680	1,971.101	-16.850	-	-37,170.840	-29,244.510
717	-30,982.390	2,286.460	-13.550	-	-35,579.620	-26,385.150
718	-33,320.480	1,954.418	-17.050	-	-37,250.100	-29,390.860
719	-34,170.650	2,742.336	-12.460	-	-39,684.480	-28,656.810
720	-36,816.350	2,625.333	-14.020	-	-42,094.930	-31,537.760
Constant	35,497.880	2,070.540	17.140	-	31,334.780	39,660.980
Sigma_u	61,699.879					
Sigma_e	100,979.350					
Rho	0.272					
R-sq:						
Within	0.0114					
Between	0.0056					
Overall	0.0056					
Obs. per group						
Min	1.000					
Avg.	7.800					
Max	32.000					
		F(31,48)	0.0000			
Corr(u_i, Xb)	0.0408	Prob > F	0.0000			

This table shows the entire regression output for regression 6.2 under fixed effects model VI, with *Trans* as dependent variable, estimated by individuals. The regression number, dependent variable, estimation method, and grouping method of the panel are listed in the first row. The table shows the number of total observations under the dependent variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for the independent variable *Ret,* the time dummy variables and the intercept, the corresponding robust standard errors, t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of time periods observed per group. Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the correlation between the error term component μ_i and the regressors.

Table D3: Complete Regression Output 6.3

Regression 6.3 - Trans - Fixed Effects - By Type						
Number of obs.		*28,154.000*				
Number of groups (Type)		*8.000*				
	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Ret	- 56,390.920	28,173.760	- 2.000	0.045	- 111,612.900	- 1,168.983
Constant	9,298.261	693.880	13.400	-	7,938.223	10,658.300
Sigma_u	2,845.883					
Sigma_e	99,202.949					
Rho	0.001					
R-sq:						
Within	0.0001					
Between	0.4398					
Overall	0.0002					
Obs. per group						
Min	517.000					
Avg.	3,519.200					
Max	8,597.000					
		F(1,28145)	4.010			
Corr(u_i, Xb)	0.0229	Prob > F	0.045			
F-Test that all u_i=0:		F(7,28145)	4.1700			
		Prob > F	0.0001			

This table shows the entire regression output for regression 6.3 under fixed effects model VI, with *Trans* as dependent variable, estimated by grouping according to types. The regression number, dependent variable, estimation method, and grouping method of the panel are listed in the first row. The table shows the number of total observations under the dependent variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for the independent variable *Ret* and the intercept, the corresponding robust standard errors, t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of time periods observed per group. Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the correlation between the error term component μ_i and the regressors. Lastly it contains the F test statistic and corresponding p-value for testing under fixed effects models whether fixed effect error term μ_i is indeed zero.

Table D4: Complete Regression Output 6.4

Regression 6.4 - Trans - Fixed Effects - By Type						
Number of obs.		*28,154.000*				
Number of groups (Type)		*8.000*				
	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
Ret	- 88,130.630	95,180.270	- 0.930	0.354	- 274,688.600	98,427.300
t						
690	6,562.699	102,035.600	0.060	0.949	- 193,432.100	206,557.500
691	24,019.510	99,582.860	0.240	0.809	- 171,167.700	219,206.700
692	19,748.670	99,415.290	0.200	0.843	- 175,110.100	214,607.400
693	28,053.910	99,305.270	0.280	0.778	- 166,589.200	222,697.000
694	20,718.830	99,234.800	0.210	0.835	- 173,786.200	215,223.800
695	19,083.640	99,194.050	0.190	0.847	- 175,341.500	213,508.800
696	47,993.490	99,184.400	0.480	0.628	- 146,412.700	242,399.700
697	8,594.731	99,172.370	0.090	0.931	- 185,787.900	202,977.400
698	15,541.370	99,202.040	0.160	0.876	- 178,899.400	209,982.200
699	- 3,485.786	99,129.740	- 0.040	0.972	- 197,784.900	190,813.300
700	- 650.642	99,111.450	- 0.010	0.995	- 194,913.900	193,612.600
701	571.905	99,114.700	0.010	0.995	- 193,697.700	194,841.500
702	- 28,358.830	99,093.050	- 0.290	0.775	- 222,586.000	165,868.300
703	1,186.907	99,082.280	0.010	0.990	- 193,019.200	195,393.000
704	816.721	99,108.260	0.010	0.993	- 193,440.300	195,073.700
705	- 9,537.732	99,184.200	- 0.100	0.923	- 203,943.600	184,868.100
706	256.564	99,050.400	-	0.998	- 193,887.000	194,400.100
707	- 4,471.057	99,142.600	- 0.050	0.964	- 198,795.400	189,853.200
708	3,051.664	99,043.690	0.030	0.975	- 191,078.800	197,182.100
709	1,933.163	99,024.150	0.020	0.984	- 192,159.000	196,025.300
710	- 2,122.398	99,004.210	- 0.020	0.983	- 196,175.400	191,930.700
711	- 1,965.577	99,007.400	- 0.020	0.984	- 196,024.900	192,093.700
712	- 8,719.171	99,089.410	- 0.090	0.930	- 202,939.200	185,500.900
713	- 3,284.651	98,998.050	- 0.030	0.974	- 197,325.600	190,756.300
714	- 5,249.229	98,991.670	- 0.050	0.958	- 199,277.700	188,779.200
715	- 8,708.907	98,986.270	- 0.090	0.930	- 202,726.800	185,309.000
716	- 7,884.197	98,980.480	- 0.080	0.937	- 201,890.700	186,122.300
717	- 3,990.553	98,993.080	- 0.040	0.968	- 198,021.800	190,040.700
718	- 5,167.798	98,975.490	- 0.050	0.958	- 199,164.500	188,828.900
719	- 6,934.495	98,988.470	-0.070	0.944	-200,956.700	187,087.700
720	- 2,069.164	98,982.770	- 0.020	0.983	- 196,080.200	191,941.800
Constant	12,895.340	98,961.810	0.130	0.896	- 181,074.600	206,865.300
Sigma_u	2,418.421					
Sigma_e	98,950.159					
Rho	0.001					
R-sq:						
Within	0.0063					
Between	0.6274					
Overall	0.0066					
Obs. per group						
Min	517.000					
Avg.	3,519.200					
Max	8,597.000					
		F(32,28114)	5.5900			
Corr(u_i, Xb)	0.0611	Prob > F	0.0000			
F-Test that all u_i=0:		F((7, 28114)	3.0100			
		Prob > F	0.0037			

This table shows the entire regression output for regression 6.4 under fixed effects model VI, with *Trans* as the dependent variable, estimated by grouping according to types. The regression number, the dependent variable, estimation method, and grouping method of the panel are listed in the first row. The table shows the number of total observations under the dependent variable, and number of groups (grouping variable ID) observed (rows 2 and 3). It further contains the coefficient estimates for the independent variable *Ret,* the time dummy variables and the intercept, the corresponding robust standard errors, t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). Note that standard errors are adjusted for clusters in the model portfolios. The error term components sigma_u and sigma_e, and the fraction *rho* of individual fixed effects variance μ_i are presented below the coefficient estimates. The table further contains the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of time periods observed per group. Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the correlation between the error term component μ_i and the regressors. Lastly it contains the F test statistic and corresponding p-value for testing under fixed effects models whether fixed effect error term μ_i is indeed zero.

Appendix E: Individual & Stereotype Differences

Appendix E1: Model VII – First Between Estimation Model

Table E1: Complete Regression Output 7.0

Regression 7.0 - Trans - Between Estimation						
Number of obs		*29,148.000*				
Number of groups (ID)		*3,740.000*				
	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Ret	809,566.100	139,611.000	5.800	-		535,844.900
Constant	- 745.370	2,421.171	- 0.310	0.758	-5,492.315	4,001.574
R-sq:						
Within	0.0002					
Between	0.0089					
Overall	0.0001					
Obs. per group						
Min	1.000					
Avg.	7.800					
Max	32.000					
		F(1,3738)	33.6300			
sd(u_i + avg(e_i.))	60,756.3800	Prob > F	0.0000			

This table shows the entire regression output for the first between estimation, model VII, with *Trans* as the dependent variable. The regression number, the dependent variable estimated, and the estimation method are listed in the first row. The table contains the coefficient estimate for the independent variable *Ret* and for the intercept, the corresponding robust standard errors, z test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). The table also indicates the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of observed time periods per group (grouping variable ID). Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the standard deviation of the between error (fixed effect error term plus average of overall error term).

Appendix E2: ANOVA

Table E2: ANOVA by Investor Types

Analysis of Variance for Types					
Source	SS	df	MS	F	Prob > F
Between groups	298,500,000,000.000	7.000	42,642,000,000.000	4.510	0.000
Within groups	277,230,000,000,000.000	29,300.000	9,461,800,000.000		
Total	277,530,000,000,000.000	29,307.000	9,469,700,000.000		

Bartlett's test for equal variances:	
Chi2(7)	28,000.000
Prob>chi2	0.000

This table presents the ANOVA for the variable *Trans* between investor types. It shows the sum of squares, degrees of freedom, mean squares, and the F test statistic (columns 2-5) for the hypothesis test of no difference among investor types' population mean. Column 6 shows the resulting p-value for testing the hypothesis. An additional table below shows the output for Bartlett's test for equal variances, with the Chi-squared test statistic and the resulting p-value.

Appendix E3: Multiple Mean Comparison, Scheffe

Table E3: One-way Comparison of Average Transactions by Type, Scheffe

Comparison of Average Trans by Type							
Scheffe							
Row Mean - Col Mean							
	FOR	FOU	FYR	FYU	MOR	MOU	MYR
FOU	-971.000						
	1.000						
FYR	-3,092.070	-2,121.070					
	1.000	1.000					
FYU	-5,305.850	-4,334.850	-2,213.780				
	0.942	0.882	1.000				
MOR	1,697.950	2,668.950	4,790.020	7,003.810			
	1.000	0.995	0.994	0.495			
MOU	2,747.650	3,718.650	5,839.720	8,053.500	1,049.700		
	0.998	0.844	0.968	0.034**	1.000		
MYR	-2,680.320	-1,709.320	411.750	2,625.540	-4,378.270	-5,427.970	
	0.999	1.000	1.000	0.997	0.958	0.675	
MYU	-4,328.000	-3,357.000	-1,235.930	977.850	-6,025.950	-7,075.650	-1,647.680
	0.968	0.905	1.000	1.000	0.478	0.002***	1.000

This table shows the output for the multiple-mean comparison after the Scheffe correction. The third row shows how the differences are computed. The investor types are listed in the first column, and fourth row, constituting the matrix. Values on the top within the matrix indicate the difference between a mean of an investor type (row) and another type (column). The value below indicates the p-value for rejection of the null for no difference in means. Significance levels of 10%, 5%, and 1% are marked with symbols *,**, and ***, respectively. A description of the types can be found in Table 1.

Appendix E4: Mixed Model Output

Table E 4.1 Mixed Model Regression Output

Regression 7.2 - Trans - Mixed Effects - All Investors						
Number of obs.		*28,154.000*				
Number of groups (All)		*1.000*				
	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Ret	- 7,352.444	11,997.600	- 0.610	0.540	- 30,867.320	16,162.430
Type						
FOU	-931.8359	3192.504	-0.29	0.77	-7189.028	5325.357
FYR	-2918.369	3638.948	-0.8	0.423	-10050.58	4213.838
FYU	-5306.163	3104.326	-1.71	0.087	-11390.53	778.2048
MOR	1846.388	3670.824	0.5	0.615	-5348.294	9041.071
MOU	2924.431	3545.552	0.82	0.409	-4024.723	9873.586
MYR	-2384.164	3249.474	-0.73	0.463	-8753.015	3984.687
MYU	-4187.622	3103.606	-1.35	0.177	-10270.58	1895.334
Constant	9703.34	3083.912	3.15	0.002	3658.984	15747.7
Obs. per group						
Min	28,154.000					
Avg.	28,154.000					
Max	28,154.000					
		Wald chi2(8)	54.0400			
Log likelihood	- 350,556.460	Prob > chi2	0.0000			

This table shows the regression output for the mixed model originally performed to use the delta-method on the random effects of investor types, with *Trans* as dependent variable. The regression number, dependent variable estimated, the estimation method, and the grouping variable are listed in the first row. Rows 2 and 3 show the total number of observations, and the number of groups used. The table contains the coefficient estimates for the independent variables *Ret* and *Type* and for the intercept, the corresponding standard errors, the z test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). The table also indicates The rows below that contain the number of observed time periods per group (grouping variable All). Under the main regression output, the table contains the Wald Chi-squared test statistic, and corresponding p-value for model fitness testing.

Table E 4.2 Random-Effects Parameters

Random-Effects Parameters

Residual: Independent, by type

	Estimate	Std. Err.	[95% Conf.Interval]	
FOR: var(e)	9.74E+09	4.30E+08	8.94E+09	1.06E+10
FOU: var(e)	2.19E+09	5.55E+07	2.08E+09	2.30E+09
FYR: var(e)	1.94E+09	1.21E+08	1.72E+09	2.19E+09
FYU: var(e)	4.24E+08	1.12E+07	4.02E+08	4.46E+08
MOR: var(e)	8.21E+09	2.56E+08	7.73E+09	8.73E+09
MOU: var(e)	2.65E+10	4.04E+08	2.57E+10	2.73E+10
MYR: var(e)	1.91E+09	6.40E+07	1.79E+09	2.04E+09
MYU: var(e)	1.19E+09	1.85E+07	1.15E+09	1.23E+09

This table shows the random-effects parameters for each investor type, i.e. their individual variance effect resulting from the mixed regression model. The types are listed in column 1. The second column shows the variance estimate, and columns 3 and 4 show the corresponding standard error and 95% confidence interval for significance testing.

Appendix F: Regressions – Second Between Estimation Model

Appendix F1: Model VIII

Table F1: Complete Regression Output 8.1

Regression 8.1 - Trans - Between Estimation - By Individual						
Number of obs		*29,148.000*				
Number of groups (ID)		*3,740.000*				
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Ret	649,465.600	160,594.300	4.040	-	334,604.600	964,326.500
t	598.491	297.070	2.010	0.044	16.056	1,180.925
Constant	- 426,861.200	211,522.900	- 2.020	0.044	- 841,572.900	- 12,149.560
R-sq:						
Within	0.0011					
Between	0.0100					
Overall	0.0006					
Obs. per group						
Min	1.000					
Avg.	7.800					
Max	32.000					
		F(2,3737)	18.8600			
Sd(u_i + avg(e_i.))	60,731.5400	Prob > F	0.0000			

This table shows the entire regression output for regression 8.1 under the second between estimation, model VIII, with *Trans* as dependent variable, and grouped by individuals. The regression number, dependent variable estimated, estimation method, and grouping variable are listed in the first row. The table contains the coefficient estimate for the independent variable *Ret*, the time trend variable *t* and the intercept, the corresponding robust standard errors, the t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). The table also indicates the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of observed time periods per group (grouping variable ID). Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the standard deviation of the between error (fixed effect error term plus average of overall error term).

Table F2: Complete Regression Output 8.2

Regression 8.2 - Trans - Between Estimation - By Individual						
Number of obs		*30,352.000*				
Number of groups (ID)		*3,754.000*				
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
t	1,263.666	256.865	4.920	-	760.057	1,767.275
Constant	- 892,969.300	183,936.300	- 4.850	-	- 1,253,594.000	- 532,344.400
R-sq:						
Within	0.0072					
Between	0.0064					
Overall	0.0024					
Obs. per group						
Min	1.000					
Avg.	8.100					
Max	32.000					
		F(1,3752)	24.2000			
Sd(u_i + avg(e_i.))	60,691.2300	Prob > F	0.0000			

This table shows the entire regression output for regression 8.2 under the second between estimation, model VIII, with *Trans* as dependent variable, and grouped by individuals. The regression number, dependent variable estimated, estimation method, and grouping variable are listed in the first row. The table contains the coefficient estimate for the independent time trend variable *t* and the intercept, the corresponding robust standard errors, the t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). The table also indicates the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of observed time periods per group (grouping variable ID). Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the standard deviation of the between error (fixed effect error term plus average of overall error term).

Table F3: Complete Regression Output 8.3

Regression 8.3 - Trans - Between Estimation - By Type						
Number of obs		*28,154.000*				
Number of groups (Type)		*8.000*				
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
Ret	- 307,164.100	2,427,391.000	- 0.130	0.904	- 6,546,971.000	5,932,643.000
t	- 1,504.748	1,540.963	- 0.980	0.374	- 5,465.919	2,456.423
Constant	1,085,863.000	1,071,329.000	1.010	0.357	- 1,668,076.000	3,839,801.000
R-sq:						
Within	0.0017					
Between	0.5296					
Overall	0.0019					
Obs. per group						
Min	517.000					
Avg.	3,519.200					
Max	8,597.000					
		F(2,5)	2.8100			
Sd(u_i + avg(e_i.))	2,333.4170	Prob > F	0.1518			

This table shows the entire regression output for regression 8.3 under the second between estimation, model VIII, with *Trans* as dependent variable, and grouped by investor types. The regression number, dependent variable estimated, estimation method, and grouping variable are listed in the first row. The table contains the coefficient estimate for the independent variable *Ret*, the time trend variable *t* and the intercept, the corresponding robust standard errors, the t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). The table also indicates the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of observed time periods per group (grouping variable *Type*). Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the standard deviation of the between error (fixed effect error term plus average of overall error term).

Table F4: Complete Regression Output 8.4

Regression 8.4 - Trans - Between Estimation - By Type						
Number of obs		*29,308.000*				
Number of groups (Type)		*8.000*				
	Coef.	Std. Err.	t	P>t	[95% Conf.Interval]	
t	- 1,694.314	610.609	- 2.770	0.032	- 3,188.421	- 200.208
Constant	1,216,766.000	435,637.800	2.790	0.031	150,798.700	2,282,733.000
R-sq:						
Within	0.0020					
Between	0.5620					
Overall	0.0023					
Obs. per group						
Min	543.000					
Avg.	3,663.500					
Max	8,850.000					
		F(1,6)	7.7000			
Sd(u_i + avg(e_i.)	2,043.5200	Prob > F	0.0322			

This table shows the entire regression output for regression 8.4 under the second between estimation, model VIII, with *Trans* as dependent variable, and grouped by investor types. The regression number, dependent variable estimated, estimation method, and grouping variable are listed in the first row. The table contains the coefficient estimate for the independent time trend variable *t* and the intercept, the corresponding robust standard errors, the t test statistic, and the p-value and 95% confidence interval for significance testing of each coefficient (columns 2-6). The table also indicates the R-squared measures for between, within, and overall variation of the regression. The rows below that contain the number of observed time periods per group (grouping variable *Type*). Under the main regression output, the table contains the F test statistic, and corresponding p-value for model fitness testing, as well as the standard deviation of the between error (fixed effect error term plus average of overall error term).