Essays on Household Finance and Individual Investor Behaviour

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Abstract

This dissertation studies factors that influence individual investor behaviour using two unique proprietary datasets which cover the investment fund choices, fund switches and asset allocation decisions for over 600,000 individual investors in New Zealand. The first study looks at return chasing. I investigate whether investors use past returns to choose funds during a period with particularly volatile returns, before and after the 2008 Global Financial Crisis. The findings suggest that investors chase returns and investors are affected by past quarterly, half-yearly and annual returns. Funds with positive past returns see more investors choose their fund, while funds with negative returns see investors leave their fund. The second study explores the role of financial advice on asset allocation. I find that people who receive financial advice invest significantly more in equity. Women, older and wealthier investors are more likely to receive advice than others. However, the differences in returns of people who receive advice and those that do not, are marginal. I investigate the impact of financial advice differently to previous studies which use brokers, dealers, bank-employees and computer generated algorithms. I show that using personal, face-to-face financial advice result in different findings. The third study tests the relative importance of personal characteristics, peer effects and financial advice on asset allocation. Surprisingly, household peer effects rather than personal characteristics dominate investment decisions. In fact, all peer effects combined (household effects, work place effects and neighbourhood effects) are twice as important as personal characteristics.

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Table of Contents

Table of Tables

Table of Figures

Appendix

Chapter 1 Introduction

1.1 Introduction

This dissertation studies factors influencing individual investor behaviour. The first study looks at the relation between past returns and fund selection. The second study investigates the relation between financial advice and asset allocation. The final study explores the relative importance of investor personal characteristics, peer effects and financial advice on asset allocation. All three studies have their genesis in Campbell's (2006) work in the field of household finance. Household finance can be broadly defined as the investigation of how individual investors and small units, for example, households (as opposed to corporate investors) make financial decisions related to savings, investing and portfolio choice (Barber & Odean, 2000, 2001; Grinblatt & Keloharju, 2000, 2001).

The questions and themes I explore here are not, in and of themselves, new. Studies that investigate individual investor behaviour date back to at least the 1970s (see Friend and Blume, 1975). Rather, it is the quality and kind of data I use here that facilitates our understanding of individual investor behaviour. This is not uncommon. In many respects, it is the quality of the data that is responsible for advances in the field of household finance. Quality data has provided opportunities to analyse financial behaviour in unique ways. In view of the necessity for high-quality data for the growth and development of household finance as a field, Campbell (2006) outlines what he considers to be the five qualities and characteristics of an ideal dataset for the study of household finance:

First, it would cover a representative sample of the entire population. It is particularly important to have good coverage by both age and wealth, since many aspects of financial behaviour vary with these characteristics. Second, for each household the dataset would

measure both total wealth and an exhaustive breakdown of wealth into relevant categories. Third, these categories would be sufficiently disaggregated to distinguish among asset classes, and ideally would capture specific individual assets so that one could measure household diversification within asset classes. Fourth, the data would be reported at a high level of accuracy. Finally, the dataset would follow households over time; that is, it would be a panel dataset rather than a series of cross-sections. (p. 3-4)

Barber and Odean (2001) and Grinblatt and Keloharju (2000, 2001) advance our understanding of individual investor behaviour through the use of discount brokerage records of individual stock trades in the United States and data from the Finnish Central Securities Depositary, respectively. These studies provide insight into how overconfidence affects trading behaviour, and how domestic and foreign investors behave differently.

The sources of data I use come from two unique proprietary datasets and it satisfies many of Campbell's criteria. The first database comes from a large New Zealand bank, which operates as a KiwiSaver provider. KiwiSaver is New Zealand's national investment savings scheme. The data contains the investor accounts of 196,513 individual investors. The data includes information on age, gender, tax code and fund choice from October 2007 to December 2010, and additional fund switching information where investors have changed funds. The second dataset comprises of 405,107 individual investor accounts from four large KiwiSaver providers. The data is representative of the overall New Zealand household and firm size composition and includes information on age, gender, level of funds under management, tax rate, default enrolment, financial advice, household location, who investors live with, location of where investor works and members he/she works with, hhousehold postcode, asset allocation information and fund switching

behaviour. I use the first database for essay one and the second database for essays two and three. Since the datasets I use come from different KiwiSaver providers this means that they also contain different information and variables. A direct implication of this is that I am unable to test and control for the same set of variables among my three studies. For instance, my first essay which looks at past returns and fund selection does not control for financial advice or peer effects because the database does not include the information available to do so. Where I am able, I include as many control variables as possible in order to maintain continuity of topics and themes covered in this thesis, however, because the data come two separate outlets each chapter should be read as standalone paper.

It is important to note that the large datasets I use may contribute to the small standard errors and strong statistical significance in some instances. While little can be done about this, I acknowledge this fact and treat the discussion of these results with appropriate caution.

The difficulty of obtaining high-quality data remains a central challenge to the study of household finance. The studies I present in this dissertation could not have been undertaken without the involvement of, and help from, the data providers. In total, the data collection period spanned over 18 months. This lends itself to further consideration, especially given the apparent reliance on good data to advance our field(s) of study. The following section summarises the main findings and contributions of each study.

1.2 Main findings and contribution to the literature

1.2.1 Past returns and fund selection

As already noted, the first study looks at the relation between past returns and investment fund choice. I investigate whether past performance impacts fund choice, how

demographic characteristics play a role in return chasing, and whether in hindsight it pays off to switch funds in pursuit of past performance. What makes this study unique is that it looks at the individual rather than the institutional investor, the latter having been studied extensively.[1] The literature focussing on return chasing behaviour among ordinary investors is far less developed. While there are empirical studies that find a positive relation between past returns and investment behaviour, these studies focus on other questions and do not directly test for return chasing.[2] The closest study focussing on return chasing is Clark-Murphy, Gerrans and Speelman (2009), who investigate return chasing among Australian superannuation investors. The specific nature of the differences between our studies is discussed at length later in this thesis.

The study finds that past returns significantly affect fund choice. Investors are affected by quarterly, half-yearly and annual past returns, but not monthly returns. A 1% difference in annual returns increases fund enrolment by 1.6%, which is equivalent to 787 investors per year. Investor demographic characteristics also play a role in fund selection and at the level of asset allocation decisions. For example, women are less likely to choose equity assets than men. Females, younger and relatively wealthier investors are also more sensitive to differences in past performance between fund choices and are more prone to chase past returns. When an investor switches funds I find that their propensity to chase past returns is dependent on the fund they initially select. Past returns matter in both initial and subsequent fund switching choices made by the investor. Past returns are also

[1] There is a large field of literature that shows the existence of a smart money effect, which documents mutual fund money flows to funds that perform better after the money arrives, displaying the superior fund selection abilities of investors (Gruber, 1996; Keswani & Stolin, 2008; Sapp & Tiwari, 2004; Zheng, 1999).

[2] For example, Agnew, Balduzzi and Sunden (2003) focus on US 401(k) plan trades and investor inertia, Cronqvist and Thaler (2004) investigate how the design of pension schemes can affect investor behaviour and Choi et al. (2009) investigate the relation between reinforcement learning and savings behaviour.

not indicative of future performance and in hindsight fund switching does not lead to higher returns.

This study contributes to the literature in four ways. First, I provide findings on the extent to which investors chase returns, which was not previously known. Second, I look at the importance of relative returns of funds within the same fund family and the effect that this has on fund selection and fund switching. Third, since I am able to investigate *changes* in investment fund choices before, during and after the 2008 Global Financial Crisis period, the data provides a unique opportunity to examine fund switching activity during a volatile period. Fourth, I am able to add to the understanding of how people in the general population make retirement fund decisions. As Thaler (2005) points out, individuals are becoming increasingly responsible for their own financial well-being, therefore, it is of interest to see how people make these types of retirement fund choices.

1.2.2 Financial advice and asset allocation of individual investors

Essay two focuses specifically on *who* receives face-to-face financial advice, what is the impact of that advice on portfolio asset allocation and whether receiving advice increases portfolio returns. Households often seek professional advice from financial planners, however, they continue to behave in ways that are difficult to reconcile with standard models even after receiving advice (Campbell, 2006). I find that people who receive financial advice differ significantly in their asset allocation holdings compared to people who do not receive advice. Three key findings are presented in the second paper. First, female investors, relatively older investors and investors with higher levels of funds under management (invested wealth) are more likely to receive financial advice. On average, women are 8.2% more likely to receive financial advice than men. Second, advised investors hold more equity assets. Men tend to hold more equity assets than

women, relatively older investors tend to invest less in equity assets and investors with relatively higher funds under management invest more in equity assets. Third, on a risk-adjusted basis, differences in returns between advised and non-advised investors are marginal at best. I find that advised accounts earn higher returns than un-advised accounts in years where equity markets perform well and underperform un-advised accounts in years where equity markets experience low returns. During the Global Financial Crisis in 2008, advised accounts underperformed un-advised accounts by 2.5%.

The contribution of this study is that it widens our understanding of the role that financial advice has on asset allocation and performance using one of the largest datasets. Further, this study measures financial advice differently from other studies. Financial advice is measured by incidents of face-to-face advice. Previous studies do not differentiate between different types of financial advice, or break down the diverse effects that different types of advice can have on investors. For instance, the use of brokers, dealers, bank-employees and even computer generated algorithms has been treated in the literature as receiving 'advice'. In reality, however, the role and influences of these different types of 'advice' on investor behaviour are considerably different.[3] The ability to measure financial advice in a more personalised and direct way (face-to-face) compared to previous studies enables the results from this study to be void of some of the disadvantages that come from using brokerage data.[4] The findings of this paper challenge what was previously known in regards to which investors are more likely to receive

[3] See Bhattacharya et al. (2012), Bluethgen et al. (2007), Chalmers and Reuter (2012) and Hackethal et al. (2012).
[4] Goetzmann and Kumar (2008), Hackethal et al. (2012) and Hoechle et al. (2013) point out some of the shortcomings of using brokerage data to study financial advice.

advice, the impact of financial advice on equity exposure, and differences in returns between advised and non-advised investors.

1.2.3 The relative importance of factors that influence the asset allocation decisions of individual investors

Essay three investigates a combination of factors and their effect on asset allocation. We examine the relative importance of investor personal characteristics, peer effects and financial advice on asset allocation.[5] There is a large body of literature that suggests personal characteristics and financial advice are important in decision making. There is also a growing body of literature on the possibility that peer effects, between neighbours and co-workers, may play a role, particularly with respect to stock market participation. To test the relative importance of these factors we run a 'horse-race' to determine which set of factors have the greatest effect on investor choice(s). To the best of the author's knowledge, however, no study considers all factors jointly and also allows for the peer effects of investors who live in the same household, while focusing on asset allocation decisions. This, as Campbell (2006) points out, is likely due to the difficulty of obtaining data.

The study shows that personal characteristics, household, workplace, neighbourhood peer effects and financial advice all affect asset allocation decisions, however, some factors are more important than others. Household peer effects seem to have the dominant influence on decisions. We find that almost two-thirds (64%) of people hold the exact same investment fund - and therefore identical asset allocation - as the people they live with in the same household. Household peer effects explain the most variation in asset

[5] Essays one and two are solo authored. Essay two has been accepted for publication and is forthcoming in the *Pacific Accounting Review*. Essay three is co-authored with my supervisors Professor Ben Jacobsen and Professor Ben Marshall. I therefore change my writing tone from using 'I' to 'we' to reflect this collaborative work.

allocation decisions when looking at each variable on its own, at 15.5%. This is followed by personal characteristics explaining 9.7% of the variation. Workplace and neighbour peer effects are also important, but to a lesser extent. Combining household, workplace and personal characteristics substantially improves the explanatory power of all of the models. Combined, these effects explain 25% of the variation in the asset allocation choices of individuals. Leaving out peer effects, or personal characteristics, when investigating asset allocation leads to omitted variable bias and, as a result, biased estimates. We also establish a causal relation between individual and peer investment asset allocation choices. We find that an individual is more likely to hold more of the same asset class when their household members and co-workers do. We find that most of the signs and magnitudes of factors are the same as in previous studies (which look at these factors individually), so the bias does not appear to be too severe. Fund switching confirms the importance of household and workplace peer effects. Investors are likely to switch if their peers switch funds. We perform several robustness checks and find that people in the same household affect asset allocation more than any other factor.

This study provides several contributions to the literature. It is the first paper to investigate a comprehensive list of personal and environmental factors in order to jointly study the relative importance of these factors in relation to each other. The paper uses a database that is representative of a national population to understand mutual fund behaviour. Most studies focus on stock ownership, however, this study focuses on the impact on investment fund choices. As we know the asset allocation of the funds, it allows us to analyse the impact of peer effects on actual asset allocation decisions, controlling for other factors. This study examines the investment choices of individuals within the same physical household unit, which, to the best of the author's knowledge, no one has done to date. Previous studies in the peer effects literature have either used workplace or

neighbourhoods as measures for peer effects. The proxies used to measure these locations often cover large geographic areas, such as zip codes or states, which are less precise than measuring the physical household directly. Moreover, studies regarding workplace peer effects show mixed results, so we add to this body of work. This study also combines household and workplace peer effects, as well as incorporating whether a person received financial advice. It is the first paper to study the interaction between all these variables and determine whether personal characteristics dominate environmental factors (peer effects) or the other way around.

Chapter 2 Past returns and fund selection

2.1 Introduction

This paper investigates the relation between past returns, fund selection, fund switching, and the propensity of investors to chase past returns based on investor demographic characteristics within a national investment savings. It asks the following questions: What is the role of past returns in individual investor fund selection? Do investors chase past returns? If so, what is the time frame of past returns that investors use to make selections for fund choices? How do investor demographics relate to the fund choice selection process? Which investors are more prone to chase past returns? Does it pay off to switch funds based on past fund performance? In asking these questions, this paper hopes to contribute to our limited understanding of the relation between past returns and investor behaviour. There is evidence that suggests past returns are related to investment fund choices, but little is known about *who* is more likely to chase returns. Only a handful of studies directly test the relation between past returns and fund choice among everyday investors. There is also a noteworthy absence of empirical studies that investigate the relation between past returns and fund selection, a deficit that is perhaps due to limited datasets that that track individual investor behaviour and enable the relation(s) to be closely examined.

This study differs from previous studies in several ways. It employs a large proprietary database that records investor behaviour, offering an alternative data source to the survey data that are typically used. Previous studies that have looked at the relation between past returns and fund choice primarily use survey-based data to test this relation. As Campbell (2006) notes, even the best survey data have several deficiencies. Surveys tend to under-cover and oversample the wealthy and have high refusal rates. The author notes that even

people who wish to provide data may have difficulty answering detailed questions accurately. Further, previous studies find that past returns are related to investment choice, among other factors, but do not explore the relation between fund switching and investor characteristics. For example, Gerrans (2004) and Clare (2006), using Australian data, show that fund ratings, fees, and account consolidation are other significant factors that influence investment fund selection. Capon, Fitzimons, and Prince (1996) find that fund manager reputation also plays an important role in mutual fund selection in the United States. However, Cronqvist and Thaler (2004) find that Swedish pension investors are influenced by recent returns, suggesting that the timing of a pension programme launch has a stronger impact on the asset allocations of the participants.

This paper focuses on a different set of questions than previous studies that have also used large proprietary datasets. For example, Barber and Odean (2001) investigate the relation between overconfidence and trading behaviour among individual investors in the United States. They find that men trade 45% more than women and that trading reduces men's net returns. Agnew, Balduzzi, and Sunden (2003) investigate investor inertia in US 401(k) plans. They find that investors are inert in their asset allocation decisions and are unlikely to make changes to their accounts. Stock selections in US 401(k) plans are only weakly correlated to returns. Choi et al. (2009) explore the relation between personal experience and savings decisions. They find that investors tend to over-extrapolate from their past experiences and people who experience high rates of return from their 401(k) account increase their savings rate to a greater extent than investors who experience less rewarding savings returns. The paper that is perhaps closest to this study is that of Clark-Murphy, Gerrans, and Speelman (2009), who focus on return chasing among Australian superannuation investors. They find evidence that age is significantly related to return chasing and also note that past returns have a weak effect on fund switching. A significant

point of difference between their work and this study is the method used to define return chasing. Clark-Murphy, Gerrans, and Speelman use *t*-tests to compare differences in returns between an investor's new and old funds. In other words, they simply compare the returns of new funds against those of the old fund and not whether the choice made is actually a function of return chasing. By contrast, I look at the difference between an old fund and *all* other fund options available in the fund family. Rather than just exploring the difference in returns between fund choices ex post, I test whether investors are switching into funds with the highest *relative* past return. While this difference may appear subtle, it is significant because it tests whether investors who switch funds are choosing to switch into a better-performing fund than the one in which they were originally invested.

This study also differs markedly from previous studies addressing similar questions on account of the quality and scope of the data; the dataset used here meets several of the criteria put forth by Campbell (2006) as an ideal dataset for exploring household finance.[6] Using a sample of 196,513 individual investors from KiwiSaver, a retirement savings scheme in New Zealand, I look at fund choices and fund switching and test the influence of past returns on fund selection in both of these instances. The use of KiwiSaver investor data allows us to investigate how a large group of the general New Zealand population pick investment funds and how their investment decisions may change over time, given past performance relative to other fund options. In total, the KiwiSaver population covered in this study makes up for 14% of all KiwiSaver members, as at November 2010. Observing fund choice and fund switching is a reliable way to ascertain whether the

[6] The dataset used meets four of the five criteria put forth by Campbell (2006) that makes an ideal dataset, in that it is representative of the entire population, covering age and wealth; it contains information on asset allocation; the data are reported with a high degree of accuracy; and the data cover behaviour over time.

investment choices of investors are related to past returns, because I am provided with at least two observations to test the same hypothesis.

This paper finds that past returns play a significant role in fund selection. I find that investors chase past returns, that is, select funds with the highest past performance out of the number of funds available to them in the fund family. Funds with relatively higher returns experience more fund enrolments from investors. For example, a 1% difference in annual fund returns increases fund enrolment by 1.6%, which is equivalent to 787 investors per year. Past returns could affect fund selection because investors pay attention to past returns and switch funds due to their perception that these returns will continue or past returns might be associated with changes in investor risk aversion, which causes investors to switch funds. Either way, past returns are significantly related to fund choice.[7] I find that investors tend to use a relatively longer time horizon of performance information on which to base their fund selection decisions. For instance, while monthly returns do not affect fund selection, quarterly, half-yearly, and annual returns have a significantly positive influence on fund choice.

This paper also finds that demographic characteristics affect fund choice. An investor's gender, age, and tax rate also significantly affect fund choice. Relatively older investors are risk averse and more likely to hold cash and conservative funds than balanced and growth funds. On the other hand, people in higher tax brackets and who are presumably wealthier are more risk seeking in their investment fund choices than those in lower income tax groups. Even when controlling for demographic characteristics, I find that past returns affect fund selection in a number of different ways. Some investors are more

[7] Risk aversion changes due to other factors can also affect fund choice. My study only focuses on fund choice driven by past returns (either through the risk aversion channel or otherwise). I discuss this in more detail with the results in Section 4.1.

likely to chase returns than others. I find that female investors, relatively younger investors, and those investors in higher income brackets are more sensitive to past returns and prone to chase returns.

Younger investors are more likely to choose funds with higher relative returns and favour more exposure of equity in investment funds over cash and fixed interest investments. The link between investor wealth and past returns is less persistent. I find evidence that investors in lower tax brackets tend to be more sensitive to changes in relative returns. In other words, for the same return differential between funds, younger investors are more likely to choose the investment with higher relative returns. Return chasing during fund switches (i.e. subsequent fund choices beyond the initial enrolment into KiwiSaver) is dependent on the initial fund choice. For instance, I find that investors holding balanced funds exhibit stronger return chasing behaviour. Investors previously holding cash and conservative funds are relatively less likely to be influenced by past returns.

Does it pay off to switch funds based on past performance? I test whether switching leads to higher returns ex post. The results do not provide any evidence to suggest that investors earn higher returns after changing investment funds. While this is not the focus of this study, there is a large field of literature that shows the existence of a smart money effect. The smart money effect is when mutual fund money flows to funds that perform better after the money arrives, displaying the superior fund selection abilities of investors (Gruber, 1996; Zheng, 1999; Sapp & Tiwari, 2004; Keswani & Stolin, 2008). A plausible reason for the difference in results could be that the smart money effect usually encapsulates the behaviour of relatively more sophisticated investors, such as institutional investors, whose focus on fund selection and past returns may be entirely different. Thus,

the role of past returns may form only one portion of the overall smart money effect. Another reason for the difference in results could be that investors pay attention to past returns and switch funds due to their perception that these returns will continue or past returns affect changes in investor risk aversion, which causes investors to switch funds.[8]

2.2 KiwiSaver institutional features, investor inertia, and the 2008 global financial crisis

The New Zealand government introduced the KiwiSaver scheme in 2006 to encourage active retirement savings. Over 30% of the New Zealand population is involved in the KiwiSaver scheme (New Zealand Government Actuary, 2010; Morningstar, 2010) and the scheme accounts for approximately 10% of the managed funds industry by value of funds under management and represents one-quarter of New Zealand's superannuation assets (Reserve Bank of New Zealand, 2010). All New Zealanders aged 18 to 65 starting new jobs are automatically enrolled in this scheme. The compulsory opt-in and voluntary opt-out are unique features of the savings and investment scheme. Currently, it is the only auto-enrolment scheme in the world used on a national scale (O'Connell, 2009). Self-employed and unemployed individuals must choose their own schemes in KiwiSaver (New Zealand Inland Revenue Department, 2010a).

Since I am studying the impact of past returns on fund choice, it makes sense to focus on a period where past returns change a great deal in both directions. Given that the 2008 global financial crisis falls within my sample period, I have a natural experiment to test the role of past returns over periods of high volatility. My sample period begins in July

[8] Risk aversion changes due to other factors can also affect fund choice. Our study only focuses on fund choice driven by past returns (either through the risk aversion channel or otherwise). We discuss this in more detail in results Section 4.1.1.

2007, just prior to the global financial crisis.[9] The global financial crisis has been described as 'the worst financial crisis since the Great Depression' (Crotty, 2009, p.1). The ability of members to make appropriate investment decisions during the global financial crisis generated considerable discussion. I find that investors who joined KiwiSaver up to August 2007 are more likely to change funds than those newly joining the scheme after the global financial crisis. For instance, the fund switching activity of those members who joined prior to the global financial crisis is 5%, compared to the average switching activity taking place over the entire sample period of 1.1%. While the difference in absolute terms may seem minimal, the marginal difference is that investors who joined before the global finance crisis are five times more likely to change funds. Notably, however, among the total fund switches in my sample, over one-third (35%) of switches were undertaken by investors who joined KiwiSaver before the global financial crisis.[10] Further, the national fund switching activity is at 2.4%, which suggests that the likelihood of switching is broadly in line with fund changes, on average.[11]

In support of my findings, earlier studies also show investor inertia and low levels of investor choice and participation beyond the entrance into investment schemes.[12] For example, in the first three years following the introduction of a Swedish retirement plan scheme, the proportion of participants who made changes was, on average, 2.5%. Gerrans

[9] Griffiths, Kotomin, and Winters (2011) indicate the official commencement of the global financial crisis on 9 August 2007. Milunovich (2011) suggests phase 1 of the global financial crisis started on 20 August 2007.

[10] For robustness, I calculate fund switching proportional to enrolments and also adjust the global financial crisis period starting date to September 2008 (the collapse of Lehman Brothers, which is a commonly used event to mark the commencement). I expect more members joined KiwiSaver just prior to the global financial crisis because of the timing of KiwiSaver's introduction and, hence, expect these members to be well represented in the switching. Doing so, I find that 2.2% of investors who joined prior to September 2008 changed funds over my sample period.

[11] National switching activity is computed using statistics from the New Zealand Government Actuary (2010).

[12] Inertia is also found in US 401(k) investment schemes (Samuelson and Zeckhauser, 1988; Andersen & Zeldes, 2002).

(2010) finds that, while the overall percentage of people who change their balance or level of contribution to their retirement savings is low (6.5% across funds), 65% of changes occurred during the global financial crisis period, compared to 35% of changes in the pre-global financial crisis period. The parameters used in previous studies in this field differ from mine in a number of ways. For instance, Gerrans (2010) defines investor choices as an investor's change in the level of savings contributions and marks the time period of the global financial crisis differently. I focus specifically on the connection between past returns, fund selection, and switching behaviour.

Since the scheme applies to all New Zealanders, on average, the participants in my KiwiSaver dataset are relatively inexperienced investors. Studies suggest that the design features of retirement savings schemes affect the behaviour of investors (Gerrans & Yap, 2010) and that the timing of their introduction to a savings programme can significantly affect their asset allocation choices (Cronqvist & Thaler, 2004). Since the introduction of the scheme, a number of financial incentives have been provided to encourage involvement in KiwiSaver, including a NZ$1,000 tax-free 'kick-start' savings from the government, member tax credit (a payment from New Zealand Inland Revenue Department) of up to NZ$1,040 per year, and the potential of utilising a first-home deposit subsidy.[13] These incentives proved effective in attracting KiwiSaver enrolment. As shown in a New Zealand Inland Revenue Department (2008) survey, approximately one-third of the members who joined KiwiSaver in the first six months did so as a result of the financial incentive provisions.

[13] The member tax credit will be reduced to NZ$521 per year from 30 June 2012 (New Zealand Parliament, 2011).

KiwiSaver contributions are locked in until the member reaches retirement age (65 years old). Members can, however, make withdrawals to purchase a first home or for reasons such as illness, financial hardship, or absence from New Zealand (New Zealand Inland Revenue Department, 2010b). As of 1 April 2008, employers are required to make compulsory matching contributions, starting at a minimum of 1% of the employee's gross salary and increasing by 1% each year. Employer contributions were reduced to a fixed 2% in November 2008 and the New Zealand government increased the contribution rate to 3% from 1 April 2013.[14]

There are three ways for members to join KiwiSaver. Investors can join a scheme through a provider company of their choice, through a provider selected by their employer, or through auto-enrolment by the New Zealand Inland Revenue Department on their behalf. The third alternative is used if the individual does not meet the first two options. Members who do not choose a scheme are placed in one of the six default providers (New Zealand Inland Revenue Department, 2010b). As of 30 June 2010, six default providers and 54 registered schemes operate in New Zealand. Once in a scheme, investors choose investment funds options, which are open-end mutual funds. Funds are similar to mutual funds and vary in asset allocation. When members join schemes through auto-enrolment, the conservative fund option is normally chosen by default.

2.3 Data and methodology

I use the individual investment fund choices of 196,513 investors from a large non-default KiwiSaver provider over the period from October 2007 to November 2010.

[14] See http://www.beehive.govt.nz/release/fact-sheet-%E2%80%93-kiwisaver-changes.

Choosing funds offered by the same provider has an advantage in that factors that have been shown to determine fund flows, such as advertising, fees, and expenses, are standardised across funds, so these do not drive the results.[15] Furthermore, the importance of data coming from a non-default provider is that the investors did not automatically enter these funds but, instead, made a choice to do so.[16]

The data contain information on participants' gender, age, tax code, initial fund choice from October 2007 to December 2010, and additional fund choices where investors chose to switch funds. In my sample, investment fund switching did not commence until January 2008. The four fund options available in my sample are cash, conservative, balanced, and growth funds. All investments are multi-sector funds, with the exception of the cash fund. The asset allocations of investment funds are shown in Table 2.1.

Table 2.1 Investment fund asset allocation

	Cash	Conservative	Balanced	Growth
Cash	100%	30%	5%	5%
NZ Fixed Interest		30%	20%	11%
International Fixed Interest		15%	12%	7%
Listed Property		5%	5%	10%
NZ Shares		10%	20%	25%
International Shares		10%	33%	38%
Alternative Investments			5%	5%

I source investment fund asset allocation information from a large non-default KiwiSaver provider.

Table 2.2 provides summary statistics of investor demographics and fund switches. The ratio of males to females is evenly split (48% male and 52% female). As shown in Table 2.2, the conservative fund is the most popular choice, with 49% of total investors

[15] Fund administration fees are constant across all funds. Fund management increases with fund choice riskiness. Fees are 30, 55, 65, and 70 basis points of funds under management for cash, conservative, balanced, and growth funds, respectively. To the best of my knowledge, fund management fees are in line with the industry average for all KiwiSaver funds (Jain & Wu, 2000; Cooper, Gulen & Rau, 2005; Khorana, Servaes, & Wedge, 2007).

[16] In my sample, 7% of the participants joined KiwiSaver passively through their employer, compared to the national average of 15%. Calculations are based on statistics from New Zealand Inland Revenue's (2009) September evaluation survey.

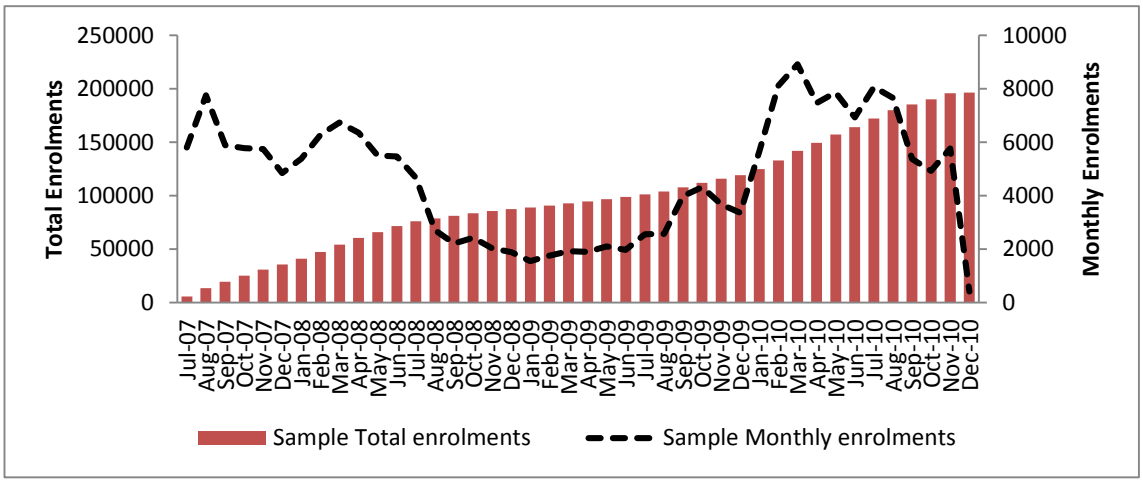
in my sample choosing this fund. Fund enrolment trends between my sample and the national KiwiSaver enrolment pattern are shown in Figure 2.1 and 2.2.

Table 2.2 Summary statistics for investor demographics and fund switches

Gender		Male (%)	Female (%)	Total
Cash		0.44	0.56	26,005
Conservative		0.47	0.53	97,167
Balanced		0.48	0.52	39,881
Growth		0.52	0.48	33,460
Total		93,965	102,548	196,513
Tax Group		Low (%)	Middle (%)	High (%)
Cash		0.19	0.63	0.18
Conservative		0.15	0.55	0.30
Balanced		0.19	0.57	0.24
Growth		0.25	0.53	0.22
Total		35,165	110,028	51,320
Age	<15 (%)	15-39 (%)	40-59 (%)	60+ (%)
Cash	0.22	0.28	0.26	0.23
Conservative	0.24	0.38	0.28	0.10
Balanced	0.27	0.36	0.31	0.06
Growth	0.42	0.36	0.19	0.03
Total	53,778	71,227	52,833	18,675
Switches		Into (%)	Out of (%)	Net (%)
Cash		0.33	0.16	0.17
Conservative		0.15	0.47	-0.32
Balanced		0.19	0.21	-0.02
Growth		0.33	0.16	0.18
Total		2,129	2,129	

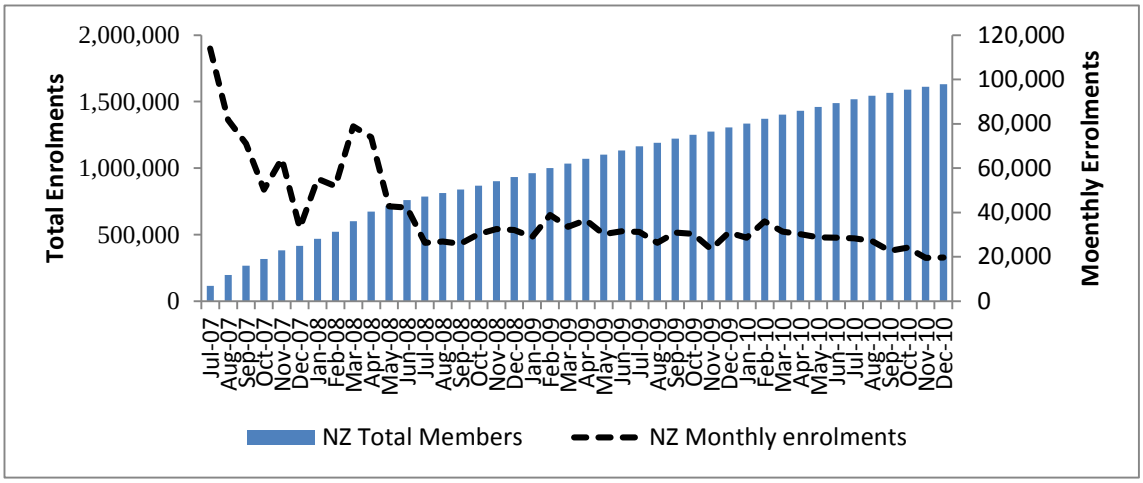
I source individual investor data from a large non-default KiwiSaver provider covering the period July 2007-December 2010.

Figure 2.1 Sample KiwiSaver fund enrolment July 2007- December 2010



Distribution of KiwiSaver sample fund enrolments and monthly enrolments

Figure 2.2 New Zealand KiwiSaver fund enrolment July 2007- December 2010



Source: Ministry of Economic Development (2011).

In addition, fund switching activity indicates that the most popular fund to switch into was the growth fund (making up 33% of switches into a fund) and the least popular fund to remain in was the conservative fund (46% of switches out of a fund). Since the conservative fund has, however, the highest number of investors in total, accurate interpretations cannot be made by observing fund switching trends alone. Fund switching from one fund to another on day *t* may be primarily affected by relative returns several months prior to the time when the fund switch is recorded. Therefore, the decision to change investment funds is unobservable until the transaction is processed. For this reason, I use a combination of return intervals to account for the time between past returns

and fund switching. I match lagged fund relative returns with monthly fund switching activity. This enables us to detect the influence of returns on investors who may take longer periods to respond to past relative returns since the decisions to change funds may manifest over time.

I obtain monthly, quarterly, half-yearly, and annual fund returns data from the Morningstar database from October 2007 to December 2010. The investment funds offered in my sample are indicative of the broad spectrum of all mutual fund products and, in some cases, are identical in asset class allocation. For instance, in a balanced fund, the proportion of equity to bonds, property, and cash asset allocation mirrors the industry average of other balanced funds in asset allocation. I compare the performance of funds selected by investors in my sample with the performance of other KiwiSaver funds. I find the returns of funds included in my sample to be representative and report the average monthly investment fund returns over my sample period in Table 2.3. I also obtain stock market returns of the New Zealand Stock Exchange (NZX50) Total Returns Index and the Dow Jones Total Returns Index from July 2006 to December 2011 from *Datastream* and the three-month New Zealand Treasury bill rate and the three-month US Treasury bill rate over the same period from *Global Financial Data*. I use these stock market indices' returns and Treasury bill rates as a check for robustness in later sections.

Table 2.3 A summary of monthly investment fund returns (October 2007- December 2010)

	Cash	Conservative	Balanced	Growth
Mean	0.333	0.28	0.105	-0.003
Median	0.267	0.423	0.259	0.239
Maximum	0.731	2.196	4.465	5.369
Minimum	-0.029	-2.208	-4.659	-5.6
Std. Dev.	0.168	1.007	2.369	2.857
Skewness	0.866	-0.642	-0.325	-0.329
Kurtosis	3.407	3.218	2.756	2.798
Observations	38	38	38	38

This table shows the summary statistics of monthly returns from October 2007 to December 2010 for the cash, conservative, balanced and growth fund. Returns are obtained from Morningstar and are reported net of fees.

It is imperative to consider the relation between fund choice and past returns over several intervals, because the results in many finance areas are sensitive to the interval of observation. Therefore, including various data frequencies can verify the robustness of results (Hong & Stein, 1999; Driesprong, Jacobsen & Maat, 2008; Berkman & Truong, 2009). Previous studies on the choice of individual retirement savings, such as that of Clark-Murphy, Gerrans, and Speelman (2009), also report similar return intervals. In addition, as a test for robustness, I use equity index returns to determine whether past returns of equity markets generally affect fund choice. If, for some reason, investors do not follow their investment fund returns but, instead, pay attention to the returns of the New Zealand stock market index (NZX50) and Dow Jones Index listed each night on the daily 6 p.m. news to gauge fund performance, then the use of alternative returns will provide further insight into the link between past returns and fund choice.

To test the effect of past fund relative returns on investment fund enrolment, I estimate the following regression:

$$Change\ in\ Enrolment\ Fraction_{i,t} = \alpha + \beta_1 Relative\ Return_{ij,t-1} + \varepsilon_{i,t} \quad (1)$$

where $Change\ in\ Enrolment\ Fraction_{i,t}$ is the difference between the monthly enrolment fraction for fund *i* and the average enrolment fraction of fund *i* over the sample period from July 2007 to December 2010; α is the constant term; $Relative\ Return_{i,t-1}$ is the lagged relative return for fund i, which is calculated as the return of fund *i* minus the maximum return among the alternative funds *j* at time *t* - 1; and $\varepsilon_{i,t}$ is the error term. I run all ordinary least squares models with Newey-West standard errors with 1, 3, 6 and 12-period lags respectively for monthly, quarterly, half yearly and annual returns. Using Newey-West standard errors can correct the effects of correlation in the error terms in

regressions applied to time series data. The estimator is used to try to overcome autocorrelation and heteroskedasticity in the error terms in the model.

The model used in Equation 1 tests if funds with the highest *relative* past return experiences a positive inflow of enrolments in the period following large differentials between fund *i* (the chosen fund) and fund *j* (the highest of the alternative choices). A key assumption made is that people in the KiwiSaver population are relatively naïve or relatively unsophisticated investors, therefore, if investors are 'return chasing' then the fund with the highest relative past return should have more people joining that fund than on average.

To differentiate between return chasing in the initial fund choice at enrolment and subsequent changes to fund choice, I use the following regression to test the relation between fund switching and relative returns:

$$Switch\ Activity_{ij,t} = \alpha + \beta_1 (X_j - X_i)_{t-1} + \varepsilon_{i,t}, \quad (2)$$

where $Switch\ Activity_{ij,t}$ is the monthly proportion of switching from fund *i* to fund *j* out of the total number of switches taking place in month *t*, α is the constant term, $X_j - X_i$ measures the difference in past returns between the new fund X_j and the old fund X_i, and $\varepsilon_{i,t}$ are Newey-West standard errors with 1, 3, 6 and 12-period lags respectively for monthly, quarterly, half yearly and annual returns. The question that ultimately the model shown in Equation 2 is trying to answer is whether investors switch funds from lower returning fund to higher ones? The main variable of interest in this model is the sign of the coefficient which shows whether the difference in past returns between the new fund and old fund is funds is positive or negative. If investors are chasing past returns when switching funds then the difference in returns between funds should be positive.

To confirm the role of investor demographics on fund choice I test the influence of gender, age, and tax group on the asset allocation of the fund choice selected by the investor using an ordinary least squares regression:

$$AssetAllocation_{ij} = \alpha_i + \beta_1 Female_i + \beta_2 Age_{it} + \beta_3 Tax\ Rate_i + \varepsilon_i \qquad (3)$$

where $AssetAllocation_{ij}$ represents the percentage of assets held in asset class *i* out of *j* asset categories available (where *j* = 4 the asset classes are cash, bonds, property and equity). The term α_i is the constant term; $Female_i$ is a dummy variable equal to one if the KiwiSaver member is female; Age_{it} represents the age of the investor in years; $Tax\ Rate_i$ is the tax rate of the investor; and ε_i is the error term. I also use White robust standard errors to control for heteroskedasticity.

To test the robustness of return chasing and to control for the effects of demographic characteristics, I use the following regression:

$$Change\ in\ Enrolment\ Fraction_{i,t} = \alpha + \beta_1 Relative\ Return_{ij,t-1} + \beta_2 Female_{ij,t} + \beta_3 Age_{ij,t} + \beta_4 Tax_{ij,t} + \varepsilon_{i,t,} \qquad (4)$$

where the variables are the same as in Equation 1, $Female_{i,t}$ is the percentage of females joining fund *i* in month *t* , $Age_{i,t}$ is the average age of investors joining fund *i* in month *t*, Tax_{it} is the average tax rate of investors joining fund *i* in month *t*, and ε_i are Newey-West standard errors with 1, 3, 6 and 12-period lags respectively for monthly, quarterly, half yearly and annual returns.

To measure whether investor demographic characteristics affect the propensity to chase returns, I add interaction terms in the following regression to capture this effect, if any:

$$Change\ in\ Enrolment\ Fraction_{i,t} = \alpha + \beta_0 RR_{ij,t-1} + \beta_1 Female_{ij,t} + \beta_2 Age_{ij,t} + \beta_3 Tax_{ij,t} + \gamma_1 RR_{ij,t-1} * Female_{ij,t} + \gamma_2 RR_{ij,t-1} * Age_{ij,t} + \gamma_3 RR_{ij,t-1} * Tax_{ij,t} + \varepsilon_{i,t}, \quad (5)$$

where the variables are the same as in Equations (1) and (4), $RR_{ij,t-1} * Female_{ij,t}$ is an interaction term between $Relative\ Return_{i,t-1}$ and the percentage of female enrolments in month t, $RR_{ij,t-1} * Age_{ij,t}$ is the interaction between relative returns and the average age of enrolments in month t, $RR_{ij,t-1} * Tax_{\mathrm{ij,t}}$ is the interaction term between relative returns and the average tax rate of enrolments, and $\varepsilon_{\mathrm{i,t}}$ are Newey-West standard errors with 1, 3, 6 and 12-period lags respectively for monthly, quarterly, half yearly and annual returns.

2.4 Results

2.4.1 Univariate results

2.4.1.1 Past returns and enrolment

Fund enrolments are the investment fund choices selected when KiwiSaver members first join the scheme. Table 2.4 shows the effect of past returns on fund choice and how relative returns between funds can affect enrolment fund selection.

Table 2.4 Past returns: Fund enrolments

Panel A: Pooled Enrolments				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarterly	Half-year	Annual
Returns	-0.006	0.012**	0.018***	0.016***
	(-0.599)	(1.994)	(5.026)	(7.840)
Constant	-0.038*	-0.001	0.025	0.053***
	(-1.714)	(-0.062)	(1.131)	(2.870)
Observations	152	140	128	112
Panel B: Enrolments by Fund				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarterly	Half-year	Annual
Cash Fund				
Returns	-0.034	-0.006	0.005	0.011***
	(-1.580)	(-0.531)	(1.034)	(7.026)
Constant	-0.042	0.014	0.043	0.078**
	(-0.800)	(0.330)	(0.922)	(2.319)
Observations	38	35	32	28
Conservative Fund				
Returns	-0.013	-0.005	-0.003	-0.005
	(-1.383)	(-0.364)	(-0.555)	(-0.822)
Constant	-0.002	-0.002	-0.006	-0.0344***
	(-0.108)	(-0.0447)	(-0.225)	(-3.492)
Observations	38	35	32	28
Balanced Fund				
Returns	-0.002	0.025***	0.025***	0.014***
	(-0.245)	(3.338)	(6.355)	(3.792)
Constant	-0.049	0.008	0.037	0.039
	(-1.479)	(0.232)	(1.027)	(1.472)
Observations	38	35	32	28
Growth Fund				
Returns	0.012	0.017	0.024***	0.019***
	(0.738)	(1.621)	(4.053)	(9.019)
Constant	-0.052	-0.034	0.010	0.062*
	(-1.165)	(-0.536)	(0.155)	(1.976)
Observations	38	35	32	28

This table reports the results of the OLS regression of past returns on investment fund enrolment from Equation 1. I use Morningstar investment fund return data from July 2007 – December 2010. Monthly, quarterly, half-yearly and annual returns are calculated on a rolling basis.

$Change\ in\ Enrolment\ Fraction_{i,t} = \alpha + \beta_1 Relative\ Return_{ij,t-1} + \varepsilon_{i,t}$,

where $Change\ in\ Enrolment\ Fraction_{i,t}$ is the difference between the monthly enrolment fraction for fund *i* and the average enrolment fraction of fund *i* over time, α is the constant term, $Relative\ Return_{i,t-1}$ is the lagged relative return for fund *i*, which is calculated by the return of fund *i* minus the maximum return among the alternative funds *j* at time *t-1*, and $\varepsilon_{i,t}$ are the Newey-West standard error terms. Panel A shows the pooled fund choice of all investment funds, and Panel B shows the change in fund enrolment by individual fund. The t-statistic relates to the null hypothesis that the mean equals zero. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

My results show a positive and significant relation between past fund returns and investment fund choice. The positive relation suggests that investors chase returns; however, past returns can affect fund choice through two channels. One scenario is that past returns directly affect fund choice and investor risk aversion remains constant.

Another scenario is that past returns affect changes in risk aversion, which affects fund choice. In both cases, past returns drive fund choice. Harrison et al. (2005), Andersen et al. (2008) and Sahm (2007) provide empirical evidence that risk aversion is stable over time. While risk tolerance differs greatly across individuals, stemming from characteristics such as gender and ethnicity, risk tolerance is unaffected by changes in income and wealth. Aging and changes in macroeconomic conditions provide some systematic changes in an individual's risk tolerance; however, major life events (such as job loss and health issues) do not permanently alter willingness to take risks (Sahm, 2007). Harrison et al. (2005) and Andersen et al. (2008) find that preferences are stable over seven-month and 17-month time separations, respectively.

On the other hand, Blackburn, Goetzmann, and Ukhov (2007) find that changes in risk aversion are related to past returns. Similarly, Strahilevitz, Odean, and Barber (2011) also highlight that people become more risk averse after trading stocks as a result of past returns. Using brokerage account data, the authors show investors have a propensity to repurchase individual stocks they previously sold at a gain and to avoid stocks they sold for a loss. Whether people chase returns (by choosing funds with high past returns relative to funds with low past returns) or past returns affect fund choice via changes in risk aversion, my results show that investors do pay attention to past returns when selecting investment funds.

There is no precedent for how to separately measure the influence of risk aversion and that of past returns. I am not denying that risk aversion may affect fund choice on its own accord. People can change funds due to changes in risk aversion, just as people can change funds due to the influence of friends or family, advertising, fees, or other reasons.

Changes can occur in investment choice without changes in return; however, this is not the focus of my study.

My results reveal that, on average, fund enrolments are affected by medium- to long-term returns rather than short-term returns. Monthly returns do not appear to drive fund choice; however, quarterly, half-yearly, and annual returns are positively related to fund selection. As shown in Table 2.4 Panel A, when fund enrolments are pooled together, a 1% difference in annual relative returns increases the selection of funds by 1.6%, which translates to approximately 787 additional investors per year.

By analysing fund choice individually, I notice that the relation between funds and past returns differs. For instance, the selection of balanced and growth funds is most affected by quarterly, half-yearly, and annual returns, while the selection of the conservative fund is not affected by past relative returns over any period, as indicated by the insignificant coefficients in Table 2.4 Panel B. This finding suggests that people choosing the conservative fund do so regardless of the fund's past returns. I find that enrolment into the cash fund is positively related to annual past returns, however, are unrelated to returns over the shorter term such as monthly, quarterly and half-yearly returns. This may be attributed to investors focusing more on long-term performance or perhaps, regardless of past returns, some investors will always prefer cash. Nearly all KiwiSaver investment statements and information packages provided by KiwiSaver providers emphasise the importance of understanding short-term return volatility. Clark-Murphy, Gerrans, and Speelman (2009) find that switching funds based on 12-month returns consistently generates differences in returns between new and old funds. This contrasts with monthly returns, where the results are more inconsistent. Therefore, my results may indicate that investors value long-term returns, relatively speaking. Another

explanation for a negative relation observed in the cash fund and no relation observed in the conservative fund may be that extremely risk-averse investors favour the cash and conservative funds. Due to their being the safer investment options, these funds are selected regardless of the returns generated.

The relation between past returns and fund choice is strongest among balanced funds investors. Table 2.4 Panel B, shows that quarterly and half yearly returns trigger the largest change in fund enrolment, where, on average, a 1% difference leads to a 2.5% fund enrolment increase in any given month. At the time this paper is written, the average investor has NZ$5,000 invested in his or her account, therefore this could translate to approximately NZ$7.4 million worth of fund flow for the balanced option.[17]

2.4.1.2 Switching

I also explore the relation between fund switching and past returns. Table 2.5 indicates that past fund returns are positively related to fund choice over quarterly and annual intervals, but not at the monthly or half-year level. This means that on average investors are moving into funds with higher past returns and when the difference in past returns is relatively larger, more fund switching occurs. Interestingly, the significance of quarterly and annual results coincide with which the frequency which the KiwiSaver provider in my sample sends fund performance statements to investors, over quarterly and annual intervals. This potentially reveals the importance of performance statements and the frequency which returns are communicated to investors.

[17] The average KiwiSaver account was NZ$2,650 in 2009 and NZ$5,800 in 2011 (Parker, 2009; Bond, 2011).

Table 2.5 Past returns: Fund switches

Panel A: Pooled Switches – all switches				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarterly	Half-Year	Annual
Period Return	0.102	0.332**	0.201	0.209**
	(0.406)	(2.100)	(1.581)	(2.051)
Constant	0.083***	0.083***	0.083***	0.083***
	(16.34)	(12.80)	(10.44)	(8.628)
Observations	420	420	420	420
Panel B: Switches by fund				
Switch Direction	(1)	(2)	(3)	(4)
	Monthly	Quarterly	Half-Year	Annual
Switch into Cash Fund				
Conservative Fund	-0.261	1.676	1.269	0.640
	(-0.133)	(1.643)	(1.248)	(1.038)
Constant	0.157***	0.156***	0.159***	0.163***
	(5.843)	(4.954)	(4.704)	(4.309)
Balanced Fund	-0.227	0.278	-0.006	0.061
	(-0.326)	(0.818)	(-0.0227)	(0.260)
Constant	0.102***	0.099***	0.101***	0.101***
	(6.184)	(4.774)	(4.285)	(4.667)
Growth Fund	1.083*	0.858**	0.445**	0.468***
	(1.824)	(2.524)	(2.319)	(3.141)
Constant	0.090***	0.084***	0.089***	0.090***
	(6.249)	(5.933)	(4.875)	(8.170)
Switch into Conservative Fund				
Cash Fund	0.772	1.232***	0.773***	0.476***
	(1.294)	(4.161)	(3.643)	(3.576)
Constant	0.038***	0.039***	0.037***	0.0349***
	(4.628)	(5.153)	(4.354)	(3.402)
Balanced Fund	-0.433	0.014	0.122	0.132
	(-1.013)	(0.0773)	(0.747)	(1.192)
Constant	0.050**	0.049***	0.048***	0.048***
	(8.170)	(6.925)	(6.731)	(7.536)
Growth Fund	0.174	0.160	0.154	0.137
	(0.482)	(0.868)	(1.364)	(1.437)
Constant	0.055***	0.054***	0.054***	0.054***
	(8.007)	(6.040)	(5.636)	(6.038)
Switch into Balanced Fund				
Cash Fund	0.468*	0.436***	0.355***	0.207***
	(1.801)	(2.863)	(3.194)	(3.588)
Constant	0.040***	0.042***	0.040***	0.039***
	(4.138)	(3.861)	(3.569)	(3.170)
Conservative Fund	-1.168	-0.375	-0.203	-0.006
	(-1.277)	(-1.057)	(-0.759)	(-0.025)
Constant	0.114***	0.113***	0.114***	0.115***
	(9.754)	(8.289)	(8.278)	(9.642)
Growth Fund	-0.634	-0.217	0.116	0.358**
	(-1.522)	(-0.882)	(0.638)	(2.676)
Constant	0.021***	0.021***	0.020***	0.018***
	(4.915)	(3.959)	(4.226)	(4.773)
Switch into Growth Fund				
Cash Fund	0.117	0.185	0.259***	0.221***
	(0.285)	(1.205)	(2.775)	(3.352)
Constant	0.074***	0.076***	0.076***	0.075***
	(5.796)	(5.408)	(6.681)	(7.123)
Conservative Fund	-0.554	0.229	-0.077	0.292
	(-0.703)	(0.503)	(-0.294)	(1.014)
Constant	0.187***	0.191***	0.188***	0.193***
	(12.11)	(10.73)	(10.30)	(16.55)
Balanced Fund	1.493	1.635*	0.986	1.084**
	(0.882)	(1.793)	(1.330)	(2.481)
Constant	0.066***	0.070***	0.069***	0.0726***
	(5.306)	(4.707)	(4.446)	(4.402)
Observations	35	35	35	35

This table contains the results of the OLS regression of past returns' effects on fund switching from Equation 2. I use Morningstar investment fund return data from December 2007- December 2010. The return series used in this table is shorter, because fund switching did not commence until January 2008. Monthly, quarterly, half-yearly and annual returns are calculated on a rolling basis. $Switch\ Activity_{ij,t} = \alpha + \beta_1(X_j - X_i)_{t-1} + \varepsilon_{i,t}$, where $Switch\ Activity_{ij,t}$ is the monthly proportion of switching from fund *i* to fund *j* out of the total number of switches taking place in month *t*, α is the constant term, $X_j - X_i$ measures the difference in past returns between the new fund X_j and the old fund X_i, and $\varepsilon_{i,t}$ are the Newey-West standard error terms. Panel A shows the pooled fund switches between all fund switching combinations and Panel B shows fund switching observations by individual switch combinations. The t-statistic relates to the null hypothesis that the mean equals zero. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

I find that past returns affect individual fund switching combinations considerably more than in fund enrolments and pooled switched results, as evidenced by the larger coefficients. Table 2.5 Panel B, shows the relation between relative returns and the likelihood of switching between two specific funds, such as from cash to growth fund.

The results in Panel B allow us to extrapolate the relation between fund choice and relative returns between fund options. For example, I find that a 1% difference in quarterly returns of the balanced and growth funds increases fund switching activity from balanced funds to growth funds by 1.635 times. It seems that investors who switch funds pay attention to differences between fund returns. I find that all coefficients in Panel B of Table 2.5 have positive coefficients. This suggests that investors who switch funds on my sample are chasing past returns. Fund switching activity increases when the difference in fund returns between the new fund and old fund choice is relatively larger.

For robustness, I also test the relation between fund switching and general equity market returns. Since I cannot ensure that all investors have access to the same set of Morningstar investment fund returns, I replace fund returns with stock market indices of the New Zealand Stock Market Index (NZX50) and the Dow Jones Returns Index. I investigate whether investors might gauge their fund performance in relation to how equity markets are performing and whether equity returns, more generally, induce fund switching. I find that fund switching to funds with increased riskiness is positively related to the returns of stock market indices (e.g. fund switches from cash to growth).

Table 2.6 Stock market index returns and fund switches

Panel A: Pooled Switches – New Zealand Stock Market Index				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarter	Half-Year	Annual
Fund risk profile increase	1.060*	1.143**	1.134***	0.737***
	(1.716)	(2.456)	(3.569)	(4.069)
Constant	0.571***	0.593***	0.610***	0.597***
	(9.091)	(8.225)	(9.392)	(9.666)
Fund risk profile increase	-1.060*	-1.143**	-1.134***	-0.737***
	(1.716)	(2.456)	(3.569)	(4.069)
Constant	0.428**	0.406***	0.389***	0.402***
	(6.823)	(5.626)	(5.995)	(6.515)
Observations	35	35	35	35
Panel B: Pooled Switches – Dow Jones Stock Market Index				
Fund risk profile increase	0.324	0.506	0.593**	0.483***
	(0.700)	(1.247)	(2.379)	(6.019)
Constant	0.523***	0.529***	0.533***	0.535***
	(10.04)	(7.964)	(8.092)	(8.793)
Fund risk profile increase	-0.324	-0.506	-0.593**	-0.483***
	(-0.701)	(-1.248)	(-2.381)	(-6.020)
Constant	0.476***	0.471***	0.467***	0.464***
	(9.142)	(7.091)	(7.092)	(7.626)
Observations	35	35	35	35

This table contains the results of the OLS regression of past returns' effects on fund switching from Equation 2. I use the NZX50 Total Returns Index and Dow Jones Total Returns Index, as well as the three-month New Zealand Treasury Bill and three-month US Treasury Bill rates from July 2006- December 2010. Returns are calculated on a rolling basis at monthly, quarterly, half-yearly and annual intervals. $Switch\ Activity_{ij,t} = \alpha + \beta_1(X_j - X_i)_{t-1} + \varepsilon_{i,t}$, where $Switch\ Activity_{ij,t}$ is the monthly proportion of switching from fund *i* to fund *j* out of the total number of switches taking place in month *t*, α is the constant term, $X_j - X_i$ measures the difference in past returns between the stock market index X_j and the three-month Treasury Bill rate X_i, and $\varepsilon_{i,t}$ are the Newey-West standard error terms. Fund risk profile increase means the investor switches from a fund with more risky assets (equity) and a fund risk profile decrease means moving to a fund with less risky assets as measured by asset allocation. Panel A shows the pooled fund switches between all fund switching combinations and Panel B shows fund switching observations by individual switch combinations. The t-statistic relates to the null hypothesis that the mean equals zero. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2.6 Panel A, shows fund switches decreasing in risk profile, such as switches from growth to conservative, increase when the New Zealand Stock Market Index underperforms the New Zealand three-month Treasury bill rate. These results suggest that when equity markets are performing well, investors are more likely to switch into funds with higher risk profiles and more equity exposure. When equity returns are low, investors are more likely to select safer funds, such as cash or relatively conservative options. This may partly explain why the conservative fund was the most popular choice (49% of investors in my sample) during the global financial crisis period, when equity

underperformed relative to other asset classes. I also run the same regression using the Dow Jones Total Returns Index, as shown in Panel B of Table 2.6. Note that the relation between equity index returns and fund switching is similar between the New Zealand Stock Market Index and the Dow Jones Total Returns Index; however, the Dow Jones has smaller coefficients and only returns over the half-yearly and annual periods are statistically significant. This result suggests that investors are more affected by returns in the New Zealand equity market than the US equity market. The results support my univariate analysis that past returns over a one-year period affect fund selection.

2.4.2 Fund choice and demographic characteristics

The next relation I explore is between investor demographic characteristics and the asset allocation choice of investors, a measure of fund riskiness. Table 2.7 shows the relation between age, gender, and personal investor tax rate and asset allocation of the funds selected by investors. I find that age is negatively related to equity investment and positively related to cash investment. A plausible reason explaining this is that either older people are more risk averse, or perhaps it is simply that my results reflect the fact that older investors have less human capital than younger investors and therefore choose to invest more conservatively. I find that women are more risk averse than men in their asset allocations as indicated by their negative coefficient signs. Females also show to hold less in property and equity assets than men by -0.002 and -0.014, respectively. This finding is in line with previous literature which show that women tend to hold relatively safer assets than men.[18] I also find that investors' personal income tax rate is negatively related to both cash and equity asset clashes. This suggests that people with relatively higher tax rates hold smaller proportions of cash and equity assets and more in bonds and property

[18] See Bajtelsmit, Bernasek & Jianakoplos, 1999; Hinz, McCarthy, & Turner, 1997; Bernasek & Shwiff, 2001; Watson & McNaughton, 2007.

assets. It could suggest that investors in the highest tax rates are not necessarily using KiwiSaver as their main investment savings vehicle for retirement since previous literature tends to show that people with greater wealth are more likely to invest in stocks and equity related products than people with less wealth as the literature suggests (Agnew & Szykman, 2005; Van Rooij, Lusardi, & Alessie , 2011; Lusardi & Mitchell, 2007).

Table 2.7 Demographics and asset allocation

VARIABLES	(1) cash	(2) bonds	(3) property	(4) equity
age	0.002***	-0.0003***	-0.0003***	-0.002***
	(64.23)	(-14.26)	(-82.20)	(-68.21)
female	0.014***	0.002***	-0.002***	-0.014***
	(10.86)	(2.934)	(-14.11)	(-13.91)
taxrate	-0.025***	0.028***	0.001***	-0.005***
	(-24.68)	(50.84)	(14.78)	(-5.685)
Constant	0.271***	0.264***	0.058***	0.407***
	(114.1)	(208.0)	(252.2)	(207.9)
Observations	196,513	196,513	196,513	196,513

This table reports the results from the ordinary least squares regression model the relation between demographics and asset allocation of funds.
$AssetAllocation_{ij} = \alpha_i + \beta_1 Female_i + \beta_2 Age_{it} + \beta_3 Tax\ Rate_i + \varepsilon_i$. Where $AssetAllocation_{ij}$ represents the percentage of assets held in asset class *i* out of *j* asset categories available (where *j* = 4 the asset classes are cash, bonds, property and equity). The term α_i is the constant term, $Female_i$ is a dummy variable equal to 1 if the KiwiSaver member is female, Age_i is the age of the investor in years, Tax_i is the tax rate of investors and ε_i are White Heteroskedasticity-consistent standard errors. The p-value relates to the null hypothesis that the mean equals zero. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

2.4.3 Past returns and demographic characteristics as robustness checks

Since results from Table 2.7 show that demographics affect fund choice, I must control for these effects in my main model. Table 2.8 shows that, after controlling for the gender, age, and wealth of investors, the positive link between past returns and fund choice prevails. Panel A in Table 2.8 shows that a 1% difference in relative returns over the half-yearly and annual periods increases fund enrolment by 1.7 and 1.6%, respectively. What is interesting to note is that in the presence of past returns personal demographic characteristics are no longer statistically significant. We can see that the coefficients for age, gender and investor personal income tax are all insignificant in the pooled model

presented in Panel A of Table 2.8. As we move to Panel B we find similar results however age and gender roles become significant again for the cash, conservative and growth fund. For example, across all return series displayed in Table 2.8 females are more likely to enrol into the cash fund and less likely to enrol into the conservative and growth fund.

Table 2.8 Past returns, investor demographics and fund choice

Panel A: Pooled Enrolments				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarterly	Half-year	Annual
Returns	-0.007	0.011*	0.017***	0.016***
	(-0.655)	(1.881)	(4.801)	(9.421)
Female	0.008	0.007	0.005	0.004
	(0.954)	(1.008)	(0.707)	(0.844)
Age	0.0008	0.003	-0.003	-0.010
	(0.100)	(0.334)	(-0.329)	(-1.456)
Tax	-0.036	-0.034	-0.007	0.020
	(-1.408)	(-1.197)	(-0.304)	(1.188)
Constant	0.201	0.153	-0.007	-0.280
	(0.344)	(0.246)	(-0.0145)	(-0.720)
Observations	152	140	128	112
Panel B: Enrolments by Fund				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarterly	Half-year	Annual
Cash Fund				
Returns	-0.035	-0.002	0.003	0.005**
	(-1.565)	(-0.273)	(0.859)	(2.763)
Female	0.033*	0.027**	0.026***	0.015***
	(1.915)	(2.606)	(2.923)	(3.849)
Age	-0.007	0.011	0.013	0.007
	(-0.433)	(1.431)	(1.424)	(0.689)
Tax	0.036	0.022	0.018	0.033
	(0.997)	(1.359)	(0.849)	(1.227)
Constant	-2.232**	-2.188***	-2.126***	-1.615***
	(-2.675)	(-4.317)	(-5.073)	(-4.655)
Observations	38	35	32	28
Conservative Fund				
Returns	-0.007	0.009	0.008**	-0.003
	(-1.071)	(1.249)	(2.426)	(-1.495)
Female	-0.013***	-0.010***	-0.011***	-0.011***
	(-3.318)	(-3.731)	(-3.945)	(-4.436)
Age	0.004	0.007	0.004	0.010
	(0.888)	(1.368)	(0.607)	(1.306)
Tax	0.041**	0.039**	0.050**	0.019
	(2.461)	(2.338)	(2.424)	(0.647)
Constant	-0.258	-0.419	-0.462	-0.112
	(-0.720)	(-1.468)	(-1.371)	(-0.275)
Observations	38	35	32	28
Balanced Fund				
Returns	-0.005	0.014**	0.014**	0.008
	(-0.699)	(2.181)	(2.752)	(1.346)
Female	0.011	0.008	0.006	0.015*
	(1.319)	(1.495)	(1.518)	(1.857)
Age	0.007	0.004	-0.002	-0.002
	(0.913)	(0.831)	(-0.633)	(-0.206)
Tax	-0.092***	-0.084***	-0.051*	-0.050
	(-3.284)	(-3.388)	(-1.936)	(-0.941)
Constant	0.915	0.989*	0.693	0.231
	(1.405)	(1.748)	(1.376)	(0.345)
Observations	38	35	32	28
Growth Fund				
Returns	0.006	0.006	0.015***	0.013***
	(0.451)	(0.637)	(3.181)	(14.30)
Female	0.003	0.0005	-0.005	-0.01*
	(0.299)	(0.0432)	(-0.783)	(-1.793)
Age	-0.008	-0.016*	-0.026***	-0.023***
	(-0.628)	(-1.739)	(-6.917)	(-4.421)
Tax	-0.106***	-0.0992***	-0.048***	-0.016
	(-2.764)	(-3.030)	(-3.255)	(-1.151)
Constant	2.036**	2.29***	1.985***	1.582***
	(2.383)	(3.247)	(5.521)	(3.819)
Observations	38	35	32	28

This table reports the results of the OLS regression of past returns on investment fund enrolment from Equation 4, including control variables for robustness. I use Morningstar investment fund return data from July 2007 – December 2010. Monthly, quarterly, half-yearly and annual returns are calculated on a rolling basis. $Change\ in\ Enrolment\ Fraction_{i,t} = \alpha + \beta_1 Relative\ Return_{ij,t-1} + \beta_2 Female_{ij,t} + \beta_3 Age_{ij,t} + \beta_4 Tax_{ij,t} + \varepsilon_{i,t}$, where $Change\ in\ Enrolment\ Fraction_{i,t}$ is the difference between the monthly enrolment fraction for fund *i*

and the average enrolment fraction of fund *i* over time, α is the constant term and $Relative\ Return_{i,t-1}$ is the lagged relative return for fund *i*, which is calculated by the return of fund *i* minus the maximum return among the alternative funds *j* at time *t-1*. $Female_{i,t}$ is the percentage of females joining fund *i* in month *t* dummy, $Age_{i,t}$ is the average age of investors joining fund *i* in month *t*, Tax_{it} is the average tax rate of investors joining fund *i* in month *t* and ε_i are Newey-West standard errors. Panel A shows the pooled fund choice of all investment funds, and Panel B shows the change in fund enrolment by individual fund. The t-statistic relates to the null hypothesis that the mean equals zero. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

I next address how investor demographic characteristics affect the propensity to respond to past returns by adding interaction terms between the relative returns and demographic variables. Table 2.9 shows the impact of demographics and returns on fund choice. For instance, a statistically significant gender coefficient means that men and women differ in fund choice. The inclusion of interaction terms between demographics and relative returns reveal the additional effects of return chasing by investor characteristic. A positive coefficient for the gender interaction term means that women are more likely to join funds with higher relative returns than men are. A positive coefficient of the age interaction term means that relatively older investors chase returns more than relatively younger investors do. Similarly, a positive coefficient between tax interaction and relative returns shows that members in higher tax brackets differ in fund choices more than those in lower tax bands. While the age, gender, and tax variables control for the effect of demographics on fund enrolments, their interaction with relative returns shows that women and younger and wealthier investors are more sensitive to past returns and are more prone to return chasing.

Table 2.9 Investor demographics: Sensitivity to returns

Panel A: Pooled Enrolments				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarterly	Half-year	Annual
Returns	-0.773*	-0.753***	-0.255***	-0.126***
	(-1.766)	(-5.051)	(-2.925)	(-2.838)
Female	0.018*	0.016*	0.009	0.008
	(1.742)	(1.880)	(0.971)	(1.655)
Age	-0.004	-0.020*	-0.015	-0.017*
	(-0.436)	(-2.470)	(-1.636)	(-1.794)
Tax	-0.029	0.031	0.027	0.0451*
	(-1.014)	(1.329)	(1.315)	(1.820)
RR*Female	0.016**	0.008***	0.002	0.001
	(2.057)	(3.847)	(1.618)	(1.421)
RR*Age	-0.006	-0.020***	-0.006***	-0.002*
	(-1.081)	(-4.679)	(-3.688)	(-1.848)
RR*Tax	0.003	0.049***	0.018***	0.007**
	(0.255)	(5.959)	(4.374)	(2.303)
Constant	-0.290	-0.852*	-0.541	-0.701**
	(-0.418)	(-1.665)	(-1.120)	(-2.185)
Observations	152	140	128	112
Panel B: Enrolments by Fund				
	(1)	(2)	(3)	(4)
VARIABLES	Monthly	Quarterly	Half-year	Annual
Cash Fund				
Returns	-1.139	-0.402	0.019	0.281
	(-1.644)	(-1.385)	(0.0765)	(1.623)
Female	0.0665**	0.038***	0.024***	0.016*
	(2.591)	(2.876)	(3.716)	(1.803)
Age	-0.025	-0.031**	0.008	-0.003
	(-0.907)	(-2.472)	(0.404)	(-0.104)
Tax	0.060	0.078***	0.032	0.038
	(0.960)	(3.738)	(1.099)	(0.752)
RR*Female	0.030**	0.008*	0.002	-0.0009
	(2.107)	(1.718)	(0.766)	(-1.370)
RR*Age	-0.009	-0.022***	0.0003	0.002
	(-0.857)	(-3.263)	(0.075)	(0.863)
RR*Tax	-0.009	0.035**	-0.007	-0.014*
	(-0.376)	(2.142)	(-0.590)	(-1.831)
Constant	-3.895***	-2.548***	-2.106***	-1.403***
	(-2.819)	(-3.890)	(-4.955)	(-2.997)
Observations	38	35	32	28

Conservative Fund				
Returns	0.306	0.066	0.308**	0.304***
	(1.069)	(0.271)	(2.065)	(3.551)
Female	-0.019***	-0.006	-0.009	-0.014**
	(-3.576)	(-0.728)	(-1.011)	(-2.245)
Age	0.008	0.019***	0.008	0.014**
	(1.236)	(4.844)	(1.433)	(2.715)
Tax	0.037	0.016	0.0208	-0.016
	(1.469)	(0.858)	(0.960)	(-1.643)
RR*Female	-0.007*	0.00005	-0.0008	-0.001
	(-1.741)	(0.006)	(-0.317)	(-1.269)
RR*Age	0.003	0.009**	0.002**	0.001**
	(0.925)	(2.557)	(2.746)	(2.668)
RR*Tax	-0.001	-0.018*	-0.018***	-0.013***
	(-0.125)	(-1.757)	(-2.905)	(-5.167)
Constant	0.046	-0.528	-0.164	0.590*
	(0.0848)	(-1.291)	(-0.426)	(1.963)
Observations	38	35	32	28
Balanced Fund				
Returns	-0.859	0.093	0.004	-0.095
	(-1.087)	(0.506)	(0.047)	(-1.559)
Female	0.013	0.001	0.002	0.001
	(1.367)	(0.157)	(0.190)	(0.180)
Age	-0.004	0.001	-0.003	-0.016***
	(-0.438)	(0.281)	(-0.401)	(-4.608)
Tax	-0.072*	-0.081**	-0.0372	0.018
	(-1.897)	(-2.659)	(-0.947)	(0.813)
RR*Female	0.014	-0.001	-0.001	-0.0009
	(1.094)	(-0.399)	(-0.881)	(-1.121)
RR*Age	-0.021**	-0.006*	0.002	-0.003
	(-2.094)	(-1.752)	(0.507)	(-1.359)
RR*Tax	0.038*	0.009	-0.0002	0.012**
	(1.742)	(1.284)	(-0.024)	(2.637)
Constant	0.757	1.403	0.701	0.065
	(0.862)	(1.653)	(0.877)	(0.102)
Observations	38	35	32	28
Growth Fund				
Returns	-1.811	-0.134	0.239*	-0.090***
	(-1.673)	(-1.157)	(1.817)	(-3.661)
Female	0.008	0.0106	-0.007	-0.0007
	(0.638)	(0.959)	(-0.925)	(-0.189)
Age	-0.005	-0.0137	-0.014*	-0.027***
	(-0.378)	(-1.310)	(-1.866)	(-6.025)
Tax	-0.121**	-0.117***	-0.103**	-0.001
	(-2.512)	(-2.889)	(-2.416)	(-0.105)
RR*Female	0.035	0.004**	-0.001	0.001***
	(1.688)	(2.406)	(-0.624)	(4.128)
RR*Age	-0.017	-0.002	0.008*	-0.0005
	(-1.132)	(-0.346)	(1.890)	(-1.336)
RR*Tax	0.025	0.0005	-0.021**	0.003***
	(0.816)	(0.0384)	(-2.112)	(2.901)
Constant	1.963*	2.034***	2.795***	0.904***
	(1.889)	(3.291)	(4.925)	(3.173)
Observations	38	35	32	28

This table reports the results of the OLS regression of the propensity of investors to chase returns by demographic characteristics; gender, age, and tax group; as in Equation 5. I use Morningstar investment fund return data from July 2007 – December 2010. Monthly, quarterly, half-yearly and annual returns are calculated on a rolling basis. $Change\ in\ Enrolment\ Fraction_{i,t} = \alpha + \beta_1 RR_{ij,t-1} + \beta_2 Female_{ij,t} + \beta_3 Age_{ij,t} + \beta_4 Tax_{ij,t} + \beta_5 RR_{ij,t-1} *$

$Female_{ij,t} + \beta_6 RR_{ij,t-1} * Age_{ij,t} + \beta_7 RR_{ij,t-1} * Tax_{ij,t} + \varepsilon_{i,t}$, where $Change\ in\ Enrolment\ Fraction_{i,t}$ is the difference between the monthly enrolment fraction for fund *i* and the average enrolment fraction of fund i over time, α is the constant term, Relative $\text{Return}_{i,t-1}$ is the lagged relative return for fund i, $Female_{i,t}$ is the percentage of females joining fund *i* in month *t* dummy, $Age_{i,t}$ is the average age of investors joining fund *i* in month *t* and Tax_{it} is the average tax rate of investors joining fund *i* in month *t*. $RR_{ij,t-1} * Female_{ij,t}$ is an interaction term between $Relative\ Return_{i,t-1}$ and the percentage of enrolments that are female in month t, $RR_{ij,t-1} * Age_{ij,t}$ is the interaction between relative returns and the average age of enrolments in month t, $RR_{ij,t-1} * Tax_{ij,t}$ is the interaction term between relative returns and the average tax rate of enrolments, and $\varepsilon_{i,t}$ are the Newey-West standard errors. Panel A shows the pooled fund choice of all investment funds, and Panel B shows the change in fund enrolment by individual fund. The t-statistic relates to the null hypothesis that the mean equals zero. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

I find that younger investors are more sensitive to returns, based on the negative and statistically significant coefficients. The age variable tests whether older investors are more sensitive to relative returns and fund choice. For instance, a 1% difference in the relative return between funds increases the likelihood of younger investors selecting the fund with the higher return by 0.2%. This translates to approximately 86 more investors per month, or 1,036 investors per year. If investors have NZ$5,000 in their KiwiSaver accounts, on average, this would provide an injection of over NZ$5.1 million into the fund, with high relative returns. In a similar study, Clark-Murphy, Gerrans, and Speelman (2009) report that the likelihood of return chasing increases with age. They support the idea that older investors are more prone to return chasing due to their awareness of the level of saving adequacy and, thus, they have greater incentive to change their financial situation accordingly (Skinner, 2007).

In contrast to Clark-Murphy, Gerrans, and Speelman (2009), I find that age is negatively related to return chasing. Instead, my findings support Samuelson's (1989) investment asset allocation age theory and common financial advisor advice (Vanguard Investments, 2005); their ideas suggest that younger investors should take more risks, progressively decreasing exposure to relatively risky equity in favour of cash and fixed interest investments as they near retirement.

The relation between relative returns and demographics is not as strong in an examination of individual funds. A positive gender interaction coefficient means that women are more likely to chase returns than men are. As shown in Table 2.9, Panel B, women are more likely to chase returns in cash and growth fund enrolments, whereas gender plays a negative role in conservative fund return chasing and no role in balanced fund enrolment. Younger investors are more likely to chase returns in cash, balanced, and growth funds; however, older investors are more sensitive to the returns of the conservative fund. This outcome may reflect greater risk aversion among older investors and, therefore, greater likelihood to chase returns in conservative options.

The link between investor tax rate and relative returns is also weaker at the individual fund level. The sign of the interaction term between returns and investor tax rate, as displayed in Table 2.9, Panel B, changes over different return periods. While people in lower tax rates seem more sensitive to relative returns in the conservative fund, no consistent pattern exists between wealth and past returns.

2.4.4 'Smart' fund switching

Fund selection is very important for investors; however, investor attention to returns before and after fund switches is not well documented.[19] To assess whether fund switching leads to higher fund returns, I compute a *t*-test to measure the differences between the new fund and the old fund. I find that investors tend to join funds with higher past returns when first joining KiwiSaver and that fund switching does not lead to higher returns. This contrasts with the results of Clark-Murphy, Gerrans, and Speelman (2009), who find that new investment choices are significantly better than previous choices over the trailing

[19] The work of Clark-Murphy, Gerrans, and Speelman (2009) is, to my knowledge, the only other paper that explicitly focuses on fund switching and compares returns before and after a change in choice.

one-month, six-month, and 12-month periods. Table 2.10 shows the differences between fund returns for investors who switch funds. Investors earn lower returns in monthly, quarterly and annual period returns when they switch funds. On average, investors who switch are worse off after funds are reallocated to new fund choices. For instance, when annual returns are compared, fund switching reduces the returns of those who switch by 1%. In hindsight, I provide evidence that switching funds does not generate higher fund returns. This is expected for a population of individual investors who are auto-enrolled and may have joined the scheme unconsciously, by default.

Table 2.10 Fund switching payoff

	Mean	T-stat
Monthly	-0.07	-1.95*
Quarterly	-0.15	-12.61***
Half-Yearly	0.06	0.45
Annual	-1.04	-6.68***

This table reports the t-statistic of the difference between fund returns for investors who switched funds in the month, quarter, half year and year after the switch takes place. The difference in returns is the return on the new fund minus the return on the old fund I use Morningstar investment fund return data from February 2008– January 2011. Returns are calculated on a rolling basis.

My finding is consistent with that of Frazzini and Lamont (2008), who suggest that individual investors have the ability to make the wrong decision and send their money to mutual funds, which own stocks that do poorly over the subsequent years. Barber, Odean, and Zheng (2005) indicate that the majority of individuals will not gain from return chasing because of the tendency to overestimate their ability to identify superior funds based on past performance. In fact, Frazzini and Lamont (2008) show that poor fund selection decisions cost investors 0.84% on their return per year. If fund managers and mutual fund providers recognise the propensity of investors to chase returns, then the implication is that managers could try to induce fund switching behaviour. For instance, if managers turn their attention to attaining recognition for top returns rather than focusing

on maximising risk-adjusted returns, investors may chase the funds awarded with the best short-term performance (Brown, Harlow & Starks, 1996; Chevalier & Ellison, 1997).

2.5 Conclusion

Past returns affect the fund choices of individual investors. I find that past monthly returns do not affect fund selection; however, quarterly, half-yearly, and annual returns have a significant positive influence on investment fund choice. I observe both the investment fund enrolments and fund switching activity of nearly 200,000 members of KiwiSaver, a New Zealand retirement investment savings scheme. Previous studies investigate the role of past returns on investor behaviour through surveys and limited empirical evidence of the relation between past returns and investment fund choice exists.

I find that investor demographics such as gender, age, and wealth affect fund selection. Also the propensity to chase past returns depends on demographic characteristics and the initial fund chosen. Female investors are more likely to choose funds with higher relative past returns than men are, while younger investors and wealthier investors are more prone to select funds with higher relative past returns. Past returns are, however, not indicative of future performance and fund switching does not lead to higher returns.

Since KiwiSaver is a relatively new investment scheme, there are some limitations to this research in terms of the sample period and data availability. Since research revealing the relation between investment fund performance and individual investor behaviour on a nationwide scale is scarce, this study has demonstrated an area of research of growing relevance. Thus, KiwiSaver stands to provide opportunities to further explore the evolution of investor behaviour in future longitudinal studies. As aggregate savings increase and fund values grow within the KiwiSaver scheme, investor fund choices, fund

switches, and transfers between providers will become increasingly important to all stakeholders. In addition, the growth of the KiwiSaver scheme will contribute to New Zealanders' well-being. Through identifying a clear and significant relation between past returns and fund choice, my paper provides a key implication for future research in regards to the way in which investment performance is communicated.

Chapter 3 Financial advice and asset allocation of individual investors

3.1 Introduction

KiwiSaver has played a significant role in the development of New Zealand capital markets since its introduction in 2007. This paper studies the impact of financial advice on asset allocation within the context of KiwiSaver investor behaviour and discusses some of the implications that financial advice has on individual investor behaviour.[20] Using a proprietary dataset containing information of 405,107 individual investors in the national retirement investment savings scheme; three key questions are explored. Who receives financial advice? Do people who get financial advice have a different asset allocation than people who do not? And finally, does financial advice lead to superior returns?

The findings of this paper show firstly, female investors, relatively older investors and investors with higher funds under management (invested wealth) are more likely to receive financial advice. Secondly, investors who receive advice hold riskier assets than non-advised investors, that is, less cash and bond assets and more property and equity asset classes. Investor demographic characteristics such as gender, age and funds under management also play as significant factors on asset allocation. Men who receive advice invest more in riskier assets. For example, men who receive advice on 49% of their asset allocation in equity assets compared 42% for men without advice. Women who receive financial advice also invest in riskier assets more than women who have not received advice (47% in equity investment compared to 41% equity investment, respectively), however women hold marginally safer assets than men. Older investors tend to hold safer

[20] This paper has been accepted for publication in the *Pacific Accounting Review*.

assets compared to younger investors. Controlling for financial advice however, relatively older investors who receive advice will take on more risk than peers of the same age who have not received advice. In addition, the level of funds under management is positively related to the level of risk taken in investment fund asset allocation. The greater the wealth invested in KiwiSaver funds by investors, the higher the proportion of property and equity investment is held. However, if we were to compare two investors with identical levels of invested wealth, the investor who receives financial advice tends to hold a higher proportion of cash and property assets and fewer bond assets. Lastly, when returns are compared over the five-year period in which KiwiSaver has been in operation, investors who received advice marginally outperform investors who did not receive advice by 5 basis points. Furthermore, returns are higher for advised accounts when equity markets perform well.

To date, only a handful of empirical studies analyse the relation between financial advice and asset allocation and their findings are mixed. For instance, Mullainathan, Nöth and Schoar (2012) find that advice is positively related to equity exposure, but Kramer (2012) finds advised accounts in the Netherlands contain significantly less equity and more fixed income securities. Recent studies also report contrasting results regarding whether advised trading accounts outperform non-advised accounts. Bergstresser, Chalmers and Tufano (2009) find a negative relation between adviser involvement and investor performance in US mutual funds while Hackethal, Haliassos and Jappelli (2012) show risk-adjusted returns are lower for advised portfolios caused by higher trading costs using German data, and Hoechle, Ruenzi, Schaub, and Schmid (2013) document advisors hurt performance in Swiss trading accounts. In direct contrast however, studies also show that advised accounts are better diversified and are in line with predefined model

portfolios (Shapira & Venezia, 2001; Bluethgen, Gintschel, Hacklethal, & Mueller, 2007; & Bhattacharya, Hackethal, Kaesler, Loos and Meyer; 2012).

This paper makes three key contributions to the existing literature. Firstly, a new proprietary dataset, KiwiSaver, is used to understand the relation of financial advice and individual investor decisions in an auto-enrolment setting[21]. This study meets three key criteria for investigating household finance based on Campbell (2006) requirements to study household finance. First, the data covers a representative sample of an entire population. The data includes investor accounts of 405,107 individuals, which represents 23% of the total KiwiSaver population, and is the largest sample so far used to study individual investor behaviour in New Zealand. Second, wealth can be distinguished between four separate asset classes. Wealth measures in my data can be split into the level of funds under management for each investor in the sample, the investor tax rate, and also the proportion of wealth held in cash, bonds, property and equity assets. Third, data is reported at a high level of accuracy. The data reports the investment savings accounts of New Zealand's national retirement savings scheme, and comes directly from the KiwiSaver providers who hold the individual accounts. Compared with previous studies such as Bluegthen et al. (2007), Chalmers and Reuter (2012), Hackethal et al. (2012), and Bhattacharya et al. (2012) this study provides a more extensive dataset allowing for improved investigation of the relation between financial advice and individual investor asset allocation.

Secondly, unlike previous studies, this paper employs the use of financial adviser data, instead of broker-level data. The distinction between the two is important since financial

[21] KiwiSaver is a defined-contribution retirement savings scheme launched in New Zealand in 2007. KiwiSaver is the world's first auto-enrolment scheme on a national scale which provides a unique setting to be exploring individual investor behaviour.

advisers provide face-to-face investment advice rather than brokers who typically data brokerage firm advisers are typically employees of the banks who are providing the investment product, and therefore less independent.[22] Previous studies tend not to differentiate according to where advice has come from or what constitutes 'advice', which make comparisons between results less precise. For instance, advice received from brokers, dealers, bank-employees and computer-generated algorithms in reality are not the same thing but have all been categorized as receiving advice in studies.[23] In this study I employ a more direct measure to record financial advice, which is significant point of difference from previous studies since dealers, brokers and advisers face different regulations under the law and hence serve different roles. The main difference lies in the standard of care which financial advisers must provide. Investment advisers are fiduciaries to their clients which mean they have a duty to serve in the best interests of their clients. The standard of care differs for brokers and dealers, who mainly provide execution services and may not provide personalised advice. In New Zealand, only Authorised Financial Advisers (AFAs) are able to provide investment planning and discretionary management services to clients and give personalised advice on KiwiSaver investment products. The data provides the ability to measure advice at a more personalised level than previous studies and are void of some of the disadvantages that come from using brokerage data. As suggested by Goeztmann and Kumar (2008), brokerage portfolios may not represent serious investments but investors 'play-money' accounts. Hoechle et al. (2013) argue while evidence based on brokerage accounts are insightful, there are limitations on the conclusions drawn on financial behaviour. Finally,

[22] For example, Hackethal et al. (2012) use data from a German brokerage and bank. They refer to financial advisers as Independent Financial Advisers (IFA) and state that 90% of IFAs in their sample are bank-employees who typically place orders on behalf of the client.
[23] See Bluethgen, Gintschel, Hacklethal and Mueller (2007), Chalmers and Reuter (2012), Hackethal, Haliassos and Jappelli (2012) and Bhattacharya, Hackethal, Kaesler, Loos and Meyer (2012).

the use of online brokerage data may attract only a selected sample of a population that is interested in trading and may not be representative as discussed in Hackethal et al. (2012).

Thirdly, KiwiSaver also provides a new opportunity to explore the effect(s) that a national pension scheme can have on long term development of New Zealand capital markets. The contribution of KiwiSaver to the New Zealand capital market so far appears twofold. The retirement scheme provides continuous liquidity to the New Zealand share market. For example, as at March 2013 KiwiSaver has a reported NZ$14.48 billion of funds under management (Douglas, 2013), of which 10.1% is invested in New Zealand shares. While the translation of fund flow does not appear large in the full context of the $NZ50 billion market capitalisation of the New Zealand share market, "the effect of regular fund flows is relentless", (Douglas, 2011, p.15). Evidence from Australia shows that since introduction of its national superannuation system in 1992 over half of the Australian share market (AUD$ 1.4 trillion market capitalisation at end of March 2012) is attributable to Australian superannuation flows (see Turnball, 2013). Despite the differences between the New Zealand and Australian superannuation systems, it seems fair to say that KiwiSaver will ultimately strengthen and deepen New Zealand capital markets over the long run if investment allocation is invested in New Zealand shares.

KiwiSaver also helps increase the awareness of investment options more generally. It does so by raising the awareness of investment options available in assets classes such as, bonds and equity, that are outside of New Zealand's traditional love affair with property investment (see Khaled & Lattimore, 2008). Since KiwiSaver was introduced in 2007 the retirement investment savings scheme has reached 2.1 million New Zealanders, as at

May 2013.[24] The penetration of enrolment into KiwiSaver reflects both directly and indirectly the number of retail and 'mum-and-dad' investors that are participating in New Zealand capital markets through their holdings of investment funds. KiwiSaver has lifted the profile of retirement savings and the investment options. As stated by the Capital Market Taskforce (2009, p.30) raising public awareness of investment options available will in the long run will foster stronger domestic capital markets). In addition to this, the New Zealand Inland Revenue (2012b, p26) annual KiwiSaver evaluation supports that KiwiSaver is a growing part of the overall New Zealand managed funds market and that "in terms of investment into New Zealand, KiwiSaver schemes continue to have a higher proportion invested locally compared to other forms of superannuation".

3.2 Data

I use two datasets in this study. The first dataset consists of proprietary KiwiSaver account information and the second dataset contains KiwiSaver returns obtained from the Morningstar database. Combining the two datasets allows me to assess how individual investors behave in relation to receiving financial advice and how the performance of funds differs between investors. I obtain the primary dataset from four large KiwiSaver investment fund companies. The data includes information on 405,107 individual investor accounts.[25] Of the four large KiwiSaver providers, two are large retail banks, one is a mutual fund investment firm, and the fourth KiwiSaver provider is a government

[24] See New Zealand Inland Revenue (2012a). Website http://www.kiwisaver.govt.nz/statistics/ks-stats-13-05-31.html

[25] There is an implicit assumption made the 405,107 individual accounts are independent which was made at the time of generating the results for this essay. This paper was then published in the Pacific Accounting Review under this assumption and subsequent household data became available to study in later chapters.

default-provider.[26] The data is cross-sectional and recorded on 30 June 2011. As the data comes from four separate providers this provides a wider representation of the population involved in KiwiSaver and reduces potential KiwiSaver provider bias. The KiwiSaver population I observe covers 23% of the total KiwiSaver population as at 30 June 2011, where there are 1.76 million investors in total.[27] In order to assess whether the data used in this study is representative of the total KiwiSaver population, comparisons in dataset summary statistics are measured against Zhang (2011), which also uses KiwiSaver data from a separate large KiwiSaver provider. Zhang (2011) uses the individual investment fund choices of 196,513 investors from a large non-default KiwiSaver provider over the period of October 2007 to November 2010. When investor demographics are compared between the two datasets, the variables of age, gender, tax and funds under management are in line with previous studies.

Table 3.1 provides the descriptive statistics of the number of investors, and information related to investor gender, age, level of funds invested, tax rate, financial advice, and the average asset allocation for the asset categories of cash, bonds, property and equity. The table shows that 40,776 investors from the total sample of 405,107 have received financial advice. This equates to 10% of the total sample. Each individual in the dataset holds at least 1 investment fund and 13 investment funds at most. Of the 13 investment fund options available to choose from, 6 investment funds are multi-asset funds (including cash, bond, property and equity asset allocations) and 7 are single asset-funds (cash,

[26] Default providers are an important component of KiwiSaver. Default providers have special contracts with the New Zealand Government that require them to meet additional reporting requirements, with default providers' activities and their default investment funds being closely monitored. This is because KiwiSaver members joining default providers have not specified a choice of provider (or investment fund for that matter); hence, they are placed in relatively conservative investments (New Zealand Inland Revenue 2012a).
[27] See New Zealand Inland Revenue (2012a). Website http://www.kiwisaver.govt.nz/statistics/ks-stats-11-06-30.html

domestic bonds, international bonds, domestic property, international property, domestic equities and international equities).

Table 3.1 Descriptive statistics

Panel A: Full Sample								
VARIABLES	n	Mean	S.D.	Min	0.25	Median	0.75	Max
Female	211,424	0.52	0.5	1	1	1	1	1
Male	193,683	0.48	0.5	0	0	0	0	0
Age	405,107	34	18	0	20	32	49	70
FUM	405,107	4823	5970	100	1189	2301	6618	221612
ZFUM	405,107	6.30e-08	1.00	-0.81	-0.61	-0.42	0.30	36.3
Tax Rate	405,107	19.9	6.35	0	17.5	17.5	28	28
Financial Advice	405,107	0.10	0.3	0	0	0	0	1
Cash	405,107	0.15	0.2	0	0.04	0.1	0.2	1
Bonds	405,107	0.35	0.2	0	0.16	0.29	0.6	1
Property	405,107	0.08	0.05	0	0.03	0.08	0.12	1
Equity	405,107	0.42	0.24	0	0.17	0.42	0.68	1
Panel B: Financial Advice Sub-sample								
VARIABLES	n	Mean	S.D.	Min	0.25	Median	0.75	Max
Female	21,371	0.52	0.5	1	1	1	1	1
Male	19,405	0.48	0.5	0	0	0	0	0
Age	40,776	45	17	0	35	48	59	69
FUM	40,776	11,214	9,926	100	4,686	9,300	14,761	22,162
Panel C: Non-Financial Advice Sub-sample								
VARIABLES	n	Mean	S.D	Min	0.25	Median	0.75	Max
Female	190,053	0.52	0.5	1	1	1	1	1
Male	174,278	0.48	0.5	0	0	0	0	0
Age	364,331	33	17	0	20	30	48	70
FUM	364,331	4108	4850	100	1166	1984	5414	181010

Table 1 shows the descriptive statistics of the number of investors, and information related to investor gender, age, level of funds under standardised variables, level of funds under management, tax rate and financial advice, as well as the average asset allocation for the asset categories cash, bonds, property and equity. Panel A of Table 1 shows the full sample descriptive statistics, Panel B displays information on gender, age and funds under management for investors who receive financial advice, and Panel C displays information for investors who have not received financial advice.

Panel A of Table 3.1 shows the descriptive statistics of the full sample and Panel B and Panel C of Table 3.1 splits the summary statistics into financial advice and non-advice sub-samples, respectively. The ratio of men and women in the full sample is relatively even, with 193,683 males and 211,424 females (48% and 52%, respectively). The ratio of men and women who do receive financial advice does not differ from the ratio of men and women who do not receive advice. As shown in Panel A of Table 3.1 the average age of the full sample is 34 years of age. Investors who receive advice are relatively older,

with an average age of 45, as shown in Panel B, while non-advised investors have an average age of 33, as shown in Panel C. The average level of funds under management in the full sample of investors is NZ$4,823. The average level of funds under management for investors who receive advice is NZ$11,214, compared to NZ$4,108 for investors who have not received advice.

The proportion of investors receiving financial advice in the data is representative and broadly in line with previous survey based evidence in New Zealand. I find that ten percent of investors in the sample receive financial advice. Currently, the total number of New Zealanders who receive financial advice is not known at the aggregate level. Due to a lack of publicly available data on financial advice in New Zealand past studies have relied on survey based information to gauge the proportion of New Zealanders who receive advice. For instance, in a survey of 1,000 KiwiSaver investors, Matthews (2011; 2012) finds that 18% to 22% of the sample rely on financial advice. More recently, the New Zealand Commission of Financial Literacy and Retirement Income 2013 national survey of 852 participants reported that 15% of New Zealanders obtain information from a financial adviser (Colmar Brunton 2013). A survey undertaken by Roy Morgan New Zealand found that, over a 13 year period between 2000 and 2013, only 4.6% of the 12,000 New Zealanders surveyed received independent financial advice for managed funds, superannuation and retirement related financial matters (Roy Morgan New Zealand 2013).

The measure I use to capture financial advice is a discrete variable. A binary variable is equal to one when an investor has received finance advice and is zero otherwise. I define the role of a financial adviser as the giving of financial advice; which means the making of a recommendation, or the provision of advice, in relation to acquiring, or

disposing of, a financial product. In New Zealand, only Authorised Financial Advisers are allowed to give personalised advice on KiwiSaver, which is a category one investment product under the Financial Advisers Act 2008.[28] Authorised Financial Advisers are individually registered and authorised by the Financial Markets Authority (New Zealand's financial markets regulatory body) to provide financial adviser services. They can provide investment planning and discretionary management services, and will generally provide advice on more complex products. In my sample only people who receive face-to-face advice from a registered Authorised Financial Adviser is considered to have received financial advice. This significantly differs from previous studies, such as Bluethgen et al. (2007), Chalmers and Reuter (2012) and Hackethal et al. (2012), which employ the use of investor relationships with brokers, dealers and bank-employees to study the effect of financial advice.

3.3 Methodology and results

3.3.1 Who receives financial advice

A probit model is used to identify which investors are more likely to receive financial advice based on their demographic characteristics.

$$\text{Financial Advice}_i = \alpha + \beta_1 \text{Age}_i + \beta_2 \text{Female}_i + \beta_3 \text{ZFUM}_i + \varepsilon_i \quad (1)$$

The dependent variable *Financial Advice*$_i$ is a binary variable that takes the value of 1 if an investor receives financial advice, and is 0 otherwise. α is the constant term; *Age*$_i$ is the age of the investor in years; *Female*$_i$ is a dummy variable, which equals to 1 if the investor is female and 0 if the investor is male; Z*FUM*$_i$ is the standardised variable of the

[28] Category one products are products with more of an investment focus, including shares, managed funds and KiwiSaver. http://www.fma.govt.nz/glossary/category-1-products (Financial Markets Authority, 2013).

level of funds under management in an investor's KiwiSaver account. $ZFUM_i$ is calculated by creating a z-score whereby the funds under management variable is standardised to have a mean of 0 and standard deviation of 1 and ε_i is the error term.

Table 3.2 shows the results of the probit model. Receiving financial advice is positively related to the variables age, female and funds under management. This means that the probability of investors receiving advice increases with age, that female investors are more likely to receive advice than males, and that the propensity to receive advice increases as the level of funds under management increases.

Table 3.2 Who receives advice

VARIABLES	Financial Advice
Age	0.011***
	(59.53)
Female	0.082***
	(13.94)
ZFUM	0.397***
	(152.83)
Constant	-1.832***
	(-230.69)
Observations	405,107
McFadden R^2	0.1681

Table 2 reports the results from the probit regression with the financial advice dummy as the dependent variable. $Financial\ Advice_i = \alpha + \beta_1 Age_i + \beta_2 Female_i + \beta_3 ZFUM_i + \varepsilon_i$
where the dependent variable $Financial\ Advice_i$ is a binary variable that takes the value of 1 if an investor received financial advice and 0 otherwise. α is the constant term; Age_i is the age of the investor in years; $Female_i$ is a dummy variable, which equals to 1 if the KiwiSaver member is female and 0 if the investor is male; $ZFUM_i$ is the standardised value of funds under management in the investor's KiwiSaver account; and ε_i is the error term. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

The interpretation of the coefficients in a probit model measures the increase in the probability attributed to a 1-unit increase in a given independent variable and is dependent both on the values of the other predictors and the starting value of the given predictors. Therefore, in order to identify the economic significance of the results, values must be substituted into the equation. For example, if the average age (31) and average funds

under management (NZ$4,823) is substituted into the probit model, the model shows that women are 8.2% more likely to receive financial advice than men. The probability of receiving advice for a 34-year old male compared with a 35-year old male, controlling for the level of funds under management, shows that older men are more likely to receive advice by 1.1%. As a third example, when the probability of receiving advice for a 34-year old male who has the average level of funds under management (NZ$4,823) is compared with the probability of receiving advice for a 34-year old male has who NZ$10,000 funds under management, the model shows that male investors with a greater level of funds invested are 34% more likely to receive advice. As a robustness check, an OLS model is used to check the economic significance and the magnitude of the coefficients.[29]

Investor demographic characteristics appear to affect the probability of receiving financial advice in different contexts. As mentioned earlier, Bluethgen et al. (2007) and Hackethal et al. (2012) find that financial advisers mostly serve younger investors with less wealth, rather than older investors with higher levels of funds under management. These differences in findings could perhaps be explained by the nature of investment activity studied. For instance, the essence of KiwiSaver is to invest for retirement and, hence, could attract interest from people who are closer in age to retirement, whereas, there is no retirement savings focus observed in Bluethgen et al. (2007) and Hackethal et al. (2012). Controlling for age and gender the findings in Table 3.1 show that the probability of receiving financial advice is significantly related to the level of funds under management.

[29] The findings in the OLS model are consistent with the base probit model.

Figure 3.1 shows the probability of investors receiving advice as a function of funds under management. The probabilities are calculated by multiplying the maximum likelihood estimates from the probit model with substituted figures of average investor age, gender and funds under management contained within the sample. Figure 1 shows the break points, where the probability of receiving advice dramatically jumps at given levels of funds under management. For instance, a balance of NZ$20,000-NZ$30,000 in invested funds results in the largest change in the probability of receiving advice, as indicated by the steepest part of the curve.

Figure 3.1 Probability of receiving financial advice and funds under management

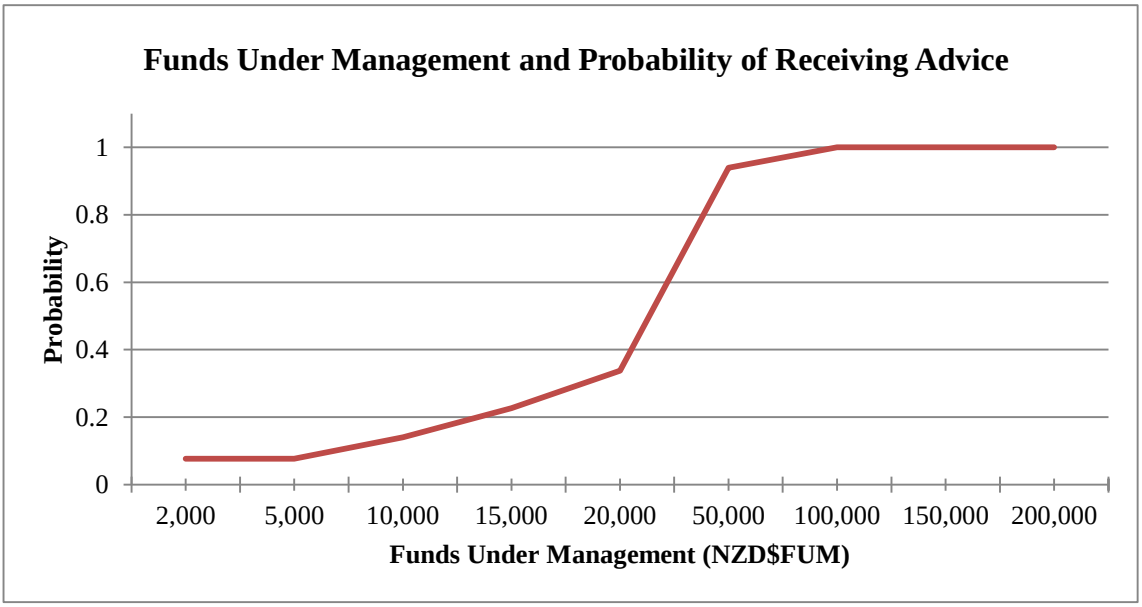


Figure 1 shows the probability of receiving financial advice as a function of funds under management. The probabilities are calculated by multiplying the maximum likelihood estimates from the probit model with substituted figures of average investor age, gender and funds under management information contained within the sample.

3.3.2 The impact of financial advice on asset allocation

To test the impact of financial advice on investment fund asset allocation both univariate and multivariate analysis are used. The univariate analysis explores the one dimensional influence of financial advice on asset allocation, whereas the multivariate analysis investigates the effect of advice on asset allocation in the context of investor demographic characteristics. While the multivariate results may appear to be repetitive of

the univariate results, it is necessary to explore the findings of both types of analysis because demographic characteristics ought to be explored in tandem to the effect of financial advice on asset allocation.

The effect of financial advice is apparent when asset allocations are compared between investors who do receive financial advice with investors who do not in the univariate analysis. Investors who receive financial advice hold far riskier asset allocations. Gender, age and funds under management also significantly influence the way investors behave. Table 3.3 presents the means and t-statistics of investor asset allocation for advised and non-advised investors by gender, age and funds under management.[30] Panel A of Table 3.3 presents the cash, bonds, property and equity asset holdings by financial advice and gender. Panel B shows the asset allocation of investors with, and without, financial advice by age groups, while Panel C shows the asset holdings of investors by funds under management. When analysing the total sample Panel A shows that investors who receive advice hold less cash and bond assets, and more property and equity assets. Investors who receive advice hold on average 11% in cash assets in their portfolios, compared with 16% in cash assets held by investors who do not receive advice.

Men who receive advice invest more in riskier assets than men who do not receive advice (49% equity investment compared to 42% equity investment, respectively). Women who receive financial advice also invest more in riskier assets than do women who have not received advice (47% in equity investment compared to 41% equity investment, respectively), however women hold marginally safer assets than men. As shown in Table 3.3 age and the level of funds under management are significantly related to asset allocation. As age increases less of the relatively riskier assets categories

[30] Analysis of differences in medians showed no significant differences in the results for means.

(property and equity) and greater proportions of safer assets (cash and bonds) are held. While age decreases risky asset investment for investment for investors both with and without financial advice, Panel B of Table 3.3 shows that advised investors tend to hold less cash and bond assets, and more property and equity assets than un-advised counterparts within the same age group. For example, an investor who receives advice and is aged between 51 and 70 is likely to hold 39% of their investments in equity assets compared to 25% for an investor of the same age who has not received advice. Panel C shows that, once again, investors who have received financial advice hold riskier assets than non-advised investors, however, investors with relatively higher funds under management tend to hold greater amounts of cash and bonds than property and equity assets, compared with investors with lower levels of funds under management.

Table 3.3 Financial advice asset allocation means

VARIABLES		n	Cash	Bonds	Property	Equity
		Panel A: Gender				
All	Financial Advice	40776	0.11	0.35	0.1	0.48
	Non Advice	364331	0.16	0.32	0.07	0.42
	T-stat		-45.5***	35.1***	88.9***	49.7***
	Total Sample	405107	0.15	0.35	0.08	0.42
Males	Financial Advice	19405	0.1	0.31	0.1	0.49
	Non Advice	174278	0.15	0.35	0.08	0.42
	T-stat		-39.7***	-35.1***	34.8***	42.7***
	Total Males	405107	0.14	0.35	0.08	0.43
Females	Financial Advice	21371	0.11	0.33	0.1	0.47
	Non Advice	190053	0.16	0.35	0.07	0.41
	T-stat		-41.1***	-23.0***	34.0***	34.0***
	Total Females	405107	0.16	0.35	0.07	0.42
		Panel B: Age				
VARIABLES		n	Cash	Bonds	Property	Equity
Age 0-20	Financial Advice	4717	0.06	0.23	0.11	0.60
	Non Advice	100537	0.11	0.22	0.10	0.58
	T-Stat		-13.8***	4.57***	-17.8***	6.54***
	Total Sub-Sample	105254	0.10	0.22	0.10	0.58
Age 21-35	Financial Advice	5843	0.07	0.23	0.11	0.58
	Non Advice	110329	0.14	0.36	0.08	0.43
	T-Stat		-31.9***	-42.5***	59.0***	46.1***
	Total Sub-Sample	116172	0.14	0.35	0.08	0.44
Age 26-50	Financial Advice	11872	0.08	0.30	0.11	0.52
	Non Advice	78031	0.15	0.43	0.07	0.36
	T-Stat		-49.3***	-82.5***	90.2***	89.8***
	Total Sub-Sample	89903	0.14	0.41	0.07	0.38
Age 51-70	Financial Advice	18344	0.15	0.38	0.08	0.39
	Non Advice	75434	0.25	0.46	0.05	0.25
	T-Stat		-47.2***	-52.9***	89.7***	0.01
	Total Sub-Sample		0.23	0.44	0.05	0.28
		Panel C: Funds Under Management				
VARIABLES		n	Cash	Bonds	Property	Equity
$100-$2000	Financial Advice	5330	0.08	0.26	0.10	0.55
	Non Advice	183001	0.14	0.30	0.08	0.47
	T-Stat		-19.9***	-14.8***	33.4***	23.1***
	Total Sub-Sample	188331	0.14	0.30	0.08	0.47
$2001-$5000	Financial Advice	5314	0.11	0.30	0.10	0.49
	Non Advice	83216	0.17	0.38	0.07	0.37
	T-Stat		-22.0***	-28.0***	44.5***	36.4***
	Total Sub-Sample	88530	0.17	0.38	0.07	0.38
$5001-$10000	Financial Advice	11309	0.14	0.34	0.09	0.43
	Non Advice	60842	0.18	0.41	0.06	0.35
	T-Stat		-19.1***	-35.5***	46.9***	39.2***
	Total Sub-Sample	72151	0.17	0.40	0.07	0.36
$10001+	Financial Advice	18823	0.10	0.32	0.10	0.48
	Non Advice	37272	0.15	0.42	0.07	0.36
	T-Stat		-42.6***	-68.4***	62.7***	67.3***
	Total Sub-Sample	56095	0.13	0.39	0.08	0.40

This table reports the means and t-statistics of portfolio asset allocation for advised and non-advised investors overall, by gender, age and funds under management. Panel A presents the cash, bonds, property and equity asset holdings by financial advice and gender. Panel B shows the asset allocation of investors with, and without, financial advice by age groups and Panel C shows the asset holdings of investors by funds under management.

To assess the influence of financial advice on asset allocation, while controlling for investor demographic effects, a multivariate ordinary least squares (OLS) regression analysis is used. The main multivariate model is as follows:

$$\%\ \text{Asset Allocation}_i = \alpha + \beta_1 \text{FinancialAdvice}_i + \beta_2 \text{Age}_i + \beta_3 \text{Age}^2_i + \beta_4 \text{Female}_i$$

$$+ \beta_5 ZFUM_i + \beta_6 Tax_i + \beta_7 Default_i + \varepsilon_i \qquad (2)$$

The dependent variable *Asset Allocation*$_i$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio for investor *i* (where *j* = 4 and asset classes are cash, bonds, property and equity). α is the constant term; *FinancialAdvice*$_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; *Age*$_i$ is the age of the investor in years; *Age*^2_i is the squared term of *Age*$_i$[31]; *Female*$_i$ is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; Z*FUM*$_i$ is the standardised value of funds under management in the investor's KiwiSaver account; *Tax*$_i$ is the personal income tax rate of the investor; *Default*$_i$ is a dummy variable which equals to 1 if the investor has joined a government default KiwiSaver provider and ε_i is the error term.[32]

The main results from the OLS model are presented in Table 3.4. When age, gender and the level of funds under management are included in the multivariate regression, financial advice remains negatively related to investment in safer asset classes, and positively related to investment in riskier asset classes.

[31] Since the relation between age and asset allocation could also be non-linear, an age-squared variable is added to the main multivariate regression.
[32] Regressions are later run as a system of equations to check correlations of the error terms.

Table 3.4 Multivariate framework: Financial advice and demographic characteristics

VARIABLES	Cash	Bonds	Property	Equity	Cash	Bonds	Property	Equity
Financial Advice	-0.056***	-0.024***	0.021***	0.061***	-0.014***	-0.007***	0.011***	0.011***
	(-64.1)	(-25.4)	(44.9)	(57.9)	(-6.76)	(-2.84)	(7.54)	(3.63)
Age	-0.003***	0.003***	8.86e-05***	6.02e-05	-0.003***	0.003***	0.0001***	0.0002**
	(-39.9)	(56.1)	(5.25)	(0.832)	(-40.1)	(53.9)	(7.21)	(2.31)
Age^2	0.0001***	0.00001***	-0.00002***	-0.00002***	0.0001***	0.00001***	-0.00002***	-0.00002***
	(72.7)	(10.5)	(-65.2)	(-87.1)	(73.8)	(12.1)	(-68.7)	(-90.4)
Female	0.002***	0.004***	-0.001***	-0.005***	0.0018***	0.002***	-0.001***	-0.003***
	(3.715)	(7.69)	(-6.38)	(-8.94)	(2.84)	(3.54)	(-4.51)	(-5.30)
ZFUM	-0.018***	-0.014***	0.005***	0.026***	-0.022***	-0.010***	0.005***	0.027***
	(-53.9)	(-44.4)	(40.35)	(62.9)	(-53.6)	(-29.3)	(58.9)	(59.4)
Age*FA					-0.001***	-0.001***	0.0002***	0.002***
					(-21.5)	(-8.44)	(9.11)	(24.1)
Female*FA					0.003**	0.020***	-0.004***	-0.019***
					(2.10)	(11.5)	(-4.10)	(-9.86)
ZFUM*FA					0.014***	-0.009***	0.001***	-0.007***
					(23.8)	(-11.9)	(3.06)	(-8.08)
Default	0.051***	0.242***	-0.046***	-0.248***	0.051***	0.241***	-0.045***	-0.247***
	(97.7)	(430.4)	(-332.9)	(-364.3)	(97.1)	(425.8)	(-332.1)	(-361.5)
Tax	0.0003***	0.005***	-0.001***	-0.005***	0.0004***	0.005***	-0.001***	-0.005***
	(6.37)	(109.9)	(-64.4)	(-85.3)	(6.79)	(110.7)	(-65.8)	(-86.5)
Constant	0.120***	0.074***	0.121***	0.684***	0.18***	0.076***	0.121***	0.686***
	(85.5)	(69.4)	(376.3)	(492.7)	(82.5)	(70.7)	(391.8)	(495.3)
Observations	405,107	405,107	405,107	405,107	405,107	405,107	405,107	405,107
R-squared	0.099	0.474	0.318	0.453	0.100	0.475	0.319	0.454

$FinancialAdvice_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; Age_i is the age of the investor in years; $Female_i$ is a dummy variable, which equals to 1 if the investor is female and 0 if the investor is male; and $ZFUM_i$ is the standardised value of funds under management in the investor's KiwiSaver account. Age_i*$FinancialAdvice_i$, $Female_i$*$FinancialAdvice_i$, and $ZFUM_i$*$FinancialAdvice_i$ are interaction terms between Age_i, $Female_i$, $ZFUM_i$ and $FinancialAdvice_i$; Tax_i is the personal income tax rate of the investor; $Default_i$ is a dummy variable, which equals to 1 if the investor has joined a government default KiwiSaver provider; and ε_i is the error term. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

As presented in columns (1), (2), (3) and (4) of Table 3.4, receiving financial advice reduces cash and bond holdings by 5.6% and 2.4%, respectively, while it increases property and equity class investment by 2.1% and 6.1%, respectively. One interpretation may be that people who receive advice are risk-averse and receiving financial advice corrects for the underweight of their risky assets. An alternate interpretation could be that financial advisers encourage risk-taking behaviour by recommending that investors increase the proportion of assets held in property and equity over that held in cash and bond assets. This result is in line with Mullainathan et al. (2012), who find that advice tends to promote a higher equity mix. Bergstresser et al. (2009) and Bhattacharya et al. (2012) discuss the conflict of interest between the financial adviser remuneration structure and the investment products recommended by advisers. For instance, since products usually associated with higher risk, such as equities, also generate higher fees for advisers, this could potentially explain why equities are more frequently held by advised clients.

Table 3.4 reveals that the relation between age and asset allocation is non-linear for all four asset categories. The coefficients of age are U-shaped for cash and inverted U-shaped for property and equity assets. This suggests that, as an investor gets older, they are likely to increase (decrease) holdings in equity (cash), however, upon nearing retirement they will increase (decrease) holdings at a lower rate. Investors nearest to retirement age (age 65) hold the highest proportion of cash and bond assets in their portfolios and the lowest level of equity and property assets. This result comes as little surprise as it falls in line with the life-cycle theory which states that younger investors can afford to take more risks with investments because they have greater human capital (Bodie et al. 1992; Cocco et al. 2005).

Females have positive coefficients in cash and bonds regressions and negative coefficients in property and equity regressions, which is in line with the univariate results in Table 3.3. The OLS results from Equation 2 show that the level of funds under management is positively related to risk-taking, which differs from the univariate analysis results. When age, gender and financial advice are controlled for, the funds under management are found to be positively related to risky assets. As the balance of an investor's account increases by 1%, 0.5% more property assets and 2.7% more equity assets are held. The link between wealth and financial sophistication offers a potential explanation of why higher levels of funds under management may increase risk taking. Hilgert et al. (2003) show a strong link between financial knowledge and financial behaviour. Calvet et al. (2007) find that households with greater financial sophistication, as measured by wealth or education, tend to invest more efficiently, but also more aggressively (in riskier assets).

While the investor tax rate and enrolment method into KiwiSaver funds is not the main focus of the paper, it remains important to control for these variables. The tax rate, for instance, could proxy for an investor's income level and the enrolment method could explain how different account types affect asset allocation. As shown in Table 3.4, the higher an investor's tax rate (or presumably their income level) the greater the amount of cash and bonds, and the lower the amount of property and equity assets, held. This suggests that investors in higher tax brackets invest more conservatively, which goes against the relation identified between the level of funds under management and risky asset investment and invites further thought. One might expect that in the absence of a capital gains tax in New Zealand that high tax rate investors would allocate more of their portfolio to equity assets. However, in the context of KiwiSaver there is a possibility that some people only see their KiwiSaver accounts as 'play money', or simply only put

enough into their accounts in order to claim the government tax credit. A 3000 person survey conducted by the Financial Services Council in New Zealand found that KiwiSaver members over age 55, male, with a degree, and retired former business managers, senior professionals, executives and government officials were more likely to only invest the minimum into their accounts to claim the tax credit (Stevenson, 2013). Furthermore, it is not surprising that default-enrolment into KiwiSaver is positively related to cash and bond assets, and negatively related to property and equity assets, since investors who enrol by default are placed in Conservative funds, which are heavily invested in cash and bond assets.

Interaction terms between age, gender and funds under management with financial advice are next added to the OLS framework to control for the possible effects between advice and demographic characteristics. The variables in Equation 3 are identical to those in Equation 2 except for the addition of three interaction terms:

$$\%\ Asset\ Allocation_i = \alpha + \beta_1 FinancialAdvice_i + \beta_2 Age_i + \beta_3 Age^2{}_i + \beta_4 Female_i + \beta_5 ZFUM_i + + \beta_6 Tax_i + \beta_7 Default_i + \beta_8 Age*FinancialAdvice_i + \beta_9 Female*FinancialAdvice_i + \beta_{10} ZFUM*FinancialAdvice_i + \varepsilon_i \quad (3)$$

Columns (5), (6), (7) and (8) of Table 3.4 show the results from Equation 3. When interaction terms are included in the regression analysis, the financial advice variable remains statistically significant, however, the coefficients reduce in size. The interaction term between age and financial advice is negative for cash and bond assets, while it is positive for property and equity holdings. This means that relatively older investors who receive advice hold a higher proportion of riskier assets than investors of the same age

who do not receive advice. On the whole, advised-accounts tend to invest more in equity and less in cash assets compared to non-advised accounts, however, the proportion of risky-assets held by investors who receive advice decreases with age and the proportion of cash assets held increases with age. Put more simply, older investors take on less risk than younger investors, however, older investors who receive advice take on more risk than those of the same age who do not receive advice.

The interaction term between female and financial advice is positively related to cash and bond investment, and negatively related to property and equity holdings. This result supports the univariate results presented in Table 3.3, reflecting that women who receive financial advice hold relatively safer asset allocations than men who receive advice. In addition, the interaction term between funds under management and financial advice is positively related to cash and property assets, and negatively related to bonds and equity investment. This implies that investors who receive advice with relatively higher levels of wealth invested in KiwiSaver hold more cash and property assets than unadvised investors with the same level of funds invested. A plausible explanation for this is that investors who have high levels of wealth and also receive financial advice may prefer to hold cash because KiwiSaver makes up only a small percentage of their total net wealth.

In the analysis of financial advice and asset allocation, it is important to control for self-selection bias because investors with particular characteristics may be more likely to receive financial advice than others. The Heckman correction procedure is a standard approach to correct for self-selection bias. Following Heckman (1979), a two-stage estimation procedure is calculated to control for self-selection bias. In the first stage of the estimation a probit model is performed. In the second stage, the inverse mills ratio (lambda) is generated using the coefficients from the probit model. The inverse Mills ratio

(lambda) is the ratio of the probability density function to the cumulative normal distribution. Lambda is included as an additional explanatory variable in the ordinary least squares regression to control for self-selection.

In addition, since the total weight of asset allocations in aggregate must equal to one, the error terms of the main OLS analysis might be correlated between equations. To control for seemingly uncorrelated regressions (SUR) each asset class is run as a system of equations with other asset classes.

Table 3.5 reports the results from the Heckman and SUR models. Panel A reports the results from the Heckman model and Panel B presents the results from the SUR model. As shown in Table 3.5, lambda (the inverse mills ratio) is statistically significant across all four Heckman correction models, which means that self-selection bias indeed exists. Controlling for self-selection bias, however, the results from the Heckman model are in line with the results from the main OLS analysis shown in Table 3.4. Furthermore, running the OLS regressions as a system of equations does not change the main results.

Table 3.5 Robustness checks: Seemingly unrelated regressions model and Heckman model

	Panel A: Heckman				Panel B: SUR			
VARIABLES	Cash	Bonds	Property	Equity	Cash	Bonds	Property	Equity
Financial Advice	-0.017***	-0.007***	0.012***	0.013***	-0.014***	-0.007***	0.011***	0.011***
	(-8.19)	(-2.93)	(8.02)	(4.52)	(-4.90)	(-3.17)	(16.8)	(3.98)
Age	-0.003***	0.003***	7.92e-05***	7.10e-06	-0.003***	0.003***	0.0001***	0.0002**
	(-37.8)	(53.9)	(4.74)	(0.10)	(-46.6)	(55.7)	(7.49)	(2.47)
Age^2	0.0001***	0.00001***	-0.00002***	-0.0001***	0.0001***	0.00001***	-0.00002***	-0.0001***
	(74.5)	(12.1)	(-69.2)	(-91.1)	(92.9)	(13.9)	(-72.4)	(-95.8)
Female	0.0039***	0.002***	-0.001***	-0.005***	0.002***	0.002***	-0.001***	-0.003***
	(5.88)	(3.79)	(-8.58)	(-8.11)	(2.90)	(3.49)	(-3.34)	(-5.29)
ZFUM	-0.0003	-0.008***	-2.18e-05	0.009***	-0.022***	-0.010***	0.005***	0.027***
	(-0.32)	(-7.78)	(-0.07)	(7.57)	(-52.1)	(-30.9)	(52.7)	(70.2)
Age*FA	-0.001***	-0.001***	0.0002***	0.001***	-0.001***	-0.001***	0.0003***	0.001***
	(-17.0)	(-8.07)	(7.30)	(20.7)	(-21.1)	(-10.4)	(20.1)	(26.9)
Female*FA	0.005***	0.020***	-0.004***	-0.021***	0.003*	0.020***	-0.004***	-0.019***
	(3.26)	(11.5)	(-4.54)	(-10.7)	(1.68)	(12.6)	(-8.81)	(-10.2)
ZFUM*FA	0.0062***	-0.009***	0.003***	0.0001	0.014***	-0.009***	0.001***	-0.007***
	(10.4)	(-12.6)	(8.69)	(0.14)	(19.7)	(-15.6)	(7.21)	(-10.2)
Default	0.051***	0.241***	-0.045***	-0.247***	0.051***	0.241***	-0.045***	-0.247***
	(96.7)	(426.1)	(-333.5)	(-361.8)	(58.2)	(356.7)	(-234.4)	(-305.9)
Tax	0.0004***	0.005***	-0.001***	-0.005***	0.0004***	0.005***	-0.001***	-0.005***
	(7.45)	(111.0)	(-66.9)	(-87.5)	(6.25)	(124.5)	(-72.3)	(-93.8)
Lambda	0.380***	0.029*	-0.086***	-0.323***				
	(25.8)	(1.67)	(-16.5)	(-18.5)				
Constant	-0.172***	0.054***	0.186***	0.932***	0.117***	0.076***	0.121***	0.686***
	(-15.2)	(4.13)	(47.5)	(70.3)	(83.4)	(70.5)	(394.1)	(535.2)
Observations	405,107	405,107	405,107	405,107	405,107	405,107	405,107	405,107
R-squared	0.101	0.475	0.320	0.455	0.100	0.475	0.319	0.454

FinancialAdvice$_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; *Age$_i$* is the age of the investor in years; *Female$_i$* is a dummy variable, which equals to 1 if the investor is female and 0 if the investor is male; and Z*FUM$_i$* is the standardised value of funds under management in the investor's KiwiSaver account. *Age$_i$*FinancialAdvice$_i$*, *Female$_i$*FinancialAdvice$_i$*, and *ZFUM$_i$*FinancialAdvice$_i$* are interaction terms between *Age$_i$*, *Female$_i$*, Z*FUM$_i$* and *FinancialAdvice$_i$*; *Tax$_i$* is the personal income tax rate of the investor; *Default$_i$* is a dummy variable, which equals to 1 if the investor has joined a government default KiwiSaver provider; and ε_i is the error term. Lambda is the inverse Mills ratio in the Heckman model. *, **, and *** denotes statistical significance at the 10%, 5% and 1% levels, respectively.

3.3.3 The impact of financial advice on short term returns

This section compares the differences in portfolio returns between advised and non-advised investors. Before proceeding, however, a number of caveats are in order. A key limitation of the data is that I do not know the exact date which financial advice is received. Therefore, measuring the effect of financial advice on portfolio returns over a long sample period becomes problematic, especially if an investor only recently received advice. As the variable I use to measure financial advice cannot be any less noisy than how they are currently provided, the inferences I make from the tests which follow rely heavily on the assumption: that financial advice was received at the time that KiwiSaver was introduced in 2007. I justify this assumption on the basis that all investors who have received advice received their advice during the process of joining their KiwiSaver scheme and fund. Therefore, it seems plausible to assume that all advice must have taken place between the inception date of KiwiSaver from July 2007 to 30 June 2011. Returning, then, into the question, since financial advice impacts asset allocation, varying levels of riskiness in asset allocation should lead to differences in performance. Differences in returns are calculated as the average returns for investors who received advice minus the average returns to investors who did not receive advice. T-tests are computed to determine whether statistical differences in returns exist between the two groups of investors.

Table 3.6 reports the returns and risk-adjusted returns of advised and non-advised accounts. The returns used are KiwiSaver investment fund returns obtained from Morningstar Direct for 2007 to 2012, and all returns are reported net of fees. Panel A of Table 3.6 shows the differences in annual returns, five-year returns and risk-adjusted returns for advised and non-advised investors; Panel B and Panel C present the differences

in returns by financial advice and gender, respectively; and Panel D presents the average KiwiSaver returns from all KiwiSaver investment funds from 2008 to 2012.[33]

Table 3.6 Differences in KiwiSaver portfolio performance 2008-2012

Panel A: Full Sample				
	Financial Advice	Non- Advice	Difference	T-stat
Annual Return (%)	(1)	(2)	(1) – (2)	
2008	-12.90	-10.38	-2.52	-46.1***
2009	13.28	11.72	1.56	60.8***
2010	6.93	6.65	0.27	43.3***
2011	2.41	2.96	-0.55	-43.2***
2012	14.58	13.10	1.49	60.1***
Return 2008-2012	4.86	4.81	0.05	1.98***
Sharpe Ratio	0.072	0.078		
Panel B: Female				
	Financial Advice	Non-Advice	Difference	T-stat
Annual Return (%)	(1)	(2)	(1) – (2)	
2008	-12.40	-10.21	-2.19	-34.2***
2009	13.11	11.83	1.48	51.1***
2010	6.92	6.68	0.30	30.8***
2011	2.52	2.92	-0.48	-32.1***
2012	14.39	13.20	1.39	49.3***
Return 2008-2012	4.91	4.81	0.10	18.8***
Sharpe Ratio	0.078	0.079		
Panel C: Male				
	Financial Advice	Non-Advice	Difference	T-stat
Annual Return (%)	(1)	(2)	(1) – (2)	
2008	-13.44	-10.57	-2.87	-42.0***
2009	13.47	11.83	1.64	53.5***
2010	6.93	6.68	0.25	23.3***
2011	2.30	2.92	-0.63	-38.0***
2012	14.80	13.20	1.59	53.5***
Return 2008-2012	4.81	4.81	0.00	-0.58
Sharpe Ratio	0.067	0.078		
Panel D: Average Performance of KiwiSaver Funds				
Annual Return (%)	Cash	Conservative	Balanced	Growth
2008	5.91	-0.08	-10.9	-15.67
2009	3.69	6.62	12.83	15.77
2010	3.29	4.77	6.11	5.48
2011	3.19	3.63	1.18	-3.56
2012	3.48	6.67	12.01	14.73
Overall Return (%) 2008-2012	3.91	4.32	4.23	3.35

This table reports the mean and t-statistics of the annual returns, differences in returns and risk-adjusted returns from 2008 to 2012 for investors who have received financial advice, compared to investors without financial advice. Panel A compares the returns of the full sample of investors. Panels B and C show the differences in returns by gender. Panel D shows the average performance of all KiwiSaver funds across cash, conservative, balanced and growth funds from 2008 to 2012. The Sharpe ratios present risk-adjusted returns and are calculated by dividing excess returns (portfolio return less the NZ 90-day T-bill) by the standard deviation of the portfolio excess return. All other returns used are annual KiwiSaver investment fund returns obtained from Morningstar and are calculated net of fees.

[33] These funds include 128 KiwiSaver investment funds available from the Morningstar Direct database.

Over the five-year period in which KiwiSaver has been in operation advised accounts do not appear to perform significantly better than un-advised accounts. At first glance, the results in Table 3.6 indicate that advised accounts earn higher returns than un-advised accounts in years where equity markets perform well, and underperform un-advised accounts in years where equity markets experience low returns. For instance, during the global financial crisis in 2008, advised accounts underperform advised accounts by 2.52%. This finding, however, is unsurprising owing to the fact that advised accounts tend to hold more equity assets than non-advised accounts. Due to the differences in asset allocation between advised and non-advised accounts risk-adjusted returns must be calculated to make performance more comparable.[34] When risk is uncontrolled those investors who receive advice marginally outperform investors who do not receive advice by 5 basis points. On a risk-adjusted basis, however, advised accounts slightly underperform non-advised accounts. The results in Table 3.6 show that advised accounts consistently underperform un-advised accounts from 2008 to 2012 when Sharpe ratios are taken into consideration. Panels A, B and C of Table 3.6 report lower Sharpe ratios for advised accounts compared to non-advised accounts; 0.072 compared to 0.078 for the entire sample, 0.078 compared to 0.079 for females, and 0.067 compared to 0.078 for males. The results in Table 3.6 are in line with previous research. Similar to Bodie (2003), if the objective of receiving advice is to increase portfolio performance, then financial advice fails to generate significantly higher returns. As shown in Panel B, women who receive advice outperform women who do not receive advice by 1.48%, 0.30% and 1.39% in 2009, 2010 and 2012, respectively. Advised women, however, underperform non-advised women by -2.19% and -0.48% in 2008 and 2011, respectively. Similar results are

[34]Sharpe ratios are used to compare risk-adjusted returns between advised and non-advised accounts. Sharpe ratios are calculated by dividing excess returns (portfolio return less the NZ 90-day T-bill) by the standard deviation of the portfolio excess return.

found in Panel C of Table 3.6, which shows that men who receive advice outperform men who do not receive advice by 1.64%, 0.25% and 1.59% in 2009, 2010 and 2012, respectively; however, they underperform non-advised men by 2.89% and -0.63% in 2008 and 2011, respectively. The figures presented in Panel A, Panel B and Panel C are in line with the average investment fund returns, as shown in Panel D. For instance, in 2008 and 2011, growth funds receive negative returns, while they receive positive returns in 2009, 2010 and 2012.

Since KiwiSaver has a limited return series-history, hypothetical returns are generated to extend the study period and test the robustness of the main results. Hypothetical returns are calculated using the average asset allocation weights of the accounts held and the market return indices. The return indices are drawn from Morningstar Direct from January 2000 to December 2012 and the average asset allocation holdings are obtained from the analysis shown in Table 3.3. The market benchmarks used in each asset class are in line with the benchmarks used by Morningstar for multi-sector funds, and are market indices that are frequently referred to within the Australasian finance industry.[35] Since the returns used in the robustness check are not actual KiwiSaver fund returns, the focus of the analysis is to test the effect that significant differences in asset allocation between advised and non-advised groups at the aggregate level may have on portfolio returns had the average asset allocation been held by investors over a longer time period than the one available.

[35] The ANZ NZ 90 Day Bank Bill is used to represent Cash returns, ANZ NZ Government Stock to represent Domestic Fixed Interest returns, the Barclays Global Aggregate Bond Index to represent International Fixed Interest return, the NZX Property Index and S&P/ASX 200 A-REIT indices to represent the Australasian Property Market returns, the UBS Global Investors Ex NZL property index to represent the International Property Market return, the Cat 50% NZX 50 & 50% S&P/ASX 200 index to represent the Australasian Equity returns and the MSCI World Ex Australia to represent the International Equity Market returns.

Table 3.7 Differences in hypothetical portfolio performance 2000-2012

Returns	N	Female (%)	T-stat	Male (%)	T-stat	All (%)	T-stat
Monthly	240	0.010	0.62	0.015	0.69	0.012	0.65
Quarterly	49	0.037	0.57	0.051	0.64	0.044	0.6
Annual	12	0.244	0.68	0.324	0.72	0.281	0.7

This table shows the t-statistics for differences in hypothetical portfolio returns generated between female investors who attain advice and female investors without advice, male investors with advice compared with male investors without advice, and investors who receive advice compared with investors without advice. The returns used were calculated based on hypothetical asset allocation fund holdings and market return indices.

Analysing monthly, quarterly and annual returns, t-tests are conducted to evaluate whether differences in portfolio returns exist between investors who receive advice and investors who do not. Table 3.7 presents the results of the t-test for hypothetically constructed portfolio returns. The hypothetical portfolio returns derived from advised-client asset allocations are not statistically different from the returns of non-advised clients over monthly, quarterly, or annual periods from 2000 to 2012. An insignificant difference in returns between advised and non-advised investors is not surprising, because the difference in fund choice and asset allocation is marginal when averages are used. In the short term it appears that asset allocation does not have a large effect on returns. This begs the question, what is the worth of financial advice if returns do not significantly differ? Evidence from a US study shows that people may be unable to see the financial benefits of receiving financial advisor until after they receive it for over a decade. Cummings and James (2014) investigate the impact that financial advisors have on wealth outcomes among older adults (aged 60 and over) in America. They find that using a financial advisor is significant and positively related to subsequent net worth among older adults, "especially on net worth values more than a decade after using professional financial advice" (Cummings & James, 2014, p. 22). This outcome suggests that in the case of KiwiSaver it may be simply be too soon to tell whether people are better off financially from having received advice.

3.4 Conclusion

The contribution of this study is twofold: (1) It is the first study that investigates the impact of financial advice on KiwiSaver individual investor behaviour; and (2) it also makes a contribution to the wider understanding of the role of financial advice on asset allocation and performance. The proprietary data used in this study offers the ability to answer earlier research questions with greater precision. The precision in the measure of investor behaviour on a representative nationwide sample and financial advice has provided further clarity to earlier studies. The first finding of this paper challenges what was previously known regarding who receives financial advice. It finds that women, older investors and investors with relatively higher levels of funds under management tend to receive financial advice more than others. The second finding reaffirms the earlier work of Mullainathan et al. (2012), while it challenges Kramer (2012) in terms of the level of equity exposure an investor holds under advice. Investors who receive advice hold risker asset allocations; that is, lesser proportions of cash and bond assets, and greater proportions of property and equity assets. Finally, in line with earlier evidence from US, German and Swiss coming returns of advised and non-advised investor accounts (Bergstresser et al. 2009; Hackethal et al. 2012; Hoechle et al. 2013), the third finding of this paper shows that differences in returns between advised and non-advised accounts appear, at best, marginal.

Ultimately, a broader contribution made by this paper is that it adds to the growing body of knowledge in the area of Household Finance. Household Finance poses challenges to traditional finance frameworks, because the decisions of households are difficult to measure (Campbell, 2006). "Many households seek advice from financial planners and other experts, yet some households make decisions that are hard to reconcile

with this advice or with any standard model" (Campbell 2006, p. 1554). KiwiSaver offers a new lens to observe individual investor behaviour and investigate the reasons why households behave the way they do. The findings of this paper raise questions for traditional frameworks in regards to explaining who might seek financial advice, and why they do so. Topics which require more research attention should be focused on establishing best practice(s) on how to provide financial advice, so that it can reach those who are in need. Another future research focus is to consider innovative ways to empower households to want to improve their level of financial literacy in a manner that will promote effective financial decision making. It may be that conversation(s) between the financial adviser and the individual ought to be brought into the household, or between friends and family. After all, where is a better place to start exploring household financial behaviour than with those people who are closely attached to us.

Chapter 4 The relative importance of factors that influence the asset allocation decisions of individual investors

4.1 Introduction

We use a large and unique proprietary database to investigate the relative importance of factors that determine the asset allocation choices and fund switching decisions of individual investors.[36] This database has information on which mutual funds investors hold, their personal characteristics, the households and neighbourhoods they live in, the places they work, and whether or not they have received financial advice. We also have information on when investors switch funds. The database consists of over 40,000 individual investor accounts of investors living in 28,000 households in 450 different neighbourhoods and working in 14,000 unique companies. Of these investors, almost 7,000 received financial advice. Since we know the asset allocations of the mutual funds in which these participants invest, this allows for a comprehensive study of the personal and environmental factors reported in the literature as being important in asset allocation decisions. We can also compare the importance of these factors relative to each other.

There is a vast literature that suggests personal characteristics and financial advice are important in financial decision making. There is also a growing literature on the possibility that neighbours and co-workers play a role, particularly with respect to stock market participation. However, to the best of our knowledge, no study considers all factors jointly or allows for the peer effects of investors who live in a same household in

[36] This paper is co-authored with my supervisors Professor Ben Jacobsen and Professor Ben Marshall. I use 'we' to reflect this collaborative work.

focusing on asset allocation decisions.[37] This, as Campbell (2006) points out, is likely due to the difficulty of obtaining data. Our data come from four large KiwiSaver providers in New Zealand. KiwiSaver is a voluntary, work-based savings initiative of the New Zealand government. Begun in 2007, KiwiSaver is a defined contribution pension scheme similar to the U.S. 401(k) scheme. In total, these four providers hold one-quarter of the market share of the KiwiSaver fund market as measured by funds under management in a large number of different mutual funds.[38]

We find that all factors are important in asset allocation decisions, but some factors are more so than others. Peer effects in households (people living at the same physical address, who may be family members or friends) dominate asset allocation decisions. When comparing investment fund choices between peer groups, we find that almost two-thirds (64%)[39] of people hold the exact same investment fund—and therefore identical asset allocation—as the people they live within the same household, compared to a maximum of 25% of investors holding the same mutual fund in our overall sample. So, people in the same household are at least 2.5 times more likely to hold the same fund as others in their household. This household peer effect explains around 15% of the variation of asset allocation choices. This may be partially caused by what one might consider the ultimate peer effect, where one household member makes investment decisions for others.[40]

[37] In this study we apply the term *peer effects* in the general sense of the word. We interpret *peer effects* to mean the effect that people may have on others with whom they are close to or closely connected to. We treat co-workers and people who live in the same household or neighbourhood as peers. We are not strict in the sense of limiting the definition of *peer effects* to be the influence of a person of the same age, status, or ability as another.

[38] Reported as at July 2011.

[39] Appendix 4.2 shows how the calculation is made.

[40] This result also confirms other findings on household peer effects.

This household peer effect seems strong and may even be a greater influence on choice than an investor's personal characteristics. The personal characteristics we can identify explain 10% of total variation in asset allocation choices. Personal characteristics and household peer effects combined are the two most important sets of factors. However, the asset allocation decisions of individual investors are also positively related to those asset allocation choices of their co-workers (people employed by the same company). One-third (34%) of people hold the same investment funds as their co-workers do (which is also more than the maximum of 25% in the overall sample). So, people in the same company are at least 1.4 times more likely to hold the same fund as others in their workplace. These co-worker effects alone explain 5.1% of the variation in individual asset allocation choices.

Combining workplace, household, and personal effects substantially improves the explanatory power of models for asset allocation choices. Combined, these effects explain 25% of the variation in the asset allocation choices of individuals. After we take household and workplace peer effects into account, we still find that neighbourhood peer effects play a role, although they are relatively marginal compared to other environmental factors. People in the same postal code area tend to invest similarly (even if we control for the fact that these people may have similar personal characteristics). Our results also confirm that investors who have received financial advice tend to hold significantly larger positions in equity. However, the contribution to the R2 of these two factors combined seems relatively marginal, since the explained variation only increases by 1.8%, to 26.8%, if we add these factors to the other effects.

Our results suggest that omitting peer effects or personal characteristics when investigating asset allocation leads to an omitted variable problem and can thus

bias estimates. The explained variation of all peer effects combined is 19.8%, versus 9.7% for personal characteristics. However, our study confirms most of the signs and magnitudes of factors in many previous studies focusing on subsets of these factors.[41] This result suggests that this bias may not be too severe, although our results indicate that not controlling for personal characteristics when looking at household effects can cause a serious omitted variable bias.

We also establish a causal relation between an individual's asset allocation choice and the choice of their household members and co-workers. We follow an approach similar to Brown et al. (2008) to test for causal peer effects. We create an instrumental variable for household peers and co-workers choice by using the co-workers of household peer's and the household members of co-worker's. Our dataset provides a unique opportunity to test for causality by using an individual's peer's peers to instrument for the behaviour of peers. To give an example, let us assume that A and B work together and B is married to C, ordinarily we would not expect C's behaviour to affect A's unless there are strong peer effects between A and C directly or via B. We find that a one-percent increase in equity holdings by household peers would results in an individual holding 0.306 percent more of equity. Likewise for co-worker peer effects, we find that a one-percent increase in equity holdings by co-workers would lead to an individual holding of 0.295 percent more of equity assets. An explanation of this causal peer effect is most likely caused by social interaction between B and C via A or directly between B and C. Our results are in line with Brown et al. (2008) who also establish a causal relation between an individual's decisions whether to hold stocks and average stock market participation of the individual's community. The causal peer effects which we find are further supported by

[41] Barber and Odean (2001), Agnew, Balduzzi and Sunden (2003), Bodie (2003), Hong, Kubick, and Stein (2004), and Brown et al. (2008).

our other findings which show that investors are more likely to switch funds when their peers switch.

In robustness tests, we find similar results for the mean squared errors in so-called "hold out" tests (where we predict a random subset of 20% of the sample based on the other 80%). If anything, these tests suggest that personal characteristics matter even less compared to the peer effects we consider. Wald tests confirm most of our results, with the exception of the neighbourhood tests: a joint Wald test on all neighbourhood factors finds no added value. Switching behaviour seems to confirm further the importance of household and workplace peer effects. Investors are likely to switch funds if peers switch funds. On average, investors switch funds only 1% of the time. The probability of an investor switching funds if a household or workplace peer switches within the previous six-month period is 10% or 6.7%, respectively, if we look at switches within the same six-month period. While fund switching by both household members and co-workers increases the likelihood of individuals switching funds, fund switches by household members occur two to three times more often.

This study contributes to the literature in several ways. As we noted earlier, it is the first to include a comprehensive list of personal and environmental factors (and specifically household peer effects) jointly, which allows us to study the relative importance of these factors in relation to each other. In addition, our study focuses on investors who are representative of the total population and we look at the asset allocation implicit in their mutual fund selection. Most other peer effect studies tend to focus on stock market participation or stock market trading. Our study indicates that peer effects are important not only in active investing (Heimer, 2014) but also in passive investment decisions. Moreover, we can follow investors over time and look at the changes they

make, which allows us to verify some of our findings on peer effects for their asset allocations holdings. If we combine these features, our study fills an important gap, since it fulfils many of the criteria of an ideal dataset to study household finance, as put forward in Campbell's (2006) presidential address. Furthermore, our study is the first to add financial advice to the mix.

Our database allows us, to a large extent, to merge three different strands of the literature, relating to personal characteristics, peer effects, and financial advice. The impact of personal characteristics on financial decisions has been studied by many papers. There are also a number of papers on peer effects, the main difference with our study being that these studies only consider subsets of all the factors we combine here.

There is considerable evidence that a number of personal characteristics affect asset allocation decisions. Ackert, Church, and Englis (2002) find age influences investors' choice of risky assets. There are several possible reasons for this. First, Cocco (2005) suggests investment in housing by younger investors results in limited ability to invest in stocks. Second, as individuals reach retirement age, they likely look to reduce risk by decreasing the stock–bond ratio. Gender is another important determinant. Women appear to take a more conservative approach to investing. As Jacobsen, Lee, Marquering and Zhang (2014) show, based on international data, this can be due to either women being more risk averse or less optimistic or their perceiving stock markets as being riskier than men do. While, as Barber and Odean (2001) document, less overconfidence can have such benefits as reducing wealth destruction due to excessive portfolio turnover, high risk aversion can also have disadvantages, such as lower allocation to stocks and less benefit from the equity premium, as highlighted by Sunden and Surette (1998). Love (2010) finds that changes in family status also affect asset allocation. For instance, divorce leads

women to move to safer asset allocations and men to move to riskier allocations. Agnew and Szykman (2005) show financial literacy is related to education and income and these factors influence asset allocation. Finally, Barnea, Cronqvist, and Siegel (2010) use Swedish data on identical and fraternal twins to prove that genetics play an important role in asset allocation. Our study differs because we also include peer effects in our analysis.

There is a growing literature on peer effects. Hong, Kubik, and Stein (2004) find that more social households that interact more with their neighbours or attend church are more likely to participate in the stock market. Brown, Ivković, Smith and Weisbenner (2008) show, based on zip codes, a causal relation between stock ownership and the average stock market participation of an individual's community. Heimer (2014) finds that social interaction is more prevalent among active rather than passive investors. Ng and Wu (2012) find that Chinese investors at the same branch of a brokerage firm tend to make similar trading decisions. Kaustia and Knüpfer (2012) look at Finnish data and add that this effect might be caused by peer performance rather than valuable information exchange. Whether peer effects exist in the workplace is less clear. Hvide and Östberg (2013) show that the stock market investment decisions of Norwegian investors are positively correlated with those of their co-workers.[42] Little is known about household peer effects and asset allocation decisions, although earlier research suggests its importance. For instance, Barber and Odean (2001) show that the largest differences in trading behaviour are between single men and single women rather than between married men and married women. More closely related to our study, a survey by Gilbert, Hyde, Tourani-rad and Le (2013) finds that 42% of KiwiSaver investors at a New Zealand

[42] They include family members as a control variable but include not only household members (spouses and children), but also parents, grandparents, grandchildren, siblings, uncles, aunts cousins, nieces, and nephews not living in the same household.

university were the primary financial decision maker, 46% shared the responsibility, and 7% abdicated the responsibility (i.e. to a financial advisor). This gives some indication of the number of people who might be making decisions for the entire household, compared with otherwise. Our results show that these household peer effects are important even when compared to personal characteristics. Lu (2011) finds that 401(k) plans are influenced by those of co-workers, but Beshears, Choi, Laibson, Madrian and Milkman (2011) show that providing co-workers' savings information decreases savings in 401(k) plan enrolment. Our study differs from these studies because we focus on the relative importance of many different peer effects and personal characteristics. Additionally, as mentioned before, we consider the asset allocation decisions of individuals rather than stock market participation or stock market trading.

Further, there is a growing literature that examines the role of financial advice in investor behaviour. Using the same database of New Zealand investors, Zhang (2014) finds female investors, relatively older investors, and investors with more funds under management are more likely to receive financial advice. The difference between the samples is that Zhang uses a KiwiSaver sample of 400,000 investors, while we use a smaller subset of that sample (40,000), with peer group information as well as financial advice information. In addition, Zhang finds that investors who receive advice hold riskier assets than non-advised investors do and that the differences in portfolio performance between advised and non-advised investors are marginal. These findings support the results of Mullainathan, Nöth, and Schoar (2012), who conduct an audit study of the market for advice in the greater Cambridge and Boston area in the United States and find that asset allocation is positively related to equity exposure. In contrast, however, using a database from the Netherlands, Kramer (2012) finds that advised portfolios contain significantly less equity. Meanwhile, the effect of financial advice on performance is also

mixed. Bergstresser, Chalmers, and Tufano (2009) and Hackethal, Haliassos, and Jappelli (2012), using data from a German brokerage firm, find that the returns of advised portfolios are lower than those of unadvised accounts, mainly due to higher trading costs. However, Bhattacharya, Hackethal, Kaesler, Loos, and Meyer (2012), also using German brokerage firm data, find that taking advice is associated with an improvement in portfolio performance, but only a fraction of investors are willing to accept and follow advice.

4.2 Data

To study the asset allocation of individual investors, we obtain data from four large KiwiSaver providers in New Zealand. In total, they hold one-quarter of the market share of the KiwiSaver fund under management market share. The data contain personal, demographic, geographic, and employment information. KiwiSaver is a voluntary, work-based savings initiative of the New Zealand government. Started in 2007, KiwiSaver is a defined contribution pension scheme similar to the U.S. 401(k) scheme. In total, 13 investment funds are available for investors to choose from within each fund family.[43] The data are cross-sectional and report information as of June 30, 2011, with the exception of fund switches, whose switching dates we can observe. Information on fund switching is available if investors made changes to their asset allocation or switched investment funds between July 1, 2007 (the commencement date of KiwiSaver), and June 30, 2011. The variables we use are individual investor age, gender, funds under management, tax rate, investment fund choice, the asset allocation of funds, the name and location of the company where the investor works, the household residence,

[43] The funds are cash, conservative, conservative–balanced, balanced, balanced–growth, growth, domestic (Australasian) bonds, international bonds, domestic property, international property, domestic equity, international equity, and socially responsible.

neighbourhood information, information on whether the investor received financial advice, the investor's enrolment method into KiwiSaver, and whether the investor switched investment funds (made asset allocation changes). We try to use the same/similar variables as are commonly adopted in the literature to proxy for an investor's personal characteristics, for instance, age, gender, and wealth. We do not have a direct measure of wealth, so we use the log of funds under management invested by the investor as our proxy. We use tax rate as a proxy for investor income and default enrolment as our measure of the level of investor inertia (Madrian & Shea, 2001). A socioeconomic variable that we cannot directly control for is the level of education. Here, we rely on the unobserved correlation between education and other investor demographic characteristics, such as age, gender, wealth, and tax rate, to indirectly account for education. Strong evidence in the economics literature suggests education and earnings are highly correlated (e.g., Kennickell & Sunden, 1997; Qian, 1998; Jianakolpos & Bajtelsmit, 2002). Massa and Simonov (2011), who investigate whether college is a focal point of an investor's life, adopt a similar approach by building additional education controls in their study, using parental income and geographic and gender distribution. Further, since we also have information on the personal characteristics of household, workplace, and neighbourhood peer group members, we can construct measures of peer group control to account for potential differences in average peer effects across demographic groups.

We form household peer groups by matching identical residential street addresses and co-worker peer groups by matching company names and locations. We also generate neighbourhoods by grouping individuals by their postal code. To identify the exact geographic locations where people live, we match individuals together using information on their unit number, house number, street, suburb, city, and postal code. We remove all

post office box (PO Box) addresses from our sample due to the difficulty of determining whether people with the same PO Box reside in the same physical household. Co-workers consist of groups of two persons or more working in the same company in the same office. Similar to earlier studies that observe peer effects between co-workers, we may potentially underestimate the true peer effects because co-workers may have never met. As a safety measure, we also match postal codes against company codes to verify that the geographic location we identify is where an individual works, since some companies operate under the same name but in multiple locations. Please note we use the word *company* as a blanket term to cover a multitude of business enterprises and structures that may exist in the workplace.

The composition of households and companies sizes in our sample is representative of New Zealand households and companies, respectively. Table 4.1 shows the distribution of household and company sizes contained in the sample. Of the 28,380 households contained in the final sample, 66% of individuals live in a house with two people. This result is in line with the census showing "households containing just one or two usual residents made up over half of New Zealand households, at 56.6%" (New Zealand, 2002, p15). Of the 14,392 companies in the sample, 94% of all individuals work in a firm with two to 25 co-workers.

Table 4.1 Household size and company size

Panel A			
Household Size	Frequency	Percentage	Cum Percentage
2	18750	66.1%	66%
3	5530	19.5%	86%
4	2652	9.3%	95%
5	966	3.4%	98%
6	316	1.1%	99%
7	121	0.4%	100%
8	45	0.2%	100%
Total Households	28380	100.0%	100%
Panel B			
Company Size	Frequency	Percentage	Cum Percentage
2-25	13515	93.9%	94%
26-100	672	4.7%	99%
101-200	119	0.8%	99%
201-1000	72	0.5%	100%
1001-5000	14	0.1%	100%
Total Companies	14392	100.0%	100%

This table shows the distribution of household size and company size contained in the sample in panels A and B, respectively. There are 28,380 households in total, of which 66% are 2 person households. There are 14,392 companies in the sample and 94% of all individuals included in the sample work in a company with 2 to 25 people. This is in line with the average firm size of New Zealand companies as calculated by the New Zealand Treasury, which shows that 91% of firms in New Zealand have fewer than 20 employees (Mills & Timmins, 2004).

The distribution of company sizes in our sample is in line with the average firm size of New Zealand companies. Mills and Timmins (2004) show 91% of firms in New Zealand have fewer than 20 employees. It is also worth noting that the size and distribution of enterprises in New Zealand are analogous to those in a number of other Organisation for Economic Co-operation and Development (OECD) countries. As such, this result may provide ways to assess the comparability of findings from studies undertaken in different countries and also help contextualize the results presented in this paper. For example, the proportion of small firms (with fewer than 20 employees) in New Zealand is similar to that in Denmark, Finland, Germany, and Italy. The proportion of people employed in firms with fewer than 20 employees is also close to that in Australia, Denmark, Finland, the Netherlands, and Portugal (Mills & Timmins, 2004, p.9-10).

We draw 42,187 investors from a pool of 405,107 KiwiSaver accounts to compose our dataset. We remove individuals belonging to households and companies with fewer than two persons because peer groups cannot be established. Single-person households and companies, however, are still reported in later sections for comparative purposes.[44] In total our samples contains 14,392 unique companies, 28,380 households, and 462 neighbourhoods.[45] We create a number of new variables to capture potential household and company effects that may influence investor asset allocation. If birds of a feather do indeed flock together then it would be interesting to see the relation between individual asset choice and the demographic effects of people in their peer group. For instance, if an investor has older co-workers or co-workers with relatively high sums invested in their account compared to the investor's, how might this impact the investor's personal investment choice(s)? The household, company, and neighbourhood variables we use are average age, the proportion of females, average funds under management, the average tax rate, household size, company size, the number of neighbours, and, most importantly, the average asset allocations of household members, co-workers, and neighbours. We generate these control variables because the literature suggests that the composition of the household and workplace can influence financial decisions with regard to the assessment of risk and loss. For example, Bogan, Just, and Dev (2013) find that a male presence in the workplace increases the probability of selecting a higher-risk investment.

[44] Single-person households, on average, hold more cash and bonds and less property and equity than multi-person households do and hold relatively more in equity, property, and cash assets and less in bond than multi-person companies do. On average, single-person households hold a conservative–balanced fund, while multi-person households tend to hold a balanced fund, which is riskier. Single-person companies, on average, hold a balanced fund and companies with two or more individuals, on average, hold conservative–balanced funds, which are less risky. See the descriptive statistics in Appendix 4.1.

[45] The reduction in sample size results from having to remove observations that do not contain information on both household *and* company information. The membership in KiwiSaver of households and of employed members is in line with KiwiSaver individual investor surveys (Colmar Brunton, 2010). The survey reports that it is more common in households with couples for just one partner to be a KiwiSaver member than it is for both partners to be KiwiSaver members (19% compared to 13%, respectively).

Hong, Kubik, and Stein (2004) report that educated households with above-average wealth are more likely to participate in the stock market if they interact with peers than others. Bär, Kempf, and Ruenzi (2011) find that team size has a moderating effect on investment behaviour.

Similar to the methodology applied by Lu (2011), we construct each person's household- and company-level asset allocation by taking the average of the asset allocation of all the other participants in the household and company. We calculate household, company, and neighbourhood demographic variables by excluding the respective individual in question. By excluding an individual investor's details from the investor's own household, company, and neighbourhood average enables the interpretation of variables to involve the effects of their peers only.

A summary of key variables is presented in Table 4.2. The level of funds under management, the proportion of male to women, and age distribution are in line with the figures reported by annual KiwiSaver evaluation reports by the New Zealand Inland Revenue (2013). For example, average funds under management are NZD$7,231, which is slightly under the NZD$8500 to NZD$10,000 range reported by New Zealand Inland Revenue (2013) and the gender distributions are comparable, with 54% of our sample and 52% of the national sample being female. The proportion of default-enrolled investors in our sample is 8%. This is lower than the national average for default enrolment, as shown by Douglas (2014). We may observe fewer default-enrolled investors in our sample because those included in the sample interact (live and work) with other people. As shown in Table 4.2 the mean and median of a number of variables presented have large differences due to the data distribution. For instance, the average company size is 358 co-workers; however, the median company size is only 18. The higher average is caused by

25% of firms in the sample that have a higher number of co-workers (between 199 and 3,463). Only 1% of the 42,187 individuals in our sample switch funds. This figure is akin to other New Zealand reports on fund switching, as well as international studies (Madrian & Shea, 2001; Cronqvist & Thaler, 2004; Gerrans, 2012; Matthews, 2011).[46] We do not discuss all the control variables in our sample here; however, we present their results in later sections.

[46] Cronqvist and Thaler (2004) find only 2.5% of Swedish investors changed to retirement plans in the first three years following the introduction of a new Swedish retirement plan scheme. Gerrans (2012) shows using Australian retirement data the overall percentage of people who change their balance or level of contribution to their retirement savings is 6.5%. Matthews (2011) finds than less than 5% of KiwiSaver members have switched between funds at the same provider.

Table 4.2 Summary statistics

Variable	N	Mean	Std. Dev.	Min	25Q	Median	75Q	Max
Funds Under Management (FUM)	42187	7232	7167	102	2255	5099	10192	214855
Female	42187	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Age	42187	40.2	13.9	15.0	27.0	41.0	51.0	69.0
Tax Rate	42187	20.8	5.9	10.5	17.5	17.5	28.0	28.0
Default Enrolment	42187	0.08	0.27	0.00	0.00	0.00	0.00	1.00
Financial Advice	42187	0.17	0.38	0.00	0.00	0.00	0.00	1.00
Cash Asset Allocation	42187	0.14	0.18	0.00	0.04	0.10	0.20	1.00
Bond Asset Allocation	42187	0.36	0.18	0.00	0.16	0.40	0.50	1.00
Property Asset Allocation	42187	0.08	0.05	0.00	0.03	0.08	0.12	1.00
Equity Asset Allocation	42187	0.43	0.21	0.00	0.17	0.42	0.68	1.00
Company Size	42187	358	780	2	4	18	199	3463
Company Female Percentage	42187	0.47	0.29	0.00	0.24	0.49	0.67	1.00
Company Average Age	42187	40.0	8.0	19.0	35.0	40.3	44.9	68.5
Company Average FUM	42187	6907	4019	246	4080	6248	9052	61933
Company Average Tax Rate	42187	21.8	3.1	10.5	20.1	22.1	23.8	28.0
Household Size	42187	3	1	2	2	2	3	8
Household Female Percentage	42187	0.48	0.26	0.00	0.33	0.50	0.50	1.00
Household Average Age	42187	36.0	13.4	16.0	25.0	34.0	45.0	69.0
Household Average FUM	42187	6034	5148	136	2352	4506	8185	111909
Household Average Tax Rate	42187	19.7	4.6	10.5	17.5	18.0	22.8	28.0
Log(FUM)	42187	8.48	0.93	4.62	7.72	8.53	9.23	12.30
Log(FUM) Household	42187	8.40	0.79	4.91	7.76	8.41	9.01	11.60
Log(FUM) Company	42187	8.68	0.60	5.51	8.31	8.74	9.11	11.00
Log(FUM) Neighbour	41970	8.89	0.17	6.33	8.79	8.79	8.79	11.00
Neighbourhood Size	42187	558	406	5	209	575	772	1466
Neighbourhood Female Percentage	42132	0.54	0.10	0.48	0.52	0.54	0.56	0.58
Neighbour Average Age	42132	40.8	7.3	37.2	39.1	40.3	41.7	43.1
Neighbour Average Tax Rate	42132	21.1	3.5	15.5	20.5	20.9	21.4	25.5

This table provides the descriptive statistics of the data, which contains demographic information, asset allocation composition, and household, co-worker and neighbour-peer group information. There are 42,187 individual investors in the sample, as denoted by N. The mean of the variables, their minimum, maximum, median and standard deviation, as well as the 25th and 75th quartiles are presented. FUM is presented in New Zealand Dollars (NZD), gender is a percentage of females in the sample, age is expressed in years, tax rate is a percentage, default enrolment is expressed as a percentage of investors in the sample who were automatically enrolled into KiwiSaver, financial advice is expressed as the percentage of investors who received professional financial advice from an Authorised Financial Adviser in New Zealand, asset allocation by asset class is the average proportion of assets held in the all investors portfolio, company size is the average number of employees in a company, householdsize is the number of investors living at the same physical address and neighbourhood size is the number of investors living in the same postcode. The household, company and neighbour peer group control variables of female percentage, average age, average tax rate and log of FUM are calculated for each household, company and neighbourhood in the total sample using individual investor information.

4.3 Methodology

To generate our main results, we use an ordinary least squares (OLS) model to test the relative importance of personal characteristics; household, workplace, and neighbourhood peer effects; and financial advice on asset allocation. We use clustered standard errors to control for serial correlation in errors (we cluster by company, household, and neighbourhood). Similar regression models that link investor choices to group choices have been used in literature; however, they focus on different variables (Bertrand, Luttmer & Mullainathan, 2000; Ivković & Weisbenner, 2007; Hvide & Östberg, 2013). We show our full model as follows:

$$
\begin{aligned}
&Asset\ allocation_{i,j,h,c,n} \\
&\quad = \alpha + HouseholdAssetAllocation_{i,j,h} \\
&\quad + CompanyAssetAllocation_{i,j,c} + Age_i + Female_i + LogFUM_i \\
&\quad + TaxRate_i + Financial\ advice_i + Default_i + Householdsize_{i,h} \\
&\quad + HouseholdFemalePercentage_{i,h} + HouseholdLogfum_{i,h} \\
&\quad + HouseholdTaxrate_{i,h} + Householdage_{i,h} + CompanySize_{i,c} \\
&\quad + CompanyFemalePercentage_{i,c} + CompanyLogfum_{i,c} \\
&\quad + CompanyTaxrate_{i,c} + CompanyAge_{i,c} + NeighborhoodSize_{i,n} \\
&\quad + NeighborFemalePercentage_{i,n} + NeighborLogfum_{i,n} \\
&\quad + NeighborTaxrate_{i,n} + NeighborAge_{i,n} + \varepsilon_{i,j,h,c,n}
\end{aligned}
\qquad (1)
$$

where $Asset\ allocation_{i,j,h,c,n}$ is the percentage of asset allocation for j asset class categories available in the KiwiSaver fund portfolio (where $j = 4$ and the asset classes are cash, bonds, property, and equity) for investor i who lives in household h and works in company c. The term α is a constant; $HouseholdAssetAllocation_{i,j,h}$ is the average asset allocation within asset class j for all investors in household h, excluding the individual investor i; $CompanyAssetAllocation_{i,j,c}$ is the average asset allocation within asset class j for all investors in company c, excluding individual investor i; Age_i is

the investor's age in years;[47] $Female_i$ is a dummy variable that equals one if the investor is female and zero if the investor is male; $LogFUM_i$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_i$ is the investor's personal income tax rate; $Financial\ advice_i$ is a dummy variable that equals one if the KiwiSaver member has received financial advice;[48] $Default_i$ is a dummy variable that equals one if the KiwiSaver member enrolled in KiwiSaver by default enrolment; $Householdsize_{i,h}$ is the total number of investors in household *h*; $HouseholdFemalePercentage_{i,h}$ is the percentage of female members in household *h*, excluding investor *i*; $HouseholdLogfum_{i,h}$ is the log of average funds under management of household members in household *h*, excluding investor *i*; $HouseholdTaxrate_{i,h}$ is the average tax rate of household members in household *h*, excluding investor *i*; and $Householdage_{i,h}$ is the average age of household members in household *h*, excluding investor *i*. The calculations of the control variables for co-worker and neighbourhood characteristics are identical to those of household characteristics described above; however, the variables are denoted *c* for the unique company in which investor *i* works and *n* for the postal code in which investor *i* lives. The term $\varepsilon_{i,j,h,c,n}$ is the clustered error term.

4.4 Results

This section considers the results of tests that assess the relative importance of personal characteristics; household, workplace, and neighbourhood peer effects; and financial advice on asset allocation. First, we discuss the overall findings, comparing the relative

[47] We also add an Age^2_i term to control for the non-monotonic relationship of an investor's age relative to asset allocation; however, we drop this variable from the regression models because it is nearly multicollinear with the Age_i variable.

[48] We do not add control variables (interaction terms) for financial advice and demographic variables. We find the interaction terms are highly correlated with general personal characteristics, which would lead to near-multicollinearity. There is not enough of a difference between the full sample and the sub-sample of people who received financial advice to warrant separate control variables. We present a correlation matrix in Appendix 4.8.

importance of each set of variables; then, we go into further detail by breaking down the results for each model that we investigate. We present a summary of each model's performance by showing their R^2 in Table 4.3. We model each group of explanatory variables individually and then add different combinations of grouped explanatory variables to compare each model's relative performance in explaining asset allocation decisions. We run seven models in the following order: We look at personal characteristics and then household effects, personal and household effects combined, workplace effects, personal household and workplace effects combined, personal household effects, workplace neighbourhood and financial advice effects, and finally all peer effects (household, workplace, and neighbourhood) with financial advice, but excluding personal characteristics.

Table 4.3 Asset allocation: R-squares of models

OLS Model	Cash	Bonds	Property	Equity	Average
Personal	4.6%	2.1%	10.6%	21.5%	9.7%
Household	16.7%	14.5%	12.6%	18.3%	15.5%
Personal + Household	18.4%	27.1%	17.4%	30.4%	23.3%
Personal + Workplace	5.3%	24.0%	13.2%	25.4%	17.0%
Personal + Household + Workplace	18.0%	29.7%	19.1%	33.3%	25.0%
Personal + Household + Workplace + Neighbourhood +FA	19.4%	31.1%	21.6%	35.0%	26.8%
Household + Workplace + Neighbourhood + FA	17.8%	20.0%	17.4%	24.1%	19.8%

This table shows a summary of the R2 of all our OLS models across asset classes; cash, bonds, property, and equity; and the respective average R2 across asset classes. The model that explains the most variation in asset allocation is the full model, which includes personal effects, household, co-worker, neighbourhood and financial advice effects.

Overall, our results show that all factors are important in asset allocation decisions, but some are more important than others. Judging by the R^2 in Table 4.3 we can see that peer effects in households dominate asset allocation decisions. The R^2 value of the household model is 15.5%, which is almost two times greater than the R^2 value of the personal effects model of 9.7%. When we combine personal and household effects into the same model, we find that R^2 improves considerably, to 23.3%. This indicates that the combination of the two sets of factors provides one of the best combinations to investigate

asset allocation decisions. Workplace peer effects are also important in explaining the asset allocation decisions of individuals. When we only look at workplace effects, the R^2 is only 5.1%; however, it improves to 17% if we combine workplace effects with personal characteristics. If, however, we adjust our model to control for personal, household, and workplace effects, this substantially improves our model's explanatory power. The combined model describes 25% of the variation in asset allocation choice. While both household members' and co-workers' asset allocation choices are significant and positively related to the asset allocation choices of individuals, the household effect has a much larger impact.

In the next model, which we refer to as our full model, we account for all variables in our dataset, which includes neighbourhood effects and financial advice. Although this full model has the highest R^2 value (26.8%) out of the models shown in Table 4.3, we find that the addition of neighbour effects and financial advice contributes to the overall explanation of asset allocation only marginally. The R^2 value improves by 1.8%, to 26.8%, when neighbourhood effects and financial advice are controlled for, compared to an R^2 of 25% in the previous model without these controls. We can also see that factors included in the full model, such as workplace and neighbourhood effects and financial advice, will add only 3.5% in terms of explanatory power to the model that only uses household peer effects and personal characteristics to explain asset allocation.

In the last model presented in Table 4.3 we run all variables together, but this time without personal effects, to see how our model can explain asset allocation decisions without knowing an individual's personal characteristics. We find that R^2 drops to 19.7%, suggesting that personal characteristics are important to know; however, if we had to choose between knowing only personal characteristics (R^2 of 9.7%) or only peer effects

and financial advice information, we would prefer to have the peer effects information. Our results suggest that considering one group of factors and not the other could lead to an omitted variable problem. However, the coefficients of personal characteristics do not change sign or statistical significance when household effects are added, suggesting that this bias may not be severe. We discuss this in more detail in the next section.

4.4.1 Personal and household effects

Table 4.4 presents the results of the personal characteristics model, the household peer effects model, and the combined personal and household effects model. Overall, we find that personal characteristics and household peer effects are significantly related to asset allocation choices; however, the combined model provides a better estimation of investor asset allocation decisions.

Table 4.4 Asset allocation: Personal effects and household peer effects

VARIABLES	(1) cash	(2) bonds	(3) property	(4) shares	(5) cash	(6) bonds	(7) property	(8) shares	(9) cash	(10) bonds	(11) property	(12) shares
age	0.002***	0.005***	-0.001***	-0.006***					0.002***	0.005***	-0.0009***	-0.006***
	(31.1)	(63.2)	(-53.6)	(-69.8)					(22.9)	(51.0)	(-32.8)	(-51.6)
sex	-0.005***	0.006***	0.0003	-0.0006					-0.007***	0.008***	0.0001	-0.001
	(-3.22)	(2.93)	(0.62)	(-0.26)					(-4.06)	(4.32)	(0.113)	(-0.775)
logfum	-0.027***	-0.032***	0.011***	0.048***					-0.023***	-0.035***	0.009***	0.047***
	(-22.6)	(-23.1)	(25.3)	(27.3)					(-13.0)	(-17.4)	(17.64)	(18.8)
taxrate	0.0006***	0.007***	-0.001***	-0.006***					0.0007***	0.007***	-0.001***	-0.007***
	(4.05)	(25.6)	(-17.3)	(-20.3)					(3.27)	(23.4)	(-14.2)	(-18.6)
default_enrolmethod	0.021***	0.113***	-0.022***	-0.113***					0.014***	0.097***	-0.019***	-0.092***
	(4.69)	(8.65)	(-8.29)	(-7.61)					(3.38)	(7.63)	(-7.27)	(-6.51)
assetallocation_household					0.369***	0.213***	0.199***	0.253***	0.379***	0.283***	0.214***	0.325***
					(30.1)	(30.4)	(12.2)	(38.7)	(31.1)	(40.6)	(12.7)	(50.7)
female_h_percentage					-0.0007	-0.0004	0.0001	0.001	-0.007**	0.005	0.0006	0.001
					(-0.25)	(-0.09)	(0.11)	(0.23)	(-2.16)	(1.51)	(0.69)	(0.26)
avg_h_age					0.001***	0.002***	-0.0007***	-0.003***	-0.0003***	-0.001***	0.0001	0.001***
					(19.1)	(27.8)	(-25.1)	(-34.9)	(-3.25)	(-13.0)	(0.615)	(12.2)
logfum_h					-0.022***	-0.032***	0.011***	0.047***	0.001	0.007***	0.0008	-0.005**
					(-18.8)	(-17.0)	(20.4)	(22.2)	(0.548)	(3.25)	(1.29)	(-2.07)
avg_h_taxrate					0.0006***	0.006***	-0.001***	-0.005***	2.85e-05	-0.002***	0.0001*	0.002***
					(3.37)	(18.6)	(-14.0)	(-14.9)	(0.104)	(-6.78)	(1.95)	(5.68)
householdsize					0.003***	0.003***	-0.0003	-0.005***	-0.0010	-0.009***	0.001***	0.010***
					(3.72)	(3.580)	(-1.41)	(-4.45)	(-1.15)	(-10.5)	(5.73)	(9.47)
Constant	0.244***	0.280***	0.052***	0.424***	0.200***	0.322***	0.018***	0.180***	0.189***	0.242***	0.0285***	0.212***
	(24.7)	(26.4)	(14.6)	(31.0)	(18.5)	(22.2)	(4.19)	(10.1)	(17.3)	(20.6)	(6.61)	(14.3)
Observations	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187
R-squared	0.046	0.206	0.106	0.215	0.167	0.145	0.126	0.183	0.184	0.271	0.174	0.304

Where the dependent variable $AssetAllocation_{i,j,h,c}$ is the percentage of asset allocation for j asset class categories available in the KiwiSaver fund portfolio (where $j = 4$ and asset classes are cash, bonds, property and equity) for investor i who lives in household h and works in company c. α is the constant term; $AssetAllocationHousehold_{i,j,h}$ is the average asset allocation within asset class j for all investors in household h excluding the individual investor i; Age_i is the age of the investor in years; Sex_i is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; $LogFUM_i$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_i$ is the personal income tax rate of the investor; $Defaul\_enrolmethodt_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; $HouseholdSize_{i,h}$ is the total number of investors in household h; $FemaleHPercentage_{i,h}$ is the percentage of female members in household h excluding investor i; $LogfumH_{i,h}$ is the logged value of average funds under management of household members in household h excluding investor i; $AvgHTaxrate_{i,h}$ is the average tax rate of household members in household h excluding investor i; $AvgHage_{i,h}$ is the average age of household members in household h excluding investor i; and $\varepsilon_{i,j,c,h}$ is the error term clustered by company.

In the personal characteristics model alone, we can see that all demographic variables are statistically significant. As column (4) of Table 4.4 shows, age is negatively related to equity exposure. This finding is in line with previous studies that find relatively older investors tend to hold smaller proportions of equity (Bodie, 2003 and Cocco, 2005).[49] We find that the level of funds under management is positively related to equity investment. The coefficient of *logfum* in column (4) shows that a 1% increase in the level of funds invested will lead to a 0.048% increase in equity assets held. This result confirms the findings presented by Hong, Kubick, and Stein (2004), who also find that wealth increases equity ownership. We find that gender is only statistically significant for the cash and bond regression and insignificant for property and equity assets. We find that the tax rate and default enrolment are negatively related to equity investments. Our measure of investor inertia, as proxied by the default enrolment variable, provides a nice reality check for our results, since we expect people who are inert to hold more cash and less equity because the default fund—namely, the conservative fund—is composed this way. Our findings also confirm the degree of investor inertia documented in the literature. A number of studies demonstrate the degree of investor inertia among individual investors using 401(K) plans in the United States. They show that once an investment choice has been made, changes to accounts rarely take place (Samuelson & Zeckhauser, 1988; Ameriks & Zeldes, 2002; Agnew, Balduzzi & Sunden, 2003). Although this degree of investor inattention may not be too harmful, since switching funds for the wrong reasons, such as past return chasing, can be an investment mistake (Zhang, 2011).

[49] We also include an age-squared term in earlier versions of the paper, but we drop the variable from the regression models because we find that age and age squared have near-multicollinearity. See the correlations table in Appendix 4.7.

In the household peer effects model presented in columns (5) to (8) of Table 4.4 we find that household peer effects are significantly related to individuals' asset allocation decisions. Before even turning to multivariate analysis, we observe in our data that 64% of all households invest in the same fund as other members in their household.[50] We check that the similarity of investment fund choice between household members is not driven by coincidence and compare differences in asset allocation in our full sample. We find that there is considerable variance in the asset allocation in our sample, as presented earlier in Table 4.2. There is less similarity in fund choice between people living in different households compared to the fund choices of members living in the same household.[51] The main variable of interest in the household effects model is household asset allocation and its relation to investor asset allocation. Columns (5) to (12) of Table 4.4 show that in all cases the asset allocation of household peers has a significant and positive impact on individual investor asset allocation. The coefficient of *HouseholdAssetAllocation* is consistently positive and significant in the cash, bonds, property, and equity asset classes.

In columns (9) to (12) of Table 4.4 we present the findings for the combined personal characteristics and household peer effects model. Comparing the three models in Table 4.4 we can see that the combined model provides the best estimations of the three. Column (12) of Table 4.4 shows that, on average, an investor would hold 0.325 percent more equity if, on average, other household members invested one percent more point in equity assets. While none of the household asset allocation coefficients change in statistical

[50] The univariate results are summarised in Appendix 4.2.

[51] The most common fund held by investors in the total population is the growth fund, where we observe one in four investors in the total sample holding the same fund. This compares to two thirds of households investing in identical funds to the people they live with and one-third of individuals holding the same funds as their co-workers. Further, the similarity in fund choice within the household and workplace are not simply an observation of KiwiSaver members joining the same default fund, since the proportion of default enrolments is low and only contributes to 8% of the total sample.

significance or sign between models, it is worth noting that all the household peer effect controls (percentage of females, average age, average funds under management, average tax, and household size) change coefficient signs compared to the results in the household model presented in columns (5) to (8). For example, the coefficient for household average age is -0.003 in column (8) and changes to 0.001 in column (12). The dramatic change in signs of the coefficients suggests that excluding personal characteristics when looking at household effects causes serious omitted variable bias in the model. As we later show in the breakdown of models to come (in the next table), the signs and magnitudes of the household control variables presented in the combined model in Table 4.4 stabilise and remain robust in all other models.

Based on our household peer effect results, it could be that the asset allocation decisions in one household are simply set by other members. Although we cannot distinguish the relation between household members, for example, whether the household members are husband and wife or flat mates, it is feasible that the strength of peer effects in our sample is driven to a large extent by one member of the household (the ultimate peer effect). The extent to which this scenario applies to households in our sample is unknown and unobservable. However, this does not seem to be the case in all the households we consider. For instance, Gilbert et al. (2013) conduct a survey among KiwiSaver investors from a New Zealand university and find that that 42% were the primary financial decision maker, 46% shared the responsibility, and 7% abdicated the responsibility (i.e., to a financial advisor). Gilbert et al. provide some indication of the proportion of households that might have asset allocation choices made by one person. Whether or not household members are family members optimising their household investment strategy and choosing to invest in the same assets (what we interpret as the ultimate peer effect) or whether it is a peer effect among non-family members, knowing

the extent to which asset allocations are similar among people who live together is interesting in and of itself.

Although we do not know which household peers are family members or otherwise, youth investors (people aged 18 years and under) could live at home with a parent. To identify this potential family relationship in our data, we compare the fund choices of all our youth investors with that of other household members. When we compare fund choices between youth and other household members, we find that the similarity in fund choice is no different from the results from our full sample: 68.1% of youth hold the same funds as the other household members and 34.2% hold the same funds as their co-workers.[52] The household peer effect we find in this study supports the findings of Barnea, Cronqvist, and Siegel (2010), who investigate differences in the financial behaviour of identical twins. The authors find both a genetic and a household–environment component that contribute to variation in investor behaviour. They find that, among twins, the family environment has an effect on the investment behaviour of young individuals, but it is not long lasting and disappears as an individual gains experience. The authors find evidence that frequent contact between twins results in similar investment behaviour beyond what can be explained by a genetic factor. Given that in our study we directly measure the investment choices of people living in the same household environment, the intensity of contact between people who live together provides a potential explanation for our strong household peer effect observations.

Our study adds to the literature that examines household peer effects. Few empirical studies observe the behaviour of household financial decisions, mostly because

[52] Again, controlling for youths holding default funds, we find that the most common fund held in youth accounts is the growth fund.

information on households making such asset allocation decisions is rare. Davis (1976) provides a comprehensive overview of decision making in the household. The author states that embedded in understanding household financial decisions is the difficulty of two key issues: first, the ability to identify relative influence and total influence between household members from the data and, second, the ability to explain variability in a person's involvement in financial decisions. As Ashraf (2009, p. 1245) states:

> Household outcomes depend on decisions made by spouses who may often disagree … a large and growing literature in economics provides evidence from several countries that household savings and investment are significantly affected by how decision-making power is allocated between women and men.

Previous studies have implied that the head of the household, who usually dominates decision making, is often male. For instance, Sung and Hanna (1996, p. 17) investigate the role of risk tolerance in a family setting and find that:

> Married couples are more like households headed by a single male than like households headed by a single female, as the predicted risk tolerance level of households headed by a single male is not significantly different from that of otherwise similar married couples.

Barber and Odean (2001) also show the greatest difference in investor overconfidence, as reflected by trading behaviour, exists between single men and single women rather than between married men and women. The literature inherently implies that gender is the key determining factor in household asset allocation decisions.

4.4.2 Workplace, personal, and household effects

Table 4.5 presents the findings from our personal characteristics and workplace model in columns (1) to (4) and those of the same model plus household effects in columns (5) to (8). The personal, household, and workplace effects model has a higher R^2 than the two models. In both models presented in Table 4.5 the peer asset allocation variables of

household members and co-worker choices are significant and positively related to individuals' asset allocation choices. Once again, we are not too surprised to see that the asset allocation choices of co-workers is significantly related, since before even turning to multivariate analysis we observe that 34% of the people in our sample choose to invest in the same fund as their co-workers.

The key point of Table 4.5 is that workplace peer effects also contribute significantly to asset allocation decisions; however, if we compare the R^2 values of the workplace effects model with those of the household effects model, we find that household peer effects dominate workplace peer effects.[53] This result contrasts with that of Hvide and Östberg (2013), who find that the economic impact of co-worker investment choices are double that of family investment choices. A possible explanation for the difference in results between our study and Hvide and Östberg's is that they do not control for family member effects at the physical household level. Because location is not accounted for, it is possible that extended family members who are not in close geographic proximity to one another communicate less about their investments than those in close proximity to each other.

When both workplace and household peer effects are considered, all the personal characteristic results are robust and remain stable (as they were presented in the personal characteristics model in Table 4.4). The only variable that changes between the models presented in Table 4.4 and Table 4.5 is gender. As mentioned earlier, columns (4) and (8) of Table 4.4 show that there are no differences in equity holdings between men and women if we consider only personal characteristics and household peer effects. When we

[53] We run a model where we consider only workplace effects. We find that workplace effects have an R^2 of only 5%. Given that, it is the lowest R^2 out of all the models. We report the results in Appendix 4.9.

make corrections to our model and add controls for personal characteristics and household and workplace peer effects as shown in column (8) of Table 4.5, we find that gender begins to play a role in equity asset allocation.

The gender coefficient is negative and statistically significant, which means that, on average, women hold 0.4% less equity than men. This finding is in line with previous research, which frequently suggests that women are more risk averse than men (Cohn, Lewellen, Lease & Schlarbaum, 1975; Sunden & Surette, 1998; Agnew et al., 2003). We explore gender differences further by looking at fund choices in male-only and female-only households in our sample. Again, we find evidence that women invest less in equity assets than men do. Male-only households most commonly choose the growth fund, while female-only households most commonly choose the conservative fund. We also test whether single-sex households differ in asset investment choice from the rest of the sample. We find that the differences are not significant for our full sample. We observe that 35% of male-only households invest in the same fund as other household members, whereas 39% of investors in female-only households hold identical funds as other household members.[54]

Table 4.5 also shows that only the age of co-workers and the *logfum* values of co-workers' control variables are statistically significant over all asset categories cash, bonds, property, and equity. Column (8) of Table 4.5 shows that the average age of co-workers is positively related to equity investment and their tax rate is negatively related to equity assets.

[54] We also consider male- and female-only companies. We find that the results are similar to those of single-gender households, at 35% and 36%, respectively.

Table 4.5 Asset allocation: Co-worker peer effects, personal effects and household peers effects

VARIABLES	(1) cash	(2) bonds	(3) property	(4) equity	(5) cash	(6) bonds	(7) property	(8) equity
age	0.00297***	0.00506***	-0.00112***	-0.00699***	0.00262***	0.00544***	-0.000997***	-0.00710***
	(29.32)	(56.25)	(-47.33)	(-65.69)	(22.45)	(48.11)	(-31.49)	(-50.58)
sex	-0.00577***	0.00757***	0.000356	-0.00233	-0.00681***	0.0102***	6.57e-05	-0.00392*
	(-2.847)	(3.803)	(0.554)	(-1.050)	(-3.120)	(4.960)	(0.0930)	(-1.688)
logfum	-0.0297***	-0.0372***	0.0122***	0.0555***	-0.0258***	-0.0384***	0.0104***	0.0531***
	(-18.13)	(-25.49)	(24.59)	(27.94)	(-12.83)	(-19.64)	(18.27)	(20.95)
taxrate	0.000701***	0.00704***	-0.00117***	-0.00669***	0.000652***	0.00767***	-0.00120***	-0.00730***
	(3.693)	(24.36)	(-15.71)	(-19.87)	(2.861)	(23.23)	(-13.48)	(-18.82)
default_enrolmethod	0.0190***	0.107***	-0.0205***	-0.106***	0.0123***	0.0927***	-0.0179***	-0.0874***
	(5.308)	(10.40)	(-9.612)	(-9.714)	(3.489)	(9.158)	(-8.178)	(-8.161)
assetallocation_company	0.185***	0.317***	0.255***	0.343***	0.133***	0.282***	0.204***	0.295***
	(8.473)	(22.25)	(7.823)	(24.90)	(7.373)	(20.68)	(6.206)	(22.55)
assetallocation_household					0.375***	0.268***	0.199***	0.307***
					(30.88)	(39.19)	(12.11)	(47.62)
female_h_percentage					-0.00741**	0.00561*	0.000609	0.000592
					(-2.147)	(1.678)	(0.667)	(0.152)
avg_h_age					-0.000363***	-0.00148***	-9.39e-06	0.00167***
					(-3.020)	(-12.39)	(-0.226)	(11.46)
logfum_h					0.000424	0.00517**	0.00140**	-0.00281
					(0.205)	(2.508)	(2.183)	(-1.123)
avg_h_taxrate					2.67e-05	-0.00195***	0.000170*	0.00195***
					(0.0976)	(-6.886)	(1.767)	(5.755)
householdsize					-0.00106	-0.00909***	0.00146***	0.00980***
					(-1.146)	(-10.35)	(5.501)	(9.560)
c_female_percentage	-0.000561	0.00366	0.000303	-0.00352	0.00244	0.00305	0.000328	-0.00497
	(-0.145)	(0.852)	(0.235)	(-0.724)	(0.678)	(0.746)	(0.263)	(-1.088)
avg_age	-0.000839***	-0.00178***	0.000370***	0.00270***	-0.000593***	-0.00156***	0.000300***	0.00228***
	(-5.214)	(-9.730)	(6.540)	(12.77)	(-4.075)	(-9.060)	(5.237)	(11.48)
logfum_c	0.00897***	0.0173***	-0.00420***	-0.0270***	0.00798***	0.0149***	-0.00379***	-0.0237***
	(3.841)	(6.521)	(-5.517)	(-8.747)	(3.751)	(5.762)	(-4.848)	(-7.992)
avg_taxrate	-0.000325	-0.00192***	0.000283*	0.00284***	5.93e-05	-0.00172***	0.000134	0.00227***
	(-0.914)	(-4.340)	(1.932)	(5.956)	(0.182)	(-4.087)	(0.911)	(4.969)
firmsize	4.00e-06***	-5.91e-07	-6.72e-07	-2.58e-06	3.75e-06***	2.01e-07	-7.50e-07	-3.36e-06*
	(3.350)	(-0.295)	(-1.079)	(-1.255)	(3.871)	(0.100)	(-1.244)	(-1.735)
Constant	0.196***	0.136***	0.0436***	0.323***	0.143***	0.122***	0.0251***	0.137***
	(13.85)	(8.503)	(8.318)	(19.07)	(10.28)	(7.475)	(4.419)	(7.675)
Observations	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187
R-squared	0.053	0.240	0.132	0.254	0.188	0.297	0.191	0.333

Where the dependent variable $AssetAllocation_{i,j,h,c}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and asset classes are cash, bonds, property

and equity) for investor i who lives in household h and works in company c. α is the constant term; $AssetAllocationHousehold_{i,j,h}$ is the average asset allocation within asset class j for all investors in household h excluding the individual investor i; $AssetAllocationCompany_{i,c,t}$ is the average asset allocation within asset class j for all investors in company c excluding the individual investor i; Age_i is the age of the investor in years; Age^2_i is the squared term of Age_i; Sex_i is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; $LogFUM_i$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_i$ is the personal income tax rate of the investor; $DefaultEnrolMethod_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; $HouseholdSize_{i,h}$ is the total number of investors in household h; $FemaleHPercentage_{i,h}$ is the percentage of female members in household h excluding investor i; $LogfumH_{i,h}$ is the logged value of average funds under management of household members in household h excluding investor i; $AvgHTaxrate_{i,h}$ is the average tax rate of household members in household h excluding investor i; $AvgHage_{i,h}$ is the average age of household members in household h excluding investor i; $Firmsize_{i,c}$ is the total number of investors in company c; $CFemalePercentage_{i,c}$ is the percentage of female members in company c excluding investor i; $LogfumC_{i,c}$ is the logged value of average funds under management of investors in company c excluding investor i; $AvgTaxRate_{i,c}$ is the average tax rate of investors in company c excluding investor i; $AvgAge_{i,c}$ is the average age of co-workers in company c excluding investor i and $\varepsilon_{i,j,c,h}$ is the error term clustered by company.

4.4.3 Neighbours, financial advice, peers, and personal characteristics

Table 4.6 shows the results of our full model, which investigates personal characteristics; household, workplace, and neighbour peer effects; and financial advice. Of all the models we look at, the full model has the highest overall R^2, 26.8%, as shown earlier in Table 4.3. The main findings of Table 4.6 show that neighbour peer effects and financial advice significantly affect asset allocation decisions; however, their overall contribution to the R^2 of the model is marginal in comparison to other factors such as household and personal effects. The asset allocation of neighbours (people living in the same postal code) has a positive and significant effect on the asset allocation of an individual. As shown in column (4) of Table 4.6, the asset allocation of neighbours in equity is 0.108, which means that, on average, an investor holds 10.8 percent more in equity if the investor's neighbours hold one percent more in equity assets.

The strength and magnitude of our neighbour effect result are in line with the findings of previous studies that address the same/similar questions or various constitutive parts (e.g., either the workplace or the neighbourhood in isolation). Previous studies tend to use variables that encompass larger geographic areas, such as zip code, city, Metropolitan Statistical Area (MSA), or state area codes, as proxies to measure neighbourhood peer effects. For instance, Hong, Kubick, and Stein (2004) find "social investors," who attend church regularly and talk to their neighbours, are more likely to participate in the stock market if their peers do so. Brown et al. (2008) use MSAs[55] in the United States and find similar results. A 10-percentage point increase in average ownership in one's community leads to a four-percentage point increase in the likelihood of individual also owning

[55] An MSA is a geographical region with a relatively high population density at its core and close economic ties throughout the area. There are 381 MSAs in the United States, in total.

stocks. This study also contributes to the literature by identifying the relative importance of different types of peer effects. We find that the importance of neighbourhood effects seem to play a far lesser role in explaining asset allocation decisions if household and workplace peer effects are controlled for. This result highlights the drawback of studies using large populations covering only large geographical areas: the true effects of social interaction may become diluted, since "it is difficult to imagine a consultant living in Manhattan discussing her pension portfolio with a supermarket manager in Brooklyn, New York," as Lu states (2011, p 7.).

Column (4) of Table 4.6 also shows the relation between financial advice and asset allocation decisions. Financial advice increases the proportion of assets held in equity assets. Investors who receive advice hold 8.3% more equity, on average, in their accounts. This finding is also in line with previous literature that reports that receiving advice increases risky asset investments (Zhang, 2014). According to Hackethal, Haliassos, and Jappelli (2012), financial advisors often receive financial incentives to encourage their clients to increase their equity investments. Therefore, it should come as no surprise that advised investors take greater risks in their investment positions. This case also holds in New Zealand, where equity investments charge higher fees than funds with smaller proportions of risky assets.

We find that none of the neighbourhood control variables are significant across all asset categories, with the exception of *logfum_pc*. Column 4 of Table 4.6 shows that a 1% increase in the level of funds under management by neighbours will lead to a 0.015% decrease in equity assets held by the investor. This negative relation between funds under management invested by neighbours and equity investment is also found between co-worker and household member funds under management variables (-0.026% and -

0.012%, respectively). We also find that all personal, household and workplace coefficients are robust and consistent with earlier results presented in Table 4.5.

Table 4.6 Asset allocation: All peer effects, financial advice and personal characteristics

VARIABLES	(1) cash	(2) bonds	(3) property	(4) shares	(5) cash	(6) bonds	(7) property	(8) shares
assetallocation_company	0.128***	0.278***	0.202***	0.291***	0.111***	0.223***	0.184***	0.234***
	(6.990)	(19.95)	(6.502)	(21.28)	(6.090)	(15.84)	(5.892)	(16.48)
assetallocation_household	0.368***	0.264***	0.186***	0.298***	0.359***	0.203***	0.174***	0.237***
	(30.66)	(39.21)	(11.45)	(47.61)	(29.75)	(29.41)	(11.01)	(36.32)
assetallocation_neighbour	0.170***	0.135***	0.242***	0.108***	0.171***	0.141***	0.253***	0.127***
	(4.301)	(5.509)	(5.958)	(4.970)	(4.292)	(5.277)	(6.176)	(5.379)
age	0.00265***	0.00550***	-0.00102***	-0.00716***				
	(22.59)	(49.20)	(-32.46)	(-51.03)				
sex	-0.00648***	0.0102***	3.71e-06	-0.00423*				
	(-3.004)	(4.950)	(0.00542)	(-1.849)				
logfum	-0.0247***	-0.0365***	0.00975***	0.0508***				
	(-12.16)	(-18.49)	(16.90)	(19.68)				
taxrate	0.000700***	0.00772***	-0.00122***	-0.00735***				
	(3.033)	(23.19)	(-13.46)	(-18.80)				
default_enrolmethod	0.00723**	0.0848***	-0.0149***	-0.0771***				
	(2.009)	(8.244)	(-6.788)	(-7.078)				
fa	-0.0399***	-0.0615***	0.0232***	0.0818***	-0.0390***	-0.0632***	0.0238***	0.0828***
	(-20.70)	(-22.15)	(19.52)	(27.58)	(-20.36)	(-23.43)	(19.98)	(28.05)
c_female_percentage	0.00187	0.000901	0.000886	-0.00288	0.00475	-0.00442	0.000756	0.000368
	(0.514)	(0.214)	(0.718)	(-0.606)	(1.501)	(-1.023)	(0.677)	(0.0786)
avg_age	-0.000517***	-0.00149***	0.000276***	0.00217***	0.000870***	0.00165***	-0.000273***	-0.00188***
	(-3.552)	(-8.531)	(4.940)	(10.75)	(6.384)	(9.777)	(-5.161)	(-9.385)
logfum_c	0.00914***	0.0173***	-0.00461***	-0.0267***	0.00121	0.00324	-0.00112	-0.00800**
	(4.309)	(6.523)	(-6.009)	(-8.902)	(0.593)	(0.895)	(-1.273)	(-2.085)
avg_taxrate	0.000244	-0.00141***	3.90e-05	0.00189***	0.00102***	0.00499***	-0.000930***	-0.00449***
	(0.759)	(-3.423)	(0.279)	(4.257)	(3.199)	(9.877)	(-6.188)	(-8.158)
firmsize	3.71e-06***	6.65e-08	-7.16e-07	-3.19e-06	4.16e-06***	3.22e-06	-1.23e-06**	-6.28e-06**
	(3.639)	(0.0342)	(-1.273)	(-1.588)	(4.474)	(1.242)	(-2.165)	(-2.367)
female_h_percentage	-0.00673**	0.00626*	0.000379	-0.000636	-0.00140	0.00137	-0.000109	-0.000394
	(-1.982)	(1.881)	(0.426)	(-0.167)	(-0.458)	(0.388)	(-0.132)	(-0.0991)
avg_h_age	-0.000264**	-0.00135***	-6.56e-05	0.00144***	0.00164***	0.00253***	-0.000764***	-0.00376***
	(-2.215)	(-11.34)	(-1.594)	(10.10)	(17.07)	(26.22)	(-23.39)	(-32.14)
logfum_h	0.00495**	0.0121***	-0.00123*	-0.0122***	-0.0183***	-0.0274***	0.00849***	0.0412***
	(2.322)	(5.762)	(-1.919)	(-4.719)	(-12.38)	(-18.47)	(18.92)	(23.65)
avg_h_taxrate	-4.11e-05	-0.00203***	0.000177*	0.00201***	0.000339*	0.00498***	-0.000905***	-0.00435***

	(-0.151)	(-7.138)	(1.828)	(5.934)	(1.727)	(18.07)	(-12.06)	(-14.48)
householdsize	-0.00101	-0.00839***	0.00121***	0.00875***	0.00273***	0.00249***	-0.000460*	-0.00399***
	(-1.085)	(-9.471)	(4.540)	(8.481)	(2.884)	(2.605)	(-1.703)	(-3.536)
female_pc_percentage	0.00356	0.0102	-0.00444	-0.0320**	0.00388	0.0101	-0.00451	-0.0352**
	(0.310)	(0.919)	(-1.333)	(-2.510)	(0.334)	(0.821)	(-1.290)	(-2.431)
avg_pc_age	-0.000627***	-0.00110***	6.30e-05	0.000824***	-0.000644***	-0.00107***	5.62e-05	0.000806***
	(-2.772)	(-4.279)	(0.871)	(2.941)	(-2.767)	(-3.907)	(0.759)	(2.665)
avg_pc_tax	-0.000348	-0.000758	-0.000439***	-0.00135**	-0.000259	-0.000752	-0.000466***	-0.00170***
	(-0.706)	(-1.239)	(-2.847)	(-2.234)	(-0.511)	(-1.148)	(-2.928)	(-2.582)
logfum_pc	0.0152***	0.0137***	-0.00552***	-0.0151***	0.0159***	0.0187***	-0.00640***	-0.0200***
	(3.205)	(2.813)	(-3.685)	(-2.826)	(3.337)	(3.472)	(-4.094)	(-3.400)
neighbourhoodsize	5.47e-06**	-5.85e-06***	-2.88e-07	-9.83e-07	5.87e-06***	-6.17e-06***	-3.21e-07	-1.56e-06
	(2.479)	(-2.820)	(-0.472)	(-0.398)	(2.632)	(-2.721)	(-0.507)	(-0.581)
Constant	-0.0482	-0.0882**	0.102***	0.378***	-0.0423	-0.122**	0.110***	0.490***
	(-1.189)	(-2.009)	(7.254)	(7.980)	(-1.044)	(-2.497)	(7.523)	(9.301)
Observations	41,970	41,970	41,970	41,970	41,970	41,970	41,970	41,970
R-squared	0.194	0.311	0.216	0.350	0.178	0.200	0.174	0.241

Where $Asset\ allocation_{i,j,h,c,n}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and asset classes are cash, bonds, property an Where the dependent variable A*ssetAllocation*$_{i,j,h,c}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and asset classes are cash, bonds, property and equity) for investor *i* who lives in household *h* and works in company *c*. α is the constant term; *AssetAllocationHousehold*$_{i,j,h}$ is the average asset allocation within asset class *j* for all investors in household *h* excluding the individual investor *i; AssetAllocationCompany*$_{i,c,t}$ is the average asset allocation within asset class *j* for all investors in company *c* excluding the individual investor *i; Age*$_i$ is the age of the investor in years; Age^2_i is the squared term of *Age*$_i$; *Sex*$_i$ is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; *LogFUM*$_i$ is the logged value of funds under management in the investor's KiwiSaver account; *TaxRate*$_i$ is the personal income tax rate of the investor; *DefaultEnrolMethod*$_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; *HouseholdSize*$_{i,h}$ is the total number of investors in household *h*; *FemaleHPercentage*$_{i,h}$ is the percentage of female members in household *h* excluding investor *i*; *LogfumH*$_{i,h}$ is the logged value of average funds under management of household members in household *h* excluding investor *i*; *AvgHTaxrate*$_{i,h}$ is the average tax rate of household members in household *h* excluding investor *i*; *AvgHage*$_{i,h}$ is the average age of household members in household *h* excluding investor *i*. The calculation of control variables for co-worker and neighbour characteristics are identical to the calculation of household characteristics described above, however, the variables are denoted with *c* for the unique company investor *i* works in and *pc* for the postcode that investor *i* lives in. $\varepsilon_{i,j,h,c,n}$ is the clustered error term.

4.4.4 Causal household and co-worker peer effects

Our dataset presents a unique opportunity to test for causality of peer effects. We perform an Instrumental Variable (IV) estimation model where we use a peer's peer as an instrumental to test for causal peer effects. In order to make a true causal claim we need an exogenous variable, that is, a variable which is not related to any of the other variable in the system, unobserved or observed. For instance, if we take the example that A and B are married, C and D are married and that A and C work together then we could instrument D for C to see if C's affects A's choice. We make the assumption that the effect of the instrumental variable controlling for peer choice is zero and that the instrumental variable and the error term are uncorrelated. If the instrumental variable is significant it means that the mostly likely explanation for causal peer effects is social interaction between A and D through C, or social interaction directly between A and D.

We use the instrumental variable as an exogenous shock to clean out any endogenous relationship between a person's asset allocation and their peer's asset allocation. The most common method of achieving this is two-stage least squares (2SLS). In the first stage we predict the value of peer effects on the instrumental variable and in the second stage we use the predicted value of the peer effects based on the instrument in an OLS regression to predict the individual's choice.

Our IV estimation is as follows:

$$
\begin{aligned}
&Asset\ allocation_{i,j,h,c,n} \\
&\quad = \alpha + HouseholdIV_{i,j,h} + CompanyIV_{i,j,c} + Age_i + Female_i \\
&\quad + LogFUM_i + TaxRate_i + Financial\ advice_i + Default_i \\
&\quad + Householdsize_{i,h} + HouseholdFemalePercentage_{i,h} \\
&\quad + HouseholdLogfum_{i,h} + HouseholdTaxrate_{i,h} \\
&\quad + Householdage_{i,h} + CompanySize_{i,c} \\
&\quad + CompanyFemalePercentage_{i,c} + CompanyLogfum_{i,c} \\
&\quad + CompanyTaxrate_{i,c} + CompanyAge_{i,c} + \varepsilon_{i,j,h,c,n}
\end{aligned}
\qquad (2)
$$

where $Asset\ allocation_{i,j,h,c,n}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and the asset classes are cash, bonds, property, and equity) for investor *i* who lives in household *h* and works in company *c*. The term α is a constant; $HouseholdIV_{i,j,h}$ is the average co-worker asset allocation within asset class *j* for investors in household *h*, excluding the individual investor *i;* $CompanyIV_{i,j,c}$ is the average household peer asset allocation within asset class *j* for investors in company *c*, excluding individual investor *i;* and all remaining controls are identical to the main line regression. Where there are more than one co-worker peer and household peer for investor *i*, we select the instrument selected by random. The IV estimation has two stages. The first isolates the part of the independent variable that is correlated with the error term, when then regress household/co-worker peer effects on the coworker/household peer instrumental variable, compute the predicted values, then in step two, regress the dependent variable (individual's asset allocation) on the predicted values using an OLS model.

We present the IV estimation model in Table 7. The results show that significant causal peer effects exist between household members and individuals and also between co-workers and individuals. In columns (1) to (4) of Table 7 we show the estimation results using the co-workers of household peers as the household instrument, columns (5) to (8)

show the results using household peers of co-workers as the co-worker instrument and columns (9) to (12) show the full results using both household and co-worker instrumental variables. The results across all regressions are close to the results presented in earlier tables Table 4.4 and Table 4.5. Column 12 of Table 7 shows that a one-percent increase in equity holdings by household peers would results in an individual to hold 0.306 percent more of equity. Likewise for co-worker peer effects, the coefficient presented in Column 12 indicates that a one-percent increase in equity holdings by co-workers would lead to an individual holding 0.295 percent more equity.

In general we find that the results from the IV estimation strongly support our main OLS results. Coefficients of other control variables such as age, gender, funds under management and tax code also do not vary from our base OLS results presented in earlier tables. In later sections, we reconfirm that our results are driven by true causal peer effects when we investigate fund switching between household peers and co-worker peers. We find that if a household peer or co-worker peer switches funds that an individual is more likely to also switch funds.

While it is most likely that social interaction takes place between peers it is still possible that other factors may explain our results Even with our very comprehensive set of control variables there may still be unobserved time-varying factors that are correlated with the household instrument and co-worker instrument we use. For example, there might be unobserved common shocks such that people in the same city or area react in a similar way given the same information set, and therefore, the causal peer effect we find is not guaranteed to be caused by social interaction or word of mouth effects.

Table 4.7 Instrumental Variable estimation model

VARIABLES	(1) cash	(2) bonds	(3) property	(4) shares	(5) cash	(6) bonds	(7) property	(8) shares	(9) cash	(10) bonds	(11) property	(12) shares
householdIV	0.369***	0.302***	0.233***	0.338***					0.353***	0.273***	0.197***	0.306***
	(28.26)	(36.99)	(10.66)	(45.88)					(26.50)	(32.89)	(9.405)	(41.91)
companyIV					0.424***	0.398***	0.324***	0.378***	0.299***	0.324***	0.219***	0.295***
					(8.354)	(15.34)	(6.316)	(17.24)	(6.813)	(13.53)	(4.320)	(14.04)
Neighbor_assetalln									0.172***	0.130***	0.238***	0.101***
									(4.415)	(5.368)	(5.749)	(4.681)
age	-0.007***	0.004***	0.0008***	0.002***	-0.008***	0.003***	0.001***	0.003***	-0.006***	0.004***	0.0008***	0.001***
	(-14.52)	(10.32)	(7.402)	(4.761)	(-13.85)	(6.590)	(8.673)	(6.932)	(-13.52)	(10.28)	(6.994)	(3.207)
agesq	0.0001***	0.00001**	-0.0002***	-0.0001***	0.0001***	0.00002***	-0.0002***	-0.0001***	0.0001***	0.00008	-0.0002***	-0.0001***
	(18.84)	(2.203)	(-15.73)	(-20.82)	(18.03)	(3.629)	(-17.20)	(-19.90)	(18.25)	(1.367)	(-15.76)	(-18.80)
sex	-0.002	0.009***	-0.0008*	-0.006***	0.0002	0.008***	-0.0008	-0.008***	-0.0005	0.010***	-0.001*	-0.009***
	(-1.403)	(5.310)	(-1.690)	(-3.109)	(0.133)	(4.437)	(-1.349)	(-3.594)	(-0.240)	(5.246)	(-1.665)	(-4.110)
logfum	-0.019***	-0.035***	0.009***	0.044***	-0.028***	-0.037***	0.011***	0.053***	-0.022***	-0.036***	0.009***	0.047***
	(-11.90)	(-20.23)	(19.34)	(22.12)	(-17.76)	(-25.27)	(23.31)	(27.13)	(-11.21)	(-18.47)	(15.49)	(18.56)
taxrate	0.001***	0.007***	-0.001***	-0.007***	0.001***	0.007***	-0.001***	-0.007***	0.001***	0.007***	-0.001***	-0.007***
	(5.721)	(33.39)	(-19.39)	(-29.54)	(7.806)	(25.51)	(-18.02)	(-22.06)	(5.794)	(24.00)	(-15.09)	(-20.43)
fa									-0.041***	-0.061***	0.023***	0.083***
									(-21.85)	(-22.37)	(19.80)	(28.41)
default_enrolmethod	0.013***	0.096***	-0.018***	-0.091***	0.016***	0.107***	-0.020***	-0.104***	0.006**	0.084***	-0.014***	-0.076***
	(6.774)	(26.36)	(-22.59)	(-21.92)	(5.855)	(10.95)	(-9.871)	(-9.827)	(2.172)	(8.484)	(-6.785)	(-7.036)
c_female_percentage					0.002	0.005	-0.0003	-0.006	0.004	0.001	0.0003	-0.005
					(0.575)	(1.267)	(-0.271)	(-1.448)	(1.222)	(0.405)	(0.289)	(-1.147)
avg_age					-0.001***	-0.002***	0.0003***	0.002***	-0.0007***	-0.001***	0.0002***	0.001***
					(-6.029)	(-10.64)	(5.561)	(11.44)	(-4.001)	(-8.740)	(3.519)	(8.586)
logfum_c					0.016***	0.020***	-0.005***	-0.029***	0.014***	0.019***	-0.004***	-0.027***
					(6.018)	(7.466)	(-5.742)	(-9.138)	(6.023)	(6.913)	(-5.316)	(-8.455)
avg_tax					-0.001***	-0.003***	0.0004***	0.003***	-0.0004	-0.002***	0.0007	0.001***
					(-3.277)	(-5.703)	(2.667)	(6.071)	(-1.227)	(-4.111)	(0.402)	(3.530)
firmsize					0.00003***	-0.00001	-0.00004	-0.00001	0.0002***	-0.00004	-0.0005.33	-0.00002
					(3.427)	(-0.844)	(-0.730)	(-0.829)	(3.386)	(-0.242)	(-0.989)	(-1.224)
female_h_percentage	-0.003	0.005*	-0.00001	-0.002					-0.003	0.006**	-0.0003	-0.003
	(-1.216)	(1.761)	(-0.0216)	(-0.584)					(-0.915)	(1.978)	(-0.339)	(-1.000)
avg_h_age	-0.001***	-0.001***	0.0002***	0.002***					-0.0009***	-0.001***	0.0001**	0.002***
	(-9.094)	(-13.93)	(4.251)	(18.58)					(-7.699)	(-11.71)	(2.353)	(14.87)
logfum_h	-0.0004	0.007***	0.0007	-0.005**					0.003	0.012***	-0.001*	-0.011***
	(-0.230)	(3.581)	(1.071)	(-2.180)					(1.607)	(5.838)	(-1.758)	(-4.600)
avg_h_tax	0.00008	-0.002***	0.0002**	0.002***					0.000225	-0.002***	0.0001*	0.002***
	(0.301)	(-7.641)	(2.198)	(6.665)					(0.085)	(-7.311)	(1.872)	(6.050)
householdsize	-0.0014	-0.009***	0.001***	0.010***					-0.001	-0.008***	0.001***	0.009***

	(-1.573)	(-11.59)	(5.911)	(10.68)					(-1.529)	(-9.514)	(4.750)	(8.904)
female_pc_percentage									0.0008	0.009	-0.003	-0.028**
									(0.0789)	(0.862)	(-1.106)	(-2.194)
avg_pc_age									-0.0005***	-0.001***	0.00005	0.0007***
									(-2.581)	(-4.242)	(0.788)	(2.811)
avg_pc_tax									-0.0002	-0.0006	-0.0004***	-0.001**
									(-0.499)	(-1.068)	(-3.066)	(-2.400)
logfum_pc									0.013***	0.013***	-0.005***	-0.013**
									(2.781)	(2.691)	(-3.419)	(-2.512)
neighborhoodsize									0.00007**	-0.0005***	-0.00006	-0.0002
									*			
									(3.228)	(-2.710)	(-1.086)	(-1.095)
Constant	0.347***	0.254***	-0.0017	0.061***	0.308***	0.141***	0.0071	0.155***	0.085**	-0.086*	0.069***	0.231***
	(27.73)	(21.52)	(-0.416)	(4.730)	(19.30)	(7.277)	(1.173)	(8.027)	(2.100)	(-1.858)	(4.764)	(4.687)
Observations	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	41,970	41,970	41,970	41,970
R-squared	0.197	0.271	0.179	0.312	0.060	0.238	0.139	0.265	0.201	0.310	0.221	0.357

where $Asset\ allocation_{i,j,h,c,n}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and the asset classes are cash, bonds, property, and equity) for investor *i* who lives in household *h* and works in company *c*. The term α is a constant; $HouseholdIV_{i,j,h}$ is the average co-worker asset allocation within asset class *j* for investors in household *h*, excluding the individual investor *i;* $CompanyIV_{i,j,c}$ is the average household peer asset allocation within asset class *j* for investors in company *c*, excluding individual investor *i;* and all remaining controls are identical to the main line regression. Where there are more than one co-worker peer and household peer for investor *i*, we select the instrument selected by random. The IV estimation has two stages. The first isolates the part of the independent variable that is correlated with the error term, when then regress household/co-worker peer effects on the coworker/household peer instrumental variable, compute the predicted values, then in step two, regress the dependent variable (individual's asset allocation) on the predicted values using an OLS model.

4.5 Robustness checks

In the following section we apply the holdout test, seemingly unrelated regressions, the Wald test, and the incremental *F*-test as robustness checks of our main findings. We also report the results of using clustered standard errors and White errors, with Heckman self-selection correction, as well as standardising all variables in the model for comparison purposes, which we report in Appendices 4.4 and 4.5.

4.5.1 Holdout Test

In this section, we check the robustness of the relative importance of personal characteristics and household, workplace, neighbourhood, and financial advice variables in explaining asset allocation decisions. We perform a holdout test to formally assess the predictive ability of all the peer effects models (workplace, household, and neighbourhood peer effects) against all the other models that we can assess (personal effects and financial advice models). We also include a model that includes a constant term only, with no explanatory variables. We can then use this model as a benchmark of the relative improvement of adding particular combinations of explanatory variables. Taking matters to an extreme, we compare combinations of explanatory variables to see whether *any* of the models are better at determining asset allocation than simply using the average asset allocation figure. We follow the methodology outlined by Ebbes, Papies, and van Heerde (2011) to select between our competing models. Ebbes, Papies, and van Heerde (2011, p. 11) note that the "holdout sample validation has important merits because it can be used to select models and assess whether the estimated relationship hold beyond the observations used for estimation." We carry out the holdout test by splitting our set of observations into an estimation sample (containing 80% of the sample) to estimate the model parameter and then applying the fitted model to the holdout sample

(20% remaining sample) to predict the values of the dependant variable, which are then compared to the observed values. We calculate the sum of the squared residuals and compare the mean of the squared error terms to determine which model has the lowest estimation error.

Table 4.8 Holdout test

Mean Squared Errors	Cash	Bonds	Property	Equity	Average	Relative Importance
Constant	3.27%	3.29%	0.23%	4.19%	2.74%	-
Personal	3.05%	2.62%	0.20%	4.71%	2.65%	3.50%
Household	2.67%	2.83%	0.20%	3.67%	2.34%	14.50%
Personal + Household	2.57%	2.43%	0.19%	3.11%	2.07%	24.40%
Personal + Workplace	2.56%	2.33%	0.19%	2.97%	2.01%	26.60%
Personal + Household + Workplace	3.03%	2.50%	0.20%	3.31%	2.26%	17.70%
Personal + Household + Workplace + Neighbourhood +Financial advice	2.53%	2.29%	0.18%	2.90%	1.98%	27.90%
Household + Workplace + Neighbourhood + Financial advice	2.62%	2.65%	0.19%	3.42%	2.22%	18.90%

This table reports the mean of squared error (MSE) terms to compare which model has the lowest estimation error using the Hold-out test. We test what happens to prediction accuracy if we leave either personal effects or peer effects out of the full estimation model. We carry out the holdout test by splitting our set of observations into an estimation sample (containing 80% of the sample) to estimate the model parameter, then, applying the fitted model to the holdout sample (20% remaining sample) to predict the values of the dependant variable, which are then compared to the observed values. We report the MSE by asset class, the average MSE by model and the relative 'importance' of each model compared to the MSE of the model which measures the constant term only (we treat this as the base that the percentage of relative importance is calculated on).

We calculate the relative importance of the variables included in each of our seven models compared to a model that measures only a constant term. As shown in the last column of Table 4.8, overall, the full model improves model estimation the most out of the seven models. The full model (personal characteristics; household, workplace, and neighbour peer effects; and financial advice) reduces the mean of the squared error terms by 27.9% across asset classes. The next best combinations of variables to use when examining asset allocation decisions are the personal and household effects model and the personal and workplace effects model, both of which result in relatively high reductions in estimation error of 24.4% and 26.6%, respectively. The worst-performing model according to the holdout test is the personal characteristics model, which has the smallest reduction in the mean squared error term, 3.5%. The results from the holdout test suggest that, ideally, it is best to be able to control for all the variables presented in the

full model. However, suppose we cannot control for all types of factors included in the full model; then, it would be better to know an investor's household peer effects than the investor's personal characteristics. We find that the household peer effects model is more than four times better at reducing estimation errors than the personal characteristics model alone (when we compare the reduction in the mean squared error relative to that of the constant-term model, 14.5% and 3.5%, respectively).

4.5.2 Seeming Unrelated Regression and the Wald Test

In this paper, we use household, workplace, and neighbourhood peer effects, as well as personal characteristics and financial advice variables, to explain asset allocation decisions. Since neighbourhood effects are the more commonly used set of factors in the literature to examine peer effects, we want to test whether neighbourhood effects remain central to asset allocation decisions if we control for all other types of effects (personal, household, and workplace effects and financial advice). In other words, does the inclusion of other factors reduce the explanatory power of neighbourhood effects? We run a seemingly unrelated regression model and apply a joint Wald test to see whether the introduction of personal, household, and workplace effects and financial advice *statistically changes* the explanatory power of neighbour peer effects. We run this test both ways; that is, we test to see if the coefficients of neighbour effects change when all other factors are added to the model and also whether household and workplace effects, personal characteristics, and financial advice variables change when neighbour variables are factored in. Remarkably, as reported in Table 4.9, our results show that all neighbourhood factors become insignificant when other peer effects and personal effects are considered. These results indicate that if a model uses only neighbour information to explain an individual's asset allocation decision, then the estimation results of that model may be unreliable due to omitted variable bias.

Table 4.9 Seemingly unrelated regressions and Wald test: Neighbours versus all other factors

Panel A: Cash and Bonds								
VARIABLES	(1) Cash	(2) Cash	(3) Cash	(4) Wald	(5) Bonds	(6) Bonds	(7) Bonds	(8) Wald
AssetAll_company		0.024***	0.024***	0.00		0.086***	0.086***	0.22
		(5.56)	(5.58)	0.979		(21.3)	(21.3)	0.639
AssetAll_household		0.071***	0.071***	0.04		0.082***	0.082***	0.48
		(35.2)	(35.4)	0.850		(31.57)	(31.64)	0.489
AssetAll_neighbour	0.002		0.0002	0.03	0.0116		0.0002	0.48
	(0.196)		(0.251)	0.859	(0.706)		(0.25)	0.487
age		0.0005***	0.0005***	0.00		0.0017***	0.001***	0.53
		(12.27)	(12.3)	0.947		(33.6)	(33.7)	0.468
sex		-0.001	-0.001	0.00		0.0032***	0.003***	0.00
		(-1.37)	(-1.37)	0.996		(2.87)	(2.88)	0.948
logfum		-0.004***	-0.004***	0.00		-0.011***	-0.011***	0.09
		(-6.52)	(-6.54)	0.972		(-13.0)	(-13.0)	0.770
taxrate		0.0001	0.0001	0.00		0.002***	0.002***	0.21
		(1.43)	(1.43)	0.993		(21.1)	(21.1)	0.647
fa		-0.007***	-0.007***	0.00		-0.018***	-0.018***	0.09
		(-7.71)	(-7.74)	0.956		(-15.2)	(-15.3)	0.760
default_enrolmethod		0.001	0.001	0.00		0.026***	0.026***	0.12
		(0.98)	(0.99)	0.995		(15.7)	(15.7)	0.723
c_female_percentage		0.0002	0.0002	0.00		0.0003	0.0003	0.00
		(0.19)	(0.192)	0.996		(0.191)	(0.19)	0.995
c_avg_age		-0.0001*	-0.0001*	0.00		-0.0004***	-0.0005***	0.02
		(-1.75)	(-1.76)	0.997		(-6.40)	(-6.41)	0.893
logfum_c		0.001**	0.0018**	0.00		0.005***	0.005***	0.01
		(2.19)	(2.19)	0.995		(5.34)	(5.35)	0.911
C_avg_taxrate		0.00004	0.00004	0.00		-0.0004**	-0.0004**	0.00
		(0.35)	(0.35)	0.999		(-2.50)	(-2.51)	0.958
firmsize		7.16e-07	7.16e-07	0.00		7.44e-08	7.41e-08	0.00
		(1.59)	(1.60)	0.993		(0.13)	(0.13)	0.993
female_h_percentage		-0.001	-0.001	0.00		0.001	0.001	0.00
		(-0.86)	(-0.86)	0.998		(1.02)	(1.02)	0.984
avg_h_age		-0.00005	-0.00005	0.00		-0.0004***	-0.0004***	0.02
		(-1.14)	(-1.14)	0.997		(-7.31)	(-7.33)	0.875
logfum_h		0.0009	0.0009	0.00		0.004***	0.0040***	0.01
		(1.12)	(1.13)	0.998		(3.83)	(3.83)	0.921
avg_h_taxrate		-7.28e-06	-7.29e-06	0.00		-0.0006***	-0.0006***	0.01
		(-0.061)	(-0.061)	0.999		(-4.30)	(-4.31)	0.927
householdsize		-0.0001	-0.0001	0.00		-0.002***	-0.002***	0.02
		(-0.37)	(-0.37)	0.990		(-5.60)	(-5.61)	0.894
female_n_percentage	-0.001		-4.27e-06	0.07	-0.00494		-7.81e-06	0.38
	(-0.271)		(-0.008)	0.786	(-0.615)		(-0.018)	0.538
avg_n_age	9.71e-05		-3.69e-07	0.64	5.62e-05		-1.15e-06	0.13
	(0.793)		(-0.038)	0.425	(0.347)		(-0.134)	0.722
avg_n_tax	-0.0002		-1.67e-06	0.64	-0.000515		-3.11e-06	1.84
	(-0.804)		(-0.08)	0.424	(-1.363)		(-0.155)	0.174
logfum_n	-0.002		9.78e-06	0.85	0.00174		2.45e-05	0.30
	(-0.915)		(0.051)	0.357	(0.555)		(0.146)	0.583
neighbourhoodsize	-0.0000002		6.67e-09	0.06	-0.000003***		-0.00000002	7.68***
	(-0.238)		(0.085)	0.806	(-2.781)		(-0.326)	0.00
Constant	0.159***	0.127***	0.127***		0.350***	0.252***	0.252***	
	(7.64)	(20.2)	(19.6)		(12.98)	(33.7)	(33.2)	
Observations	41,970	41,970	41,970		41,970	41,970	41,970	
R-squared	0.000	0.067	0.067		0.001	0.162	0.162	

Panel B: Property and Equity								
VARIABLES	(1) Property	(2) Property	(3) Property	(4) Wald	(5) Equity	(6) Equity	(7) Equity	(8) Wald
AssetAll_company		0.024***	0.024***	0.00		0.086***	0.086***	0.22
		(5.56)	(5.58)	0.979		(21.3)	(21.3)	0.639
AssetAll_household		0.071***	0.071***	0.04		0.082***	0.082***	0.48
		(35.2)	(35.4)	0.850		(31.57)	(31.64)	0.489
AssetAll_neighbour	0.002		0.0002	0.03	0.0116		0.0002	0.48
	(0.196)		(0.251)	0.859	(0.706)		(0.25)	0.487
age		0.0005***	0.0005***	0.00		0.0017***	0.001***	0.53
		(12.27)	(12.3)	0.947		(33.6)	(33.7)	0.468
sex		-0.001	-0.001	0.00		0.0032***	0.003***	0.00
		(-1.37)	(-1.37)	0.996		(2.87)	(2.88)	0.948
logfum		-0.004***	-0.004***	0.00		-0.011***	-0.011***	0.09
		(-6.52)	(-6.54)	0.972		(-13.0)	(-13.0)	0.770
taxrate		0.0001	0.0001	0.00		0.002***	0.002***	0.21
		(1.43)	(1.43)	0.993		(21.1)	(21.1)	0.647
fa		-0.007***	-0.007***	0.00		-0.018***	-0.018***	0.09
		(-7.71)	(-7.74)	0.956		(-15.2)	(-15.3)	0.760
default_enrolmethod		0.001	0.001	0.00		0.026***	0.026***	0.12
		(0.98)	(0.99)	0.995		(15.7)	(15.7)	0.723
c_female_percentage		0.0002	0.0002	0.00		0.0003	0.0003	0.00
		(0.19)	(0.192)	0.996		(0.191)	(0.19)	0.995
c_avg_age		-0.0001*	-0.0001*	0.00		-0.0004***	-0.0005***	0.02
		(-1.75)	(-1.76)	0.997		(-6.40)	(-6.41)	0.893
logfum_c		0.001**	0.0018**	0.00		0.005***	0.005***	0.01
		(2.19)	(2.19)	0.995		(5.34)	(5.35)	0.911
C_avg_taxrate		0.00004	0.00004	0.00		-0.0004**	-0.0004**	0.00
		(0.35)	(0.35)	0.999		(-2.50)	(-2.51)	0.958
firmsize		7.16e-07	7.16e-07	0.00		7.44e-08	7.41e-08	0.00
		(1.59)	(1.60)	0.993		(0.13)	(0.13)	0.993
female_h_percentage		-0.001	-0.001	0.00		0.001	0.001	0.00
		(-0.86)	(-0.86)	0.998		(1.02)	(1.02)	0.984
avg_h_age		-0.00005	-0.00005	0.00		-0.0004***	-0.0004***	0.02
		(-1.14)	(-1.14)	0.997		(-7.31)	(-7.33)	0.875
logfum_h		0.0009	0.0009	0.00		0.004***	0.0040***	0.01
		(1.12)	(1.13)	0.998		(3.83)	(3.83)	0.921
avg_h_taxrate		-7.28e-06	-7.29e-06	0.00		-0.0006***	-0.0006***	0.01
		(-0.061)	(-0.061)	0.999		(-4.30)	(-4.31)	0.927
householdsize		-0.0001	-0.0001	0.00		-0.002***	-0.002***	0.02
		(-0.37)	(-0.37)	0.990		(-5.60)	(-5.61)	0.894
female_n_percentage	-0.001		-4.27e-06	0.07	-0.00494		-7.81e-06	0.38
	(-0.271)		(-0.008)	0.786	(-0.615)		(-0.018)	0.538
avg_n_age	9.71e-05		-3.69e-07	0.64	5.62e-05		-1.15e-06	0.13
	(0.793)		(-0.038)	0.425	(0.347)		(-0.134)	0.722
avg_n_tax	-0.0002		-1.67e-06	0.64	-0.000515		-3.11e-06	1.84
	(-0.804)		(-0.08)	0.424	(-1.363)		(-0.155)	0.174
logfum_n	-0.002		9.78e-06	0.85	0.00174		2.45e-05	0.30
	(-0.915)		(0.051)	0.357	(0.555)		(0.146)	0.583
neighbourhoodsize	-2.37e-07		6.67e-09	0.06	-3.58e-06***		-2.24e-08	7.68***
	(-0.238)		(0.085)	0.806	(-2.781)		(-0.326)	0.00
Constant	0.159***	0.127***	0.127***		0.350***	0.252***	0.252***	
	(7.64)	(20.2)	(19.6)		(12.98)	(33.7)	(33.2)	
Observations	41,970	41,970	41,970		41,970	41,970	41,970	
R-squared	0.000	0.067	0.067		0.001	0.162	0.162	

Where $Asset\ allocation_{i,j,h,c,n}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and asset classes are cash, bonds, property and equity) for investor *i* who lives in household *h* and works in company *c*. α is the constant term; $AssetAllHousehold_{i,j,h}$ is the average asset allocation within asset class *j* for all investors in household *h* excluding the individual investor *i*; $AssetAllCompany_{i,j,c}$ is the average asset allocation within asset class *j* for all investors in company *c* excluding the individual investor *i*; Age_i is the age of the investor in years; Sex_i is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; $LogFUM_i$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_i$ is the personal income tax rate of the investor; $Financial\ advice_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; $DefaultEnrolMethod_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; $Householdsize_{i,h}$ is the total number of investors in household *h*; $FemaleHPercentage_{i,h}$ is the percentage of female members in household *h* excluding investor *i*; $LogFumH_{i,h}$ is the logged value of average funds under management of household members in household *h* excluding investor *i*; $AvgHTaxrate_{i,h}$ is the average tax rate of household members in household *h* excluding investor *i*; $AvgHAge_{i,h}$ is the average age of household members in household *h* excluding investor *i*. The calculation of control variables for co-worker and neighbour characteristics are identical to the calculation of household characteristics described above, however, the variables are denoted with *c* for the unique company investor *i* works in and *n* for the postcode that investor *i* lives in. $\varepsilon_{i,j,h,c,n}$ is the clustered error term.

We run another joint Wald test to examine the impact of peer effects factors on the personal characteristics model and vice versa. Table 4.10 shows that the addition of peer effects and personal characteristic variables to the unconstrained model seriously affects and sometimes switches the signs of the coefficients in the constrained model. Variables with a statistically significant Wald test statistic, as presented in columns (4), (8) of Panel A and B in Table 4.10 can be interpreted as follows. The inclusion of peer effects/personal characteristics in the unconstrained model (full model) significantly changes the coefficients of the parameters in the personal characteristics/peer effects model, that is, the constrained model. For example, columns (2) and (3) of Panel A in Table 4.10 show that the coefficients of CompanyAssetAllocation are 0.0141 and 0.0147, respectively. While both coefficients of CompanyAssetAllocation are significant, we can see that the Wald test statistic 0.03 is not. This means that the inclusion of personal characteristics in the unconstrained model presented in column (3) does not significantly change the explanatory power of the coefficient in the constrained model presented in column (2).

Overall, the results from the Wald test suggest that both personal characteristics and peer effects are important and need to be included in the model or there may be omitted variable bias. Gender, however, seems to be the only variable that is unaffected by omitted variable bias. The results from Table 4.10 show that the variables for age, the ages of household members, the ages of co-workers, the wealth of co-workers, and the wealth of household members significantly change in the unconstrained (full) model compared to the results in the constrained model. Gender is the only variable in the model that does not change when additional variables are considered. This suggests that the effect of gender on asset allocation is resilient and that the explanatory power of other variables does not affect the explanatory power of gender.

Table 4.10 Seemingly unrelated regressions and Wald test: Personal characteristics versus household and workplace peer effects

Panel A: Cash and Bonds								
VARIABLES	(1) Cash Personal Effects	(2) Cash Peer Effects	(3) Cash Full model	(4) Cash Wald test statistic	(5) Bonds Personal Effects	(6) Bonds Peer Effects	(7) Bonds Full model	(8) Bonds Wald test statistic
Company_assetallocation		0.0141***	0.0147***	0.03				
		(3.276)	(3.921)	0.871				
Household_assetallocation		0.0520***	0.0509***	1.34				
		(26.26)	(30.03)	0.248				
c_female_percentage		0.0009	0.0008	0.02		-0.0003	-0.00005	0.05
		(0.634)	(0.644)	0.875		(-0.209)	(-0.0489)	0.830
avg_age		0.0004***	0.0003***	12.7***		0.0009***	0.0002***	150.1***
		(6.316)	(5.307)	0.000		(13.55)	(5.294)	0.000
logfum_c		-0.0026***	-0.0016**	6.07**		-0.0044***	-0.0004	28.9***
		(-3.256)	(-2.383)	0.014		(-4.795)	(-0.614)	0.000
avg_pir		0.0002*	0.0002*	0.55		0.0022***	0.0007***	128.3***
		(1.867)	(1.750)	0.459		(13.98)	(7.183)	0.000
firmsize		0.000001**	0.000001**	0.37		0.000001**	0.0000004	3.32*
		(2.036)	(2.037)	0.544		(2.420)	(1.460)	0.068
female_h_percentage		0.0003	0.00008	0.07		-0.0005	0.0003	0.33
		(0.186)	(0.0692)	0.798		(-0.309)	(0.244)	0.565
avg_h_age		0.0007***	0.0005***	101.7***		0.0013***	0.0004***	489.2***
		(17.63)	(14.13)	0.000		(27.06)	(11.67)	0.000
logfum_h		-0.0102***	-0.0075***	44.5***		-0.0165***	-0.0054***	232.4***
		(-13.52)	(-11.23)	0.000		(-19.71)	(-8.859)	0.000
avg_h_pir		0.0001	0.0001	0.32		0.0027***	0.0009***	307.0***
		(1.190)	(1.024)	0.573		(22.24)	(10.42)	0.000
householdsize		0.0010***	0.0007**	2.43		0.0029***	0.0004	43.9***
		(2.670)	(2.233)	0.119		(6.401)	(1.577)	0.000
age	-0.0009***		-0.0004***	9.84***	-0.0003*		0.0001	14.1***
	(-5.221)		(-5.481)	0.001	(-1.680)		(1.293)	0.000
agesq	0.00002***		0.00001***	39.1***	0.00004***		0.00001***	37.4***
	(9.456)		(8.728)	0.000	(10.27)		(7.674)	0.000
sex	-0.0004		-0.0001	0.14	0.0020**		0.0019**	0.02
	(-0.468)		(-0.290)	0.709	(2.076)		(2.478)	0.881
logfum	-0.0074***		-0.0023***	77.1***	-0.0120***		-0.0092***	27.2***
	(-11.56)		(-7.017)	0.000	(-18.13)		(-16.48)	0.000
pir	0.0002**		0.00007*	1.89	0.0027***		0.0021***	94.1***
	(2.128)		(1.837)	0.169	(30.13)		(27.76)	0.000
fa	-0.0049***		-0.0025***	7.06***	-0.0069***		-0.0083***	3.20*
	(-4.683)		(-5.231)	0.008	(-6.269)		(-9.887)	0.073
default_enrolmethod	0.0024		0.0007	1.66	0.0216***		0.0181***	10.5***
	(1.630)		(1.116)	0.197	(14.04)		(15.43)	0.001
bonds_company						0.0112***	0.0253***	21.2***
						(2.929)	(10.22)	0.000
bonds_household						0.00691***	0.0227***	64.7***
						(2.853)	(14.35)	0.000
property_company								
property_household								
equity_company								
equity_household								
Constant	0.198***	0.185***	0.189***		0.370***	0.333***	0.330***	
	(34.48)	(23.72)	(26.31)		(62.21)	(38.63)	(47.32)	
Observations	42,187	42,187	42,187		42,187	42,187	42,187	
R-squared	0.028	0.057	0.062		0.115	0.084	0.135	

Panel B: Property and Equity								
VARIABLES	(1) Property Personal Effects	(2) Property Peer Effects	(3) Property Full model	(4) Property Wald test statistic	(5) Equity Personal Effects	(6) Equity Peer Effects	(7) Equity Full model	(8) Equity Wald test statistic
Company_assetallocation								
Household_assetallocation								
c_female_percentage		-0.00008	-0.00001	0.06		-0.0003	-0.0005	0.02
		(-0.202)	(-0.0475)	0.809		(-0.134)	(-0.356)	0.895
avg_age		-0.0001***	-0.00005***	42.7***		-0.0012***	-0.0003***	198.6***
		(-7.791)	(-4.759)	0.000		(-15.35)	(-6.084)	0.000
logfum_c		0.0013***	0.0004***	26.2***		0.0066***	0.0003	48.3***
		(5.371)	(2.653)	0.000		(5.780)	(0.341)	0.000
avg_pir		-0.0003***	-0.0001***	26.2***		-0.0024***	-0.0008***	99.1***
		(-6.979)	(-5.054)	0.000		(-12.08)	(-6.201)	0.000
firmsize		-0.000002**	-0.000001*	1.61		-0.00002***	-0.00001***	4.21**
		(-2.053)	(-1.759)	0.201		(-3.331)	(-2.616)	0.040
female_h_percentage		-0.0001	-0.00005	0.02		-0.000008	-0.0003	0.03
		(-0.243)	(-0.204)	0.881		(-0.00425)	(-0.198)	0.873
avg_h_age		-0.0003***	-0.0001***	242.3***		-0.0023***	-0.0007***	892.5***
		(-21.18)	(-14.19)	0.000		(-36.72)	(-16.26)	0.000
logfum_h		0.0045***	0.0021***	213.0***		0.0269***	0.0098***	378.8***
		(20.37)	(13.49)	0.000		(26.33)	(12.92)	0.000
avg_h_pir		-0.0004***	-0.0002***	72.9***		-0.0027***	-0.0009***	202.4***
		(-11.51)	(-7.639)	0.000		(-18.04)	(-8.535)	0.000
householdsize		-0.0003***	-0.0001	7.81***		-0.0038***	-0.0007**	50.3***
		(-2.864)	(-1.372)	0.005		(-6.939)	(-1.992)	0.000
age	0.0002***		0.0002***	7.29***	0.0019***		0.0012***	21.3***
	(5.069)		(4.764)	0.007	(8.186)		(6.565)	0.000
agesq	-0.00006***		-0.00004***	33.0***	-0.00005***		-0.00003***	65.6***
	(-10.91)		(-10.25)	0.000	(-19.34)		(-18.09)	0.000
sex	-0.00004		-0.00006	0.01	-0.0014		-0.0016*	0.01
	(-0.158)		(-0.353)	0.906	(-1.258)		(-1.726)	0.923
logfum	0.0034***		0.0020***	109.6***	0.0196***		0.0142***	66.3
	(18.91)		(15.32)	0.000	(24.40)		(21.20)	0.000
pir	-0.0004***		-0.0002***	56.0***	-0.0029***		-0.0022***	70.1***
	(-14.59)		(-13.01)	0.000	(-26.05)		(-24.38)	0.000
fa	0.0029***		0.0023***	8.58***	0.0134***		0.0142***	0.70
	(10.13)		(12.11)	0.003	(9.725)		(14.04)	0.402
default_enrolmethod	-0.0027***		-0.0019***	8.86***	-0.0243***		-0.0192***	13.6***
	(-6.835)		(-7.139)	0.003	(-12.69)		(-13.64)	0.000
bonds_company								
bonds_household								
property_company		0.0145***	0.0146***	0.00				
		(4.785)	(7.235)	0.957				
property_household		0.0160***	0.0150***	0.72				
		(9.881)	(13.93)	0.395				
equity_company						0.0180***	0.0325***	20.3***
						(4.391)	(12.16)	0.000
equity_household						0.0179***	0.0335***	58.3***
						(6.971)	(19.84)	0.000
Constant	0.0597***	0.0571***	0.0576***		0.343***	0.374***	0.339***	
	(37.18)	(24.90)	(30.33)		(47.38)	(35.12)	(39.69)	
Observations	42,187	42,187	42,187		42,187	42,187	42,187	
R-squared	0.058	0.052	0.069		0.147	0.112	0.173	

Where $Asset\ allocation_{i,j,h,c,n}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and asset classes are cash, bonds, property and equity) for investor *i* who lives in household *h* and works in company *c*. α is the constant term; $AssetAllHousehold_{i,j,h}$ is the average asset allocation within asset class *j* for all investors in household *h* excluding the individual investor *i;* $AssetAllCompany_{i,j,c}$ is the average asset allocation within asset class *j* for all investors in company *c* excluding the individual investor *i;* Age_i is the age of the investor in years; Sex_i is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; $LogFUM_i$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_i$ is the personal income tax rate of the investor; $Financial\ advice_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; $DefaultEnrolMethod_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; $Householdsize_{i,h}$ is the total number of investors in household *h*; $FemaleHPercentage_{i,h}$ is the percentage of female members in household *h* excluding investor *i*; $LogFumH_{i,h}$ is the logged value of average funds under management of household members in household *h* excluding investor *i*; $AvgHTaxrate_{i,h}$ is the average tax rate of household members in household *h* excluding investor *i*; $AvgHAge_{i,h}$ is the average age of household members in household *h* excluding investor *i*. The calculation of control variables for co-worker and neighbour characteristics are identical to the calculation of household characteristics described above, however, the variables are denoted with *c* for the unique company investor *i* works in and *n* for the postcode that investor *i* lives in. $\varepsilon_{i,j,h,c,n}$ is the clustered error term.

4.5.3 Incremental *F*-test

We also run an incremental *F*-test to check whether adding peer effect variables to the personal effects model (and vice versa) changes the explanatory power of the coefficients of the first model. The incremental *F*-tests allow us to draw a conclusion about the importance of peer effects and personal effects in the full model (which includes both), since the explanatory variables are introduced as a block of variables rather than individually, as presented earlier in the joint Wald test.

The results in Table 4.11 show the sum of squared residuals for the peer effects, personal characteristics, and full model. We can see that, on average, the full model (which consists of peers effects and personal effects) has the lowest estimation error across cash, bonds, property, and equity asset classes. The *F*-statistics presented in Table 4.11 are all large and statistically significant in the full model. This means that the inclusion of peer effects and personal characteristics as a group of variables significantly improves the fit of the overall model to explain the asset allocation choices of individuals.

Table 4.11 Incremental *F*-test

	Cash	Bonds	Property	Equity	n	k
Personal Effects SSR	1216.09	1081.69	99.87	1425.17	42187	5
Peer Effects SSR	1091.74	1127.63	99.82	1476.71	42187	12
Full model SSR	1044.99	955.51	91.55	1222.02	42187	17
F-stat Personal Effects	575.35	464.03	319.34	584.19		
	(0.000)	(0.000)	(0.000)	(0.000)		
F-stat Peer Effects	269.47	1085.16	544.25	1255.54		
	(0.000)	(0.000)	(0.000)	(0.000)		

This table shows the SSR (sum of squared residuals) between our three models, where we look at only the peer effects OLS model, personal effects OLS model and our full model (which includes both peer and personal effect variables). The peer effects include household and workplace effects. The F-statistic reports whether the introduction of peer variables to the personal effect model, and vice versa (effect of personal effects on peer effects), are significant to the full model.

4.5.4 Peer Fund Switching

Simply exploring the static asset allocation choices of peers may not tell the whole story of how household and workplace peers affect individual investor decisions. Our data enable us to further explore whether the fund switching behaviours of household members and co-workers encourage individuals to also *change* their asset allocation. To confirm the importance of household member and co-worker peer effects and to further support our main findings of the strength of peer effects, we investigate the fund switching behaviour of investors relative to that of their peer groups.[56] We observe fund switching over three time intervals: six months, three months, and one month. Doing so reduces the likelihood of ruling out the potential of observing peer switching effects that linger over longer periods. For instance, an investor may intend to change investment funds at the same time as others but does not get around to taking action until a later time. Again, since we know from previous studies that individuals tend to display high levels of inertia (Madrian & Shea, 2001), we would be surprised to see significantly high levels of switching activity in a short period of time, such as within an interval of a month. However, since so few investors switch in the first place, we give the benefit of the doubt to investors who do switch in shorter time frames.

We use a probit model to test whether investor fund switching is related to peer fund switching. That is, what is the likelihood of an investor changing funds if someone in their household or company has changed funds? The probit model enables us to calculate the probability of fund switching while controlling for other investor characteristics. We calculate the marginal effects of the model, how much the conditional probability of fund switching changes when a peer changes funds, holding all other variables constant. If

[56] Peer groups consist of household and co-worker data only, excluding neighbour effects.

fund switching is unrelated to the fund switching activity of peer members in the household and in the workplace, we would expect the predicted probabilities to be insignificant. That is, what other people do to their investment funds should be unrelated to how the individual chooses to invest.

The full probit model is as follows:

$$
\begin{aligned}
Fund\ Switch_{i,h,c,t} \\
&= \alpha + HouseholdSwitch_{i,h,t} + CompanySwitch_{i,c,t} + Age_{i,t} \\
&+ Female_i + LogFUM_{i,t} + TaxRate_i + Financial\ advice_i \\
&+ Default_i + Householdsize_{i,h} \\
&+ HouseholdFemalePercentage_{i,h} + HouseholdLogfum_{i,h,t} \\
&+ HouseholdTaxrate_{i,h} + Householdage_{i,h,t} + CompanySize_{i,c} \\
&+ CompanyFemalePercentage_{i,c} + CompanyLogfum_{i,c,t} \\
&+ CompanyTaxrate_{i,c} + CompanyAge_{i,c,t} + \varepsilon_{i,t}
\end{aligned}
\tag{3}
$$

where the dependent variable $Fund\ Switch_{i,h,c,t}$ is a binary variable that takes the value of one if investor *i*, living in household *h* and employed by company *c*, switches investment funds at time *t* and zero otherwise. The term α is a constant; $HouseholdSwitch_{i,h,t}$ is a binary variable that takes the value of one if any member, excluding the individual investor *i*, of household *h* switches investment funds at time *t* and zero otherwise; and $CompanySwitch_{i,c,t}$ is a binary variable that takes the value of one if any member, excluding the individual investor *i*, of company *c* switches investment funds at time *t*. The remaining control variables of personal effects and household

member and co-worker peer effects are identical to those in Equation (1), described above. The term $\varepsilon_{i,t}$ is the error term. The sample size of 424,060 includes ten 6-month periods rather than eight because the first half of 2007 and second half of 2011 are included in the sample in order to create lead and lag variables.

Columns (1) and (2) of Table 4.12 report the results of our fund switching model over a six-month period, while columns (3) and (4) of Table 4.12 cover fund switching activity over a three-month period. Monthly switching activity is reported in columns (5) and (6). In summary, our fund switching results confirm the importance of household and workplace peer effects. Household member and co-worker fund switching is significantly positively related to an investor's fund switching behaviour; however, the household member has a much greater influence.

The interpretation of the coefficients in probit regressions is not as straightforward as the interpretations of the coefficients in the linear regression model. The increase in probability attributed to a one-unit increase in a given explanatory variable is dependent on both the values of the other explanatory variables and the starting value of the given predictors. To offer economic interpretations of the coefficients, we present in Table 4.12 the predicted marginal probabilities of the variables driving changes in asset allocation. The predicted probabilities of fund switching are calculated while holding all other variables in the model at their means, as shown in Table 4.2. The predicted probabilities are reported in columns (2), (4), (6), (8), (10), and (12) of Table 4.12.

Table 4.12 Peer Fund Switching

VARIABLES	(1) 6 months	(2) Marginal Effect	(3) 6 months	(4) Marginal Effect	(5) 3 months	(6) Marginal Effect	(7) 3 months	(8) Marginal Effect	(9) 1 month	(10) Marginal Effect	(11) 1 month	(12) Marginal Effect
is_h_switch	1.243***	0.1012	1.243***	0.0308	1.415***	0.0906	1.416***	0.0192	1.609***	0.0672	1.601***	0.0082
	(41.83)		(39.67)		(46.03)		(43.82)		(48.68)		(46.27)	
is_c_switch	0.423***	0.021	0.541***	0.0134	0.423***	0.0119	0.553***	0.0075	0.507***	0.0067	0.665***	0.0034
	(32.85)		(34.01)		(33.71)		(35.09)		(40.77)		(41.97)	
t1_sex			0.0128	0.0003			0.0122	0.0001			0.00909	0.00004
			(0.788)				(0.816)				(0.680)	
t1_taxrate			-0.00417**	-0.0001			-0.00409***	-0.00005			-0.00405***	-0.00002
			(-2.502)				(-2.671)				(-2.955)	
t1_age			0.0323***	0.0008			0.0296***	0.0004			0.0273***	0.00014
			(9.315)				(9.251)				(9.468)	
agesq			-0.000179***	-4.43E-06			-0.000162***	-2.21E-06			-0.000153***	-7.79E-07
			(-4.476)				(-4.414)				(-4.624)	
logfum			0.157***	0.0038			0.145***	0.0019			0.127***	0.0006
			(10.36)				(10.37)				(10.13)	
householdsize			-0.00450	-0.0001			-0.00193	-0.00002			0.000889	4.53E-06
			(-0.595)				(-0.277)				(0.143)	
h_female_percentage			-0.0238	-0.0006			-0.0214	-0.0003			-0.0192	-0.0001
			(-0.814)				(-0.795)				(-0.794)	
logfum_h			-0.0392**	-0.0010			-0.0365**	-0.0005			-0.0288*	-0.0001
			(-2.162)				(-2.185)				(-1.922)	
h_avg_taxrate			0.00483**	0.0001			0.00449**	0.00006			0.00422**	0.00002
			(2.293)				(2.318)				(2.435)	
h_avg_age			-0.00279***	-0.00007			-0.00240***	-0.00003			-0.00204***	-0.00001
			(-3.249)				(-3.033)				(-2.883)	
firmsize			-8.94e-05***	-2.22E-06			-8.84e-05***	-1.20E-06			-9.24e-05***	-4.71E-07
			(-13.72)				(-14.47)				(-16.54)	
c_female_percentage			0.0862***	0.0021			0.0778***	0.0010			0.0611***	0.0003
			(3.174)				(3.122)				(2.754)	
logfum_c			-0.0871***	-0.0022			-0.0707***	-0.000961			-0.0529***	-0.0002
			(-5.406)				(-4.782)				(-3.997)	
c_avg_taxrate			0.0137***	0.0003			0.0134***	0.0002			0.0126***	0.00006
			(5.225)				(5.555)				(5.848)	
c_avg_age			0.00277***	0.00007			0.00209**	0.00003			0.00133	6.78E-06
			(2.603)				(2.142)				(1.535)	
fa			-0.0995***	-0.0025			-0.0903***	-0.0012			-0.0802***	-0.0004
			(-6.056)				(-5.997)				(-5.974)	
default_enrol			-0.618***	-0.0153			-0.566***	-0.0076			-0.506***	-0.0025
			(-17.49)				(-17.14)				(-16.78)	
Constant	-2.453***		-4.022***		-2.677***		-4.210***		-3.013***		-4.492***	
	(-346.4)		(-29.17)		(-424.4)		(-33.19)		(-553.8)		(-39.59)	
Observations	424,060	424,060	424,060	424,060	848,120	848,120	848,120	848,120	2,544,360		2,544,360	2,544,360

The dependent variable *Individual Switch*$_{i,h,c,t}$ is a binary variable that takes the value of 1 if investor *i*, who lives in household *h* and is employed by company *c*, switches investment funds at time *t*, and is 0 otherwise. α is the constant term; *Is_H_Switch*$_{i,h,t}$ is a binary variable that takes the value of 1 if any member (excluding the individual investor in question *i*) of household *h* switches investment funds at time *t*, and 0 otherwise; *Is_C_Switch*$_{i,c,t}$ is a binary variable that takes the value of 1 if any member (excluding the individual investor in question *i*) of company *c* switches investment funds at time *t*, and 0 otherwise; *Age*$_{i,t}$ is the age of the investor in years; *Age*$^2_{i,t}$ is the squared term of *Age*$_{i,t}$; *Sex*$_i$ is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; *LogFUM*$_{i,t}$ is the logged value of funds under management in the investor's KiwiSaver account; *TaxRate*$_{i,t}$ is the personal income tax rate of the investor; *Fa*$_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; *DefaultEnrolMethod*$_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; *HouseholdSize*$_{i,h,t}$ is the total number of investors in household *h*; *HFemalePercentage*$_{i,h,t}$ is the percentage of female members in household *h* excluding investor *i*; *LogfumH*$_{i,h,t}$ is the logged value of average funds under management of household members in household *h* excluding investor *i*; *H_Avg_Taxrate*$_{i,h,t}$ is the average tax rate of household members in household *h* excluding investor *i*; *H_Avg_Age*$_{i,h,t}$ is the average age of household members in household *h* excluding investor *i*; *Firmsize*$_{i,c,t}$ is the total number of investors in company *c*; *CFemalePercentage*$_{i,c,t}$ is the percentage of female members in company *c* excluding investor *i*; *LogfumC*$_{i,c,t}$ is the logged value of average funds under management of investors in company *c* excluding investor *i*; *C_Avg_TaxRate*$_{i,c,t}$ is the average tax rate of investors in company *c* excluding investor *i*; *C_Avg_Age*$_{i,c,t}$ is the average age of co-workers in company *c* excluding investor *i* and $\varepsilon_{i,t}$ is the error term. Marginal effects are reported in columns (2), (4), (6), (8), (10) and (12).

The standalone probability of an investor switching funds in our sample is 1%. When we add control variables to test the likelihood of investors switching funds if a household member or co-worker switches funds, we find that these choices are significantly related. A positive coefficient means that an increase in fund switching by peers leads to an increase in the predicted probability of the individual investor also switching funds. For instance, over a six-month period, if a household member switches funds, the probability of an investor in the same household switching funds is 10%. Over the three-month and monthly periods, the predicted probability for investor switching reduces to 9% and 6.7%, respectively. It is plausible that investors talk to one another about fund switching but do not actually get around to taking the action of changing funds until a few months later. Investors are also affected by the switches of their co-workers. However, the probabilities of a fund switching spillover effect are much smaller among co-workers and in some cases it seems the percentage of switches between co-workers is less than the percentage of unconditional switches of 1%. The predicted probabilities of an investor switching funds if a co-worker switches funds are 2%, 1.1%, and 0.67% in the same six-month, three-month, and one-month periods, respectively. While we find that peer switching effects are robust and significantly related to an investor's likelihood of changing funds, we note that when control variables are added, in some instances the probability is reduced by half. This emphasizes the importance of personal characteristics and other peer-related factors in fund switching behaviour.[57]

[57] We also add controls for past fund returns as a robustness check to see whether the peer switching effect is strong because we are picking up the effect of people switching funds to chase high returns. We find that adding in returns to our model does not change the significance of our key variables or findings of household peer switch or co-worker peer switch. We present these results in Appendix 4.3. In addition, we also run further tests with interaction terms between personal characteristics and fund switching variables. We find that our main switching results (the likelihood of switching funds if a household and workplace peer switches funds) do not change with additional control variables. Appendix 4.4 shows the results.

We confirm the importance of household and workplace peer effects. Household member and co-worker fund switching is significantly positively related to an investor's fund switching behaviour; however, the household member has a much greater influence. Once again, this may be unsurprising since one expects the relationships between members of a home to be closer than those of co-workers. For instance, in a family setting, family members would naturally foster a source of information sharing. Our results are in direct contrast to the findings of Hvide and Östberg (2012), who report that co-worker effects are much stronger than and at times double that of family members. This begs the question why do strong peer effects exist within the workplace? Earlier research offers some insights. The literature suggests that individual investors do not have well-defined preferences and there is a tendency to pick the middle choice. Iyengar and Lepper (2000) show that limited choices lead to greater happiness and too much choice is demotivating. Whether investors even benefit from being able to choose their own retirement portfolios is contestable. Benartzi and Thaler (2002) investigate how much investor autonomy is worth and find the attractiveness of an investor's own portfolio to be indistinguishable from that of the average portfolio held by another. The stark reality of their work suggests the majority of people prefer what others hold over what they picked for themselves. In another recent field experiment of 300 investors in Brazil, Bursztyn, Ederer, Ferman and Yuchtman (2012) provide evidence that individuals learn from their peers, but that there is an effect of possession beyond that of learning. The authors find that 92% of the time investors chose an asset if they knew a peer purchased it; however, only 42% were likely to invest in the asset if they did not have information about their peer's choice. They note that if an investor purchases an asset, his/her peers may also want to purchase it, both because they learned from the investor's choice (social learning) and because the

investor's possession of the asset directly affects their utility of owning the same asset (social utility).

4.5.5 Other Robustness Checks

We apply the most robust method from the beginning of our analysis by using cluster-robust standard errors in our models. This is because data drawn from a population with a grouped structure may have correlated standard errors and failure to control for clustering in OLS regressions will underestimate standard errors and overstate *t*-statistics (Moulton, 1986). The results from our main model, as presented in Table 4.4, use standard errors clustered at the company level. We also apply clustering at the household level, as well as use White standard errors; however, the difference in results is marginal. The standard errors are slightly smaller when we cluster by company; however, the coefficients and level of statistical significance of the variables do not change. We report these other robustness checks in Appendices 4.4 and 4.5.

We also run a Heckman two-stage model to correct for potential self-selection bias in our sample. Since people may self-select into household groups or companies due to similarities in age, gender, and wealth, this can bias against our results. As we show in Table 4.13, our main results do not change when we correct for self-selection bias. Self-selection exists at the household level but not at the company level, as evidenced by the statistically significant lambda (inverse Mills ratio). It is unsurprising that self-selection exists at the household level, since we expect people living in the same household to arrive there in a self-selecting way. For instance, people may marry others with similar levels of risk aversion or characteristics similar to their own. Homophily, love of the same, is the tendency of individuals to associate and bond with those who are similar (McPherson, Smith-Lovin, and Cook (2001)). Barber and Odean (2001) find that men

trade more than women and that the difference in trading is greatest between single men and single women. This implies that financial decisions made jointly within a marriage reduce some of the gender differences related to overconfidence, since less of a gap (in trading activity) exists between married men and married women. Hamoudi (2006) also finds that married couples living in the same household tend to have similar risk preferences.

As a final check of the robustness of our main OLS results, we standardise all the variables in our sample and re-run the tests to see which group of factors has the highest relative importance in terms of driving asset allocation decisions. All variables are standardised by calculating their z-scores (by rescaling the variables to have a mean of zero and a standard deviation of one). Table 4.14 reports the results of the standardise model. Again, similar to the earlier results in Table 4.6 we find the household to be the most dominant driver of asset allocation decisions, followed closely by peer effects in the workplace.

Table 4.13 Heckman correction

VARIABLES	is_i_switch	Marginal Effects	VARIABLES	is_i_switch
1.is_c_switch	1.863***	0.167	H_switch_logfum	0.218***
	(5.528)			(2.976)
t1_sex	0.0603		H_switch_fa	0.225***
	(0.489)			(2.825)
t1_taxrate	0.00754***		H_switch_default	-0.396**
	(2.665)			(-2.245)
t1_age	0.0405***		H_switch_householdsize	-0.282***
	(10.82)			(-6.346)
agesq	-0.000127***		H_switch_Hfemalepercentage	-0.0458
	(-3.091)			(-0.281)
logfum	0.874***		H_switch_Hage	-0.0213***
	(9.047)			(-4.438)
householdsize	0.00614		H_switch_Hlogfum	-0.0688
	(0.795)			(-0.757)
h_female_percentage	-0.0316		H_switch_Htaxrate	0.00647
	(-1.046)			(0.588)
logfum_h	-0.0137		C_switch_sex	-0.00780
	(-0.725)			(-0.247)
h_avg_taxrate	0.00286		C_switch_age	-0.00122
	(1.316)			(-1.021)
h_avg_age	-0.00281***		C_switch_tax	0.00839***
	(-3.191)			(3.278)
firmsize	-0.000217***		C_switch_logfum	-0.0353*
	(-11.74)			(-1.694)
c_female_percentage	0.0526*		C_switch_fa	-0.0708**
	(1.702)			(-1.985)
logfum_c	-0.0268		C_switch_default	-0.326***
	(-1.433)			(-3.943)
c_avg_taxrate	0.00939***		C_switch_firmsize	0.000178***
	(3.250)			(8.906)
c_avg_age	0.00138		C_switch_Cfemalepercentage	0.119
	(1.170)			(1.638)
fa	-0.0672***		C_switch_Cage	0.00879***
	(-3.209)			(2.777)
default_enrol	-0.505***		C_switch_Clogfum	-0.323***
	(-12.37)			(-7.634)
1.is_h_switch	1.300**	0.106	C_switch_Ctax	0.0566***
	(2.440)			(6.980)
H_switch_sex	0.0172		lambdaH1	1,069***
	(0.239)			(7.137)
H_switch_age	0.00398		lambdaC1	-0.122
	(1.006)			(-0.0301)
H_switch_tax	-0.00340		Constant	-859.8***
	(-0.397)			(-7.275)
Observations	424,060			

This table reports the results from the Heckman correction model. All variables presented in Table 4.13 are identical to Table 4.12, only with the addition of Lambda, the inverse Mills ratio. LambdaH1 is the inverse Mills ratio for the household correction and LambdaC1 is the inverse mills ratio for the company correction. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4.14 Standardised peer effects

VARIABLES	(1) cash	(2) bonds	(3) property	(4) shares
zpersonalage	0.0350***	0.0753***	-0.0137***	-0.0971***
	(27.59)	(61.54)	(-36.62)	(-69.71)
zpersonalfemale	-0.00384***	0.00307***	0.000388	0.000260
	(-3.639)	(3.063)	(1.250)	(0.228)
zpersonalfum	-0.0196***	-0.0298***	0.00821***	0.0402***
	(-13.70)	(-21.92)	(19.49)	(25.98)
zpersonalfa	-0.0144***	-0.0221***	0.00839***	0.0297***
	(-16.48)	(-26.64)	(32.47)	(31.40)
zpersonaltaxrate	0.00528***	0.0390***	-0.00702***	-0.0368***
	(6.286)	(48.84)	(-28.39)	(-40.48)
zdefaultenrol	0.00181**	0.0217***	-0.00383***	-0.0193***
	(2.174)	(27.35)	(-15.62)	(-21.36)
zcompanyfemale	0.000646	-0.000966	0.000359	0.000541
	(0.670)	(-1.055)	(1.267)	(0.520)
zcompanyage	-0.00380***	-0.0119***	0.00223***	0.0164***
	(-3.638)	(-11.83)	(7.288)	(14.20)
zcompanyfum	0.00330***	0.00933***	-0.00234***	-0.0124***
	(3.076)	(9.147)	(-7.409)	(-10.63)
zcompanysize	0.00401***	0.000654	-0.00100***	-0.00379***
	(5.019)	(0.842)	(-4.233)	(-4.333)
zhouseholdfemale	-0.00193**	0.000909	0.000226	0.000660
	(-2.162)	(1.072)	(0.861)	(0.683)
zhouseholdage	-0.00270**	-0.0174***	-0.00104***	0.0181***
	(-2.030)	(-13.03)	(-2.636)	(11.66)
zhouseholdfum	0.00185	0.00294**	0.000230	-0.00181
	(1.268)	(2.139)	(0.536)	(-1.149)
zhouseholdsize	-0.000967	-0.00775***	0.00126***	0.00820***
	(-1.095)	(-9.247)	(4.870)	(8.611)
zcompany_assetallocation	0.00982***	0.0300***	0.00684***	0.0358***
	(12.39)	(38.24)	(28.51)	(40.10)
zhousehold_assetalloaction	0.0648***	0.0463***	0.0118***	0.0626***
	(80.76)	(56.25)	(49.31)	(65.18)
zpostcode_assetallocation	0.00563***	0.00683***	0.00300***	0.00579***
	(6.168)	(4.712)	(10.45)	(4.868)
zneighbourfemale	0.000804	0.00129	-0.000551	-0.00377***
	(0.654)	(1.106)	(-1.495)	(-2.779)
zneighbourtaxrate	-0.00154	-0.00195	-0.00124**	-0.00382**
	(-0.900)	(-1.059)	(-2.415)	(-1.983)
zneighbourage	-0.00528***	-0.00731***	0.000732	0.00630***
	(-2.912)	(-4.176)	(1.414)	(3.315)
zneighbourfum	0.00335***	0.00295***	-0.00131***	-0.00354***
	(3.214)	(2.945)	(-4.300)	(-3.164)
zneighbourhoodsize	0.00213***	-0.00234***	-9.77e-05	-0.000480
	(2.639)	(-3.059)	(-0.415)	(-0.555)
Constant	0.138***	0.356***	0.0796***	0.426***
	(178.3)	(485.6)	(350.3)	(510.6)
Observations	42,132	42,132	42,132	42,132
R-squared	0.194	0.310	0.216	0.348

Where $Asset\ Allocation_{ij}$ is the proportion of assets held by investor i in asset class j, α is the constant term, $ZPersonalEffects_i$ is a vector of the demographic variables of investor i including investor gender, age and funds under management. $ZCompanyEffects_{i,c}$ is a vector of the variables of company c that investor i is employed at. The company variables include; size of company c, percentage of females in company c, average age of employees working in company c, average funds balance of company c, and the average asset allocation holding of company c in asset class j. $ZHouseholdEffects_{i,h}$ is a vector of the variables of household h that investor i resides in, $ZNeighbourEffects_{i,n}$ is a vector of the variables of neighbourhood h that investor i resides in and $e_{i,j,c,h,n}$ is the error term.

4.6 Conclusion

People who live in the same household affect individuals' asset allocation choices more than any other factor. In this paper, we investigate the relative importance of factors that determine the asset allocation choices and fund switching decisions of individual investors, using a large and unique proprietary database. We establish a causal relation between individual and peer investment asset allocation choices. We find that an individual is more likely to hold more of the same asset class when their household members and co-workers do.

We combine personal characteristics; household, workplace, and neighbourhood peer effects; and financial advice factors together to assess their relative ability to explain variations in investor asset allocation choice. We find that all factors are important to asset allocation decisions; however, some factors are more important than others. Personal characteristics and peer effects in households (people living at the same physical address, whether family members or friends) dominate the asset allocation decisions of individuals. People who live in the same household are at least 2.5 times more likely to hold the same investment fund as others in their household. While we also find that peer effects in the workplace (co-workers working at the same company), neighbourhood peer effects (people living in the same postal code), and financial advice are also significantly related to the asset allocation decisions of investors, their overall contribution to asset allocation choice is marginal in comparison to personal characteristics and household peer effects. Our results suggest that leaving out peer effects or personal characteristics when investigating asset allocation leads to an omitted variable problem and, as a result, may bias estimates. However, our paper also confirms a number of findings from previous studies that suggest that the omitted variable bias may not be too severe.

We perform a number of robustness checks to confirm our results. We show that peer effects are much more valuable in the model than personal characteristics and, if we had to choose one set of factors over the other, we would pick peer effects, since they explain more variation in asset allocation decisions. We also find that the switching behaviour of investors further confirms the importance of household and workplace effects. We show that investors are more likely to switch investment funds if someone in their family or workplace switches funds. On average, investors switch only 1% of the time; however, if a household member switches, then the likelihood of the investor switching becomes 10%, for a six month horizon.

This study contributes to the literature in several ways. It is the first paper to incorporate a comprehensive list of personal and environmental factors to jointly study the relative importance of these factors in relation to each other. Further, we use a unique dataset that is representative of a national population to understand more about the mutual fund behaviour of individual investors. We also bring a greater level of precision and accuracy to the measurement of peer effects compared to earlier methods. Previous papers tend to use the neighbourhood as a proxy for location and the site of peer effects. This paper uses a more specific unit of measure by looking at the exact physical location where an investor lives, as well as works, and then relates the investor's choice back to the choices of his or her household and workplace peers. The data we use has enabled three different strands of the literature to merge.

Appendix 4.1 Single person and multi-person asset allocation

Panel A: Single-Person Company Asset Allocation

	Cash	*Bonds*	*Property*	*Equity*
Mean	0.207	0.233	0.088	0.472
Standard Error	0.001	0.000	0.000	0.001
Median	0.109	0.123	0.119	0.640
Mode	0.099	0.123	0.120	0.658
Standard Deviation	0.222	0.175	0.049	0.228
Sample Variance	0.049	0.031	0.002	0.052
Kurtosis	7.873	-0.579	68.716	-0.875
Skewness	3.000	0.842	3.919	-0.754
Range	0.997	0.958	0.997	0.980
Minimum	0.003	0.000	0.000	0.000
Maximum	1.000	0.958	0.997	0.980
Sum	40537	45520	17239	92293
N	195589	195589	195589	195589

Panel B: Single-Person Household Asset Allocation

	Cash	*Bonds*	*Property*	*Equity*
Mean	0.217	0.352	0.069	0.362
Standard Error	0.000	0.000	0.000	0.000
Median	0.222	0.350	0.060	0.271
Mode	0.222	0.589	0.029	0.160
Standard Deviation	0.177	0.204	0.051	0.224
Sample Variance	0.031	0.042	0.003	0.050
Kurtosis	13.121	-1.539	62.120	-1.462
Skewness	3.577	-0.133	4.503	0.219
Range	0.997	0.958	0.997	0.980
Minimum	0.003	0.000	0.000	0.000
Maximum	1.000	0.958	0.997	0.980
Sum	58025	93937	18398	96849
N	267209	267209	267209	267209

Panel C: Multi-Person Household and Company Asset Allocation

	Cash	*Bonds*	*Property*	*Equity*
Mean	0.138	0.356	0.080	0.426
Standard Error	0.001	0.001	0.000	0.001
Median	0.100	0.400	0.080	0.420
Mode	0.040	0.160	0.120	0.680
Standard Deviation	0.177	0.181	0.053	0.212
Sample Variance	0.031	0.033	0.003	0.045
Kurtosis	16.511	-1.080	65.310	-1.099
Skewness	3.974	-0.007	5.237	-0.179
Range	1.000	1.000	1.000	1.000
Minimum	0.000	0.000	0.000	0.000
Maximum	1.000	1.000	1.000	1.000
Sum	5814	15024	3359	17989
N	42187	42187	42187	42187

This table shows the descriptive statistics for asset allocation for single person households and companies and multi-person households and companies.

Appendix 4.2 Differences in peer group fund choices

	Company		Household	
Difference in fund risk profile from median	N Individuals	Percentage	N Individuals	Percentage
0*	71,473	34%	88,354	64%
1	63,734	30%	31,540	23%
2	39,281	19%	13,157	10%
3	21,298	10%	2,657	2%
4	11,197	5%	1,645	1%
5	611	0%	471	0%
6	528	0%	33	0%
7	467	0%	13	0%
8	397	0%	15	0%
9	349	0%	4	0%
10	158	0%	7	0%
11	10	0%	2	0%
12	-	0%	-	0%
Total	209,503	100%	137,898	100%

This table shows the differences in investment fund risk profile between people in the same company and household. The fund numbers represent the level of fund risk profile of the funds. For example, the fund denoted Fund 1 would be the safest, being cash, and Fund 13 would be the riskiest. The differences in fund risk profile are calculated by taking the absolute value between an investor's investment fund choice and the peer-group median fund choice. Where no difference exists between fund risk profile the individual investor and their peer group are holding the same fund (shown by 0*).

Appendix 4.3 Switching behaviour robustness check for past returns

EQUATION	VARIABLES	(1) is_i_switch	(2) Marginal Effect
is_i_switch	is_c_switch	0.536***	0.0187
		(33.38)	
	is_h_switch	1.226***	0.0943
		(38.64)	
	returns	**0.036*** **	
		(21.27)	
	t1_sex	0.0141	
		(0.861)	
	t1_taxrate	-0.0052***	
		(-3.129)	
	t1_age	0.0350***	
		(9.947)	
	agesq	-0.0002***	
		(-5.000)	
	logfum	0.159***	
		(10.39)	
	householdsize	-0.0020	
		(-0.264)	
	h_female_percentage	-0.024	
		(-0.841)	
	logfum_h	-0.046**	
		(-2.551)	
	h_avg_taxrate	0.005**	
		(2.511)	
	h_avg_age	-0.002***	
		(-3.187)	
	firmsize	-0.00008e***	
		(-13.63)	
	c_female_percentage	0.082***	
		(3.015)	
	logfum_c	-0.079***	
		(-4.876)	
	c_avg_taxrate	0.011***	
		(4.368)	
	c_avg_age	0.0028***	
		(2.684)	
	fa	-0.123***	
		(-7.439)	
	default_enrol	-0.591***	
		(-16.76)	
	Constant	-4.066***	
		(-29.09)	
	Observations	424,060	

This table reports the same probit model as in Table 4.12 with the additional returns variable. The dependent variable *Individual Switch*$_{i,h,c,t}$ is a binary variable that takes the value of 1 if investor *i*, who lives in household *h* and is employed by company *c*, switches investment funds at time *t*, and is 0 otherwise. α is the constant term; *HouseholdSwitch*$_{i,h,t}$ is a binary variable that takes the value of 1 if any member (excluding the individual investor in question *i*) of household *h* switches investment funds at time *t*, and 0 otherwise; *CompanySwitch*$_{i,c,t}$ is a binary variable that takes the value of 1 if any member (excluding the individual investor in question *i*) of company *c* switches investment funds at time *t*, and 0 otherwise; *Returns*$_{i,t-1}$ is the difference in fund returns between an investor's new fund less old fund in the six months prior to the date of switch time *t*; *Age*$_{i,t}$ is the age of the investor in years; *Age*$^2_{i,t}$ is the squared term of *Age*$_{i,t}$; *Female*$_i$

is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; $LogFUM_{i,t}$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_{i,t}$ is the personal income tax rate of the investor; $Financial\ advice_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; $Default_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; $HouseholdSize_{i,h,t}$ is the total number of investors in household *h*; $HouseholdFemalePercentage_{i,h,t}$ is the percentage of female members in household *h* excluding investor *i*; $HouseholdLogfum_{i,h,t}$ is the logged value of average funds under management of household members in household *h* excluding investor *i*; $Householdtaxrate_{i,h,t}$ is the average tax rate of household members in household *h* excluding investor *i*; $Householdage_{i,h,t}$ is the average age of household members in household *h* excluding investor *i*; $CompanySize_{i,c,t}$ is the total number of investors in company *c*; $CompanyFemalePercentage_{i,c,t}$ is the percentage of female members in company *c* excluding investor *i*; $CompanyLogfum_{i,c,t}$ is the logged value of average funds under management of investors in company *c* excluding investor *i*; $CompanyTaxRate_{i,c,t}$ is the average tax rate of investors in company *c* excluding investor *i*; $CompanyAge_{i,c,t}$ is the average age of co-workers in company *c* excluding investor *i* and $\varepsilon_{i,t}$ is the error term. Marginal effects are reported in column (2).

Appendix 4.4 Switching behaviour interaction terms

VARIABLES	(1) is_i_switch half-year	(2) is_i_switch quarterly	(3) is_i_switch monthly
C_peer_switch	1.923***	1.732***	1.236***
	(5.800)	(5.070)	(3.398)
H_peer_switch	1.351**	1.607***	1.518**
	(2.561)	(2.942)	(2.520)
t1_sex	0.0171	0.0188	0.0145
	(0.865)	(1.079)	(0.974)
t1_taxrate	-0.00721***	-0.00675***	-0.00639***
	(-3.763)	(-3.939)	(-4.301)
t1_age	0.0331***	0.0310***	0.0292***
	(9.304)	(9.424)	(9.838)
agesq	-0.000180***	-0.000169***	-0.000165***
	(-4.474)	(-4.539)	(-4.935)
logfum	0.160***	0.149***	0.129***
	(9.472)	(9.718)	(9.625)
householdsize	0.00575	0.00642	0.00679
	(0.747)	(0.910)	(1.081)
h_female_percentage	-0.0251	-0.0253	-0.0204
	(-0.836)	(-0.919)	(-0.830)
logfum_h	-0.0359*	-0.0344**	-0.0277*
	(-1.923)	(-2.005)	(-1.814)
h_avg_taxrate	0.00401*	0.00384*	0.00365**
	(1.854)	(1.942)	(2.074)
h_avg_age	-0.00228***	-0.00194**	-0.00177**
	(-2.598)	(-2.417)	(-2.465)
firmsize	-0.000214***	-0.000152***	-9.47e-05***
	(-11.59)	(-11.53)	(-11.00)
c_female_percentage	0.0604*	0.0432	0.0349
	(1.958)	(1.568)	(1.465)
logfum_c	-0.0340*	-0.0216	-0.0182
	(-1.843)	(-1.306)	(-1.265)
c_avg_taxrate	0.00943***	0.00797***	0.00692***
	(3.267)	(3.070)	(3.056)
c_avg_age	0.00183	0.000947	0.000995
	(1.555)	(0.896)	(1.081)
fa	-0.0855***	-0.0742***	-0.0636***
	(-4.341)	(-4.284)	(-4.301)
default_enrol	-0.501***	-0.461***	-0.418***
	(-12.39)	(-12.75)	(-13.25)
H_switch_sex	0.0172	0.0200	0.0308
	(0.238)	(0.266)	(0.376)
H_switch_fa	0.225***	0.253***	0.296***
	(2.831)	(3.097)	(3.357)
H_switch_default	-0.390**	-0.472**	-0.503**
	(-2.215)	(-2.438)	(-2.270)
H_switch_householdsize	-0.282***	-0.296***	-0.315***
	(-6.368)	(-6.344)	(-5.951)
H_switch_age	0.00387	0.00329	-0.00123
	(0.977)	(0.806)	(-0.278)
H_switch_tax	-0.00283	-0.00378	-0.00524
	(-0.331)	(-0.425)	(-0.531)
H_switch_logfum	0.217***	0.197***	0.218***
	(3.012)	(2.653)	(2.621)
H_switch_Hfemalepercentage	-0.0359	-0.0926	-0.250
	(-0.221)	(-0.547)	(-1.371)
H_switch_Hage	-0.0213***	-0.0236***	-0.0205***
	(-4.459)	(-4.761)	(-3.764)
H_switch_Hlogfum	-0.0714	-0.0347	-0.00768
	(-0.794)	(-0.373)	(-0.0748)
H_switch_Htaxrate	0.00529	0.00315	0.00510

	(0.481)	(0.274)	(0.408)
C_switch_sex	-0.00957	-0.0227	-0.0258
	(-0.304)	(-0.746)	(-0.863)
C_switch_age	-0.00116	-0.00173	-0.00183
	(-0.962)	(-1.494)	(-1.606)
C_switch_tax	0.00880***	0.00950***	0.0113***
	(3.433)	(3.842)	(4.641)
C_switch_logfum	-0.0387*	-0.0388**	-0.0263
	(-1.917)	(-1.977)	(-1.350)
C_switch_fa	-0.0692*	-0.0910***	-0.119***
	(-1.933)	(-2.581)	(-3.319)
C_switch_default	-0.325***	-0.388***	-0.484***
	(-3.934)	(-4.335)	(-4.679)
C_switch_firmsize	0.000177***	0.000125***	5.73e-05***
	(8.872)	(8.130)	(4.822)
C_switch_Cfemalepercentage	0.114	0.284***	0.413***
	(1.577)	(3.855)	(5.298)
C_switch_Cage	0.00846***	0.0134***	0.00941***
	(2.681)	(4.165)	(2.758)
C_switch_Clogfum	-0.320***	-0.380***	-0.376***
	(-7.612)	(-9.053)	(-8.596)
C_switch_Ctax	0.0545***	0.0760***	0.102***
	(6.749)	(9.070)	(11.25)
Constant	-4.391***	-4.527***	-4.706***
	(-29.37)	(-33.38)	(-39.33)
Observations	424,060	848,120	2,544,360

This table reports the same probit model as in Table 4.12 with the added interaction terms between company switching with control variables and household switching with control variables. This table reports the same probit model as in Table 4.5 with the added interaction terms of financial advice with company switching and financial advice with household switching. Fa*Company equals one when the investors receives advice and someone in his/her company switched funds in the last six months and zero otherwise. Fa*Household equals one when an investor receives financial advice and someone in his/her household switched funds in the last six month period.

Appendix 4.5 Asset allocation cluster household

VARIABLES	(1) cash	(2) cash	(3) cash	(4) bonds	(5) bonds	(6) bonds	(7) property	(8) property	(9) property	(10) shares	(11) shares	(12) shares
cash_company	0.136***	0.115***	0.121***	0.303***	0.252***	0.278***	0.212***	0.185***	0.192***	0.299***	0.253***	0.286***
	(8.509)	(7.448)	(7.491)	(36.77)	(33.46)	(31.83)	(5.651)	(5.091)	(4.784)	(38.14)	(35.80)	(35.63)
cash_household	0.390***	0.356***	0.365***	0.292***	0.238***	0.265***	0.226***	0.183***	0.184***	0.340***	0.261***	0.297***
	(31.33)	(28.40)	(28.43)	(43.31)	(37.44)	(35.08)	(12.42)	(10.12)	(9.517)	(56.39)	(45.65)	(44.32)
age		-0.00647***	-0.00716***		0.00448***	0.00466***		0.00100***	0.000920***		0.00163***	0.00175***
		(-13.78)	(-14.64)		(11.00)	(11.20)		(8.197)	(7.741)		(3.779)	(4.017)
agesq		0.000108***	0.000125***		-1.53e-06	1.08e-05**		-2.44e-05***	-2.46e-05***		-9.10e-05***	-0.000113***
		(17.82)	(19.25)		(-0.298)	(2.023)		(-15.70)	(-16.69)		(-17.50)	(-21.38)
sex		-0.000768	-0.000972		0.00814***	0.0107***		-0.00118***	-0.00106*		-0.00656***	-0.00912***
		(-0.488)	(-0.458)		(5.510)	(5.328)		(-2.744)	(-1.734)		(-3.893)	(-3.994)
logfum		-0.0154***	-0.0210***		-0.0243***	-0.0367***		0.00681***	0.00904***		0.0333***	0.0477***
		(-16.60)	(-11.99)		(-26.48)	(-21.20)		(26.03)	(19.61)		(31.69)	(23.68)
pir		0.00127***	0.00115***		0.00658***	0.00775***		-0.00126***	-0.00130***		-0.00659***	-0.00774***
		(9.752)	(5.293)		(43.13)	(33.46)		(-25.91)	(-18.79)		(-39.47)	(-29.98)
fa		-0.0437***	-0.0426***		-0.0612***	-0.0608***		0.0231***	0.0235***		0.0861***	0.0834***
		(-24.20)	(-23.29)		(-27.78)	(-27.12)		(20.79)	(20.92)		(35.08)	(33.60)
default_enrolmethod		0.00619***	0.00648***		0.0832***	0.0850***		-0.0150***	-0.0149***		-0.0744***	-0.0767***
		(3.085)	(3.074)		(24.65)	(25.32)		(-19.14)	(-19.14)		(-19.50)	(-20.30)
c_female_percentage			0.00349			0.00102			0.000677			-0.00418
			(1.036)			(0.320)			(0.693)			(-1.160)
avg_age			-0.000289**			-0.00148***			0.000224***			0.00195***
			(-2.131)			(-11.32)			(3.800)			(13.44)
logfum_c			0.00956***			0.0174***			-0.00467***			-0.0269***
			(5.045)			(9.583)			(-6.335)			(-13.11)
avg_pir			0.000419			-0.00135***			-3.91e-05			0.00160***
			(1.339)			(-4.139)			(-0.243)			(4.501)
firmsize			2.93e-06***			1.09e-07			-5.98e-07*			-2.64e-06**
			(2.836)			(0.112)			(-1.703)			(-2.421)
female_h_percentage			-0.00361			0.00628**			-0.000224			-0.00309
			(-1.115)			(1.974)			(-0.246)			(-0.854)
avg_h_age			-0.00106***			-0.00144***			9.03e-05*			0.00217***
			(-8.631)			(-11.46)			(1.934)			(15.58)
logfum_h			0.00419**			0.0128***			-0.00112*			-0.0118***

			(2.118)			(6.311)			(-1.906)			(-5.048)
avg_h_pir			1.84e-05			-0.00200***			0.000166*			0.00192***
			(0.0694)			(-7.112)			(1.715)			(6.260)
householdsize			-0.00104			-0.00845***			0.00131***			0.00919***
			(-1.127)			(-10.05)			(4.947)			(9.492)
Constant	0.0722***	0.256***	0.225***	0.132***	0.0630***	0.0324**	0.0446***	0.0203***	0.0373***	0.157***	0.159***	0.154***
	(30.67)	(23.59)	(14.54)	(35.39)	(6.086)	(2.258)	(15.58)	(5.206)	(7.259)	(41.50)	(14.19)	(9.221)
Observations	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187
R-squared	0.157	0.204	0.207	0.130	0.302	0.310	0.105	0.216	0.218	0.165	0.346	0.357

Where $AssetAllocation_{i,j,h,c}$ is the percentage of asset allocation for j asset class categories available in the KiwiSaver fund portfolio (where $j = 4$ and asset classes are cash, bonds, property and equity) for investor i who lives in household h and works in company c. α is the constant term; $HouseholdAssetAllocation_{i,j,h}$ is the average asset allocation within asset class j for all investors in household h excluding the individual investor i; $CompanyAssetAllocation_{i,c,t}$ is the average asset allocation within asset class j for all investors in company c excluding the individual investor i; Age_i is the age of the investor in years; Age^2_i is the squared term of Age_i; $Female_i$ is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; $LogFUM_i$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_i$ is the personal income tax rate of the investor; $Financial\ advice_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; $Default_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; $HouseholdSize_{i,h}$ is the total number of investors in household h; $HouseholdFemalePercentage_{i,h}$ is the percentage of female members in household h excluding investor i; $HouseholdLogfum_{i,h}$ is the logged value of average funds under management of household members in household h excluding investor i; $Householdtaxrate_{i,h}$ is the average tax rate of household members in household h excluding investor i; $Householdage_{i,h}$ is the average age of household members in household h excluding investor i; $CompanySize_{i,c}$ is the total number of investors in company c; $CompanyFemalePercentage_{i,c}$ is the percentage of female members in company c excluding investor i; $CompanyLogfum_{i,c}$ is the logged value of average funds under management of investors in company c excluding investor i; $CompanyTaxRate_{i,c}$ is the average tax rate of investors in company c excluding investor i; $CompanyAge_{i,c}$ is the average age of co-workers in company c excluding investor i and $\varepsilon_{i,j}$ is the error term clustered by household.

Appendix 4.6 Asset allocation White standard errors

VARIABLES	(1) cash	(2) cash	(3) cash	(4) bonds	(5) bonds	(6) bonds	(7) property	(8) property	(9) property	(10) shares	(11) shares	(12) shares
cash_company	0.136***	0.115***	0.121***	0.303***	0.252***	0.278***	0.212***	0.185***	0.192***	0.299***	0.253***	0.286***
	(8.996)	(7.869)	(7.907)	(38.76)	(35.57)	(34.06)	(6.888)	(6.249)	(5.886)	(39.62)	(37.42)	(37.34)
cash_household	0.390***	0.356***	0.365***	0.292***	0.238***	0.265***	0.226***	0.183***	0.184***	0.340***	0.261***	0.297***
	(35.67)	(32.65)	(32.63)	(53.39)	(45.52)	(43.12)	(14.92)	(12.36)	(11.65)	(68.12)	(54.42)	(53.35)
age		-0.00647***	-0.00716***		0.00448***	0.00466***		0.00100***	0.000920***		0.00163***	0.00175***
		(-14.17)	(-15.04)		(11.32)	(11.43)		(8.951)	(8.358)		(3.956)	(4.145)
agesq		0.000108***	0.000125***		-1.53e-06	1.08e-05**		-2.44e-05***	-2.46e-05***		-9.10e-05***	-0.000113***
		(18.31)	(19.78)		(-0.307)	(2.063)		(-17.18)	(-17.89)		(-18.48)	(-22.06)
sex		-0.000768	-0.000972		0.00814***	0.0107***		-0.00118**	-0.00106		-0.00656***	-0.00912***
		(-0.486)	(-0.467)		(5.373)	(5.351)		(-2.553)	(-1.642)		(-3.804)	(-4.064)
logfum		-0.0154***	-0.0210***		-0.0243***	-0.0367***		0.00681***	0.00904***		0.0333***	0.0477***
		(-16.75)	(-12.60)		(-26.96)	(-22.18)		(27.26)	(20.21)		(32.45)	(25.19)
taxrate		0.00127***	0.00115***		0.00658***	0.00775***		-0.00126***	-0.00130***		-0.00659***	-0.00774***
		(9.943)	(5.728)		(44.93)	(35.58)		(-27.61)	(-18.97)		(-40.80)	(-32.03)
fa		-0.0437***	-0.0426***		-0.0612***	-0.0608***		0.0231***	0.0235***		0.0861***	0.0834***
		(-24.34)	(-23.26)		(-29.83)	(-28.73)		(23.42)	(23.55)		(38.18)	(36.05)
default_enrolmethod		0.00619***	0.00648***		0.0832***	0.0850***		-0.0150***	-0.0149***		-0.0744***	-0.0767***
		(3.124)	(3.102)		(25.89)	(26.39)		(-20.26)	(-20.36)		(-20.43)	(-21.07)
c_female_percentage			0.00349			0.00102			0.000677			-0.00418
			(1.035)			(0.320)			(0.707)			(-1.158)
avg_age			-0.000289**			-0.00148***			0.000224***			0.00195***
			(-2.122)			(-11.41)			(4.411)			(13.52)
logfum_c			0.00956***			0.0174***			-0.00467***			-0.0269***
			(5.083)			(9.687)			(-7.405)			(-13.24)
avg_taxrate			0.000419			-0.00135***			-3.91e-05			0.00160***
			(1.351)			(-4.279)			(-0.293)			(4.567)
firmsize			2.93e-06***			1.09e-07			-5.98e-07*			-2.64e-06**
			(2.823)			(0.112)			(-1.824)			(-2.452)
female_h_percentage			-0.00361			0.00628*			-0.000224			-0.00309
			(-1.052)			(1.860)			(-0.240)			(-0.792)
avg_h_age			-0.00106***			-0.00144***			9.03e-05**			0.00217***
			(-8.804)			(-12.23)			(2.232)			(16.43)
logfum_h			0.00419**			0.0128***			-0.00112**			-0.0118***
			(2.139)			(6.442)			(-2.024)			(-5.175)

avg_h_taxrate			1.84e-05			-0.00200***			0.000166*			0.00192***
			(0.0722)			(-7.460)			(1.868)			(6.495)
householdsize			-0.00104			-0.00845***			0.00131***			0.00919***
			(-1.164)			(-10.31)			(5.399)			(9.493)
Constant	0.0722***	0.256***	0.225***	0.132***	0.0630***	0.0324**	0.0446***	0.0203***	0.0373***	0.157***	0.159***	0.154***
	(33.92)	(24.51)	(14.70)	(38.16)	(6.312)	(2.258)	(18.31)	(5.824)	(7.923)	(45.01)	(14.62)	(9.198)
Observations	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187	42,187
R-squared	0.157	0.204	0.207	0.130	0.302	0.310	0.105	0.216	0.218	0.165	0.346	0.357

Where the dependent variable $AssetAllocation_{i,j,h,c}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where $j = 4$ and asset classes are cash, bonds, property and equity) for investor *i* who lives in household *h* and works in company *c*. α is the constant term; $HouseholdAssetAllocation_{i,j,h}$ is the average asset allocation within asset class *j* for all investors in household *h* excluding the individual investor *i;* $CompanyAssetAllocation_{i,c,t}$ is the average asset allocation within asset class *j* for all investors in company *c* excluding the individual investor *i;* Age_i is the age of the investor in years; Age^2_i is the squared term of Age_i; $Female_i$ is a dummy variable which equals to 1 if the investor is female and 0 if the investor is male; $LogFUM_i$ is the logged value of funds under management in the investor's KiwiSaver account; $TaxRate_i$ is the personal income tax rate of the investor; $Financial\ advice_i$ is a dummy variable, which equals to 1 if the KiwiSaver member has received financial advice; $Default_i$ is a dummy variable which equals to 1 if the KiwiSaver member enrolled to KiwiSaver by default enrolment; $HouseholdSize_{i,h}$ is the total number of investors in household *h*; $HouseholdFemalePercentage_{i,h}$ is the percentage of female members in household *h* excluding investor *i*; $HouseholdLogfum_{i,h}$ is the logged value of average funds under management of household members in household *h* excluding investor *i*; $Householdtaxrate_{i,h}$ is the average tax rate of household members in household *h* excluding investor *i*; $Householdage_{i,h}$ is the average age of household members in household *h* excluding investor *i*; $CompanySize_{i,c}$ is the total number of investors in company *c*; $CompanyFemalePercentage_{i,c}$ is the percentage of female members in company *c* excluding investor *i*; $CompanyLogfum_{i,c}$ is the logged value of average funds under management of investors in company *c* excluding investor *i*; $CompanyTaxRate_{i,c}$ is the average tax rate of investors in company *c* excluding investor *i*; $CompanyAge_{i,c}$ is the average age of co-workers in company *c* excluding investor *i* and $\varepsilon_{i,j}$ is the white heteroscedasticity-consistent standard error term.

Appendix 4.7 Age correlation matrix

	female	age	age^2	tax	default	financial advice
female	1.00					
age	0.01	1.00				
age^2	-0.01	**0.99**	1.00			
tax	-0.15	0.09	0.07	1.00		
default	-0.05	-0.12	-0.11	0.26	1.00	
financial advice	-0.01	0.23	0.23	0.06	-0.13	1.00

This table shows the high correlation between the age and age-squared variable.

Appendix 4.8 Financial advice correlation matrix

	fa	fa_female	fa_age	fa_tax	fa_logfum	fa_firmsize	fa_householdsize
fa	1.00						
fa_female	0.69	1.00					
fa_age	**0.96**	0.65	1.00				
fa_tax	**0.95**	0.60	**0.93**	1.00			
fa_logfum	**1.00**	0.67	**0.96**	**0.96**	1.00		
fa_firmsize	0.39	0.33	0.37	0.36	0.39	1.00	
fa_householdsize	**0.94**	0.64	**0.87**	**0.89**	**0.93**	0.37	1.00

This table reports correlation matrix for the financial advice variable with interaction between financial advice and other control variables: gender, age, tax, logfum, firmsize and householdsize.

Appendix 4.9 Workplace peer effects

VARIABLES	(1) cash	(2) bonds	(3) property	(4) shares
cash_company	0.149***			
	(6.828)			
c_female_percentage	0.00757**	0.00439	-0.00171	-0.0103**
	(2.291)	(0.988)	(-1.523)	(-2.123)
avg_age	0.00201***	0.00330***	-0.000702***	-0.00438***
	(14.26)	(19.53)	(-14.29)	(-22.04)
logfum_c	-0.0190***	-0.0245***	0.00829***	0.0327***
	(-10.33)	(-7.025)	(9.924)	(8.839)
avg_pir	0.000828**	0.00825***	-0.00134***	-0.00724***
	(2.529)	(15.32)	(-9.030)	(-12.31)
firmsize	4.97e-06***	3.48e-06	-1.43e-06**	-6.89e-06**
	(3.867)	(1.194)	(-2.104)	(-2.147)
bonds_company		0.225***		
		(15.83)		
property_company			0.217***	
			(6.530)	
equity_company				0.239***
				(16.79)
Constant	0.180***	0.158***	0.0505***	0.393***
	(12.64)	(7.558)	(8.605)	(16.15)
Observations	42,187	42,187	42,187	42,187
R-squared	0.014	0.074	0.044	0.073

This table reports the results from the workplace peer effects model with all co-worker control variables. $Asset\ allocation_{i,j,h,c,n}$ is the percentage of asset allocation for *j* asset class categories available in the KiwiSaver fund portfolio (where *j* = 4 and the asset classes are cash, bonds, property, and equity) for investor *i* who works in company *c*. The term α is a constant; $CompanyAssetAllocation_{i,j,c}$ is the average asset allocation within asset class *j* for all investors in company *c*, excluding individual investor *i*; $Firmsize_{i,c}$ is the total number of investors in household *c*; $C\_FemalePercentage_{i,c}$ is the percentage of female members in company *c*, excluding investor *i*; $Logfum\_C_{i,c}$ is the log of average funds under management of co-workers, excluding investor *i*; $Avg\_pir_{i,c}$ is the average tax rate of household members in company *c*, excluding investor *i*; and $Avg\_age_{i,c}$ is the average age of co-works in company *c*, excluding investor *i*. The error term $\varepsilon_{i,j,h,c,n}$ is clustered at the workplace level.

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