MELBOURNE INSTITUTE
Applied Economic & Social Research

Working Paper Series

Retail investor expectations and trading preferences

Sarantis Tsiaplias
Qi Zeng
Guay Lim

Working Paper No. 27/21
December 2021

Retail investor expectations and trading preferences

Sarantis Tsiaplias
Melbourne Institute: Applied Economic & Social Research,
The University of Melbourne

Qi Zeng
Department of Finance, The University of Melbourne

Guay Lim
Melbourne Institute: Applied Economic & Social Research,
The University of Melbourne

Melbourne Institute Working Paper No. 27/21

December 2021

*We thank James Brugler, Antonio Gargano, Bruce Grundy, Joachim Inkmann, Patrick J. Kelly, Bryan Lim, Spencer Martin, Maurice McCourt, Alexander Michaelides, Federico Nardari, Ravi Sastry, Juan Sotes-Paladino, Thijs van der Heijden, Zhuo Zhong and Kai Li for helpful comments.

Melbourne Institute: Applied Economic & Social Research
The University of Melbourne
Victoria 3010 Australia
Telephone **+61 3 8344 2100**
Fax **+61 3 8344 2111**
Email **melb-inst@unimelb.edu.au**
Website **melbourneinstitute.unimelb.edu.au**

Abstract

Using a novel quarterly survey of 23 thousand Australian retail equity investors spanning eight years, we study the relationship between investor beliefs and their trading preferences. We provide evidence that, consistent with Mean-Variance preferences, both lower returns and higher volatility increase the marginal propensity to sell. Furthermore, we find that while demographic characteristics and investment experiences are predictive of the holding preferences of retail investors, they are uninformative about their trading directional preferences (i.e. whether to buy or sell). Our findings suggest that a representative-agent portfolio model with Mean-Variance preferences is sufficient to explain the trading directional preferences of retail investors, but not their holding patterns.

JEL classification: G11, G40, C35.

Keywords: investor expectations, shareholder surveys, trading preferences, Mean-Variance utility.

1 Introduction

Standard finance theory prescribes that a representative investor's trading decision is determined by investor beliefs about asset returns and risk. Using micro-level trading data, researchers have augmented this paradigm to learn about heterogeneity in the trading behaviour of retail investors (Barber and Odean, 2013). Researchers have also examined heterogeneity in the expectations formation process of investors and consumers (Greenwood and Shleifer, 2014; Manski, 2017; Hansen, 2017). There remains, however, significant uncertainty about the relationship between investor expectations and their trading preferences, particularly for non-professional retail investors (Giglio et al., 2020).

This paper uses a novel dataset containing the stock market expectations and trading preferences of over 23 thousand retail Australian investors over the period 2009—2017 to investigate the link between retail investors' risk and return expectations and their holding/trading preferences (as opposed to their actual trades). Specifically, the data allows us to investigate whether there is a significant relationship between investors' beliefs about stock market conditions, demographic and socio-economic characteristics, holding preferences and directional trading preferences (i.e. buying or selling).

Our analysis yields three key findings: (1) We find strong evidences of a negative marginal relationship between trading direction preferences and expected volatility. This is in addition to the confirmation that there is a positive relationship between trading direction preferences and expected returns, a result that the literature has mainly focused on so far. (2) We find a surprising result that demographic differences and investment experience provide little information regarding trading directional preferences. This finding supports the notion of a representative investor when it comes to buying/selling decisions. (3) In contrast, demographic differences and investment experience are predictive of the propensity of an investor to hold and we find that retail investors exhibit strong holding preferences. In particular, older persons are more likely to prefer holding rather than trading even after accounting for their investment experience. This is particularly so for older persons with below average income who are significantly more conservative than their higher income counterparts.

The empirical analysis relies on a quarterly survey of retail equity investors in Australia which contains information about both individual investors' risk and return expectations and their trading preferences. During each quarter over the period 2009:Q1 to 2017:Q2, approximately 1000 randomly selected investors were surveyed yielding a total sample size of approximately 23 thousand usable responses. The large sample size allows us to reliably examine the stockmarket preferences of retail investors and to consider the ramifications of demographic heterogeneity.

As part of the survey, respondents were asked about their stock return and volatility expectations, in addition to their current and future trading preferences (including ordinal data on whether one should be buying, selling or holding stocks, both now and in the next 12 months). A unique feature of the survey is that it has also collected information on investment experience. This helps furnish information on how past experiences affect the trading preferences of retail investors (Malmendier and Shanthikumar, 2007).

To qualify as a respondent, individuals were required to have direct ownership of shares of one or more companies listed on the Australian Stock Exchange (ASX). As such, all responses are from individuals that can be verified to be direct shareholders in listed companies (as opposed to individuals who own shares indirectly via investment or mutual funds). In particular, every retail investor that has acquired a share in his or her name will be recorded, and the survey is randomly sampled from the universe of such investors resulting in a representative sample of Australian retail investors. This is important as evidence about share market preferences has often been based on general surveys or experimental studies involving a high proportion of individuals who have not engaged in 'real' share trading.

Our results are informative about the influence of stock market volatility, the representativeness of the mean-variance paradigm for understanding the buying/selling decision and the importance of recognising the decision to hold (i.e. not engage in buying or selling).

First, we find a highly significant negative relationship between expected volatility and trading direction preferences, with higher expected volatility increasing the marginal propensity to sell. The literature has shown that trading is closely linked to past returns (Barber and Odean, 2000; Barber et al., 2009, 2020; Brunnermeier and Nagel, 2008; Calvet et al., 2009). However, far less is known about the link between volatility expectations and trading (see, for example, Barber and Odean (2001) which associates volatility with trading intensity). We find evidence that the selling preferences of retail investors rise sharply in response to expectations of greater stockmarket volatility (see, further, (Hudomiet et al., 2011)).

Second, the retail investor's buying or selling preference is almost solely characterised by his or her expectations regarding future stockmarket returns and volatility. In other words, the propensity to sell in response to volatility is unaffected by key demographic characteristics such as the retail investor's gender, age or income. Accordingly, retail investors have trading preferences focused on expected returns and volatility that are stable and similar across different demographic groups (Dominitz and Manski, 2011). The evidence supports the notion of a representative retail investor whose preferences regarding trading direction are broadly consistent with Mean-Variance (MV) utility.

Third, we provide novel evidence that demographic characteristics (like gender and income) and investment experience are predictive of the preference to hold. Retail investors, in general, also exhibit strong holding tendencies, even when they expect markets to rise or fall. This result is consistent with recent data in Giglio et al. (2020) based on the observed transactions of a large group of investors. A possible explanation for the relatively strong propensity to hold is the presence of trading costs (Constantinides, 1986; Davis and Norman, 1990). However, we find that the holding preferences of retail investors are tied to demographic characteristics that are unrelated to transaction costs, including gender and income. This result highlights the importance of accounting for the demographic characteristics of retail investors when determining their propensity to hold rather than trade in a given period.

Related Literature. There is an extensive literature exploring the formation of beliefs for both equity returns and economic data (Gennaioli and Shleifer, 2020; Manski, 2017). Manski (2004) and Giglio et al. (2020) discuss the relevance of survey data for this literature, arguing that survey data can assist in better understanding consumer beliefs. Conversely, a potential critique of survey data is that investors may confuse risk preferences and beliefs and, more broadly, that responses and investor behaviours may be inconsistent (Hansen, 2017). Recent research, utilising a combination of survey data and portfolio holdings to learn about consumer preferences, is provided in Giglio et al. (2020) and Ameriks et al. (2020a,b). Giglio et al. (2020), which is closest to this paper, survey a random sample of US-based clients of Vanguard every two months starting in February 2017 in linking investor beliefs to their holdings. The authors find a small but statistically significant relationship between investor beliefs and their portfolio allocation, with the sensitivity of the equity share of portfolios to perceived returns and risk being lower than that predicted by standard macro-finance models (see, further, Amromin and Sharpe (2014) and Ameriks et al. (2018)). We complement this line of study by surveying a large, broad sample of retail investors that spans a relatively long time period and is likely to be representative of retail investor preferences. Unlike the recent US studies, we do not incorporate detailed holdings data. However, we compensate for this by directly surveying retail investors on both their trading preferences and their beliefs about risk and return. This allows us to highlight demographic characteristics in the data and to identify a relationship between trading preferences and risk and return beliefs that is robust to a wide range of economic and financial conditions.

Our analysis contributes to the literature in two key aspects. First, we complement the literature on investor behaviour by linking stock market expectations with trading preferences and show that the impact of demographic characteristics and risk and return expectations for the retail investor's preference to hold is significantly different to the impact on their preference regarding the direction of trades in any given time period (viz. that investors should be buying or selling at time t). In particular, we highlight the presence of differential and significant demographic effects on the holding versus trading decisions of retail investors, but the absence of any demographic effects for investor preferences regarding the direction (i.e. buying versus selling) of a trade.

Second, we provide evidence that investor preferences regarding buying and selling can be reliably approximated using MV preferences. Although MV preferences are often assumed, the absence of data linking investor stock market expectations with their trading preferences renders this assumption potentially tenuous, particularly for non-professional retail investors. Although we cannot exclude the applicability of other more complex preference structures, our findings are novel in indicating that the trading preferences of retail investors can be reliably represented using a simple and parsimonious MV specification.

The rest of this paper is structured as follows. In Section 2 we describe our data and the econometric methodology used to examine the association between investor expectations and trading preferences. Section 3 discusses the estimated results, while Section 4 examines whether the results are consistent with MV preferences. Section 5 provides some concluding remarks. Proofs and data details are in the appendices.

2 Data and Methodology

2.1 Survey Data

The data analysed is based on a survey of retail shareholders over the period 2009:Q1 to 2017:Q2. The survey was conducted as part of a research collaboration between Global Proxy Solicitation (now part of Morrow Sodali) and the Melbourne Institute of Applied Economic and Social Research. Each quarter, a set of approximately one-thousand new, randomly selected retail shareholders were surveyed by telephone. The sample of shareholders was drawn from shareholder registry data for persons at least 18 years of age who directly own shares listed on the Australian Securities Exchange. It therefore excludes 'passive' investors (for example, through mutual funds) and non-retail investors such as investment banks or hedge funds.

The repeated, cross-sectional survey of retail investors is intended to measure the expectations and holding/trading preferences of retail stockmarket investors. The survey asks retail investors about their stock return and volatility expectations. It also asks retail investors about their preferences with respect to whether investors should currently be holding or trading (i.e. buying or selling).[1] The survey also provides information about the demographic characteristics of respondents, including their gender, age, income group, and their years of stockmarket investing experience.[2] The relevant questions are listed in Appendix A.

The survey responses are discrete and qualitative. We have removed all the 'don't know' entries for expectations regarding returns and volatility or trading preferences, in addition to individuals who failed to provide all relevant demographic information. Approximately 70 per cent of respondents answered all relevant questions resulting in a dataset of $N = 22,960$ quarter-person observations for estimation purposes. Table 1 and Figure 1 present the demographic characteristics of the respondents. The age, income and gender characteristics are reported according to their discrete groupings, while investment experience is based on self-reported years.

⟨ Insert Figure 1 and Table 1 here. ⟩

The average age of investors in our sample is 63.3 years, with a standard deviation of 9.6 years. As a point of comparison, our sample average age is below that of the Vanguard Research Initiatives survey (67.8 years) (Ameriks et al., 2018) but greater than the average age of US retail investors (50 years) in Barber and Odean (2001).

Our sample has a relatively high proportion of women (40 per cent). By comparison, about 35 per cent of respondents in Ameriks et al. (2018) are female, falling to 20 per cent

[1]In effect, the investor's response is akin to the recommendations given by financial analysts for a notional representative investor except they reflect the trading beliefs of ordinary investors.

[2]Respondents are asked about the number of years they have been investing in listed companies.

of investors in Barber and Odean (2001). The average income of respondents is approximately A$70,000, and all income groups (from 'Under $45,000' to 'More than $105,000') are sufficiently represented.

In terms of self-reported experience in financial markets, investors tend to round their answers to discrete numbers like 5 or 10 years despite given the option to report actual years of experience. The mode is 20 years and the mean is 23 years. While it is unclear how different investors interpret the term "experience", it is nevertheless clear that our sample has a wide cross-section of investors whose level of experience varies.

The distribution of trading preferences is based on the responses to the survey question: What do you think people should be doing with their shares now? The responses indicate that 19.1% of investors advocate a buy option, 3.6% indicate selling and 77.3% believe that it is preferable to hold rather than trade.

Table 2 shows how trading responses are distributed across return and volatility expectations. It is clear that trading preferences are heavily influenced by both risk and return expectations. As expected, higher expected returns are associated with a higher propensity to buy. Higher expected volatility is associated with a higher propensity to sell, with lower expected volatility inducing a preference to buy.

⟨ Insert Table 2 here. ⟩

A stylised fact that emerges from the data is the strong propensity to hold and an aversion to trading (buying or selling). Even when investors expect higher returns and lower volatility, they often reveal a preference to hold. We note that realised returns on the ASX200 over the survey period are not atypical, and do not exhibit major up- or down- turns (see Figure 2). The observed results are therefore unlikely to be characterised by unique or extreme market conditions.

⟨ Insert Figure 2 here. ⟩

2.2 Methodology

In general, the theoretical framework for portfolio choice problems assumes that continuous quantitative data is available. However, our survey responses about expected returns, expected volatility and trading preferences are ordinal. Specifically, for returns (or volatility), the survey response takes on 3 values corresponding to: (1) lower expected returns (or volatility), (2) no change, and (3) higher expected returns (or volatility). Similarly, the choices for trading take on the values (1) buy, (2) hold, or (3) sell.

To assess the relationship between trading preferences and expectations, and to determine the role of demographic factors for this relationship, we therefore adopt a hierarchical decision model that yields two sets of probabilities. The first is the probability of holding versus trading, whilst the second is the probability of buying versus selling. Our approach can be contrasted with the general approach that focuses only on buying and selling preferences. Instead, we allow (but do not impose) expectations, demographics and other variables to have a different impact on the decision to hold and on the decision to buy or sell.

The basic econometric framework follows (see, further, McCullagh and Nelder (1989)). The trading preferences made by the ith retail investor are denoted y_i and can take on three possible values

$$y_i = 1 \Longrightarrow \text{hold} \tag{1}$$

$$y_i = 2 \Longrightarrow \text{buy} \tag{2}$$

$$y_i = 3 \Longrightarrow \text{sell.} \tag{3}$$

where $y_i = 1$, for example, implies that the ith investor preference is to hold rather than to trade (buy or sell). Technically, this revealed preference is made at a particular point in time although the time subscript is omitted for notational convenience.

Define $y_{ij} = 1$ if $y_i = j$ (for $j = 1, 2, 3$) and zero otherwise. The unobserved utility associated with y_{ij} is u_{ij} and is given by

$$u_{ij} = \eta_{ij} + e_{ij} \tag{4}$$

$$\eta_{ij} = f(E_{it}(r_{t+1}), E_{it}(V_{t+1}), x_i, z_t) \tag{5}$$

where e_{ij} is a zero-mean logistic error term and η_{ij} is a linear expectations term. This term includes the investor-specific information on expected returns and volatilities ($E_{it}(r_{t+1})$ and $E_{it}(V_{t+1})$ respectively), in addition to information about individual investors x_i and overall financial and economic conditions z_t.

Define the probabilities associated with holding, buying and selling as π_{ij}, $j = 1, 2, 3$ respectively. Since choices are discrete, the ith retail investor's ex ante utility is

$$u_i = \sum_{j=1}^{J=3} = u_{ij}\pi_{ij} \tag{6}$$

with expected utility u for the representative investor estimated as $\frac{1}{N}\sum u_i$.

Parameter estimation

Given the hierarchical structure present in the preference to hold or trade (buy/sell), the ith investor's contribution to the likelihood function is given by

$$L_i = \pi_{i1}^{y_{i1}} (\pi_{i2} + \pi_{i3})^{y_{i2}+y_{i3}} \times \left(\frac{\pi_{i2}}{\pi_{i2} + \pi_{i3}}\right)^{y_{i2}} \left(\frac{\pi_{i3}}{\pi_{i2} + \pi_{i3}}\right)^{y_{i3}} \tag{7}$$

$$= p_{i1}^{y_{i1}} (1 - p_{i1})^{y_{i2}+y_{i3}} \times p_{i2}^{y_{i2}} (1 - p_{i2})^{y_{i3}} \tag{8}$$

$$p_{i1} = \frac{\exp(\rho_{i1})}{1 + \exp(\rho_{i1})} \tag{9}$$

$$p_{i2} = \frac{\exp(\rho_{i2})}{1 + \exp(\rho_{i2})} \tag{10}$$

where $\rho_{i1} = \ln\left(\frac{\pi_{i1}}{1-\pi_{i1}}\right)$, $\rho_{i2} = \ln\left(\frac{\pi_{i2}}{\pi_{i3}}\right)$ are the log-odds ratios for decisions made by the ith investor regarding whether to, respectively: (1) hold or trade, and (2) buy or sell. Note that this does not imply that the investor decides in two independent steps. Rather the decision-making process is contemporaneous and reflects the implicit restrictions embedded in the choices available to each investor. The overall log-likelihood is given by the sum of $\log L_i$ over the N investors in the dataset.

The hierarchical model is parameterised using the following structure for each investor

$$\rho_{i1} = \ln\left(\frac{\pi_{i1}}{1-\pi_{i1}}\right) = a_1 + \beta_{11}E_{it}\left(r_{t+1}\right) + \beta_{12}E_{it}\left(V_{t+1}\right) + x_i'\gamma_1 + z_t'\delta_1 \tag{11}$$

$$\rho_{i2} = \ln\left(\frac{\pi_{i2}}{\pi_{i3}}\right) = a_2 + \beta_{21}E_{it}\left(r_{t+1}\right) + \beta_{22}E_{it}\left(V_{t+1}\right) + x_i'\gamma_2 + z_t'\delta_2 \tag{12}$$

where ρ_{i1} governs holding (versus trading) preferences, and ρ_{i2} governs trading direction preferences. x_i is a set of investor-specific regressors regarding gender, age, income, and years of investment experience, and z_t is a vector containing information about a range of observed financial and economic conditions, including year-specific indicators, current and lagged actual returns on the ASX 200 (both quarterly and yearly), current ASX200 and VIX200 log-levels, current and lagged percentage changes in the VIX200 and the percentage change in real GDP.

Maximization of the overall log-likelihood yields two sets of parameters $(a_1, \beta_1, \gamma_1, \delta_1)$, $(a_2, \beta_2, \gamma_2, \delta_2)$ that provide conditional information on the extent to which the risk and return expectations impact on the preference to hold or trade (buying or selling). Importantly, we do not constrain the β coefficients and are therefore able to identify how risk and return expectations have a different impact on the preference to hold (rather than trade) as compared to the preference to buy rather than sell. Similarly, the γ coefficients allow us to examine whether demographics and investment experience (after accounting for any heterogeneity in risk and return expectations) play a similar role on holding preferences as they do on buying and selling preferences.

3 Empirical Results

Our baseline empirical study is based on the specifications presented in equations (11) and (12). To ensure the robustness of the results, we consider a range of models thereby evaluating the extent to which the response of trading preferences to risk and return expectations changes with the addition of new information. Our focus here is two-fold. One is to evaluate the relationship between holding and trading preferences with expectations regarding stockmarket returns and volatility. The other is to determine the effects of demographic characteristics on holding and trading preferences.

The parameter estimates for trading direction preferences (e.g buying and selling preferences) are in Table 3, while holding (versus trading) preferences are presented in Table 4

⟨ Insert Table 3 here. ⟩

⟨ Insert Table 4 here. ⟩

The estimates indicate that the impact of demographic variables on trading direction preferences is typically insignificant. The only exception seems to be that older (65+) investors are more likely to buy, while less experienced investors (less than 10 years of stockmarket experience) are more likely to sell. It is, perhaps, surprising that older investors (mainly retirees) exhibit a preference for buying rather than selling as according to standard life-cycle theory, retirees are assumed to hold fewer stocks. This finding suggests that older investors may be selling stocks that, in the absence of liquidity constraints, they would otherwise prefer to buy.

Conditional on the decision to trade, our estimates indicate a highly significant and economically meaningful relationship between retail investors' selling preferences and their expectations of higher stockmarket volatility. A significant association is also observed between the buying preferences of retail investors and their expectations regarding stockmarket returns. As shown in Table 3, the coefficient on the expected return is positive and statistically significant hence the odds of buying rather than selling increase as the expected return rises. We also see that the coefficient on expected volatility is negative and statistically significant indicating that the odds of buying rather than selling decrease (or, conversely, that the odds of selling increase) as the investor's expected volatility rises. Moreover, after accounting for expected returns and volatilities, demographic differences have almost no additional explanatory power for the decision to buy or sell.

Although the positive relationship between buying preferences and expected returns is largely expected, there is little evidence in the empirical literature on the relationship between trading direction preferences and subjective expected volatility (with much of the focus being on the relationship between trading and historical performance).[3] Our joint finding of a greater propensity to buy when expected returns are higher and a greater propensity to sell when expected volatility is higher is therefore significant. To understand the parameter estimates for the relationship between trading direction preferences and expected volatility, it is useful to consider the implications of the estimates for an investor expecting lower volatility and who is neutral in terms of buying or selling (i.e. 50% probability of buying versus selling). According to the parameter estimates, if the investor's expectation shifts from lower volatility to higher volatility then (all else being equal) their probability of buying – conditional on their deciding to trade - falls to 27% and their probability of selling rises to 73%. This holds irrespective of their demographic characteristics.

In contrast to the negligible informativeness of demographic characteristics for buying and selling preferences, almost all demographic characteristics are statistically significant for holding preferences. Male investors are more likely to prefer to trade (and less likely to prefer to hold); a result that is consistent with the findings in Barber and Odean (2001),

[3] For example, Barber and Odean (2001) find significant gender-based differences in trading intensities, with female investors also generally having a smaller risk exposure than males.

who find that males also trade more frequently than females and suffer more losses as a result. Investors with greater investment experience are also more likely to prefer to hold stocks suggesting that experience leads to cautiousness. Malmendier and Shanthikumar (2007) find a similar trait in older investors. Finally, higher income investors are, somewhat surprisingly, less likely to prefer holding and this may be indicative of a relationship between higher income and the willingness to accept higher risk.

The impact of age is also important for the preference to hold or trade. Older persons are more likely to prefer holding rather than trading even after accounting for their investment experience. This is particularly so for older persons with below average income who are significantly more conservative than their higher income counterparts. However, consistent with the estimates for gender and income, the impact of an investor's age on their trading direction preferences is relatively minor.

In general, we observe a similar pattern in the parameter estimates for a large number of alternative specifications. The estimates indicate salient differences in the impact of demographic factors on investor preferences. Although males are significantly more likely to prefer trading than females; conditional on revealing a preference to trade, they are not significantly more likely to prefer buying (or selling) than females. Similarly, high income individuals or those with relatively less investment experience are more likely to prefer trading than holding. Conditional on their preference to trade, however, neither income nor investment experience matter in terms of altering their propensity to buy or sell.

It is intriguing that demographic attributes and investment experience have an incremental impact (over and above return and volatility expectations) on the preference of retail investors to hold or trade, but little impact on their trading direction preferences. Instead, the investor's probability to buy or sell is consistent with that of a strictly rational individual who considers only the MV properties of shares (i.e. their expected returns and volatilities). As such, the estimates support the notion of MV-based portfolio choices for preferences regarding trading direction, where the only variables that affect the decision to either buy or sell are based on expected returns and risk. This result holds irrespective of the controls added to the regressions (including alternative linear and non-linear combinations of the controls).

Robustness to persons aged 55 years or less

To examine the sensitivity of the results to the typically older age of respondents, we re-estimate the relationship between trading intentions and key covariates such as expected returns and expected volatilities after limiting the sample to respondents aged 55 years or less. The results, presented in Table 5, show that the general relationship between trading preferences and return and volatility expectations is maintained. In terms of trading direction preferences, respondents continue to increase their propensity to purchase with higher expected returns, in addition to increasing their propensity to sell with higher expected volatility.

For trading versus holding intentions, respondents continue to increase their propensity to trade (rather than hold) with higher expected returns. A noticeable difference for younger respondents is that volatility expectations and income appear to be less important for their trading or holding intentions. In particular, the estimates indicate that higher expected volatility does not reduce the propensity to trade of the younger set of respondents, suggesting that younger retail investors are less risk averse and more concerned about returns than volatility when deciding to trade. Having decided to trade, however, younger respondents continue to rely on expected returns and volatility similarly to older respondents in terms of their trading direction preferences.

Other robustness checks

To examine the sensitivity of the results to model specification, we adopted an initial estimation approach of beginning with a simple model and progressively adding additional regressors. Pursuant to this approach, it is clear from the results in Tables 3 and 4 that the coefficients on the expected return and volatility parameters are largely invariant to additional demographic, financial and economic controls.

We have also estimated the model by allowing for asymmetric responses to the direction of: (i) expected returns; and (ii) both expected returns and expected volatility. The results for the alternative model specifications are presented in Appendix B and show that the basic findings discussed here continue to hold. Finally, we have re-estimated each of the models using a hierarchical probit specification in lieu of the hierarchical logit model. We find, however, that the results obtained using the hierarchical probit are almost identical to those of the hierarchical logit across each of the specifications considered.

4 Holding/Trading and MV utility

To understand the empirical results, this section introduces a simple mean-variance model with proportional transaction costs. The advantage of using such a model is that we can completely characterize hold, buy, and sell probabilities. In the discussion that follows, we show that a simple model with holding/trading decisions tied to the first two moments of agents' beliefs is sufficient to describe the holding/trading preferences of retail investors. We note, however, that the proposed model's predictions also hold for the more general HARA utility function under a dynamic setting (Appendix C).

Consider a model where investor preferences are given by a benchmark mean-variance utility function involving her expected portfolio return $E(R_p)$, and the portfolio's volatility σ_p in line with the following equation

$$E(u) = E(R_p) - \frac{1}{2}\gamma\sigma_p^2, \tag{13}$$

where $\gamma > 0$ captures the investor's risk aversion.

It is clear from equation (13) that mean-variance utility involves assumptions regarding the additivity of preferences involving the first and second moments of a random variable, and the sign and weight accorded to these two moments (Baron, 1977; Nakamura, 2015).

Although MV utility forms the basis for solving fundamental portfolio allocation problems (Markowitz, 1952; Tobin, 1958; Sharpe, 1964; Lintner, 1965), the empirical evidence on the validity of the specification is scant. There are, of course, hundreds of papers examining the validity of benchmark asset pricing models such as the CAPM. However, these papers rely on stockmarket returns data rather than the utility specifications of individuals. Instead, evidence on the utility specifications of individuals is largely experimental (Kroll et al., 1988; d'Acremont and Bossaerts, 2008; Boorman and Sallet, 2009; Stöckl et al., 2015; Ackert et al., 2015). Although the experiments (which tend to negate the validity of mean-variance utility) yield detailed information about the participants, two possible drawbacks for this evidence are that sample sizes are small (with results obtained over a very fine time span) and the individuals participating in the experiments tend not to be actual investors.

A key reason for the absence of direct reliable evidence on the validity of the representative investor MV utility model is the absence of data on: (i) the holding, buying and selling preferences of actual investors that can be reliably deemed to approximate the preferences of a notional *representative* investor, and (ii) the expected returns and volatilities of the same investors who have provided their holding/trading preferences. Another key reason is the absence of demographic controls across a set of investors that is large enough such as to allow for 'representative' parameter estimates on expected returns and volatility (viz. parameters that can reasonably be asserted as reflecting the 'representative' investor whose preferences are given by equation (13)).

Assume that ϕ_b and ϕ_s denote buying and selling of the portfolio, with $\phi_b > 0$ ($\phi_s > 0$) denoting buying (selling) and $\phi_b = 0$ ($\phi_s = 0$) denoting the absence of buying (selling). Without trading costs, it is well known that under equation (13) the amount traded ϕ is given by

$$\phi = \frac{E(R_p) - R_f}{\gamma \sigma_p^2} - \theta_0. \tag{14}$$

where θ_0 is the investor's initial portfolio holding. Here ($\phi_b = \phi, \phi_s = 0$) if $\phi \geq 0$, and

($\phi_b = 0, \phi_s = -\phi$) if $\phi < 0$. This indicates that trade will occur whenever investors' beliefs about returns and volatility change.

If we assume that the initial holdings are based on prior beliefs (such that θ_0 is a function of prior beliefs) then, so long as $(E(R_p) - R_f)/\sigma_p^2$ deviates from its prior value, the investor will always buy or sell. In other words, assuming a continuous distribution for the investor's prior beliefs, the probability of holding is zero. To allow for the possibility of holding, trading costs can be introduced (Constantinides, 1986; Liu, 2004). We denote trading costs for buying and selling as η_b and η_s respectively. Given the presence of trading costs, we show in Appendix D that the trading (i.e.: buying, selling and holding decisions of agents) decisions under MV utility can be summarised using the following three conditions:

Buy. The agent will buy, $\phi_b > 0, \phi_s = 0$, if and only if

$$E(R_p) - (1 + \eta_b)R_f > \gamma\sigma_p^2\theta_0. \tag{15}$$

Sell. The agent will sell, $\phi_b = 0, \phi_s > 0$, if and only if

$$E(R_p) - (1 - \eta_s)R_f < \gamma\sigma_p^2\theta_0 \tag{16}$$

Hold. The agent will hold, $\phi_b = \phi_s = 0$, if and only if the following two conditions hold:

$$E(R_p) - (1 + \eta_b)R_f < \gamma\sigma_p^2\theta_0 \tag{17}$$

$$E(R_p) - (1 - \eta_s)R_f > \gamma\sigma_p^2\theta_0. \tag{18}$$

where R_f is the risk-free rate.

These conditions show that the representative investor's holding/trading decisions are contingent on the expected return, expected volatility and risk-aversion parameters underpinning their MV utility specification. This is important as our analysis relies on both holding/trading preferences and market expectations to elicit information about the validity of MV utility. The conditions also show that the region of trading inactivity (i.e. the decision to hold) depends on the transaction cost terms η_b, η_s, and the extent to which excess returns are clearly large or small enough (taking into account the investor's level of risk aversion γ and the expected volatility σ_p^2) such as to warrant buying or selling.

4.1 MV utility

To evaluate the MV utility specification, we consider two general hypotheses on the parameters in ρ_{i2} which determines trading direction preferences (and ρ_{i1} which determines holding preferences). The weaker of the two hypotheses is that the coefficients on expected returns and volatility, β_{21} and β_{22} for trading direction (and β_{11} and β_{12} for the holding decision) are non-zero. The notion of a representative investor also requires that the coefficients on the demographic variables γ_1,γ_2 are zero.

The stronger hypothesis reconciles the direction of the estimated impact of risk and return expectations on trading preferences with those implied by the theoretical trading conditions in equations (15) - (18). In addition to $\gamma_1 = \gamma_2 = 0$, the trading conditions (15) and (16) require that $\beta_{21} > 0$ and $\beta_{22} < 0$ such that the propensity to buy increases in expected returns but declines in expected volatility. The holding conditions described above also require (at a minimum) that the β_{11} and β_{12} parameters for the buying versus selling decision in ρ_{i1} are non-zero.

From the empirical analysis, the equation describing trading direction preferences collapses from the general form in equation (12) to

$$\rho_{i2} \approx a_2 + \beta_{21} E_{it} \left(r_{t+1} \right) + \beta_{22} E_{it} \left(V_{t+1} \right)$$

such that the unobserved probability regarding the decision to buy or sell is characterised only by two random variables: expected returns $E_{it} \left(r_{t+1} \right)$ and expected volatilities $E_{it} \left(r_{t+1} \right)$. The two key parameters for trading direction preferences are therefore β_{21} and β_{22} which reflect the extent to which the investor considers expected returns and volatility in forming a preference to buy or sell. These parameters are highly significant and stable across alternative specifications that account for a range of demographic heterogeneity. In all cases, β_{21} is significantly greater than zero and β_{22} is significantly below zero as required by MV utility. The absence of any demographic-specific effects also supports the notion of a representative investor with MV utility for determining trading direction preferences.

It is possible, however, to improve on the evaluation of MV utility by also recognising that the holding conditions (17) and (18) imply that respondents who believe that returns will be higher or lower (as opposed to 'the same') (denoted $E_{it}\left(R_{t+1}\right)^{+}$ and $E_{it}\left(R_{t+1}\right)^{-}$ respectively) will also have a greater propensity to trade (as will investors who expect higher or lower expected volatility, $E_{it}\left(V_{t+1}\right)^{+}$ and $E_{it}\left(V_{t+1}\right)^{-}$ respectively). Accordingly, we also consider an extended model where the specifications in (11) and (12) explicitly examine these implied signs.

The extended model involves substituting $E_{it}\left(R_{t+1}\right)^{+}$ and $E_{it}\left(R_{t+1}\right)^{-}$ for $E_{it}\left(R_{t+1}\right)$ in equation (11), in addition to substituting $E_{it}\left(V_{t+1}\right)^{+}$ and $E_{it}\left(V_{t+1}\right)^{-}$ for $E_{it}\left(V_{t+1}\right)$. To be consistent with the holding conditions (17) and (18), the resulting coefficients on $E_{it}\left(R_{t+1}\right)^{+}$, $E_{it}\left(R_{t+1}\right)^{-}$, $E_{it}\left(V_{t+1}\right)^{+}$ and $E_{it}\left(V_{t+1}\right)^{-}$ must all be negative such that the probability of holding declines when returns or volatility are expected to change rather than stay the same.

To examine these hypotheses we consider the parameter estimates presented in Appendices B3 and B4. When ρ_{i1} in equation (11) is extended to include all four directional variables, the estimated coefficients for the direction of expected returns and volatilities are *always* negative in a manner that is consistent with the holding and trading conditions expressed in equations (15) - (18) which are based on MV utility. The coefficients are also highly significant for $E_{it}\left(R_{t+1}\right)^{+}$, $E_{it}\left(R_{t+1}\right)^{-}$ and $E_{it}\left(V_{t+1}\right)^{-}$ indicating that higher or lower expected returns increase the probability of trading, as does lower volatility (see, further, the individual estimates in Appendix B4). However, it is also clear that significant demographic-specific effects are present for holding preferences (viz. $\gamma_1 \neq 0$) thereby rejecting the notion of a representative investor with MV utility for the holding decisions of retail investors.

Overall, the estimated coefficients for both holding versus trading and buying versus selling exhibit signs that are consistent with those implied by MV utility across any of the estimated specifications. However, the evidence in favour of a representative investor is limited to trading direction preferences, with holding preferences exhibiting significant sensitivity to demographic characteristics.

5 Concluding remarks

This paper uses a novel dataset containing the stock market expectations and trading preferences of over 23 thousand retail Australian investors over the period 2009—2017 to investigate the link between retail investors' risk and return expectations and their holding/trading preferences.

We provide evidence of a significant and economically meaningful relationship between retail investors' selling preferences and their expectations of higher stockmarket volatility. As such, investors sharply increase their propensity to sell when they expect greater stockmarket volatility. Moreover, our estimates support existing evidence of a significant association between the buying preferences of retail investors and their expectations regarding stockmarket returns.

Demographic characteristics and investment experience are also shown to be predictive for the holding preferences of retail investors. In contrast, demographic characteristics and investment experience have little impact on the investors' decision to buy or sell. Accordingly, Mean-Variance preferences reasonably match the observed buying and selling propensities of retail investors irrespective of their socio-economic or demographic characteristics.

Overall, our results provide novel support for models with Mean-Variance utility for determining the trading direction of retail investors. However, they also highlight the importance of recognising the distinction between holding propensities and trading direction, with the former being heavily influenced by factors other than investor expectations about future stockmarket returns and volatilty.

References

Ackert, Lucy F., Bryan K. Church, and Li Qi, 2015, An Experimental Examination of Portfolio Choice, *Review of Finance* 20, 1427–1447.

Ameriks, John, Joseph Briggs, Andrew Caplin, Minjoon Lee, Matthew D Shapiro, and Christopher Tonetti, 2020a, Older americans would work longer if jobs were flexible, *American Economic Journal: Macroeconomics* 12, 174–209.

Ameriks, John, Joseph Briggs, Andrew Caplin, Matthew D Shapiro, and Christopher Tonetti, 2020b, Long-term-care utility and late-in-life saving, *Journal of Political Economy* 128, 2375–2451.

Ameriks, John, Gábor Kézdi, Minjoon Lee, and Matthew D Shapiro, 2018, Heterogeneity in expectations, risk tolerance, and household stock shares: The attenuation puzzle, *NBER Working Paper Series* Working Paper 25269.

Amromin, Eugene, and Steven A. Sharpe, 2014, From the horse's mouth: how do investor expectations of risk and return vary with economic conditions?, *Management Science* 60, 805–1081.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2009, Just how much do individual investors lose by trading?, *Review of Financial Studies* 22, 609–632.

Barber, Brad M, Yi-Tsung Lee, Yu-Jane Liu, Terrance Odean, and Ke Zhang, 2020, Learning, fast or slow, *The Review of Asset Pricing Studies* 10, 61–93.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *The Journal of Finance* 55, 773–806.

Barber, Brad M., and Terrance Odean, 2001, Boys will be boys: Gender, overconfidence and common stock investment, *The Quarterly Journal of Economics* 116, 261–292.

Barber, Brad M., and Terrance Odean, 2013, The behavior of individual investors, in George M. Constantinides, Milton Harris, and Rene M. Stulz, eds., *Handbook of the Economics of Finance*, volume 2, 1533–1570 (Elsevier B. V.).

Baron, David P., 1977, On the utility theoretic foundations of mean-variance analysis, *The Journal of Finance* 32, 1683–1697.

Boorman, Erie D., and Jerome Sallet, 2009, Mean–variance or prospect theory? The nature of value representations in the human brain, *Journal of Neuroscience* 29, 7945–7947.

Brunnermeier, Markus K, and Stefan Nagel, 2008, Do wealth fluctuations generate time-varying risk aversion? micro-evidence on individuals, *American Economic Review* 98, 713–36.

Calvet, Laurent E, John Y Campbell, and Paolo Sodini, 2009, Fight or flight? portfolio rebalancing by individual investors, *The Quarterly journal of economics* 124, 301–348.

Constantinides, George M, 1986, Capital market equilibrium with transaction costs, *Journal of Political Economy* 94, 842–862.

d'Acremont, Mathieu, and Peter Bossaerts, 2008, Neurobiological studies of risk assessment: A comparison of expected utility and mean-variance approaches, *Cognitive, Affective, & Behavioral Neuroscience* 8, 363–374.

Davis, Mark HA, and Andrew R Norman, 1990, Portfolio selection with transaction costs, *Mathematics of operations research* 15, 676–713.

Dominitz, Jeff, and Charles F. Manski, 2011, Measuring and interpreting expectations of equity returns, *Journal of Applied Econometrics* 26, 352–370.

Gennaioli, Nicola, and Andrei Shleifer, 2020, *A Crisis of Beliefs* (Princeton University Press).

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2020, Five facts about beliefs and portfolios, *American Economic Review* 11, 1481–1522.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Hansen, Lars Peter, 2017, Survey measurements of probabilistic macroeconomic perspectives: Challenges and limitations, *NBER Macroeconomics Annual* 32.

Hudomiet, Péter, Gábor Kézdi, and Robert J. Willis, 2011, Stock market crash and expectations of american households, *Journal of Applied Econometrics* 26, 393–415.

Kroll, Yoram, Haim Levy, and Amnon Rapoport, 1988, Experimental tests of the mean-variance model for portfolio selection, *Organizational Behavior and Human Decision Processes* 42, 388 – 410.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *The Review of Economics and Statistics* 47, 13–37.

Liu, Hong, 2004, Optimal consumption and investment with transaction costs and multiple risky assets, *The Journal of Finance* 59, 289–338.

Malmendier, Ulrike, and Devin Shanthikumar, 2007, Are small investors naive about incentives?, *Journal of Financial Economics* 85, 457–489.

Manski, Charles F., 2004, Measuring expectations, *Econometrica* 72, 1329–1376.

Manski, Charles F., 2017, Survey measurement of probabilistic macroeconomic expectations: Progress and promise, *NBER Macroeconomics Annual* .

Markowitz, Harry, 1952, Portfolio selection, *The Journal of Finance* 7, 77–91.

McCullagh, Peter, and John A. Nelder, 1989, *Generalized Linear Models* (Chapman & Hall).

Muhle-Karbe, Johannes, Max Reppen, and H Mete Soner, 2017, A primer on portfolio choice with small transaction costs, *Annual Review of Financial Economics* 9, 301–331.

Nakamura, Yutaka, 2015, Mean-variance utility, *Journal of Economic Theory* 160, 536–556.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *The Journal of Finance* 19, 425–442.

Stöckl, Thomas, Jürgen Huber, Michael Kirchler, and Florian Lindner, 2015, Hot hand and gambler's fallacy in teams: Evidence from investment experiments, *Journal of Economic Behavior & Organization* 117, 327 – 339.

Tobin, James, 1958, Liquidity Preference as Behavior Towards Risk, *The Review of Economic Studies* 25, 65–86.

Figures

Figure 1. Histograms of demographic characteristics

This figure shows histograms for the four demographic characteristics of the investors in our dataset. The sample covers 2009:Q1 to 2017:Q2.

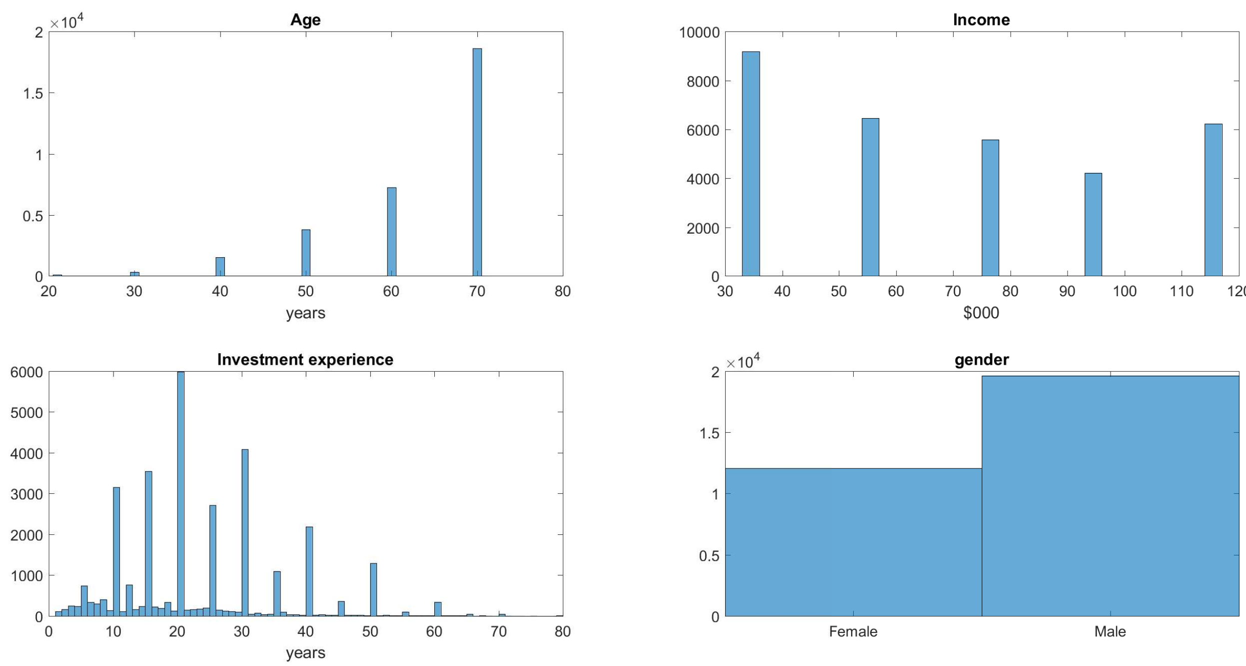
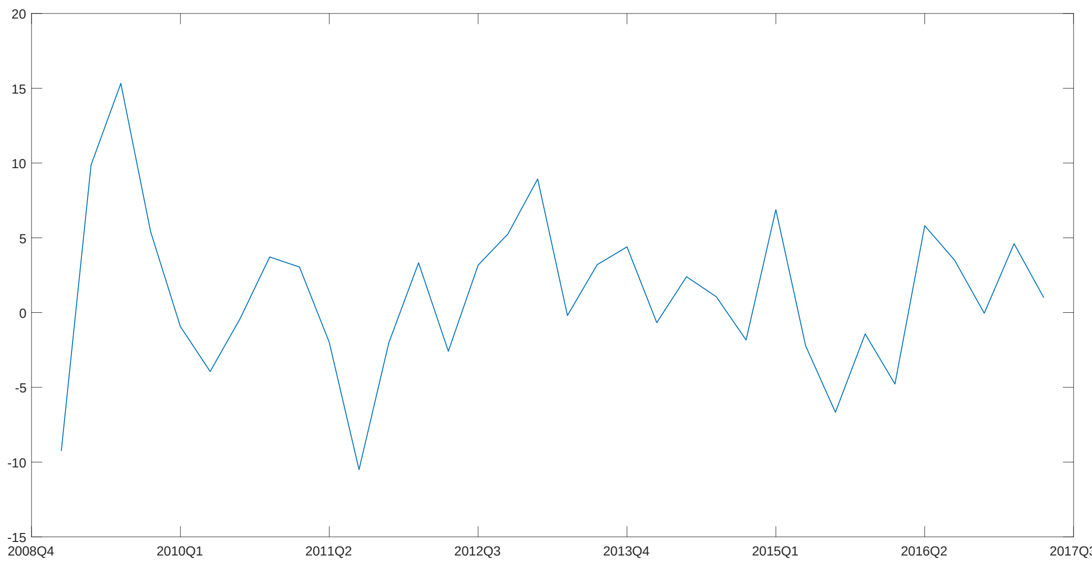


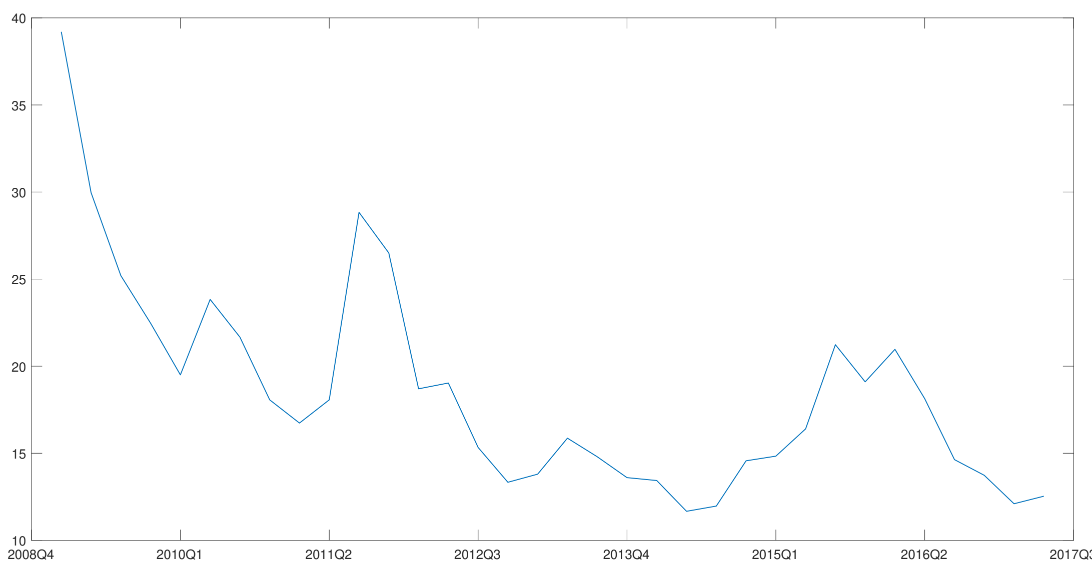
Figure 2. Time Series of ASX200

Panel A shows quarterly returns for the ASX 200 from 2009Q1 to 2017Q2. Panel B shows Australian stockmarket volatility over this period as measured by the ASX VIX 200.

Panel A: ASX 200 quarterly returns



Panel B: ASX 200 volatility (measured by the VIX).



Tables

Table 1: Summary Statistics of the Demographic Characteristics

This table shows summary statistics for the demographic characteristics of the sample. The sample covers the period between 2009Q1 to 2017Q2. Age, income and gender are discrete choices across different bins. The table reports sample averages and standard deviations based on the midpoint of each bin. Investment experience is based on self-reported years.

	Mean	Std Dev
Age	63.3	9.64
Income	69.9	29.8
Inv. exp	23.3	12.7
Male	0.61	0.49

Table 2: The distribution of trading preferences and risk/return expectations

This table shows the sample distribution of responses regarding expected stockmarket returns, expected stockmarket volatility, and trading preferences (hold, buy, sell). The sample covers the period between 2009Q1 to 2017Q2.

	Volatility Lower		
	Returns Lower	Returns Same	Returns Higher
HOLD	73.7 (%)	76.3	66.5
BUY	20.2	21.2	32.0
SELL	6.1	2.5	1.5
	Volatility Same		
	Returns Lower	Returns Same	Returns Higher
HOLD	79.0	84.2	71.1
BUY	13.6	13.3	26.6
SELL	7.3	2.5	2.3
	Volatility Higher		
	Returns Lower	Returns Same	Returns Higher
HOLD	79.0	84.2	71.1
BUY	13.6	13.3	26.6
SELL	7.3	2.5	2.3

Table 3: Hierarchical Logit Regression: Buying vs Selling

This table shows hierarchical logit regression estimates for the buy vs sell component of the model. The sample covers the period 2009Q1 to 2017Q2. Age, income and gender are discrete choice variables with each discrete choice associated with a particular bin. t-statistics are in parentheses. The following controls are included in every model: quarterly ASX200 returns (current, lagged and one-period ahead), annual ASX200 returns (current and lagged), the log-index of the ASX200, the quarterly percentage change in the VIX200 (current, lagged and one-period ahead), the log-index of the VIX200, real GDP growth, year-specific effects.

Model	1	2	3	4	5	6
a_2	24.268	24.269	25.252	24.775	23.359	24.453
	(0.893)	(0.893)	(0.927)	(0.909)	(0.858)	(0.896)
$E_{it}(r_{t+1})$	1.036	1.036	1.040	1.040	1.044	1.043
	(17.265)	(17.264)	(17.292)	(17.269)	(17.327)	(17.288)
$E_{it}(V_{t+1})$	−0.493	−0.494	−0.496	−0.496	−0.495	−0.496
	(−8.984)	(−8.991)	(−9.019)	(−8.989)	(−8.978)	(−8.984)
male		−0.042	−0.063	−0.072	−0.088	−0.309
		(−0.460)	(−0.682)	(−0.781)	(−0.941)	(−1.715)
inv. exp.(<10yrs)			−0.359	−0.298	−0.300	0.102
			(−3.084)	(−2.442)	(−2.460)	(0.460)
inv. exp.(>20yrs)			0.005	0.015	0.013	0.186
			(0.051)	(0.159)	(0.141)	(0.803)
age 65+				0.180	0.228	0.645
				(1.708)	(2.072)	(2.001)
Income - low					−0.129	0.043
					(−1.042)	(0.150)
Income - high					0.022	0.349
					(0.177)	(1.561)
male × age 65+						0.296
						(1.405)
inv. exp. (<10yrs) × age 65+						−0.593
						(−2.231)
inv. exp. (>20yrs) × age 65+						−0.199
						(−0.782)
Income - low × age 65+						−0.254
						(−0.795)
Income - high × age 65+						−0.464
						(−1.737)

Table 4: Hierarchical Logit Regression: Holding vs Trading

This table shows hierarchical logit regression estimates for the hold vs trade component of the model. The sample covers the period 2009Q1 to 2017Q2. Age, income and gender are discrete choice variables with each discrete choice associated with a particular bin. t-statistics are in parentheses. The following controls are included in every model: quarterly ASX200 returns (current, lagged and one-period ahead), annual ASX200 returns (current and lagged), the log-index of the ASX200, the quarterly percentage change in the VIX200 (current, lagged and one-period ahead), the log-index of the VIX200, real GDP growth, year-specific effects.

Model	1	2	3	4	5	6
const.	−2.437	−3.014	−1.624	−1.632	−0.407	0.130
	(−0.225)	(−0.277)	(−0.225)	(−0.225)	(−0.037)	(0.018)
$E_{it}(r_{t+1})$	−0.191	−0.188	−0.185	−0.187	−0.194	−0.195
	(−7.657)	(−7.521)	(−7.397)	(−7.479)	(−7.742)	(−7.787)
$E_{it}(V_{t+1})$	0.109	0.103	0.103	0.098	0.085	0.086
	(5.001)	(4.718)	(4.708)	(4.433)	(3.899)	(3.908)
male		−0.363	−0.374	−0.394	−0.367	−0.423
		(−10.408)	(−10.670)	(−11.169)	(−10.344)	(−6.076)
inv. exp.(<10yrs)			−0.105	−0.017	−0.027	−0.229
			(−2.321)	(−0.358)	(−0.563)	(−2.612)
inv. exp.(>20yrs)			0.128	0.131	0.126	−0.135
			(3.480)	(3.544)	(3.409)	(−1.451)
age 65+				0.296	0.159	−0.165
				(7.146)	(3.663)	(−1.314)
Income - low					0.114	−0.119
					(2.436)	(−1.014)
Income - high					−0.283	−0.304
					(−6.018)	(−3.289)
male × age 65+						0.079
						(0.987)
inv. exp.(<10yrs) × age 65+						0.270
						(2.559)
inv. exp.(>20yrs) × age 65+						0.310
						(3.051)
Income - low × age 65+						0.269
						(2.105)
Income - high × age 65+						0.020
						(0.184)

Table 5: Comparing estimates for respondents aged 55 years or less

	All respondents		Aged 55 or less	
	Coeff	t-stat	Coeff	t-stat
Buying vs Selling				
$E_{it}(r_{t+1})$	1.0438	17.327	1.2213	9.3935
$E_{it}(V_{t+1})$	-0.49484	-8.9756	-0.73886	-6.3683
male	-0.08760	-0.94067	-0.37277	-1.9479
inv. exp.(<10yrs)	-0.3001	-2.4602	-0.059463	-0.32599
Income - low	-0.1286	-1.0423	0.02002	0.066251
Income - high	0.021676	0.17664	0.409	1.7113
Holding vs Trading				
$E_{it}(r_{t+1})$	-0.19419	-7.7426	-0.21932	-4.0783
$E_{it}(V_{t+1})$	0.085946	3.8985	-0.0021052	-0.045361
male	-0.3665	-10.344	-0.43847	-6.2358
inv. exp.(<10yrs)	-0.026667	-0.56326	-0.12387	-1.7644
Income - low	0.11403	2.4363	-0.08554	-0.71943
Income - high	-0.28344	-6.0184	-0.27952	-2.984

Appendix A: Survey questions

The survey data was conducted quarterly over 8.5 years from 2009:Q1 to 2017:Q2. This paper is concerned with the responses to the following questions (listed in order).

- Do you expect the returns on shares to be higher or lower or about the same, this time next year?

  Higher
  Same
  Lower

- Do you expect there to be more or less volatility in the share market this time next year?

  Less
  Same
  More

- What do you think people should be doing with their shares now?

  Buying
  Selling
  Doing nothing

- Demographics

(1) Gender:
  Male
  Female
(2) Could you please tell me which age group you fall into, from the following groups?
  18-24 years
  25-34 years
  35-44 years
  45-54 years
  55-64 years
  65 years and over
(3) What would be your households' approximate pre-tax income?
  Under $45,000
  $45,000 - $65,000
  $65,000 - $85,000
  $85,000 - $105,000
  more than $105,000
(4) Approximately how many years have you been investing in listed companies?

Appendix B: Robustness to alternative specifications

Table B1. Hierarchical Logit Regression: Buying vs Selling

This table shows hierarchical logit regression estimates for the buy vs sell component of the model after allowing for asymmetric responses to both risk and return expectations. Asymmetricity is allowed for higher and lower expected returns (denoted by the $+, -$ superscripts on the expected return variable $E_{it}(r_{t+1})$). The sample covers the period 2009Q1 to 2017Q2. Age, income, gender are discrete choice variables with each discrete choice associated with a particular bin. t-statistics are in parentheses. The following controls are included in every model: quarterly ASX200 returns (current, lagged and one-period ahead), annual ASX200 returns (current and lagged), the log-index of the ASX200, the quarterly percentage change in the VIX200 (current, lagged and one-period ahead), the log-index of the VIX200, real GDP growth, year-specific effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
a_2	16.965	26.390	27.436	26.928	25.522	26.577
	(0.972)	(0.972)	(1.008)	(0.988)	(0.937)	(0.973)
β_{21} $[E_{it}(r_{t+1})^{+}]$	0.911	0.913	0.913	0.916	0.917	0.917
	(8.644)	(8.645)	(8.624)	(8.602)	(8.656)	(8.634)
β_{22} $[E_{it}(r_{t+1})^{-}]$	−1.152	−1.150	−1.159	−1.161	−1.163	−1.161
	(−11.327)	(−11.287)	(−11.341)	(−11.339)	(−11.368)	(−11.329)
β_{23} $[E_{it}(V_{t+1})]$	−0.491	−0.492	−0.494	−0.493	−0.492	−0.494
	(−8.972)	(−8.973)	(−9.001)	(−8.973)	(−8.960)	(−8.971)
male		−0.034	−0.055	−0.064	−0.079	−0.309
		(−0.370)	(−0.593)	(−0.693)	(−0.852)	(−1.717)
inv. exp. (<10yrs)			−0.365	−0.303	−0.305	0.093
			(−3.135)	(−2.487)	(−2.504)	(0.419)
inv. exp. (>20yrs)			−0.001	0.010	0.008	0.171
			(−0.008)	(0.099)	(0.081)	(0.741)
age 65+				0.182	0.229	0.622
				(1.723)	(2.083)	(1.935)
Income - low					−0.128	0.031
					(−1.041)	(0.107)
Income - high					0.020	0.338
					(0.165)	(1.514)
male × age 65+						0.307
						(1.458)
inv. exp. (<10yrs) × age 65+						−0.589
						(−2.218)
inv. exp. (>20yrs) × age 65+						−0.188
						(−0.739)
Income - low × age 65+						−0.238
						(−0.745)
Income - high × age 65+						−0.451
						(−1.690)

Table B2. Hierarchical Logit Regression: Holding vs Trading

This table shows hierarchical logit regression estimates for the hold vs trade component of the model after allowing for asymmetric responses to both risk and return expectations. Asymmetricity is allowed for higher and lower expected returns (denoted by the $+, -$ superscripts on the expected return variable $E_{it}(r_{t+1})$). The sample covers the period 2009Q1 to 2017Q2. Age, income, gender are discrete choice variables with each discrete choice associated with a particular bin. t-statistics are in parentheses. The following controls are included in every model: quarterly ASX200 returns (current, lagged and one-period ahead), annual ASX200 returns (current and lagged), the log-index of the ASX200, the quarterly percentage change in the VIX200 (current, lagged and one-period ahead), the log-index of the VIX200, real GDP growth, year-specific effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
a_1	0.282	−0.326	0.948	1.014	2.257	2.837
	(0.026)	(−0.029)	(0.087)	(0.092)	(0.206)	(0.259)
$\beta_{11}\ [E_{it}(r_{t+1})^{+}]$	−0.498	−0.487	−0.481	−0.487	−0.488	−0.488
	(−13.544)	(−13.199)	(−13.004)	(−13.140)	(−13.167)	(−13.178)
$\beta_{12}\ [E_{it}(r_{t+1})^{-}]$	−0.301	−0.290	−0.287	−0.290	−0.275	−0.272
	(−6.156)	(−5.922)	(−5.847)	(−5.900)	(−5.581)	(−5.535)
$\beta_{13}\ [E_{it}(V_{t+1})]$	0.119	0.113	0.112	0.107	0.096	0.096
	(5.492)	(5.187)	(5.167)	(4.886)	(4.357)	(4.358)
male		−0.352	−0.363	−0.383	−0.356	−0.421
		(−10.080)	(−10.337)	(−10.853)	(−10.040)	(−6.049)
inv. exp. (<10yrs)			−0.109	−0.018	−0.028	−0.230
			(−2.385)	(−0.374)	(−0.583)	(−2.623)
inv. exp. (>20yrs)			0.115	0.118	0.114	−0.139
			(3.129)	(3.195)	(3.066)	(−1.492)
age 65+				0.305	0.171	−0.170
				(7.341)	(3.921)	(−1.352)
Income - low					0.111	−0.122
					(2.364)	(−1.041)
Income - high					−0.279	−0.312
					(−5.917)	(−3.381)
male × age 65+						0.092
						(1.135)
inv. exp. (<10yrs) × age 65+						0.272
						(2.579)
inv. exp. (>20yrs) × age 65+						0.300
						(2.949)
Income - low × age 65+						0.271
						(2.117)
Income - high × age 65+						0.038
						(0.356)

Table B3. Hierarchical Logit Regression: Buying vs Selling

This table shows hierarchical logit regression estimates for the buy vs sell component of the model after allowing for asymmetric responses to both risk and return expectations. Asymmetricity is allowed for higher and lower expected returns and volatilities (denoted by the $+,-$ superscripts on the expected return and expected volatility variables $E_{it}(r_{t+1}), E_{it}(V_{t+1})$ respectively). The sample covers the period 2009Q1 to 2017Q2. Age, income, gender are discrete choice variables with each discrete choice associated with a particular bin. t-statistics are in parentheses. The following controls are included in every model: quarterly ASX200 returns (current, lagged and one-period ahead), annual ASX200 returns (current and lagged), the log-index of the ASX200, the quarterly percentage change in the VIX200 (current, lagged and one-period ahead), the log-index of the VIX200, real GDP growth, year-specific effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
a_2	25.667	25.651	26.643	26.116	24.707	25.742
	(0.972)	(0.924)	(0.978)	(0.959)	(0.907)	(0.943)
$\beta_{21}\ [E_{it}(r_{t+1})^{+}]$	0.922	0.925	0.923	0.921	0.927	0.927
	(8.596)	(8.598)	(8.564)	(8.532)	(8.590)	(8.557)
$\beta_{22}\ [E_{it}(r_{t+1})^{-}]$	−1.139	−1.138	−1.148	−1.150	−1.152	−1.151
	(−10.955)	(−10.195)	(−10.976)	(−10.981)	(−10.998)	(−10.966)
$\beta_{23}\ [E_{it}(V_{t+1})^{+}]$	−0.538	−0.539	−0.536	−0.532	−0.535	−0.532
	(−5.333)	(−5.339)	(−5.299)	(−5.247)	(−5.276)	(−5.248)
$\beta_{24}\ [E_{it}(V_{t+1})^{-}]$	0.434	0.435	0.444	0.447	0.442	0.448
	(3.801)	(3.804)	(3.872)	(3.893)	(3.846)	(3.892)
male		−0.034	−0.055	−0.064	−0.079	−0.308
		(−0.375)	(−0.597)	(−0.695)	(−0.857)	(−1.711)
inv. exp. (<10yrs)			−0.365	−0.303	−0.304	0.093
			(−3.128)	(−2.484)	(−2.501)	(0.422)
inv. exp. (>20yrs)			−0.001	0.010	0.008	0.172
			(−0.008)	(0.097)	(0.079)	(0.744)
age 65+				0.181	0.229	0.623
				(1.712)	(2.076)	(1.938)
Income - low					−0.129	0.032
					(−1.047)	(0.112)
Income - high					0.021	0.338
					(0.170)	(1.515)
male × age 65+						0.305
						(1.448)
inv. exp. (<10yrs) × age 65+						−0.589
						(−2.220)
inv. exp. (>20yrs) × age 65+						−0.189
						(−0.744)
Income - low × age 65+						−0.240
						(−0.752)
Income - high × age 65+						−0.451
						(−1.688)

Table B4. Hierarchical Logit Regression: Holding vs Trading

This table shows hierarchical logit regression estimates for the hold vs trade component of the model after allowing for asymmetric responses to both risk and return expectations. Asymmetricity is allowed for higher and lower expected returns and volatilities (denoted by the $+,-$ superscripts on the expected return and expected volatility variables $E_{it}(r_{t+1}), E_{it}(V_{t+1})$ respectively). The sample covers the period 2009Q1 to 2017Q2. Age, income, gender are discrete choice variables with each discrete choice associated with a particular bin. t-statistics are in parentheses. The following controls are included in every model: quarterly ASX200 returns (current, lagged and one-period ahead), annual ASX200 returns (current and lagged), the log-index of the ASX200, the quarterly percentage change in the VIX200 (current, lagged and one-period ahead), the log-index of the VIX200, real GDP growth, year-specific effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
a_1	1.681 (0.154)	1.127 (0.103)	2.342 (0.214)	2.381 (0.218)	3.494 (0.319)	4.054 (0.370)
$\beta_{11}\ [E_{it}(r_{t+1})^+]$	−0.456 (−12.097)	−0.444 (−11.747)	−0.439 (−11.588)	−0.446 (−11.751)	−0.451 (−11.856)	−0.452 (−11.895)
$\beta_{12}\ [E_{it}(r_{t+1})^-]$	−0.254 (−5.108)	−0.243 (−4.872)	−0.241 (−4.823)	−0.245 (−4.900)	−0.233 (−4.650)	−0.232 (−4.628)
$\beta_{13}\ [E_{it}(V_{t+1})^+]$	−0.061 (−1.413)	−0.070 (−1.616)	−0.067 (−1.539)	−0.067 (−1.540)	−0.067 (−1.533)	−0.063 (−1.438)
$\beta_{14}\ [E_{it}(V_{t+1})^-]$	−0.291 (−6.959)	−0.287 (−6.855)	−0.284 (−6.758)	−0.273 (−6.479)	−0.251 (−5.939)	−0.247 (−5.844)
male		−0.354 (−10.116)	−0.364 (−10.369)	−0.384 (−10.877)	−0.357 (−10.071)	−0.423 (−6.070)
inv. exp. (<10yrs)			−0.108 (−2.376)	−0.018 (−0.387)	−0.028 (−0.593)	−0.225 (−2.567)
inv. exp. (>20yrs)			0.112 (3.046)	0.115 (3.119)	0.111 (2.999)	−0.134 (−1.439)
age 65+				0.301 (7.245)	0.169 (3.875)	−0.161 (−1.283)
Income - low					0.111 (2.366)	−0.113 (−0.967)
Income - high					−0.274 (−5.812)	−0.304 (−3.289)
male × age 65+						0.092 (1.139)
inv. exp. (<10yrs) × age 65+						0.265 (2.510)
inv. exp. (>20yrs) × age 65+						0.291 (2.860)
Income - low × age 65+						0.261 (2.036)
Income - high × age 65+						0.033 (0.311)

Appendix C: A Dynamic Model of Portfolio Choice with Proportional Transaction Costs

In this appendix we briefly present a more general model on the portfolio choice decision with proportional transaction costs. The intention is to show that the decision rule obtained under mean-variance preferences in a static setting is not restrictive. We roughly follow Davis and Norman (1990). The detailed proof is available upon request.

Consider a time period between $[0, T]$. An investor maximizes expected utility:

$$\max E\left[\int_0^T e^{-\delta t} u(c_t) dt\right], \tag{19}$$

where the utility function is given by HARA utility of the form, $(c^{1-\gamma} - 1)/(1-\gamma), \gamma > 0$ with the understanding that $\gamma = 0$ corresponds log utility $\log(c)$.

The investor can invest in a risky stock and a money market account. We assume that the risk-free rate is constant $r > 0$ and the stock price follows:

$$S_t = S_0 + \int_0^t \mu S_\tau d\tau + \int_0^t \sigma S_\tau dZ_\tau, \tau \in [0, T], \tag{20}$$

where $\mu > r > 0, \sigma > 0$ are two constants, and Z_t is a standard Brownian motion. Without the transaction costs, the money market account balances, α_t, and the stock account balances, θ_t, evolve as:

$$d\alpha_t = (r\alpha_t - c_t)dt \tag{21}$$

$$d\theta_t = \mu\theta_t dt + \sigma\theta_t dZ_t. \tag{22}$$

In this case, one can define the wealth of the investor, W_t, as the sum of the money market account balances and the stock account balances,

$$dW_t = (rW_t - c_t)dt + (\mu - r)\theta_t dt + \sigma\theta_t dZ_t. \tag{23}$$

Here W_t becomes the state variable and (c_t, θ_t) are the choice variables for the maximization problem.

When transaction costs are present, we have to separately consider buying and selling. Assume the transaction cost is proportional to the amount traded, in addition to potentially different buying and selling costs, denoted as η_b, η_s respectively. The evolution of the money market account and the stock account follow

$$d\alpha_t = (r\alpha_t - c_t)dt - (1 + \eta_b)\phi_b dt + (1 - \eta_s)\phi_s dt \tag{24}$$

$$d\theta_t = (\mu\theta_t + \phi_b - \phi_s)dt + \sigma\theta_t dZ_t, \tag{25}$$

where ϕ_b, ϕ_s are the buying and selling amount of the stock.

One can show that there exists a viscosity solution to this problem such that there are two boundaries on the (α_t, θ_t) surfaces, which separate the whole space into three regions: buy, hold and sell. The actual boundary is a function of transaction costs, beliefs regarding expected returns and the risk-free rate. In the buy and sell regions, the investor will immediately trade up to the boundary between the buy and hold, sell and hold regions. Within the hold region, the investor does not trade at all. The Sharpe Ratio, $(\mu - r)/\sigma$ is within the no trading region. In fact, when the transaction cost is relatively small, one can characterize the boundaries analytically using the approximation method. This result in the boundary is a function of the first two moments (mean and variances) (Muhle-Karbe et al., 2017).

In summary, the three regions of buying, holding, and selling exist in the general dynamic model with HARA utility and geometric Brownian motion in stock prices. Under proportional transaction costs, the boundaries are straight lines and the solution is a function of the mean and variance.

Appendix D: Proof of the Trading Conditions under Proportional Transaction Costs

Consider a model where an investor's preference consists of two components. The first component is the standard utility function of future portfolio wealth, $u(W)$. The second component is a wedge/friction effect on stock holdings. In other words, the investor takes the current stock holding θ_0 as the reference point. Specifically, investor preferences take the form:

$$V(\theta_0) = E(u(W)) + \nu(\phi_b - \xi\phi_s)E(R_s), \tag{26}$$

where $\nu \geq 0$ captures the relative magnitude of the friction on the utility function, and $\xi \geq 1$ reflects the presence of asymmetry effects between buying and selling in the investor's overall utility. The terms ϕ_b, ϕ_s represent the amount of buying and selling respectively. Compared with the utility gains from holding additional stocks, the specification allows for the agent's loss to be greater when she sells the same amount of stocks. Following from the literature on behavioural biases, we assume the two components are additive.

For convenience, we also focus on the mean-variance expression for $u(W)$. This is because investors' beliefs are often assumed to focus on expected returns and volatility. To generate a closed form solution, we assume that $E(u(W))$ takes the following format:

$$E(u(W)) = E(R_p) - \frac{1}{2}\gamma\sigma_p^2, \tag{27}$$

where $\gamma > 0$ captures the investor's characteristics such as risk aversion.

To show the role frictions/behavioural effects play on the decision to not trade (hold) or trade (buy/sell) consider, for simplicity, a static 2-period setting, $t = 0, 1$. In this setting, there are only two assets: a risky stock paying gross returns R_s and a risk-free money market asset with gross returns R_f at time $t = 1$. An investor has initial wealth W_0 with θ_0 proportion invested in the stock. For simplicity, we normalize $W_0 = 1$. The resulting gross portfolio return is given by:

$$R_p = (\theta_0 + \phi_b - \phi_s)R_s + (1 - \theta_0 - \phi_b + \phi_s)R_f. \tag{28}$$

The agent's problem can be written as

$$\max_{\phi_b, \phi_s} V(R_p),$$

subject to $\phi_b \geq 0, \phi_s \geq 0$.

Denote the Lagrangian multipliers associated with the two constraints as λ_b, λ_s respectively.

$$\begin{aligned} (1+\nu)E(R_s) - R_f - \gamma(\phi_0 + \phi_b - \phi_s)\sigma_s^2 + \lambda_b &= 0 \\ -((1+\nu\xi)E(R_s) - R_f) + \gamma(\phi_0 + \phi_b - \phi_s)\sigma_s^2 + \lambda_s &= 0 \end{aligned}$$

The two Kuhn-Tucker conditions are:

$$\phi_b \lambda_b = 0$$
$$\phi_s \lambda_s = 0.$$

There are four conditions, which we discuss in turn:

(i) $\lambda_b = \lambda_s = 0$: This is not applicable as it implies that the constraints are not binding (i.e. an agent will buy and sell simultaneously).

(ii) $\lambda_b = 0, \lambda_s > 0$. This is the case where the buying constraint is not binding, so the agent buys: $\phi_b > 0, \phi_s = 0$. We can derive this condition from the first FOC:

$$\phi_b > 0 : (1+\nu)E(R_s) - R_f > \gamma \sigma_s^2 \theta_0.$$

(iii) $\lambda_b > 0, \lambda_s = 0$. This is the case in which only the selling constraint is not binding. Namely the agent only sells, $\phi_b = 0, \phi_s > 0$. We derive this from the second FOC:

$$\phi_s > 0 : (1+\nu\xi)E(R_s) - R_f < \gamma \sigma_s^2 \theta_0.$$

(iv) $\lambda_b > 0, \lambda_s > 0$. This is the case when both constraints are binding, $\phi_b = \phi_s = 0$. For this to happen, the following two conditions must hold:

$$(1+\nu)E(R_s) - R_f < \gamma \sigma_s^2 \theta_0$$
$$(1+\nu\xi)E(R_s) - R_f > \gamma \sigma_s^2 \theta_0.$$

The upshot of the condition that $\phi_b \geq 0, \phi_s \geq 0$ is that there are two bounds, $\overline{B}$ and $\underline{B}$, which show how the presence of ν, ξ affects the trading decision. In particular, the conditions show that the region of no trade depends on the relative magnitude of the effect ν and the magnitude of the asymmetry ξ between buying and selling.

THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE