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Estimation and Statistical modelling

of Financial and Economic decisions

from trading and survey data

by

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A thesis submitted in partial fulfilment of the requirements

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Contents

List of Tables

List of Figures

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Finally, I want to thank my partner, Francesca, and my family for the love and the support in the last few years.

Declarations

This thesis contains my original work and has not been submitted for examination at any institution other than the University of Warwick. Parts of Chapters 1 and 2 appeared in the working papers "Make hay while the sun shines: an empirical study of maximum price, regret and trading decisions" and "Wide framing disposition effect: An empirical study", both co-authored with Julia Brettschneider and Vicky Henderson. The basic idea was developed through joint discussions, while the implementation and write-up was done by myself. Julia Brettschneider and Vicky Henderson supervised the write-up. Parts of Chapter 4 appeared in the working paper "Age means patience to the rich but impatience to the poor" co-authored with Rebecca McDonald, Daniel Read and Umar Taj. Umar Taj provided access to the data and supervised data collection. The basic idea was developed through joint discussions with Daniel Read and Rebecca McDonald, while the implementation and the write-up were done by myself. Daniel Read and Rebecca McDonald supervised the write-up.

Abstract

We investigate the behaviour of individual financial investors and individual preferences about intertemporal choice. First, we estimate how the propensity to realise a stock in the gain domain changes, as the distance in price and the distance in time from the maximum price which realised in an investment episode change. We fit a Proportional Hazard model to estimate the propensity to sell a stock in a specific investment and find that the propensity to sell is highest at a short distance in time and high distance in price from the past maximum. We relate our results to theoretical models of Regret Theory in dynamic decisions. Second, we estimate the disposition effect from a wide framing perspective, for a sample of frequent traders. The disposition effect is the tendency of investors to realise gains at a higher rate than losses. We estimate it for several bank account compositions, using fixed effects models. We find that the disposition effect is higher when the percentage of stocks trading at a gain in a bank account is lower and it is lower when the percentage of gains is higher. We attribute the effect to a combination of anticipated regret and the preference that investors have for realising more than a stock on a given trading day, which we document. Third, we estimate the disposition effect assuming that investors define gains and losses, at a psychological level, with respect to an alternative reference point, different from the purchase price. We test three alternative rules and find that adopting the average of the realisations of the last five trading days prices (Recent rule) leads to the biggest departure of the disposition effect from the original estimate. Assuming that investors adopt the Recent rule to define their reference point leads to a much lower disposition effect, in particular if investors trade more and their trades are shorter. Fourth, we estimate intertemporal discounting in a sample of more than 50,000 individuals from 65 countries. We find that young individuals discount at the same rate, independently from income. Patience declines with age, at a faster rate, the lower the individuals rank in the income distribution. High income individuals discount at the same rate, independently of age. We develop an index of patience, defined at the country level, and find a strong correlation of it with other indices proposed in the literature and with country characteristics associated to economic development.

Abbreviations

CRSP	Centre for Research in Security Prices
DE	Disposition Effect
EU(T)	Expected Utility (Theory)
FE	Fixed Effects
FOI	Future Orientation Index
FTR	Future Time Reference
GPS	Global Preferences Survey
IDV	Individualism
LDB	Large Discount Brokerage
LL	Larger Later
LTO	Long Term Orientation
OLS	Ordinary Least Squares
PG	Percentage of Gains
PT	Prospect Theory
PGR	Proportion of gains realised
PH	Proportional hazards
PLR	Proportion of losses realised
PP	Purchase Price
RT	Regret Theory
SS	Smaller Sooner
UAI	Uncertainty Avoidance Index
WEIRD	Western Industrialised Rich Democratic
WRDS	Wharton Research Data Services

Overview

Every day we take many decisions. Some of these decisions have very high stakes, for example when we invest our money. Some of these decisions will shape our future and the rate at which we discount the future will impact our decisions today. This thesis will analyse real investment decisions in the stock market and a non incentivised survey measure of discounting. We had the possibility to analyse two unique datasets. First, we had access to actual trading decisions of US citizens in the stock market, collected in the so called Large Discount Brokerage dataset (Odean, 1998). Second, we had access to the Gallup End of Year 2015 survey. The Gallup End of Year survey is a survey conducted by Gallup International every year, at the international level and it contains demographic as well as political, sociological and economic opinions of the respondents. We analyse one question concerning time discounting, which we were permitted to ask, along the other standard question usually asked by Gallup. This work consists of four chapters. In Chapters 1 to 3 we analyse the LDB dataset, while in Chapter 4 we analyse Gallup data.

In Chapter 1 we test a dynamic extension of Regret Theory (Loomes and Sugden, 1982; Strack and Viefers, 2019) in the context of dynamic financial decisions. Regret Theory (Loomes and Sugden, 1982) is one of the most successful alternatives to Expected Utility Theory (Bleichrodt and Wakker, 2015) and it departs from Expected Utility by relaxing the axiom of transitivity. In the context of static decisions, the main difference between Expected Utility theory and Regret Theory, but also from Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), arise from the fact that a Regret agent evaluates payoffs by comparing them, under any state of the world. A big emphasis is put on big differences between two alternative payoffs induced by two alternative acts, under the same state of the world. Strack and Viefers (2019) propose an extension of Regret Theory for financial decisions where the regret component is captured by the price difference between the price of a stock the investor is trading, and the past maximum price of the stock, since the stock was purchased. We test the predictions of dynamic regret on actual trading data. We reject the hypothesis that investors stop at a threshold (stop on maximum or minimum day). Hence we reject Expected Utility theory, which prescribes that the optimal strategy for a decision maker is stopping at a threshold. We find that more sophisticated and younger investors are more likely to follow a threshold strategy. Then, we analyse the impact of the maximum price level and the day of occurrence of the maximum in an investment episode, on the propensity to sell a stock for a gain. We find that investors are more likely to sell a stock in a moment closer in time to maximum occurrence and at a price further from the running maximum price of the investment episode. This contradicts dynamic Regret Theory and might be rationalised through anticipated regret (Fioretti et al., 2018). Our methodology is innovative in this field. We are among the first to fit a Proportional Hazard model (Cox, 1972) to financial data. This guarantees a more precise estimation of the probability of selling a stock, by taking into account the entire history of the trading episode, at any point in time.

In Chapters 2 and 3 we focus on the disposition effect (Shefrin and Statman, 1985; Odean, 1998). The disposition effect is the tendency to realise gains at a higher rate than losses (Shefrin and Statman, 1985; Odean, 1998; Barber and Odean, 2013). This was first documented by Odean (1998) and since then it has been extensively studied from a theoretical, experimental and empirical perspective[1]. We study it from two unexplored perspectives: variation at the bank account level (Chapter 2) and variation as the reference

[1] See Barber and Odean (2013) for a review.

price changes (Chapter 3). In Chapter 2 we estimate the disposition effect from a wide framing perspective for a set of active traders in the Large Discount Brokerage dataset. We find that the disposition effect varies with portfolio composition. By means of fixed effect regression, we are able to pin down the within bank account variation of the disposition effect. We find that the disposition effect drops as the percentage of stocks trading at a gain in the bank account increases, and the disposition effect is close to neutral[2] once there are more than 50% of stocks at a gain in the bank account. The probability to realise a loss increases as the percentage of gains in the bank account increases. The relation between the probability of realising a gain and the percentage of gains in the bank account account follows a U-shape. We also estimate the change in the disposition effect when an investor realises more than one stock on a trading day. When investors sell a stock, they are much more likely to also realise another stock. In particular, when investors sell a loss (gain) they are also more likely to realise a gain (loss). This provides an explanation for the variation in the disposition effect, due to portfolio composition. Since investors have a preference for realising more than one stock on the same day, the probability of selling a gain (loss) will be higher if the number of gains (losses) among which the investor can choose is lower. We believe that our finding is a breakthrough in the literature on the topic. We observe that investors are not always disposition effect prone, and the disposition effect is highest when the relative number of gains in the account is lowest, which is unexpected.

In Chapter 3 we dispute the magnitude of the disposition effect, from a psychological point of view. We measure the disposition effect by defining gains and losses with respect to some alternative reference points. The underlying idea is that, from a psychological point of view, the investors might update their reference point when they evaluate a stock. For example, they might be satisfied of selling a stock for a loss, if the price is on a rising trajectory,

[2]When we say neutral, we mean that the probability of selling a gain is the same as the probability of selling a loss.

after having been on a decreasing trajectory for a while. Our hypothesis that investors update their reference point during a trading episode is backed up by the experimental evidence (Arkes et al., 2008; Baucells et al., 2011). It is still true that the disposition effect leads to a worse performance, from an accounting point of view. However, we find that it is much lower, if we define gains and losses with respect to a different reference level, other than the purchase price. In particular, when we measure gains and losses with respect to the average of the last five trading days price realisations, we find that the disposition effect is reduced by 70%. We also investigate differences based on investors' trading frequency and trades length. The main pattern we detect is that the disposition effect measured with respect to the purchase price is more likely to be low for traders who trade less often and for longer time, while the disposition effect measured with respect to recent price realisations is more likely to be low for traders who trade more but for shorter time. Since we expect that less frequent traders should be more likely to adopt the purchase price as the reference point and frequent traders should be more likely to focus on recent price realisations, our evidence points towards the idea that the disposition effect might be substantially lower, if we adopt the most appropriate reference point formation rule for any investors.

Finally, in Chapter 4 we analyse Gallup data. We elicit a measure of patience for more than 50,000 individuals from 65 countries. The question is very easy to understand and based on the actual income situation of the respondent, avoiding all the issues of converting the amount of money proposed according to the purchase power. We ask if the individual would prefer a reward equal to her monthly income now, or twice that reward in a year. We find that, within countries, individuals in the richest income quintile discount at the same rate at any age, while individuals in the poorest quintile of income discount more, the older they are. The age-patience relationships in the other income quintiles are distributed in an orderly manner between these extremes, with patience declining with age, but at a lower rate the higher the income is. We suggest that either lower income leads individuals to be less patient as they age, or that less patient individuals move downwards in the income rank as they age. We find that non religious, optimistic, happy and educated individuals are more patient. Female, unemployed, retired or disabled individuals, and those who have low confidence in vaccine effectiveness, tend to be less patient. We propose a national patience index which is highly correlated with other more sophisticated measures that are harder to elicit (Wang et al., 2016; Falk et al., 2018). Our index correlates with national characteristics linked to economic development and with cultural features that are widely considered to be associated with patience. Our findings have two main implications. First, we document a relation between income, age and time discounting which had never been detected. Second, we validate an easy to measure index of patience which can be widely used in socioeconomic surveys of households.

Chapter 1

Maximum Price, Regret and Trading Decisions

1.1 Introduction

In the present chapter, we investigate an extension of Regret Theory (RT), one of the most successful theories of decision under risk (Loomes and Sugden, 1982; Bleichrodt and Wakker, 2015; Strack and Viefers, 2019). We test an application of Regret Theory to dynamic decisions (Strack and Viefers, 2019) in the context of financial trading decisions. In this setting, Strack and Viefers (2019) show that an Expected Utility (EU) agent would always stop at an optimal threshold. That is to say, she would never sell at a price lower than a price at which she previously had the possibility to sell the stock. A Regret Theory agent does not necessarily stops at a threshold, when deciding to sell a stock and her propensity to sell increases as the price of the stock increases and decreases as the distance from the past maximum increases. We test those predictions on the LDB dataset (Odean, 1998, 1999; Dhar and Zhu, 2006; Barber and Odean, 2013).

First, we test if investors stop on the day when maximum realised for gains and on the day when minimum realised for losses and we find that only 31.6% of trading episodes in the gain domain and 25.8% of trading episodes in the loss domain are stopped on the day when maximum and minimum unfold, respectively. The discrepancy in the two figures is a corollary of the the disposition effect, the higher propensity to realise gains with respect to losses (Shefrin and Statman, 1985; Odean, 1998).

Second, we characterise those traders who are more likely to stop at a threshold and build some links with the literature on trading decisions and individual characteristics (Shapira and Venezia, 2001; Dhar and Zhu, 2006; Seasholes and Zhu, 2010; Korniotis and Kumar, 2011, 2013). We adopt a negative binomial regression to model the rate at which investors stop at a threshold and find that sophisticated investors and active traders are more likely to follow a threshold strategy and affluent and older investors are less likely to follow a threshold strategy. Males are more willing to realise losses at a threshold than females.

Most importantly, we investigate the impact of the past maximum of a stock, in a specific trading episode, on the propensity to sell that stock. We model the time to sell using a proportional hazard (PH) model (Cox, 1972). This method has the advantage of assessing the impact of the covariates over the entire time axis. A proportional hazard model incorporates all the information accumulated in time for a given episode. We take into account both the distance in price from the past maximum, the distance in time from the maximum realisation and the return of the stock. Consistent with Strack and Viefers (2019) we find that investors are more likely to realise a gain, the higher is the return. In a Dynamic Regret Theory setting, when the agent is only concerned with regret about past forgone decisions, the propensity to sell is predicted to decrease as the distance from the past maximum increases. The idea is that, ceteris paribus, if the price of the stock is further from the past maximum, the regret is higher and the investor will be less likely to stop. Figure 1.1 helps clarifying the point. The Utility of an Expected Utility agent only depends on the level of the price, hence it would be the same at any time the price hits the level highlighted in red. A Regret Theory agent would experience a higher Utility by selling the stock the first time the price reaches the price in red (left arrow in blue) than the second time (right arrow in blue). However, we find that the relationship of the propensity to realise a gain with the distance in price from the past maximum follows an inverse U-shape. It peaks when the distance in price is low but it decreases when it gets very low.

As we said, we also consider the distance in time from the past maximum. We find a strong and clear pattern: investors are less likely to sell a winning stock, the further in time the maximum price occurred. Moreover, we investigate the relation between the distance in price and the distance in time from the past maximum and find that, when the distance in time is low, investors are more likely to realise a gain, the higher is the distance in price from the past maximum. We suggest that a panic effect is the main force

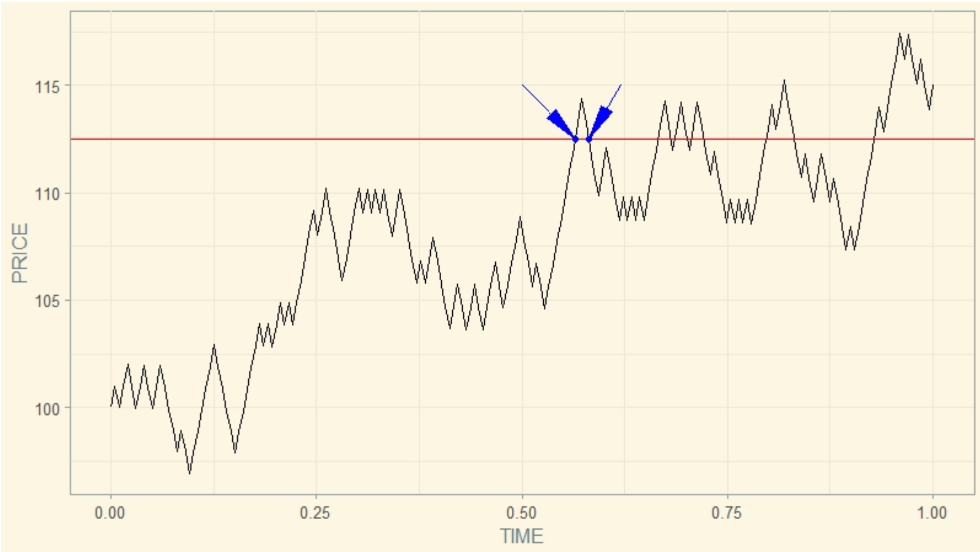

Figure 1.1: **Example of a threshold investment strategy.** The threshold is highlighted in red. The Utility of an Expected Utility agent only depends on the level of the price. A Regret Theory agent would experience a higher Utility by selling the stock the first time the price reaches the threshold (left arrow in blue) than the second time (right arrow in blue).

leading to the realisation of a stock. This finding can be rationalised with the experimental evidence in Fioretti et al. (2018). Investors anticipate the regret about the future and decide to realise the stock to avoid experiencing an even higher regret in the case the stock price keeps decreasing.

1.2 Regret and maximum price

Regret theory has already been used to explain several phenomena in finance and economics: asset pricing and portfolio choice (Gollier and Salanié, 2006; Muermann et al., 2006), personal insurance market (Braun and Muermann, 2004), why people tend to invest too little in stocks (Barberis et al., 2006), hedging with respect to currency risk (Michenaud and Solnik, 2008) and the disposition effect (Muermann and Volkman, 2006).

We are the first to perform a test of dynamic regret on empirical data. There have been three attempts to study dynamic regret in a laboratory setting. Our closest predecessor is Strack and Viefers (2019). They extend Regret Theory to dynamic trading decisions and test their predictions in a laboratory experiment. As we said, they show that an Expected Utility agent would find it optimal stopping at a threshold and her propensity to sell would not be influenced by the distance from the past maximum. A Regret Theory agent does not necessarily stops at a threshold and her propensity to sell would be increasing in the price of the stock and decreasing in the price distance from the past maximum. Their predictions are respected by subjects in the laboratory. More specifically, agents do not have a constant reservation level and they do not behave consistently in any repetition of the task. Agents do not follow a threshold strategy, i.e. they stop at a level where they decided to continue before. Agents are more willing to stop the higher the level of the price and they are less willing to stop the higher the maximum level of the price. Fioretti et al. (2018) perform a stock market experiment, where participants know beforehand whether they will observe the future prices after they sell the asset or not. When future prices are available, investors avoid regret about expected after-sale high prices (future regret). Descamps et al. (2016) study how regret influences information sampling. Participants deviate from the optimal strategy in a systematic manner: information is either mostly over-sampled or mostly under-sampled, depending on the cost of information.

There are several papers linked to the idea that the maximum point of a price process has an effect on agents' behaviour. First of all, Grinblatt and Keloharju (2001) show that high recent past returns of stocks tend to increase the propensity to sell of investors and the propensity to sell is higher when a stock hits its last month maximum price. Heath et al. (1999) show that the exercise of an option is higher when the price of the underlying stock is above its last year's peak. Barber and Odean (2008) and Huddart et al. (2009) find that the trading volume is high around both last year maximum and minimum. Finally, an experimental paper by Baucells et al. (2011) investigates the impact of the highest level in a stream of payoffs, on the formation of the reference point.

1.3 Too proud to stop: Regret in dynamic decisions

Strack and Viefers (2019) is a pioneering work in the exploration of regret in dynamic decisions. Regret has been widely studied in the context of static decisions while pretty neglected in the context of dynamic decisions. Notable exceptions are the aforementioned works by Descamps et al. (2016) and Fioretti et al. (2018). The objective of Strack and Viefers (2019) is a stopping problem. In a stopping problem, a decision maker observes a sequence of offers, which are realisations of a stochastic process X_t. After observing the n-th offer the decision maker is given the possibility to stop or keep seeing further offers. Once she chooses to go on she cannot accept forgone offers, while if she stops she cannot accept future offers. In such a decision framework, an EU maximiser would adopt a threshold strategy, meaning that she should stop the game as soon as the price reaches the gain threshold she fixed as her goal. The optimal threshold is ex-ante optimal and optimal at any point in time (there is no time inconsistency).

Definition 1. A threshold strategy $\tau(b)$ prescribes that the agent stops at time t if the value of the process X_t exceeds the cut-off b and continues otherwise, where b is a given constant. If the agent uses the cut-off strategy $\tau(b)$ she will stop at the time $\tau(b,\, X) = min\{t \geq 0\,:\, X_t \geq b\}$.

Building on Feng and Hobson (2016), Strack and Viefers (2019) show that a RT agent would not necessarily follow a threshold strategy. On top of that, she will adopt an optimal strategy which is different from the EU maximiser one. A RT agent will never find it optimal stopping under a past maximum while an EU maximiser who failed to stop at her threshold will not take into account how far above the threshold the stock went and will still find it optimal stopping at any value above her ex ante threshold. The intuition behind the hypotheses of the authors is that in the EU framework the agent only evaluates the current state of the process while in the RT context she takes into account the path of the process. More formally, a regret agent faces a disutility due to regret because she compares her choice to the one that revealed to be ex-post optimal, namely

$$Regret = \left(\max_{s \in S} U_s\right) - U_t \tag{1.1}$$

where $S = 0, 1, ..., t$ is the set of times relative to which the agent evaluates her regret. Thus the regret is driven by the difference between the maximum utility that could have been achieved and the utility actually achieved stopping at time t.

Strack and Viefers (2019) go on testing in the lab the following hypotheses, derived from their model:

• H1: Agents have a constant reservation level and they behave consistently in any repetition of the task, i.e. for all realised sequences (agents play 65 times the game) of offers $X = (X_1,\, X_2, ...) \neq \left(X_1',\, X_2', ...\right) = X'$ the level at which the agent stops the game is the same $\tau(X) = \tau\left(X'\right)$

• H2: Agents never stop under the running maximum, i.e. they never stop at a level where they decided to continue before;

• H3: Agents follow a threshold strategy, hence the stopping decision τ satisfies $\tau = \inf\{t : X_t = X_\tau\}$

• H4: Agents are more willing to stop the higher the level of the price and they are less willing to stop the higher the maximum level of the price up to the decision moment, i.e. the empirical frequency with which subjects stop at a given level x, given past maximum s is increasing in x and decreasing in s.

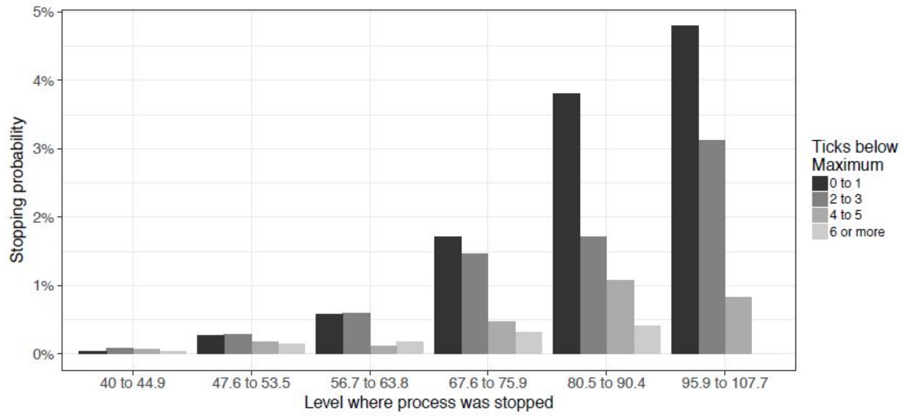

Figure 1.2: **Experimental Results from Strack and Viefers (2019).** Empirical stopping frequency per any level of the price and distance from past maximum (Figure 4 in Strack and Viefers (2019)).

In their work they are able to reject the first three hypotheses and to confirm the fourth one (see Figure 1.2). The research questions we are going to address are inspired to their hypotheses.

1.4 Data and methodology

We use two different samples of the LDB data for the two sections of the analysis presented in this chapter. We are going to explain the details of all our choices. Some of the data preparation steps are common between the two specifications and we will describe them here. We obtain price data from the CRSP (Centre for Research in Security Prices) of WRDS (Wharton Research Data Services). We exclude those stocks for which we were not able to recover price information. We remove investor-stocks records if at least one of the entries has negative commissions (which may indicate that the transaction was reversed by the broker). We remove from the sample investor-stocks that include short-sale transactions or that have positions that were opened before the starting point of our dataset. We remove those trades where the buy and sell dates coincide (Ivković et al., 2005; Ben-David and Hirshleifer, 2012).

The starting point of an investment is the first time an investor buys a stock or any time she buys it without the stock being present in the bank account at that time. The end point of an investment is the first sale date after that buy date (Shapira and Venezia, 2001; Brettschneider and Burgess, 2017). We define an episode as all the day-stock information between a buy and a sell date. An episode is classified as a gain if the selling price is higher or equal than the buy price. It is classified as a loss otherwise.

We now introduce a variable: the distance from the extreme at time t, d_t, which we will refer to as "distance". Time t is defined in terms of trading days.

Definition 2. The distance from the extreme is defined as

$$d_t = \begin{cases} \frac{t-t_{max}}{t}, & \text{if episode ends up as a gain} \\ \frac{t-t_{min}}{t}, & \text{if episode ends up as a loss} \end{cases} \tag{1.2}$$

where t is the number of days since the episode started, and t_{max} and t_{min} are the days when the current maximum and minimum prices of the episodes realised, respectively. Hence, t is always bigger or equal than t_{max} and t_{min}. These are calculated taking the starting point of an episode equal to $t = 0$.

1.4.1 Threshold strategy

Our first research question is:

- *Do investors follow a threshold strategy? Do they stop on the day when maximum or minimum realises?*
- *Which categories of investors are more likely to follow a threshold strategy?*

Threshold strategy in the loss domain is not discussed from a theoretical point of view in Strack and Viefers (2019), hence our analysis is more agnostic than the one we perform for the threshold strategy in the gain domain. We will assume that a threshold strategy is rational also for the loss domain. It is linked to the concept of "stop-loss". A stop-loss order is an order placed with a broker to buy or sell a security when it reaches a certain price. Stop-loss orders are designed to limit an investor's loss on a position in a security. When a stock falls below the stop price the order becomes a market order and it executes at the next available price. For example, a trader may buy a stock and place a stop-loss order 10% below the purchase price. Should the stock drop by 10%, the stop-loss order would be activated, and the stock would be sold as a market order. A stop-loss order is consistent with a threshold strategy. Stop-loss orders are issued in order to limit losses, since the investor might not be able to issue a selling order at any point in time or might be reluctant to realise a stock, when the price dropped significantly (disposition effect). A stop-loss, or a threshold strategy, would limit that. Hence, we can see it as a rational strategy to follow.

We take into account episodes whose length is shorter or equal to 300 days (209 trading days). We want to be sure we capture active trading decisions and that we are not looking at decisions of buy-and-hold long term investors (Benartzi and Thaler, 1995; Heath et al., 1999; Brettschneider and Burgess, 2017). We focus on the sample of bank accounts for which demographics are available. The sample is summarised in Table 1.1. It is obviously the case that an episode where the investor follows a threshold strategy is characterised by the condition $d_T = 0$ where T is the selling date for that episode. This is the proxy we are going to use to define a threshold strategy. Namely,

Definition 3. A trading episode is said to be a threshold strategy episode if $d_T = 0$.

Definition 3 gives a necessary but not sufficient condition to define an investment as a threshold episode. However, since our aim is rejecting a threshold strategy, we are only adding more obstacles to our goal by taking into account a less stringent hypothesis. Being able to reject it would imply, *a fortiori*, that a threshold strategy does not hold.

In Table 1.1 we see the distribution of some statistics for our sample. We notice that they are in line with the idea that investors suffer from the disposition effect. In particular, d_T is lower for gains than for losses. This is a signal that investors tend to realise gains quicker and have a strong aversion to realise losses at a minimum. Overall, the vast majority of trades are not consistent with a threshold strategy. Our definition of threshold strategy applies only to 31.6% of episodes in the gain domain, and to 25.8% of trades in the

Table 1.1: **Summary Statistics for the sample used in the Threshold analysis.** Gain refers to the sample where only investments which resulted in a gain are considered (return higher or equal than 0). Loss refers to the sample where only investments which resulted in a loss are considered. All refers to those bank account where at least a gain and a loss trading episode were completed. Bank accounts are classified as Cash (the standard one), Keogh or IRA (two types of retirement accounts), Margin or Schwab (two sophisticated products available to investors). Client Segment: Affluent if at any point in time she has more than $100,000 in equity, active if she makes more than 48 trades in any year and General for the residual individuals. If traders could be classified as both affluent and active they were classified as active traders.

	Gain	Loss	All
Percentage of Threshold Episodes	0.316	0.258	0.293
Number of Bank Accounts	15,624	11,390	8,674
Mean Rate of Threshold Consistency per Bank Account	0.275	0.216	0.257
Median Rate of Threshold Consistency per Bank Account	0.043	0	0.250
Mean Number of Episodes per Bank Account	4.640	3.954	11.493
Median Number of Episodes per Bank Account	2	2	6
Number of Cash Bank Accounts	2,591	1,812	1,218
Number of IRA Bank Accounts	2,798	1,674	1,227
Number of Keogh Bank Accounts	91	76	51
Number of Margin Bank Accounts	2,436	1,884	1,469
Number of Schwab Bank Accounts	7,708	5,944	4,709
Number of General Traders	10,368	7,080	5,085
Number of Affluent Traders	2,134	1,549	1,045
Number of Active Traders	3,122	2,761	2,544
Mean Age	49.70	50.58	50.25
Median Age	48	48	48
Mean Income per Bank Account	6.219	6.224	6.213
Median Income per Bank Account	6	6	6
Number of Females	1,329	949	689
Number of Males	11,947	8,717	6,627
Number of Not Professional Traders	10,362	7,672	5,916
Number of Professional Traders	880	632	462
Number of Traders with Other Occupation (even NA)	4,382	3,086	2,296

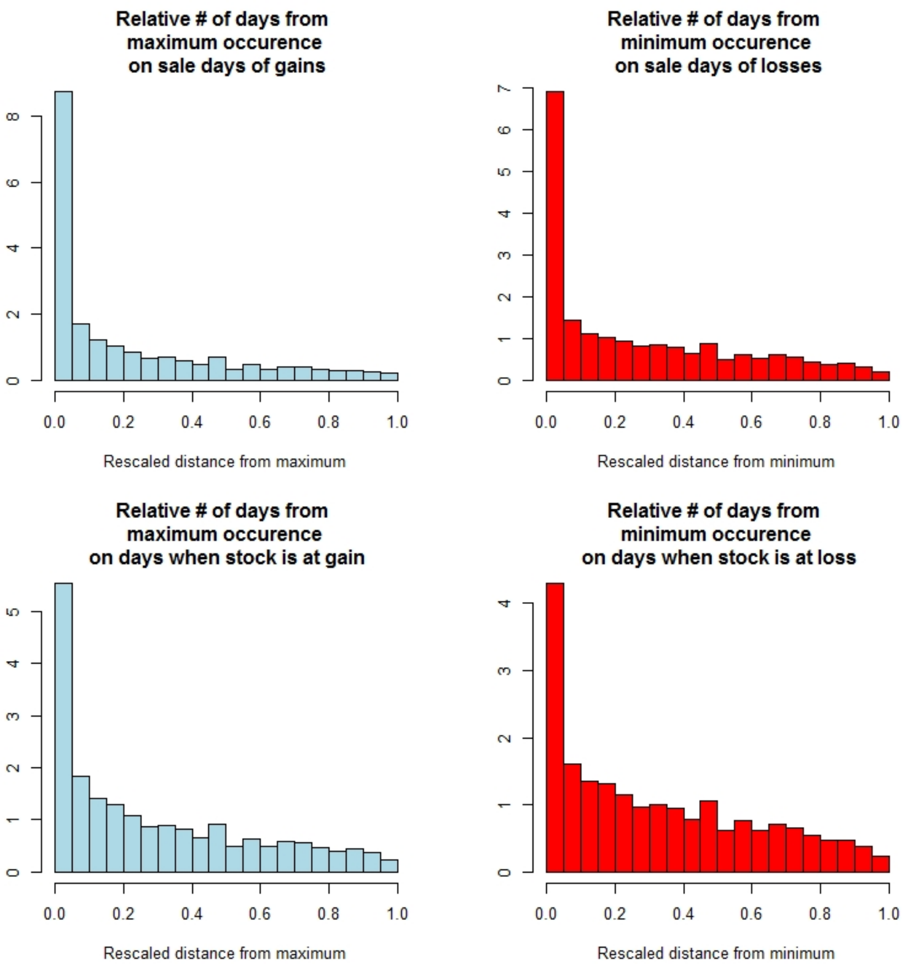

Figure 1.3: **Rescaled distance in time from the extreme.** Top-left: frequency of d_T, the rescaled distance in time from the maximum day calculated on the day when a sell for a gain took place. One observation per episode. Bottom-left: frequency of d_t, the rescaled distance in time from the maximum day calculated on any day when a stock was trading above the purchase price. One observation per trading day. Top-right: frequency of d_T, the rescaled distance in time from the minimum day calculated on the day when a sell for a loss took place. One observation per episode. Bottom-right: frequency of d_t, the rescaled distance in time from the minimum day calculated on any day when a stock was trading below the purchase price. One observation per trading day.

loss domain, as can be clearly seen in the top panels of Figure 1.3. The two bottom panels show the distribution of the rescaled distance from the extreme on any days. We can see that a maximum occurs on 17.5% of the days when a stock is trading at a gain and a minimum occurs on 13.8% of the days when a stock is trading at a loss. If investors were realising the stocks at random times, the percentage of max days on sale days of gains should be close to the percentage of max days on any days when the stock is trading at a gain and the same for minimum and losses. However, the percentage of extreme days out of sale days is much higher than the percentage of extreme days on any day. This suggests that maximum and minimum do have an impact on the propensity of the individuals to realise stocks. However, our descriptive statistics clearly hint that a threshold strategy is not consistently followed by our population of investors. We can also make an exercise inspired by the calculation of the disposition effect. We can take the number of days on which a stock was sold at a maximum and divide it by the number of days on which a maximum occurred, and call it "Proportion of maxima realised". We can take the number of days on which a stock was sold at a minimum and divide it by the number of days on which a minimum occurred, and call it "Proportion of minima realised". We then divide the proportion of maxima realised by the proportion of minima realised and we get 1.49. This is very close to the measure of the disposition effect (1.51) reported by Odean (1998). We find that the propensity to realise a stock at a maximum is around 50% higher than the propensity to realise a stock at a minimum. This is a different perspective on the disposition effect and it can be considered a consequence of it. However, in principle it could be possible that the propensity to sell at a maximum and the propensity to sell at a minimum could be the same, even in the presence of the disposition effect. Hence, this is a new insight on the topic.

In Section 1.5 we are going to investigate how the propensity to follow a threshold strategy changes at the individual level, using a negative binomial regression. We performed a Likelihood Ratio Test to check that a negative binomial model is more appropriate than a Poisson model. Negative binomial models assume the conditional means are not equal to the conditional variances. This inequality is captured by estimating a dispersion parameter (not shown in the output) that is held constant in a Poisson model. Thus, the Poisson model is actually nested in the negative binomial model. We can then use a likelihood ratio test to compare these two and test this model assumption. The Poisson distribution may be generalised by including a gamma noise variable which has a mean of 1 and a scale parameter of ν. The Poisson-gamma mixture (negative binomial) distribution that results is

$$P(Y = y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{y_i} \tag{1.3}$$

where $\mu_i = t_i * \mu$ and $\alpha = \nu^{-1}$. The parameter μ is the mean incidence rate of y per unit of exposure. Exposure may be time, space, distance, area, volume, or population size. Because exposure is often a period of time, we use the symbol t_i to represent the exposure for a particular observation. When no exposure is given, it is assumed to be one. The parameter μ may be interpreted as the risk of a new occurrence of the event during a specified exposure period, t.

In our case the exposure time t_i is the number of episodes in a bank account and μ_i is the number of threshold episodes in the same bank account. In negative binomial regression, the mean of y is determined by the exposure time t and a set of k regressor variables (the *x's*). The expression relating these quantities is

$$\mu_i = \exp(\log(t_i) + \beta_1 x_{1i} + ... + \beta_k x_{ki}) \tag{1.4}$$

often $x_1 = \mathbf{1}$, in which case β_1 is called the intercept. We estimate the vector of β coefficients through maximum likelihood.

1.4.2 Maximum price investigation

Our second research question is:

- *How does the propensity to sell a stock vary with respect to the three following variables?*
  - *Level of the price;*
  - *Distance in time from the day of running maximum realisation;*
  - *Distance in price from the running maximum.*

In this section we restrict our attention to a random sample of 13000 episodes. We look at a sample of investments which lasted no longer than 300 days (209 trading days) and resulted in a gain. The choice of restricting the sample to such a period comes from the fact that we want to guarantee the proportional hazard assumption holds and we base our estimation on the idea that investors attention does not span a very long period (Benartzi and Thaler, 1995; Brettschneider and Burgess, 2017). We restrict our attention to the gain domain since it would be difficult estimating the impact of the maximum price on the propensity to sell a stock for a loss, given that the maximum price would often coincide with the purchase price. Hence, it would be difficult to disentangle if a stock is being sold for being far from the past maximum or for being far from the purchase price. On top of that, Strack and Viefers (2019) test their predictions in a laboratory setting where stocks are on average in the gain domain (selling at a loss is a dominated strategy in their experiment). We exclude the 10% of most volatile episodes[1]. Since we are interested in how the propensity to sell a stock changes when the distance of the price from the past maximum increases, we did not want to focus on those trades where the likelihood of big intraday drops in price is high. The characteristics of our sample are summarised in Table 1.2.

Table 1.2: **Summary Statistics for the sample used in the Maximum analysis.**

Number Bank Accounts	8704
Number Trading Episodes	13000
Mean Return per Episode	1.19
Median Return per Episode	1.12
Mean length per Episode	68.07
Median Return per Episode	52

We analyse data using the proportional hazard model, developed by Cox (1972). Survival analysis models are widely used in medical research and they are relatively popular in demography and labour economics. They have recently been used in a series of financial applications (Ivković and Weisbenner, 2005; Deville and Riva, 2007; Jiao, 2015; Brettschneider and Burgess, 2017).

PH model is a semi-parametric model, aimed at describing the "time-to-event" of individuals. In our case the time to event is the time from the start to the end of an investment episode. It has the advantage of assessing the impact of covariates over the entire time axis, while for example a logistic regression only evaluates the odds of the event/non event with respect to a fixed time. Informally, a PH model incorporates all the information accumulated in time for a given episode. A logistic regression would evaluate the information

[1]We get the average daily ratio of minimum to maximum price per each investment episode and we exclude those trades where the ratio is lower or equal than 0.93

on a given day independently from the information on other days of the same episode. We now add more details to our discussion. In particular, we need to define some objects

Definition 4. Let T be a non-negative continuous random variable, representing the time until the event of interest.

$F(t) = P(T \leq t)$ denotes the distribution function and $f(t)$ the probability density function of random variable T.

$S(t) = P(T > t) = 1 - F(t)$ is the survival function. It is the probability that a randomly selected individual will survive beyond time t. It is a decreasing function, taking values in $[0, 1]$ and it equals 1 at $t = 0$ and 0 at $t = \infty$.

$\mathrm{H(t)} = -\log \mathrm{S(t)}$ is the cumulative hazard function.

The hazard function (or hazard rate) $h(t)$ measures the instantaneous risk of dying right after time t given that the individual is alive at time t.

In particular, we will fit a regression model where we evaluate the change in the hazard rate with respect to a set of covariates. That is to say, given a set of covariates $\mathbf{x}_i = (x_{i1}, x_{i2}, ..., x_{ip})$ measured for subject i, the following model is fit to the data

$$h_i(t) = h_0(t) \exp\left(\beta^t \mathbf{x_i}\right);$$

with β, a $p \times 1$ vector of parameters and $h_0(t)$ which is the baseline hazard function (i.e. hazard for a subject i with $\mathbf{x_i} = \mathbf{0}$).
The proportional hazards assumption states that the ratio of the hazards of two subjects with covariates x_i and $x_{i'}$ is constant over time:

$$\frac{h_i(t)}{h_{i'}(t)} = \frac{\exp\left(\beta^t \mathbf{x}_i\right)}{\exp\left(\beta^t \mathbf{x}_{i'}\right)}$$

The Cox PH model is a semi-parametric model. It means that it leaves the form of $h_0(t)$ completely unspecified and it estimates the model in a semi-parametric way. Then, to estimate the model we maximise a partial likelihood. Finally, we should point out that we are estimating a model with time changing covariates so it is better to define it as

$$h_i(t) = h_0(t) \exp\left(\beta^t \mathbf{x}_{it}\right)$$

To deal with unobserved heterogeneity we stratify the model based on the investor who holds the position. This means each bank account has a different baseline hazard function, which can absorb any heterogeneity not captured by the model covariates Hence, the hazard function for the i_{th} position of the j_{th} bank account is

$$h_{ij}(t) = h_{0j}(t) \exp\left(\beta^t \mathbf{x}_{ijt}\right);$$

where $\mathbf{x}_{ijt}$ is the covariate vector for the position. A final word should be spent on why we need to stratify at the bank account level. Possible reasons for there being a difference between investors include their preference for risk, their beliefs about the market (e.g. whether there is price momentum or not), their investment objectives and the particular strategy they are following. For example, some investors may trade very frequently and follow a strategy based on short term changes in stock prices. The holding periods of these investors will therefore be shorter than other investors in the sample. Differentiating investors baseline hazards can separate out this kind of difference from the effects of covariates included in the model, that are in theory common across all investors. In our results we report the pseudo R squared proposed by Xu and O'Quigley (1999). Xu and O'Quigley (1999) start from a coefficient of explained randomness derived by Kent and O'Quigley (1988). The coefficient aims at explaining the variability on the outcome looking at the distribution of time to events, given covariates. That coefficient has the following properties:

- When a covariate is unrelated to survival, and the corresponding regression coefficient it is equal to zero, it is equal to zero;
- When the effect of at least a coefficient is different from 0, it is between 0 and 1;
- It is invariant under linear transformations of covariates and under monotone increasing transformations of time.

The coefficient we use, uses the same basic ideas but looking at the distribution of covariates at each time. The construction can be carried out using routine quantities calculated during a standard proportional hazards analysis. The inference is also greatly simplified. Most importantly, the presence of time-dependent covariates presents no difficulties for Xu and O'Quigley (1999) coefficient estimation, while the one by Kent and O'Quigley (1988) is not defined in that case. In O'Quigley et al. (2005) there are further discussions on the robustness of the pseudo R-squared we use.

1.5 Threshold strategy consistency

An investment episode respects a threshold strategy if it satisfies Definition 3, hence if the stock was sold on the maximum day for gains or on the minimum day for losses. We already saw in Section 1.4 that the vast majority of trading episodes is not consistent with a threshold strategy. The unit of analysis in this section will be the bank account, since we are interested in the rate of consistency with threshold for each bank account. In Table 1.3 we analyse the rate of threshold consistency per bank account. The dependent variable in our negative binomial regression is defined as:

- N_g, the number of investments in a bank account which were realised on the day when the maximum since purchase price realised and resulted in a gain, for columns 1 and 2 of Table 1.3.
- N_l, the number of investments in a bank account which were realised on the day when the minimum since purchase price realised and resulted in a loss, for columns 3 and 4 of Table 1.3.
- $N = N_g + N_l$, for columns 5 and 6 of Table 1.3.

In columns 1 and 2 of Table 1.3 we only look at those bank accounts where at least an investment which resulted in a gain was recorded. In columns 3 and 4, we look at those bank accounts where at least an investment which resulted in a loss was recorded. In columns 5 and 6, we look at those bank accounts where at least an investment which resulted in a gain and at least one which resulted in a loss were recorded. To control for the fact that different investors completed different numbers of trading episodes, we take into account the logarithm of the number of completed episodes (completed gains, losses or all depending on the regression) as an offset. Hence, we measure how the rate of threshold consistency varies from one bank account to the other. We now introduce the covariates we are taking into account. They are all defined at bank account level.

- Dummy for the account type: Cash Account which is a standard bank account, IRA and Keogh, which are two different types of retirement accounts, Margin accounts and Schwab One accounts (more sophisticated products available to the investors);
- Client Segment: Affluent if at any point in time she has more than $\$100,000$ in equity, active if she makes more than 48 trades in any year

and General for the residual individuals. If traders could be classified as both affluent and active they were classified as active traders;

- Age in decades;
- Income is classified as a numeric variable which takes values from 1 to 9 and increases with income of the individual[2].
- Gender;
- Occupation, we follow Dhar and Zhu (2006): non-professional if the trader has a "white collar/clerical","blue collar/craftsman" or "service/sales" job; professional occupation if the trader has a "professional/technical" or "administrative/managerial" occupation; the residual category is everyone else[3].

We see that investors with margin accounts and Schwab accounts are more likely to follow a threshold strategy. In particular, investors with margin accounts show a rate of threshold consistency which is, on average, 20% higher than cash accounts both for gains and for losses, separately (almost 30% when we consider overall rate). Schwab account holders have a consistency rate which is around 10% higher than cash accounts for gains and around 15% for losses. If we believe that a threshold strategy as the rational choice for an investors, we see that more sophisticated investors (those who have margin accounts and Schwab accounts) are more likely to adopt it. This is in line with the idea that sophistication lowers investment biases (Grinblatt and Keloharju, 2001; Dhar and Zhu, 2006). Retirement accounts show a higher rate of threshold consistency than cash accounts but only when the overall rate is considered. Active traders have a higher rate of threshold consistency. That is especially true for losses (6 to 8% higher rate than general traders). That is to be expected since frequency of trading increases the chances that investors are constantly monitoring their investments. Consistency with threshold depends also on attention (Barber and Odean, 2008) since investors might lose the possibility to stop at a threshold because of inattention. Affluent traders are less consistent than general traders with a threshold strategy but the effect boils down when we take into account age. That is probably due to the fact

[2] 1 corresponds to less than $15,000 per year; 2 to $15,000 to $19,999; 3 to $20,000 to $29,999; 4 to $30,000 to $39,999; 5 to $40,000 to $49,999; 6 to $50,000 to $74,999; 7 to $75,000 to $99,999; 8 to $100,000 to $124,999; 9 to $125,000 or more

[3] To avoid having too many missing observations, also missing values were classified in the residual category.

Table 1.3: **Negative binomial regression for threshold strategy consistency.** Odds ratios with 95% c.i. of a Negative Binomial (one observation is one bank account). The dependent variable is the number of times the investor stopped at a threshold in the gain, loss or overall. Offset equal to the number of episodes in the bank account (in the gain, loss, overall).

	Gain		Loss		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Account Type (ref. Cash)						
Account Type IRA	1.068*	1.044	1.097*	1.082	1.105***	1.096**
	(0.997,1.143)	(0.965,1.129)	(0.998,1.207)	(0.971,1.206)	(1.031,1.185)	(1.012,1.187)
Account Type Keogh	1.111	1.180	1.267*	1.144	1.238**	1.262**
	(0.900,1.367)	(0.917,1.516)	(0.980,1.628)	(0.840,1.545)	(1.025,1.494)	(1.014,1.570)
Account Type Margin	1.194***	1.186***	1.237***	1.195***	1.289***	1.275***
	(1.119,1.274)	(1.099,1.280)	(1.135,1.350)	(1.080,1.324)	(1.210,1.373)	(1.184,1.374)
Account Type Schwab	1.129***	1.092***	1.152***	1.130***	1.202***	1.169***
	(1.068,1.194)	(1.023,1.167)	(1.069,1.244)	(1.033,1.236)	(1.137,1.270)	(1.094,1.248)
Client Segment (ref. General)						
Client Segment Affluent	0.905***	0.951	0.871***	0.952	0.863***	0.911**
	(0.851,0.962)	(0.884,1.023)	(0.798,0.950)	(0.860,1.053)	(0.810,0.920)	(0.844,0.981)
Client Segment Active	1.036*	1.092***	1.059**	1.078**	1.076***	1.117***
	(0.998,1.076)	(1.045,1.142)	(1.009,1.111)	(1.017,1.142)	(1.040,1.113)	(1.073,1.163)
Age (decades)		0.921***		0.958***		0.932***
		(0.906,0.936)		(0.938,0.978)		(0.919,0.946)
Income		0.990*		0.977***		0.985***
		(0.979,1.000)		(0.964,0.991)		(0.976,0.995)
Male		1.008		1.141**		1.058
		(0.931,1.093)		(1.021,1.277)		(0.979,1.144)
Occupation (ref. Other (also NA)						
Non Professional Occupation		1.060		1.004		1.031
		(0.977,1.150)		(0.898,1.121)		(0.954,1.113)
Professional Occupation		1.015		0.956		0.994
		(0.971,1.061)		(0.901,1.014)		(0.954,1.036)
McFadden Adj. R^2	0.24	0.46	0.25	0.46	0.25	0.46
Observations	15,624	11,477	11,390	8,315	8,674	6,280

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1.4: **Negative binomial regression for threshold strategy consistency (extended).** Odds ratios with 95% c.i. of a Negative Binomial (one observation is one bank account). The dependent variable is the number of times the investor stopped at a threshold in the gain, loss or overall. Offset equal to the number of episodes in the bank account (in the gain, loss, overall).

	Gain		Loss		All	
	(1)	(2)	(3)	(4)	(5)	(6)
Account Type IRA (ref. Cash)	1.032	1.029	1.081	1.081	1.076	1.068
	(0.904,1.178)	(0.905,1.172)	(0.910,1.286)	(0.914,1.281)	(0.949,1.220)	(0.946,1.207)
Account Type Keogh (ref. Cash)	1.182	1.212	1.261	1.219	1.255	1.266*
	(0.841,1.654)	(0.872,1.679)	(0.850,1.849)	(0.822,1.783)	(0.946,1.663)	(0.961,1.664)
Account Type Margin (ref. Cash)	1.219***	1.244***	1.140	1.182*	1.272***	1.292***
	(1.067,1.394)	(1.092,1.418)	(0.956,1.362)	(0.996,1.405)	(1.123,1.442)	(1.146,1.459)
Account Type Schwab (ref. Cash)	1.162**	1.154**	1.143*	1.160**	1.221***	1.216***
	(1.038,1.304)	(1.032,1.292)	(0.987,1.328)	(1.005,1.343)	(1.097,1.360)	(1.097,1.351)
Client Segment Affluent (ref. General)	1.004	0.984	0.964	0.970	0.944	0.929
	(0.906,1.111)	(0.889,1.087)	(0.834,1.111)	(0.841,1.115)	(0.850,1.047)	(0.838,1.028)
Client Segment Active (ref. General)	1.081**	1.082**	1.080*	1.097**	1.115***	1.110***
	(1.008,1.158)	(1.012,1.158)	(0.987,1.182)	(1.005,1.197)	(1.049,1.186)	(1.045,1.178)
Age (decades)	0.907***	0.909***	0.931***	0.943***	0.910***	0.917***
	(0.883,0.931)	(0.886,0.932)	(0.900,0.962)	(0.914,0.973)	(0.889,0.931)	(0.897,0.938)
Income	0.994	0.992	0.976**	0.975**	0.989	0.987*
	(0.977,1.011)	(0.976,1.008)	(0.955,0.998)	(0.955,0.996)	(0.975,1.004)	(0.973,1.002)
Male	0.975	0.968	1.083	1.129	0.975	0.989
	(0.858,1.109)	(0.854,1.099)	(0.912,1.292)	(0.954,1.344)	(0.866,1.098)	(0.882,1.111)
Non Professional Occupation (ref. Other (also NA))	1.044	1.051	0.995	1.042	1.010	1.035
	(0.909,1.196)	(0.919,1.198)	(0.822,1.196)	(0.870,1.241)	(0.887,1.147)	(0.915,1.169)
Professional Occupation (ref. Other (also NA))	1.010	1.002	0.916*	0.927*	0.975	0.973
	(0.945,1.079)	(0.939,1.070)	(0.839,0.999)	(0.852,1.010)	(0.919,1.034)	(0.918,1.031)
Experience Extensive (ref. Good)	0.926*		1.041		0.979	
	(0.853,1.005)		(0.940,1.151)		(0.913,1.049)	
Experience Low (ref. Good)	1.008		1.044		1.033	
	(0.935,1.086)		(0.944,1.154)		(0.964,1.107)	
Experience None (ref. Good)	1.066		0.835		0.973	
	(0.881,1.285)		(0.628,1.095)		(0.815,1.157)	
Knowledge Extensive (ref. Good)		0.873***		1.055		0.964
		(0.798,0.955)		(0.947,1.175)		(0.895,1.039)
Knowledge Low (ref. Good)		1.006		1.012		1.028
		(0.934,1.084)		(0.916,1.118)		(0.961,1.100)
Knowledge None (ref. Good)		1.039		1.114		1.079
		(0.932,1.158)		(0.967,1.281)		(0.980,1.188)
McFadden Adj. R^2	0.77	0.76	0.76	0.75	0.76	0.77
Observations	4,713	4,911	3,531	3,663	2,701	2,809

Note: *p<0.1; **p<0.05; ***p<0.01

that affluent traders are much older, on average, than general traders. Older investors are less likely to be consistent with threshold strategy. Every ten years, the rate of threshold consistency decreases by around 8%, 4% and 7% in the gain, loss and overall sample. This finding can be linked to the idea that older individuals have lower decision making abilities and make worse financial decisions (Korniotis and Kumar, 2011; Bruine De Bruin, 2017). The higher is the income of the traders, the less likely they are to follow a threshold strategy. Males are more likely to follow a threshold strategy than females for losses (their rate of threshold consistency is 14.1% higher). We do not see any differences based on the occupation of the traders. As can be seen from Table 1.4 both self-declared knowledge and self-declared experience do not have prognostic power to identify who is more or less likely to follow a threshold strategy.

The take home from this section is that investors do not consistently follow a threshold strategy, in line with Strack and Viefers (2019). The main differences in threshold consistency are due to age, client segment and account type. Sophisticated investors and active traders are more consistent with a threshold strategy. Affluent and older investors are less consistent than general investors with a threshold strategy. Males are more willing to realise losses at a threshold than females.

1.6 Maximum Price and stock realisation

We can now focus on the main results of the chapter. First, we introduce the variables of interest. They are measured at the daily level. The buy date of any investment episode is date 0. Every date is registered as the difference in trading days between that date and the buy date and denoted by t. Only the propensity to sell on days when the stock is trading above the buy price is estimated. That means that the information on those days in which the stock is trading at a loss is not incorporated in the estimate. We confine ourselves to estimate the propensity to sell for a gain. Hence, we thought it was not appropriate estimating the propensity to sell the stock on those days when it was trading at loss, since we constrained it to zero. To make a parallel with the medical literature, from which we borrow our estimation strategy, think about an allergy which we know can only occur during the spring. It would not make sense estimating the probability of occurrence based on the covariates measured during the winter. We define now our covariates of interest, measured at any given day t.

- Distance is the rescaled distance from the occurrence of the maximum date, as we defined it in definition 2, $\frac{t-t_{max}}{t}$. t_{max} is the day when the maximum price between day 0 and day t realised. We split it into tertiles based on the stock-bank account-day distribution. Distance is defined as low in the interval [0; 0.07]; medium in the interval [0.07; 0.34) and high in the interval [0.34; 1];

- Ratio to Max Price (Ratiomax) is the ratio of the daily closing price to the maximum price up to that time in the investment episode. On the selling date it is equal to the ratio of the selling price to the maximum price in the episode. We split it into quartiles based on the stock-bank account-day distribution. Defined as low in the interval [0.349; 0.918]; medium-low in the interval (0.918; 0.957]; medium-high in the interval (0.957; 0.981] and high in the interval (0.981; 1].

- Return is the ratio of the daily closing price to the purchase price in the investment episode. On the selling date it is equal to the ratio of the selling price to the purchase price in the episode. We split it into tertiles based on the stock-bank account-day distribution. Defined as low in the interval [1.00; 1.06]; medium in the interval (1.06; 1.17]; high in the interval (1.17, 5.53].

We rescale all the variables since we need consistency from one trading episode to another. Prices are really different from stock to stock. On top of that, we stratify the variables instead of using their continuous version for two reasons. First, to take into account non linearities. Second, to have a model which can be analysed through proportional hazard technique. In our specification the proportional hazard assumption is not violated for any of the models, where we rescale the variables. On top of that, we are able to capture the main non-linear changes in the effect of the variables. The most important implication of the proportional hazard assumption is that the effect of a covariate is constant in time. Whilst a violation of the assumption does not invalidate the model, it does significantly alter the interpretation, particularly when only hazard ratios are reported. If an effect does change over time then the hazard ratio is only an average of this process, and if it changes a lot then this average can be misleading. Take for example the distance in time from the past maximum. We analyse it both looking at the value in absolute days

Table 1.5: **Proportional Hazard model of the hazard of selling a stock. Absolute time distance.** The event is the sale. Each day when the stock is not sold is a non-event. Each observation is at stock-bank account-day level. Odds Ratios with c.i. Baseline hazard rate stratified at investor level. Clustered robust s.e. at bank account level. Distance in Time from Max Day is measured in trading days.

Dist. from Maximum Day (ref. Max Day)	
1 Day	1.093
	(0.943,1.266)
2 Days	0.929
	(0.783,1.101)
3 to 5 Days	0.742***
	(0.640,0.860)
More than 5 Days	0.413***
	(0.363,0.470)
Xu-O'Quigley R^2	0.061
Concordance	0.61
PH Assumption Valid (0.01)	NO
Time Controls	YES
Number of Trading Episodes	13,000
Number of Bank Accounts	8,704
Observations	621,849
Note:	*p<0.1; **p<0.05; ***p<0.01

(Table 1.5) and at the rescaled version (column 2 of Table 1.6). When we take into account the absolute distance in trading days from the maximum day, the proportional hazard assumption does not hold (Table 1.5). That means that the effect we find changes over time and it is only an average effect of the distance in time on the propensity to sell. To be more precise, the effect of being one day after the maximum day has a different impact on the propensity to sell a stock, if the effect is evaluated, for example, on day 7 or on day 30 since purchase. That means that we need to rescale the distance in time. The absolute distance in time from maximum realisation is much more intuitive than the rescaled distance we defined in Definition 2 but it has a much lower explanatory power for our variable of interest. Given this premise, we observe that the propensity to sell a stock is very high on the maximum day and on the two days after. More than one week (5 trading days) after the maximum realised, the propensity to sell a stock is almost 60% lower than on the maximum day. In a range between 3 to 5 trading days from maximum, the propensity to sell is 25.8% lower than on the maximum day, while there are no significant differences in the propensity to sell on the maximum day and on the two days after that. Although the difference is not significant, it is interesting to see that the propensity to sell is highest on the day after the maximum, when it is 9.3% higher than on the maximum day. Hence, the propensity to sell peaks the day after the investor missed the chance to sell at a maximum. This leads to two possible interpretations. The first one is that investors wait until the maximum unfolds and start selling in a time span which is close to it. This is an equivalent mechanism to the one proposed by Strack and Viefers (2019) for price. We suggest that regret is lower when the time distance is lower. This hypothesis is only one possible explanation for the effect we observe. We suggest that the regret component defined in Equation (1.1) can be framed in terms of time distance. In particular, we suggest that investors might experience a higher regret, the further they are from the time of the maximum realisation. Hence, that the disutility experienced by the investor is not only driven by the fact that she is stopping at a price below the past maximum but also at a distant time from the maximum day. This is not discussed in Strack and Viefers (2019) but the impact of several types of psychological distances has been explored both in the psychological literature (Maglio et al., 2013) and in the economic literature (Trautmann, 2019). Another option is attention. When the stock peaks, the investor starts paying attention to it and sells it shortly after. However, given that the PH assumption does not hold and the effects are small and not significant, we do not want to push the interpretation too far.

Table 1.6: **Proportional Hazard model of the hazard of selling a stock. Single covariates analysis.** The event is the sale. Each day when the stock is not sold is a non-event. Each observation is at stock-bank account-day level. Odds Ratios with c.i. Baseline hazard rate stratified at investor level. Clustered robust s.e. at bank account level. Ratio to Max Price is the ratio of daily closing price to maximum price up to that time in the investment episode. On the selling date it is equal to the ratio of selling price to maximum price in the episode. Low [0.349; 0.918]; Medium-Low (0.918; 0.957]; Medium-High (0.957; 0.981]; High (0.981; 1]. Distance in Time from Max Day is the standardised distance as defined in Definition 2. Low [0; 0.07]; Medium [0.07; 0.34); High [0.34; 1]. Return is the ratio of daily closing price to the purchase price in the investment episode. On the selling date it is equal to the ratio of selling price to the purchase price in the episode. Low [1; 1.06]; Medium (1.06; 1.17]; High (1.17, 5.53].

	(1)	(2)	(3)
Ratio Price to Max Price (ref. Low)			
Medium-Low	0.909		
	(0.792,1.043)		
Medium-High	1.062		
	(0.932,1.210)		
High	0.720^{***}		
	(0.619,0.837)		
Dist. in Time from Max Day (ref. Low)			
Medium		0.877^{**}	
		(0.786,0.979)	
High		0.430^{***}	
		(0.385,0.481)	
Return (ref. Low)			
Medium			2.719^{***}
			(2.435,3.035)
High			3.435^{***}
			(2.988,3.949)
Xu-O'Quigley R^2	0.020	0.061	0.10
Concordance	0.57	0.61	0.64
PH Assumption Valid (0.05)	YES	YES	YES
Time Controls	YES	YES	YES
Number of Trading Episodes	13,000	13,000	13,000
Number of Bank Accounts	8,704	8,704	8,704
Observations	621,849	621,849	621,849

Note: *p<0.1; **p<0.05; ***p<0.01

In Table 1.6 we estimate three proportional hazard models where we take into account the effect of Ratiomax, Distance and Return. We stratify the baseline hazard at the bank account level, in order to take into account differences in the propensity to realise a stock due to fixed investors' charac-

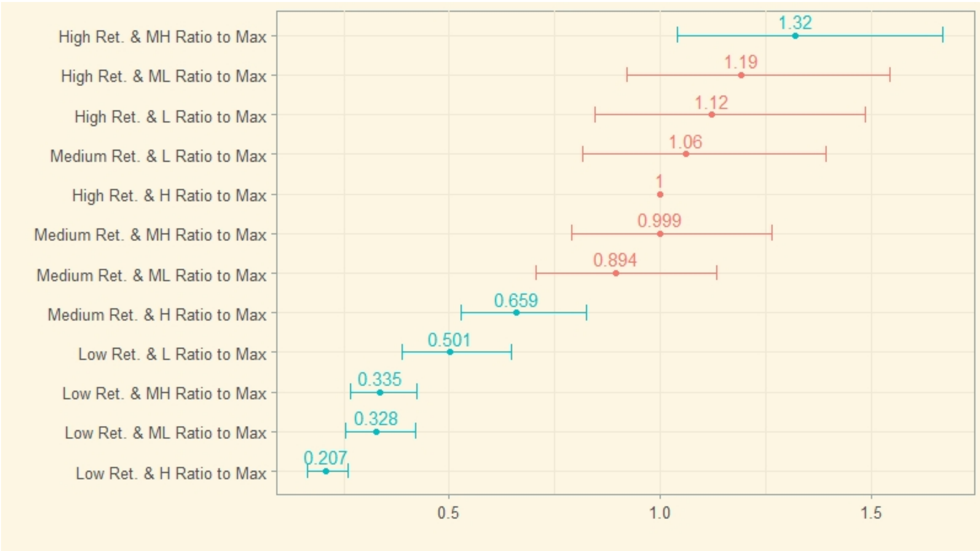

Figure 1.4: **Odds Ratio Proportional Hazard model: RatioMax and Return.** Odds Ratio from a Proportional Hazard model of the hazard of selling a stock. Each Odds Ratio corresponds to the effect of being in a given category. The event is the sale. Each day when the stock is not sold is a non-event. Each observation is at stock-bank account-day level. Clustered robust s.e. at bank account level. Blue odds ratios are significantly different from 1 ($p < 0.05$), red are not. Return is the ratio of daily closing price to the purchase price in the investment episode. On the selling date it is equal to the ratio of selling price to the purchase price in the episode. Low [1; 1.06]; Medium (1.06; 1.17]; High (1.17, 5.53]. Ratio to Max Price is the ratio of daily closing price to maximum price up to that time in the investment episode. On the selling date it is equal to the ratio of selling price to maximum price in the episode. Low [0.349; 0.918]; Medium-Low (0.918; 0.957]; Medium-High (0.957; 0.981]; High (0.981; 1]. The baseline category is "High Return and High Ratio".

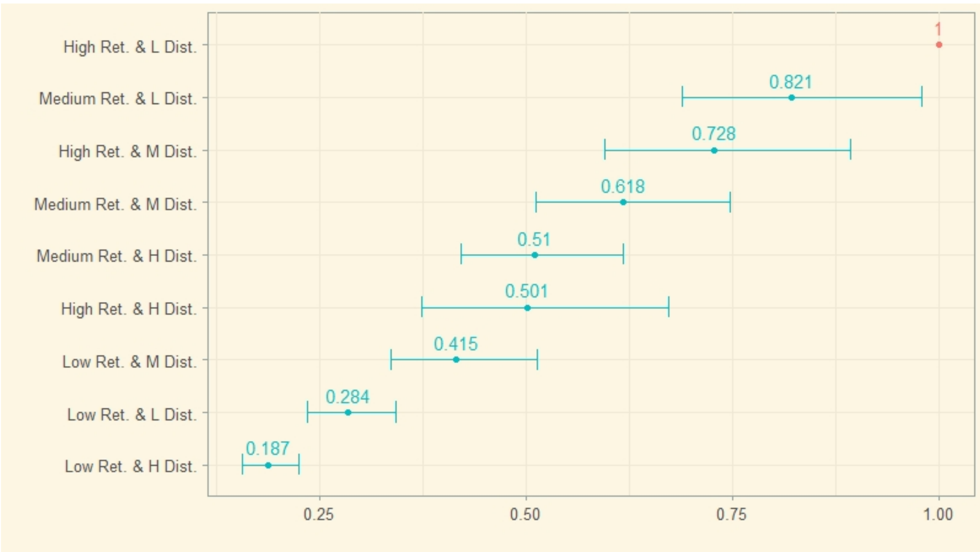

Figure 1.5: **Odds Ratio Proportional Hazard model: Distance and Return.** Odds Ratio from a Proportional Hazard model of the hazard of selling a stock. Each Odds Ratio corresponds to the effect of being in a given category. The event is the sale. Each day when the stock is not sold is a non-event. Each observation is at stock-bank account-day level. Clustered robust s.e. at bank account level. Blue odds ratios are significantly different from 1 ($p < 0.05$), red are not. Return is the ratio of daily closing price to the purchase price in the investment episode. On the selling date it is equal to the ratio of selling price to the purchase price in the episode. Low [1; 1.06]; Medium (1.06; 1.17]; High (1.17, 5.53]. Distance in Time from Max Day is the standardised distance as defined in Definition 2. Low [0; 0.07]; Medium [0.07; 0.34); High [0.34; 1]. The baseline category is "High Return and Low Distance".

teristics and we control for time effects (month and year). We see that the propensity to sell is lowest when the stock is trading close to the maximum price. The probability of selling at a high Ratiomax is 28% lower than the probability of selling at other points. This contradicts the predictions of dynamic regret, when the agent is only focused on regret about past decisions. Propensity to sell peaks at a medium-high level of the Ratiomax but differences among low, medium-low and medium-high categories are not significant. We conclude that regret does not bite as we expected. Propensity to sell is highest when price is close but not extremely close to the maximum. The pattern for Distance is quite strong and clear. Propensity to sell is 12.3% lower at a medium with respect to a low Distance and 57% lower at a high distance. To reconcile these findings with what we observed before, we notice that more than half of the times that the rescaled distance is low, it means that the distance from the past maximum is not greater than 2 days. Hence, we can say that the propensity to sell a stock peaks in those few days around maximum realisation. Higher returns increase the propensity to sell steadily. When returns are in the medium or high region (above 6% return) the rate of selling is around 3 times the rate of selling when the stock is in the Low return region (below 6%). This confirms the predictions of Strack and Viefers (2019) and the evidence in Ben-David and Hirshleifer (2012). In Figures 1.4 and 1.5 we show how the propensity to sell changes as Ratiomax and Distance change, for any levels of the Return. First, we fit a proportional hazard model where we take into account all the 9 combinations of Ratiomax and Return categories. Second, we fit a proportional hazard model where we take into account all the 9 combinations of Distance and Return categories. In both cases, we stratify the baseline hazard at the bank account level, in order to take into account differences in the propensity to realise a stock due to fixed investors' characteristics and we control for time effects (month and year). All categories in our regression are disjoint. In Figure 1.4 we report the odds ratios of the 8 coefficients for Ratiomax and Return. The analysis reported in Figure 1.4 is similar to the one carried on by Strack and Viefers (2019), which we showed in Figure 1.2. We only partially confirm their findings. You can see that the propensity to realise a stock is highest for high return levels but not in the region closest to the past maximum. For medium or low returns, we actually find that the probability of selling is highest when Ratiomax is low. Hence, the impact of the distance from the maximum is different from the one hypothesised by Strack and Viefers (2019). In Figure 1.5 we report the odds ratios of the coefficients for Distance and Return. Distance plays an important role, since investors' propensity to sell at a low distance in time from the past maximum is always higher than the propensity to sell at a high distance in time, for any level of the return. The tendency of the investors to sell at higher returns is confirmed.

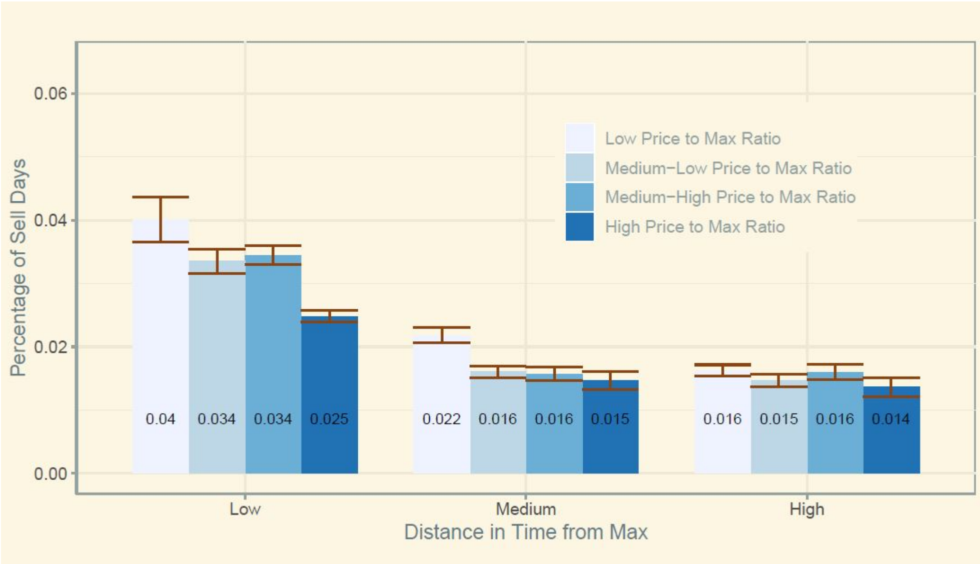

Figure 1.6: **Percentage of selling days for each combination of RatioMax and Distance.** Percentage of selling days out of all stock-bank account-days per each category (0.95 c.i.). Ratio to Max Price is the ratio of daily closing price to maximum price up to that time in the investment episode. On the selling date it is equal to the ratio of selling price to maximum price in the episode. Low [0.349; 0.918]; Medium-Low (0.918; 0.957]; Medium-High (0.957; 0.981]; High (0.981; 1]. Distance in Time from Max Day is the standardised distance as defined in Definition 2. Low [0; 0.07]; Medium [0.07; 0.34); High [0.34; 1].

Since the effect of Distance is very relevant in terms of both strength and explanatory power, we are interested in the interaction of it with the effect of Ratiomax. Table 1.7 reports the joint distribution of Ratiomax and Distance. At least 2% of stock-bank account-day observations fall in each category. From Figure 1.6 we can see that the interaction between Ratiomax and Distance suggests some relevant insights. When the Distance is low or medium, the average percentage of selling days is highest when Ratiomax is low. There is probably a panic effect, which can be framed as regret but is much deeper than what we described before. Investors are more willing to realise a gain when it is closest in time to maximum but furthest in price. If

Table 1.7: **Percentage of observations falling in any combination of RatioMax and Distance.** Percentage of stock-bank account-days falling in each category. Ratio to Max Price is the ratio of daily closing price to maximum price up to that time in the investment episode. On the selling date it is equal to the ratio of selling price to maximum price in the episode. Low [0.349; 0.918]; Medium-Low (0.918; 0.957]; Medium-High (0.957; 0.981]; High (0.981; 1]. Distance from Max Day is the standardised time distance as defined in Definition 2. Low [0; 0.07]; Medium [0.07; 0.34); High [0.34; 1].

	Low Distance from Max	Medium Distance from Max	High Distance from Max
Low Price Ratio to Max	0.02	0.10	0.13
Medium-Low Price Ratio to Max	0.05	0.10	0.10
Medium-High Price Ratio to Max	0.09	0.09	0.07
High Price Ratio to Max	0.17	0.04	0.04

regret has role, it is through this channel. Investors regret selling at a time far from the maximum. However, they sell as soon as the price decreases significantly. We can see this by looking at the fact that the percentage of sale days is 2.5% at high Ratiomax and low Distance and it is 4% at low price and low distance. Hence, it looks like anticipated regret of incurring higher losses is higher than the experienced regret given by the distance in price from the past maximum. This is in line with the evidence of anticipated regret present in Fioretti et al. (2018).

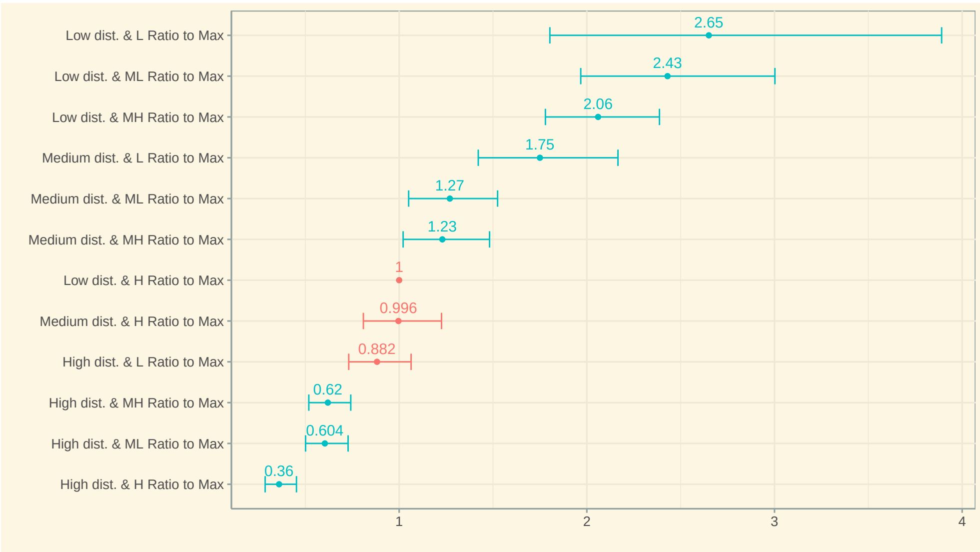

Figure 1.7: **Odds Ratio Proportional Hazard model: RatioMax and Distance.** Odds Ratio from a Proportional Hazard model of the hazard of selling a stock. Each Odds Ratio corresponds to the effect of being in a given category. The event is the sale. Each day when the stock is not sold is a non-event. Each observation is at stock-bank account-day level. Clustered robust s.e. at bank account level. Blue odds ratios are significantly different from 1 ($p < 0.05$), red are not. Ratio to Max Price is the ratio of daily closing price to maximum price up to that time in the investment episode. On the selling date it is equal to the ratio of selling price to maximum price in the episode. Low [0.349; 0.918]; Medium-Low (0.918; 0.957]; Medium-High (0.957; 0.981]; High (0.981; 1]. Distance in Time from Max Day is the standardised distance as defined in Definition 2. Low [0; 0.07]; Medium [0.07; 0.34); High [0.34; 1]. The baseline category is “Low Distance and High RatioMax”.

We fit a proportional hazard model where we take into account all the 12 combinations of Ratiomax and Distance categories. Here as well, we stratify the baseline hazard at the bank account level, in order to take into account differences in the propensity to realise a stock due to fixed investors' charac-

Table 1.8: **Odds Ratio Proportional Hazard model: RatioMax and Distance.** PH model of the hazard of selling a stock. The event is the sale. Each day when the stock is not sold is a non-event. Observations at stock-bank account-day level. Odds Ratios with c.i. Baseline hazard rate stratified at investor level. Clustered robust s.e. at bank account level. Ratio to Max Price is the ratio of daily closing price (selling price on selling days) to maximum price up to that time in the investment episode. Low [0.349; 0.918]; Medium-Low (0.918; 0.957]; Medium-High (0.957; 0.981]; High (0.981; 1]. Distance in Time from Max Day is the standardised distance as defined in Definition 2. Low [0; 0.07]; Medium [0.07; 0.34); High [0.34; 1].

Dist. in time from Max and Ratio to Max (ref. Low and High)	
Low dist. and Low Ratio to Max	2.649***
	(1.803,3.891)
Medium dist. and Low Ratio to Max	1.755***
	(1.421,2.166)
High dist. and Low Ratio to Max	0.882
	(0.731,1.064)
Low dist. and Medium-Low Ratio to Max	2.430***
	(1.968,3.002)
Medium dist. and Medium-Low Ratio to Max	1.266**
	(1.051,1.524)
High dist. and Medium-Low Ratio to Max	0.604***
	(0.501,0.728)
Low dist. and Medium-High Ratio to Max	2.061***
	(1.779,2.387)
Medium dist. and Medium-High Ratio to Max	1.230**
	(1.021,1.482)
High dist. and Medium-High Ratio to Max	0.620***
	(0.519,0.742)
Medium dist. and High Ratio to Max	0.996
	(0.809,1.226)
High dist. and High Ratio to Max	0.360***
	(0.286,0.453)
Xu-O'Quigley R^2	0.095
Concordance	0.65
PH Assumption Valid (0.05)	YES
Time Controls	YES
Number of Trading Episodes	13,000
Number of Bank Accounts	8,704
Observations	621,849
Note:	*p<0.1; **p<0.05; ***p<0.01

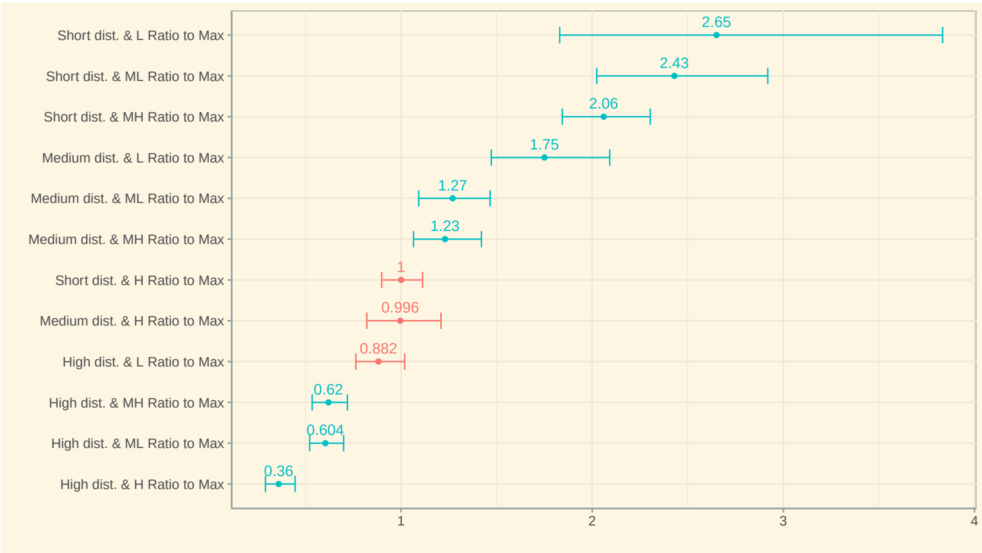

Figure 1.8: **Odds Ratio Proportional Hazard model: RatioMax and Distance. Firth and De Menezes (2004) method.** Odds Ratio from a Proportional Hazard model of the hazard of selling a stock. Each Odds Ratio corresponds to the effect of being in a given category. The event is the sale. Each day when the stock is not sold is a non-event. Each observation is at stock-bank account-day level. Clustered robust s.e. at bank account level. Blue odds ratios are significantly different from 1 ($p < 0.05$) when relying upon exact standard errors, red are not. Confidence intervals were obtained with the Quasi-Variance method of Firth (2003); Firth and De Menezes (2004). Ratio to Max Price is the ratio of daily closing price to maximum price up to that time in the investment episode. On the selling date it is equal to the ratio of selling price to maximum price in the episode. Low [0.349; 0.918]; Medium-Low (0.918; 0.957]; Medium-High (0.957; 0.981]; High (0.981; 1]. Distance in Time from Max Day is the standardised distance as defined in Definition 2. Low [0; 0.07]; Medium [0.07; 0.34); High [0.34; 1]. The baseline category is "Low Distance and High RatioMax".

teristics and we control for time effects (month and year). All categories in our regression are disjoint. Table 1.8 reports the outcome of the regression. In Figure 1.7 we report the odds ratio of the 11 coefficients. For the sake of replicability, Figure 1.8 reports the same results, where confidence intervals are measured using the quasi-variance method of Firth (2003) and Firth and De Menezes (2004). That allows the estimate of confidence intervals for all categories, including the baseline. The baseline category corresponds to "Low Distance and High Ratiomax", the ideal point to sell a stock, from an accounting perspective. We can see that all cases where distance is low are clustered at the top, when we rank categories based on the propensity to sell for each of them. All cases where distance is high are clustered at the bottom. The big exception is the baseline category, low Distance and high Ratiomax. Figure 1.7 offers a more complete interpretation to the sample averages we reported in Figure 1.6. Hazard of selling is 2.65 higher for low distance and low Ratiomax stock-days than at the baseline. In general, when the stock is close in time but not close in price to the maximum (i.e. low distance but not high Ratiomax) the hazard of selling is always estimated to be at least double than that at the baseline. The complete picture seems to suggest that reality is more complicated than how the lab describes it. Distance in price from the maximum plays a role but the effect is not nice and linear as the one observed by Strack and Viefers (2019). When distance in price is considered in isolation, the propensity to sell peaks at a point which is close but not the closest possible the to maximum. We can safely claim that traders are more willing to sell at a low distance in time from the maximum. They probably wait for a new maximum when a lot of time has passed since the last one. Hence, it is always a salient figure in their mind. However, when the distance in time is short, they are more willing to sell stocks which are further from the past maximum. We believe that panic might play a big role. It looks like investors are not extremely good at catching the best time to realise a stock and decide to realise it only when the price path shows a defined descending trend. Predictions of regret theory in a dynamic context by Strack and Viefers (2019) are only partially confirmed then.

We can advance some mechanisms to explain what we have just defined as a "panic" effect. The first one relies upon the evidence presented in Fioretti et al. (2018). In their paper, Fioretti et al. (2018) vary the information given to subjects in an experimental market. They observe that telling subjects that they will see price information after they have sold an asset leads to a phenomenon called anticipated regret. Investors focus on the regret they might experience because of future price realisations. In our setting, we suggest that investors try to minimise the regret they might experience if the future price is lower than the actual price. We suggest that when the price is dropping at a fast rate, this mechanism is stronger than when the stock is dropping at a slow rate. This explanations is tied very closely to the second one we propose. The second explanation we propose is purely beliefs driven. We suggest that when the stock is close in time but far in price from the past maximum, the investor might update her beliefs on the future trajectory of the price and overestimate the probability of future big drops, leading to higher sales. This can be exacerbated by some mechanisms like diagnostic expectations (Bordalo et al., 2019) where the probability of unlikely events is overstated after an unlikely event realised. More specifically, bad news on the past leads to an overestimate of the probability of bad news in the future. We cannot conclude that a single force is at work but we see that a panic effect is at work, in our empirical observations. This suggests that only regret about the past price is not a fully explanatory theory for investors' selling behaviour in the stock market.

1.7 Regret about what?

We tested if investors stop at an optimal ex ante threshold and are prone to regret in their decision to sell stocks. We moved from theoretical and experimental evidence of Strack and Viefers (2019). A threshold strategy implies that an investor never sells a stock at a price where she previously decided not to sell. We rejected that hypothesis for our sample of investors. We further investigated investors differences in the propensity to adopt a threshold strategy. First, we saw that investors are more willing to adopt a threshold strategy in the gain with respect to the loss domain. That is a consequence of the disposition effect, the higher propensity to realise gains with respect to losses (Shefrin and Statman, 1985; Odean, 1998; Barber and Odean, 2013). Second, we found that the main differences in the rate of threshold consistency are due to age, client segment and account type. Sophisticated investors and active traders are more consistent with a threshold strategy. Affluent and older investors are less consistent than general investors with a threshold strategy. Males are more willing to accept losses at a minimum, that is partially at odds with Barber and Odean (2001), who find that males under-perform females because of overconfidence. Affluent and older investors are more likely to depart from a rational threshold strategy, this is linked to the idea that decision making of older individuals is poorer (Korniotis and Kumar, 2011; Bruine De Bruin, 2017).

We investigated the impact of running maximum price in an investment episode on the propensity of investors to realise gains. We fitted a proportional hazard model to the decision to sell for a gain. Predictions of regret theory in a dynamic context (Strack and Viefers, 2019) are that the propensity to sell increases with the level of the price and decreases with the distance of the price from the past maximum. The first prediction was confirmed, since the propensity to sell a gain strongly increases as the return increases, consistent with Ben-David and Hirshleifer (2012). The effect of distance in price from the past maximum is not the one predicted by Strack and Viefers (2019). We did find that the propensity to sell is actually lower when the stock is trading very close to maximum price, while it is highest when the price is close to the past maximum but not in the closest region.

We also investigated the impact that distance in time from the past maximum has on the propensity to sell a stock. We found a very strong effect, with the propensity to sell a stock falling as the distance in time from the past maximum increases. On top of that, we investigated the joint effect of distance in time and distance in price from the past maximum, finding that investors are more willing to realise stocks which are closer in time but further in price from the past maximum. When time distance from the past maximum is short, the predictions of regret reverse. Investors are more willing to realise stocks, the further is the price from the maximum. Two forces are at work: investors are willing to wait for a new maximum to occur if a long time has passed since the last one and they panic when the stock price drops a short time after maximum. Anticipated regret (Fioretti et al., 2018) is a possible explanation. Investors focus on the possibility that the stock price might decrease even more and they rush to sell to minimise regret which has not materialised yet. This is also linked to the possibility that investors' perceived probability of future drops of the stock price is higher, after they experience a sharp drop right after the maximum. These findings open up the way to further experimental and theoretical work in this area. First, we believe that it would be interesting isolating the effects of time and price in a controlled laboratory setting and second, we think that it would be worth incorporating the time dimension in a theoretical dynamic model of regret.

Chapter 2

Wide Framing Disposition Effect

2.1 Introduction

In the present chapter, we shed new light on the disposition effect. In the extant literature, the disposition effect has been considered in tandem with an assumption of narrow framing (Thaler and Johnson, 1990; Barberis et al., 2006). Narrow framing, in this context, is the tendency to treat investments separately and it is well established that decision makers do narrow frame their choices, in some cases[1]. It is the tendency to see investments without considering the context of the overall portfolio. It is well known that decision makers take different decisions if they focus on each of them in isolation from the others or if they take into account more than one at the same time (Read et al., 1999). We ask the question whether a wide framing perspective might help our understanding of the disposition effect. In a wide framing perspective, investment decisions may depend on the overall portfolio composition. If investors were really adopting narrow framing, their decisions should not be influenced by the composition of the portfolio but only by the condition of the asset they are trading.

In this chapter, we relax the assumption of narrow framing and undertake an empirical investigation of the disposition effect. We focus our attention on the 5% most active traders (Richards and Willows, 2018) in the LDB dataset, who account for around 35% of the trades. We do so, in order to look at bank accounts where several stocks are traded at the same time. We

[1] Whilst the term "narrow framing" was first used by Kahneman and Lovello (1993), the more general concept of "decision framing" dates back to Tversky and Kahneman (1981).

demonstrate that portfolio effects are very relevant for the disposition effect. Our main finding concerns how the disposition effect varies as the number of stocks trading at a gain or at a loss in a bank account changes[2]. We find that the disposition effect is much weaker when the percentage of stocks trading at a gain in the account of an investor is higher. In addition, we analyse the impact that the realisation of other gains or losses in an account has on the propensity to sell a stock, and on the disposition effect itself. Investors' propensity to realise a stock is dramatically increased if they are realising another stock on the same day. Baseline propensities to sell on days when other trades do not take place are around 1%-2%. However, propensities to sell a stock at a gain (loss) rise to around 50% on days where another stock in the account is sold at a gain (loss), and to around 10% when another stock is sold at a loss (gain). This result can help to explain why the disposition effect varies with portfolio composition. Take a day when an investor has a low proportion of stocks trading at a gain in their account. Since investors have a preference for realising a gain and a loss on the same day, the propensity to realise a gain will be relatively high, whilst the propensity to realise a loss will be relatively low, giving a strong disposition effect. As the proportion of stocks trading at a gain is increased, the propensity to realise a gain will drop, and the propensity to realise a loss will rise, leading to a decrease in the strength of the disposition effect. This is indeed consistent with our main finding that the disposition effect is much weaker when the percentage of stocks trading at a gain in the account of an investor is higher.

Our work is innovative, in several aspects. It is well known that investors are subject to trading biases (Barber and Odean, 2000, 2013). We find that in some specific circumstances that is no longer true. In particular, the disposition effect is widespread in economics. We find that investors do not always show it. It is already well known that the disposition effect changes from one individual to another (Grinblatt and Keloharju, 2001; Dhar and Zhu, 2006) and it is also known that it decreases in time for a given investor as sophistication and trading experience increase (Feng and Seasholes, 2005). However, we find that it also changes at the individual level, within the same bank account, when we measure it for different account compositions. To sum up, we knew already that the disposition effect changes among investors and within investor from one point in time to another. We add that it changes

[2]In our analysis, each bank account is treated separately and investors may hold more than one account.

within investor at the same point in time, as the bank account composition changes.

2.2 Wide Framing Disposition Effect

Recent works that are closest to ours are those of Sakaguchi et al. (2019) and An et al. (2019). Sakaguchi et al. (2019) analyse data from a laboratory experiment and two datasets from trading activity: the LDB dataset and a dataset of UK based investors from the 2010's. They estimate how the disposition effect changes as the number of stocks in the gain and loss domain in a given portfolio changes. In particular, in the LDB and UK datasets, they find that the disposition effect is highest when there is only one stock trading at a loss and 2 or more stocks trading at a gain in a portfolio. The effect decreases with the number of stocks at a gain. When there is one stock at a gain and 2 or more stocks trading at a loss in a portfolio, the propensity to realise gains is lower than the propensity to realise losses. The main conclusion of Sakaguchi et al. (2019) is that the probability that a stock in the gain domain is sold is relatively constant across portfolios with different numbers of stocks in the gain domain and in the loss domain. However, they reach this conclusion after restricting the analysis to the set of sell-days when exactly one stock was sold. This influences by construction the measure of the disposition effect they obtain. In contrast, we show that investors have a strong preference for realising more than one stock on the same trading day. Sakaguchi et al. (2019) cannot capture this effect.

An et al. (2019) estimate the disposition effect separately for portfolios which are trading at a gain or at a loss. They observe that the disposition effect is weaker when the portfolio as a whole is trading at a gain (has positive paper return) than when it is trading at a loss. An et al. (2019) propose two possible explanations for their findings. The first possible explanation is related to mental accounting. When the portfolio as whole is trading at a gain investors are more likely to realise losses since they frame the sale of the losing stock as the sale of a share of the entire portfolio, hence a share of an asset which is trading at a gain. Their second explanation builds on Barberis and Xiong (2009), extending realisation utility to paper gains and losses.

There are some important differences in our analyses. Differently from us, An et al. (2019) use the entire dataset of investors regardless of whether they are frequent or infrequent traders. Furthermore, An et al. (2019) focus on the performance of the portfolio as a whole, disregarding the actual imbalance between the number of stocks which are trading at a gain or at a loss. Our analysis shows that this is important. We believe that the actual percentage of positions trading at a gain or at a loss is a salient figure in investors' mind. This idea comes from the literature on naive diversification. We suggest that selling decisions which depend on the percentage of positions at a gain in the portfolio are a form of decision heuristics, similar to naive diversification for buying (Read and Loewenstein, 1995; Benartzi and Thaler, 2001; Gathergood et al., 2019). Hence, we both take a very different psychological perspective on the topic with respect to An et al. (2019) and we expand on their findings by taking into account a much more detailed granularity of the portfolio composition. We estimate the propensity to sell gains and losses for various levels of the percentage of stocks trading at a gain. These estimates are used to compute the disposition effect across varying compositions of the bank account.

2.3 The Disposition Effect for any bank account composition

Here, we explain the reasoning and implementation of the estimation of the disposition effect stratified by percent of stocks at a gain given in Table 2.4 in Section 2.4. An example is given to demonstrate the method.

We define PGR_{At} as the proportion of gains realised in the account A on day t (realised gains divided by paper gains plus realised gains) and PLR_{At} as the proportion of losses realised in the account A on day t (realised losses divided by paper losses plus realised losses). DE_{At} is defined as the difference between PGR_{At} and PLR_{At}. We define PG_{At} as the percentage of positions trading at a gain in the account A on day t. We partition percentages into a (small) number of equally-sized gain bins and only distinguish bin numbers for PG_{At}, but they may change from day to day even within the same account. Given a particular bin number j, we can find all the days t for which PG_{At} belongs to j. We call this set of days $T_A^{(j)}$ and denote the number of days in this set by $\# T_A^{(j)}$.

We now calculate account level disposition effects restricted to days where the percent gain is in a particular bin. These disposition effects at account-gain bin level $\mathrm{DE}_A^{(j)}$ are constructed as follows. For each account A and each gain bin j, average the account-day-gain bin disposition effects $\mathrm{DE}_{At}^{(j)}$ over all days $T_A^{(j)}$. These are temporal averages and can be expressed via the formula:

$$\mathrm{DE}_A^{(j)} = \frac{1}{\# T_A^{(j)}} \sum_{\text{all days } t \text{ in } T_A^{(j)}} \mathrm{DE}_{At}. \tag{2.1}$$

We now aggregate over accounts to focus on dependency of the disposition effect on percent gain. The disposition effects at gain bin level $\mathrm{DE}^{(j)}$ are constructed as averages of the disposition effects at account-gain bin level $\mathrm{DE}_A^{(j)}$ over accounts. The collection of these over all gain bins is the percent gain stratified disposition effect. They are averages over accounts. Written as a formula, using # accounts for the total number of accounts in the data sets, we obtain

$$\mathrm{DE}^{(j)} = \frac{1}{\#\,\text{accounts}} \sum_{\text{all accounts A}} \mathrm{DE}_A^{(j)}. \tag{2.2}$$

Averaging first over days and then over accounts gives each account holder the same weight, regardless of how often and over what length of periods the account holder traded. This ensures that the estimates of the percent gain stratified disposition effect are not driven by a few particularly active traders. We include a numerical example based on the values in Table 2.1.

Table 2.1: **Gain stratified disposition effect. An Example.** Numerical example data showing two accounts A and B with 3 and 5 trading days, respectively. DE and PG bin are both at account-day level. DE refers to the disposition effect. PG bin refers to the percent of stocks at a gain, with 1 referring to $[0, 0.5]$ bin and 2 referring to $(0.5, 1]$ bin. From these we calculate summaries of the disposition effect at account-gain-bin level and at gain-bin level.

Account	Day	DE	PG bin	DE account-gain-bin	DE gain-bin
A	1	0.22	1	0.20	0.19
	2	0.18	1	0.20	0.19
	3	0.02	2	0.02	0.03
B	1	0.15	1	0.18	0.19
	2	0.05	2	0.04	0.03
	3	0.03	2	0.04	0.03
	4	0.20	1	0.18	0.19
	5	0.19	1	0.18	0.19

The calculations for the disposition effect at account-gain-bin and at gain-bin level were carried out as follows. The average disposition effects at account-gain-bin level are, using (2.1),

$$
\begin{aligned}
\mathrm{DE}_A^{(1)} &= \frac{1}{2}(\mathrm{DE}_{A1}^{(1)} + \mathrm{DE}_{A2}^{(1)}) = \frac{1}{2}(0.22 + 0.18) = 0.20 \\
\mathrm{DE}_A^{(2)} &= \mathrm{DE}_{A3}^{(2)} = 0.02 \\
\mathrm{DE}_B^{(1)} &= \frac{1}{3}(\mathrm{DE}_{B1}^{(1)} + \mathrm{DE}_{B4}^{(1)} + \mathrm{DE}_{B5}^{(1)}) = \frac{1}{3}(0.15 + 0.20 + 0.19) = 0.18 \\
\mathrm{DE}_B^{(2)} &= \frac{1}{2}(\mathrm{DE}_{B2}^{(2)} + \mathrm{DE}_{B3}^{(2)}) = \frac{1}{2}(0.05 + 0.03) = 0.04
\end{aligned}
$$

The average disposition effects at gain-bin level are, using (2.2),

$$
\begin{aligned}
\mathrm{DE}^{(1)} &= \frac{1}{2}(0.20 + 0.18) = 0.19 \\
\mathrm{DE}^{(2)} &= \frac{1}{2}(0.02 + 0.04) = 0.03
\end{aligned}
$$

The numbers in Table 2.1 were chosen to show the same message as the real data set considered in this chapter. They show that the disposition effect is negatively associated with the percentage of stocks at a gain in the account. A summary (in the style of Table 2.4) is given in Table 2.2.

Table 2.2: **Gain stratified disposition effect. An Example; Part 2.** Calculated using results of Table 2.1.

Perc. of gains	DE
[0,0.5]	0.19
(0.5,1]	0.03

2.4 Data and methodology

We restrict our attention to approximately 5% of the bank accounts present in the LDB dataset, which account for more than 35% of the investment episodes. This corresponds to bank accounts where 24 or more investment episodes were started. After restricting our attention to this subset of accounts, we censor investment episodes. We only include investment episodes where the selling date is no later than 400 days from the buying date, in line with Brettschneider and Burgess (2017). We do this in order to capture active decisions of traders rather than buy and hold decisions. After imposing this condition and deleting (a very small number of) trades for which we suspected data were misreported, we retain bank accounts where at least 20 trading episodes were completed. This resulted in 114,441 episodes from 2,783 bank accounts (Table 2.3).

Table 2.3: Summary Statistics of the sample.

Summary Statistics of the sample.	
Bank accounts	2,783
Episodes	114,441
Episodes per bank account (mean)	41.12
Episodes per bank account (median)	31
Percentage of gains in an account-stock-day (mean)	0.48
Percentage of gains in an account-stock-day (median)	0.50
Number of stocks in an account-stock-day (mean)	8.35
Number of stocks in an account-stock-day (median)	5

In this section, we give a preliminary estimate of the disposition effect that takes into account the percentage of stocks at a gain in the account. In other words, we calculate a disposition effect stratified by the current percentage of a stocks at a gain in the account, following the method explained in Section 2.3. For each bank account, on each day when at least one stock is realised, we calculate PGR and PLR following Odean (1998), where PGR is the Proportion of Gains Realised

$$\text{PGR} = \frac{\text{Realised Gains}}{\text{Realised Gains} + \text{Paper Gains}}$$

and PLR is the Proportion of Losses Realised

$$\text{PLR} = \frac{\text{Realised Losses}}{\text{Realised Losses} + \text{Paper Losses}}$$

For each such day, we calculate the disposition effect following Dhar and Zhu (2006) as the difference between PGR and PLR. For days when at least one stock is realised, we also determine the percentage of stocks which are trading at a gain in the bank account and classify it in one of four bins (0 to 0.25; 0.25 to 0.5; 0.5 to 0.75 and 0.75 to 1). Then, we calculate the disposition effect at account-gain-bin level. That is, we average the disposition effect, at account level, over all days in which a given account falls in a given gain bin. Finally, we calculate the disposition effect at the gain-bin level. That means, we average the disposition effect at account-gain-bin level over accounts, to obtain the average disposition effect for each of the four bins. The output is shown in Table 2.4. We observe striking differences in the magnitude of the disposition effect, depending on the percentage of stocks at a gain. The disposition effect is ten times larger in bin 1 than in bin 4[3].

[3] A Jonckheere-Terpstra test confirms that the DE decreases when the percentage of

Table 2.4: **Disposition effect stratified by percentage of stocks at a gain.** Disposition effect (DE) was calculated in three steps. First, disposition effect was estimated as PGR-PLR within each account on any day where at least one stock is realised. Then, these account-day disposition effects were averaged over days, stratified by the percentage of stocks at gain within each account. Here, four equally sized bins were used for the stratification. Finally, within each of these gain bins, averages over accounts were taken resulting in the four quantities listed below. A Jonckheere trend test (also known as Jonckheere-Terpstra test) confirms that the disposition effect decreases with increasing percentage of stocks at a gain ($P < 0.001$).

Perc. of gains	DE
[0.00, 0.25]	0.20
(0.25 ,0.50]	0.18
(0.50, 0.75]	0.08
(0.75, 1.00]	0.02

We can go beyond these preliminary estimates by performing regression analyses to estimate the disposition effect. The unit of observation is an account-stock-day triple (An et al., 2019). The dependent variable takes the value of 1 for sell days and 0 otherwise. While the earlier literature used logit models (Grinblatt and Keloharju, 2001; Birru, 2015), more recent works employ a linear probability model (Chang et al., 2016; An et al., 2019). In all these cases, the effects that covariates have on the different propensities to sell are mediated by an interaction with a dummy variable which indicates if a stock is trading at a gain on a specific day. Ai and Norton (2003) highlighted that the magnitude of the interaction effect in logit models does not equal the marginal effect of the interaction term and it can be of opposite sign. A linear probability model guarantees an easier interpretation of marginal effects and a robust identification of the coefficients. Furthermore, a linear approximation is sufficient, because the range of the probabilities is small and the sample size is large enough to guarantee approximately normal residuals. We model heteroskedasticity by fitting robust clustered standard errors at bank account level (Arellano, 1987). We estimate three linear probability models. The first model focuses on the impact of the percentage of stocks at a gain in the

gains increases ($p<0.001$, H_1 that the disposition effect is decreasing from bin 1 to bin 4, where bin 1 corresponds to gain percentage between 0 and 0.25 and bin 4 to gain percentage between 0.75 to 1).

account. It takes the following form:

$$y_{ijt} = \alpha + G_{ijt}\beta + D_{kijt}\delta_k + G_{ijt} \times D_{kijt}\gamma_k \tag{2.3}$$

where i refers to the bank account, j refers to the investment episode and t to the day. Then:

Response: y_{ijt} is equal to 1 on those days t when the stock traded in episode j in account i is sold, and 0 otherwise.

Gain: G_{ijt} is a dummy equal to 1 on those days t when the stock traded in episode j in account i is trading at a gain (closing price is higher than (or equal to) purchase price).

Sextile percentage of gains: D_{kijt} with k $\in$ {1,2,4,5,6} are five dummies we obtained in the following way:

- Consider all days when more than one stock was open in a given bank account.
- Calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling, traded in episode j).
- Split the percentage of stocks at a gain into six sextiles (based on the distribution of the percentage of gains at account-stock-day level). Observed sextiles are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1.
- Each dummy D_k refers to one of the sextiles, imposing the third one as the reference category.

The intercept α measures the probability of selling a loss when the percentage of gains in the account is in the third sextile. β captures the difference in the propensity to sell a gain and the propensity to sell a loss for the third sextile, the disposition effect. δ_k captures the difference in the propensity to realise a loss when the account is in the k^{th} sextile with respect to the third sextile. The sum of β and δ_k measures the disposition effect for the k^{th} sextile. We obtain out of sample prediction for the probability to sell a gain and the probability to sell a loss, for any of the gain percentage sextiles. The disposition effect is then calculated as the difference between the probability of selling a gain and the probability of selling a loss, following the widely used definition of Odean (1998).

The second and third models focus on the impact of realisations of stocks other than the one in question, distinguishing gains and losses. They take the following form:

$$y_{ijt} = \alpha + G_{ijt}\beta + I_{ijt}\delta + G_{ijt} \times I_{ijt}\gamma \tag{2.4}$$

In the second (third) model, I_{ijt} is a dummy equal to 1 if, on a given day t, at least one stock at a gain (loss), (apart from the stock traded in episode j) is realised in the bank account i. β captures the disposition effect and δ the difference in the propensity to realise a loss when a gain (a loss) is realised in the account, apart from the stock traded in episode j. The sum of β and γ captures the disposition effect on days when a stock at a gain (loss), apart from the stock traded in episode j, is realised in bank account i.

For each model described, we fit three regressions. First, the baseline model as defined in Equation (2.3) and Equation (2.4). Second, a Fixed Effects OLS regression with fixed effects at the account level. We do this to control for the propensity to sell a stock that is unique to each account. The propensity to sell may be linked to trading frequency, size or other account specific characteristics. Third, a Fixed Effects OLS regression with fixed effects at the account level and control variables for month and year (and respective interactions with the gain dummy). This is to control for differences in the propensity to sell due to time.

2.5 Variation in the Disposition Effect with Portfolio Composition

Our key finding is that from a wide framing perspective, the disposition effect vanishes for some portfolio compositions. Our first set of results are summarised in Table 2.5, which reports the estimation of model (2.3). From these estimates, we obtain out-of-sample predictions displayed in Figure 2.1 and summarised in Table 2.6. We will discuss these first. Table 2.6 reports the propensities to sell for each sextile of the distribution of the percentage of stocks trading at a gain in an account day. For example, we can see that the propensity to sell when the percentage of gains is in the first sextile and the stock is trading at a gain (gain dummy equal to 1) is 2.7%. These propensities are presented graphically in the lower panel of Figure 2.1. The disposition effect, based on the relative propensities to sell, is also reported in Table 2.6, and in the upper panel of Figure 2.1.

From the top panel of Figure 2.1, we see that the disposition effect is largest when the percentage of stocks trading at a gain in the account is lowest. The observations in the lower panel of Figure 2.1 show that the spread between the propensity to realise a gain and the propensity to realise a loss is largest when the percentage of gains in the account is in the first sextile.

In other words, investors tend to sell one of their few stocks at a gain, rather than one of the many they hold at a loss. Table 2.6 examines this in more detail by estimating the disposition effect for any sextile of the distribution of the percentage of gains in the account. It demonstrates that the disposition effect broadly decreases as the percentage of stocks trading at a gain increases. The disposition effect increases slightly from the fifth to the sixth sextile, but it is close to 0 from the fourth sextile onwards, when the percentage of positions at a gain in the account is higher than 50%.

The lower panel of Figure 2.1 displays the relative magnitudes of the propensities to realise gains and losses, which together drive the disposition effect. Our first observation is that the propensity to realise a gain varies much more than the propensity to realise a loss, for any level of the percentage of stocks at a gain in the account. In particular, the propensity to realise a loss lies between 1.08% and 1.7%, whilst the propensity to realise a gain is between 1.3% and 2.7%. The reduction of the disposition effect we described above, is largely driven by a reduction in the propensity to realise a gain as the percentage of stocks trading at a gain in the account increases.

Two technical observations arise from the more detailed analysis of the estimation of model (2.3) presented in Table 2.5. First, the effect of the percentage of stocks at a gain is not linear, hence stratifying by sextiles was appropriate. Second, estimates are fairly stable when we control for bank account and time fixed effects. The direction and magnitude of the effects are fairly stable across all specifications.

Our finding is a breakthrough in the literature on the disposition effect. We have shown that investors are not prone to the disposition effect, when the overall situation of their portfolio is positive. Other authors have demonstrated considerable variation in estimates of the disposition effect for different types of investors. Grinblatt and Keloharju (2001) observed that the disposition effect is weaker for institutional and foreign investors than for domestic investors in Finland. Dhar and Zhu (2006) found that the disposition effect is weaker for more experienced investors. Feng and Seasholes (2005) found that the disposition effect decreases in time for a given investor as sophistication and trading experience increase. What we see is different. We observe that the disposition effect varies significantly as the account composition changes. Our finding that the disposition effect decreases as the percentage of stocks trading at a gain increases is almost counter-intuitive. When the number of paper gains is higher, the difference in the propensity to realise gains and losses is smaller. When times are good, the disposition effect becomes almost non-existent.

Table 2.5: **Sextile of gains regression.** Linear probability model (given in (2.3)) where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, we split it into sextiles. Observed sextile are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category.

	OLS	FE	FE
Gain	0.00404***	0.00484***	0.00766***
	(0.000411)	(0.000498)	(0.000708)
Sextile percentage of gains (ref. Third)			
First	0.000998***	-0.00492***	-0.00530***
	(0.000302)	(0.000354)	(0.000353)
Second	-0.00139***	-0.00232***	-0.00235***
	(0.000296)	(0.000292)	(0.000294)
Fourth	-0.000406	0.00173***	0.00179***
	(0.000405)	(0.000373)	(0.000397)
Fifth	0.00115***	0.00249***	0.00258***
	(0.000260)	(0.000307)	(0.000304)
Sixth	0.00442***	0.00169***	0.00154***
	(0.000367)	(0.000370)	(0.000366)
Gain × Sextile percentage of gains (ref. Third)			
Gain × First	0.00989***	0.0110***	0.0112***
	(0.000587)	(0.000653)	(0.000654)
Gain × Second	0.00422***	0.00469***	0.00479***
	(0.000484)	(0.000522)	(0.000527)
Gain × Fourth	-0.00321***	-0.00376***	-0.00386***
	(0.000487)	(0.000512)	(0.000512)
Gain × Fifth	-0.00418***	-0.00471***	-0.00484***
	(0.000412)	(0.000438)	(0.000441)
Gain × Sixth	-0.00145**	-0.00144*	-0.00148*
	(0.000510)	(0.000574)	(0.000574)
Time FE	NO	NO	YES
N	6611755	6611755	6611755

Standard errors clustered at bank account level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.1: **Disposition effect and sextile of gain percentages.** Out of sample predictions of the linear probability model (first column in Table 2.5) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level, clustered se at bank account level). Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, and split it into sextiles. Observed sextiles are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category.
Top: Disposition effect (propensity to realise a gain minus the propensity to realise a loss) for each level of the sextiles of the distribution of the percentage of gain stocks in the portfolio. Brown line is drawn at 0 (no disposition effect).
Bottom: Probability of sale for gains and losses for each level of the sextiles of the distribution of the percentage of gain stocks in the portfolio.

Table 2.6: **Disposition effect and sextile of gain percentages.** Estimated propensity to sell a gain and propensity to sell a loss for each sextile of the distribution of the percentage of stocks trading at a gain in an account-day. Disposition effect is calculated as the difference between the propensity to realise a gain and the propensity to realise a loss. Out of sample predictions of the linear probability model (first column in Table 2.5) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level, clustered se at bank account level). Sextiles of stocks trading at a gain are obtained as follows: we calculate the percentage of stocks trading at a gain (excluding the stock for which we are estimating the probability of selling) in a given account-day, and split it into sextiles. Observed sextiles are marked by the following cut-points (these are the upper limits of each category): 0.10, 0.33, 0.50, 0.61, 0.80, 1. The third sextile is the reference category.

Sextile of gain perc.	1	2	3	4	5	6
Propensity to sell gain	0.027	0.019	0.016	0.013	0.013	0.019
Propensity to sell loss	0.013	0.011	0.012	0.012	0.013	0.017
Disposition effect	0.014	0.008	0.004	0.001	0.000	0.003

Although mental accounting is a potential explanation (An et al., 2019), we will now propose some alternative explanations for our result. A first possibility entails reference point updating. Arkes et al. (2008) showed in an experimental setting that investors update upwards (downwards) their reference point after an asset increases (decreases) in price. Investors only partially update the reference point, and they update it asymmetrically, by more in the gain than in the loss domain. Chiyachantana and Yang (2013) propose a reference point updating mechanism to explain the disposition effect. They argue that, when the stock is trading below the reference point, the investor is in the risk seeking region of the S-shaped utility function. Hence, choosing between a sure loss and a risky loss she will prefer the risky loss and hold on to the stock. If she adapted her reference point down to the current price, she would stop to perceive it as belonging to the loss domain and sell it (since it would be a choice between a sure gain and a risky gain and the investors would be in the risk averse portion of the S-shaped utility function).

We now apply this line of reasoning to our results and start with the loss domain. Suppose that the effect found by Arkes et al. (2008) holds. When the stock enters the loss domain, the investor does not immediately update the reference point downwards and the price will be lower than investor's reference point. We see in Figure 2.1 that the propensity to realise a loss is relatively constant and only increases when the percentage of stocks at a gain is very high. One possible driver for the increased propensity to realise a loss is the following: when there are only a small number of losing stocks in the account, they are evaluated as being relatively worse since the investor compares them to the large number of winning stocks. Hence, she is willing to adjust the reference point of that loss downwards to the current price and to realise losses. The propensity to realise a gain is at its highest when the percentage of stocks trading at a gain is really low (Figure 2.1). Using a similar line of reasoning, an investor considers those few gains to be relatively valuable as compared to a large number of losing stocks. She adjusts the reference points of the winning stocks upwards, closer to the running prices, which leads to a higher propensity to realise gains.

We can suggest other explanations for the pattern we observe. For example, regret (Loomes and Sugden, 1982) or disappointment (Bell, 1985; Loomes and Sugden, 1986; Jia et al., 2001; Delquié and Cillo, 2006) might play a role. Anticipated regret might explain why investors realise gains when they have relatively few winning positions. Regret refers to the idea that a decision maker would regret obtaining an outcome which is ex-post sub-optimal. When the percentage of gains is low, the worst possible outcome would be that those few gains end up in the loss domain. Hence, the investor chooses to sell them now, before their price decreases. On the other hand, when the proportion of positions at a paper gain is higher, the investor would not be as concerned that she may not realise any gain at all and would not necessarily rush to sell. The central idea of disappointment theory is that an individual forms an expectation about a risky alternative, and may experience disappointment if the outcome obtained falls short of this expectation. If investors have a well defined expectation regarding their future earnings, it is likely that their expectation will be positive, otherwise they would have not bought the stock in the first place. Hence, when the percentage of gains in the account is low, the probability of the final outcome falling short of expectations is high. Then, individuals rush to realise the few gains they have, in order to meet their ex-ante expectations.

This explanation is linked to the rational belief that if the investor has more stocks in the gain domain, then the likelihood that she will have a loss is smaller. On the other hand, if the investor has only a few stocks in the gain domain, then the likelihood that she will have a gain is small. This automatically leads to a higher propensity to realise gains when there is only a few of them in the account. In this framework, this behaviour is not irrational. If the objective of the investor is to maximise the number of investments sold for a gain, it is perfectly rational selling one of the few gains when she mainly has losses on her account, since the likelihood that many of those losses will turn into gains is small. Another possibility is that the investor updates her confidence on her own stock selection ability. In the situation where she only has a few gains, the investor might have lower confidence in her own stock selection ability. She might think that those few gains are in her account because of some lucky circumstances and rush to sell them since she became more pessimistic on her choices.

A final explanation might rely upon investor attention (Barber and Odean, 2008; Dierick et al., 2019). We see that the propensity to realise a gain is lower for balanced compositions of the bank account. It might be the case that unbalanced compositions of the portfolio lead the investor to focus their attention on their investments, and to be more active, by realising positions. We emphasise that it is very important to focus on the propensity to realise a gain and the propensity to realise a loss separately, as we do (lower panel in Figure 2.1). We are not only interested in estimating changes in the disposition effect, but also in unraveling whether they are linked to the variation in the propensity to realise a gain or the propensity to realise a loss.

2.6 The Impact of Realising Other Gains and Losses on the Propensity to Sell

In our second set of results, we investigate the impact that the realisation of *other gains or losses* in the account has on the propensity to realise a stock. Tables 2.7 and 2.9 report the results from the estimation of the linear probability models given in (2.4), where another loss or gain, respectively, is realised. From these estimates, we obtain out-of-sample predictions which are given in Tables 2.8 and 2.10, again, for the situation of another loss or gain, respectively.

Our first striking observation from Tables 2.8 and 2.10 is that investors have a high propensity to realise a stock if they are already realising another one, on a given day. In particular, the propensity to realise a loss is around 50% and the propensity to realise a gain is slightly higher than 10% on those days when another stock at a loss in the account is realised. The propensity to realise a loss is slightly smaller than 10% and the propensity to realise a gain is around 50% on those days when another stock at a gain in the account is sold. These magnitudes should be compared to baseline propensities to sell on days when another loss or gain is not realised, which are all in the region of 1%-1.7%.

Portfolio or bank account effects are very relevant. In particular, the fact the investors have a much higher propensity to realise another stock, once they have realised one, is an indication that decisions regarding stocks in the same account are correlated. Furthermore, realising a gain makes it more likely to realise another gain than to realise a loss, and realising a loss makes it more likely to realise another loss than to realise a gain. We note that this effect cannot be captured using the framework adopted by Sakaguchi et al. (2019), since they restrict their analysis to sale days where only one stock is realised in a portfolio.

How might we explain the observed behaviour? The notion of investor attention (Barber and Odean, 2008) may be relevant. If investors only pay attention to their portfolio on some days, then they also trade more on those days. Another possible explanation may be related to reference point updating, particularly for investors' realising multiple losses on the same day. Upon realising the sale of one stock trading just below its reference point, an investor may update (downgrade) her reference points on other stocks trading at paper losses as well, leading to further sales. A further possibility is simply that since realising losses is difficult, it may be a defense mechanism to realise more than one at the same time.

Whilst we demonstrate that the realisation of a gain (loss) significantly increases the propensity to realise another gain (loss), we also find that it increases the propensity to realise a loss (gain). For example, the propensity to sell a gain rises sixfold when a loss is realised on the same day (in the same account). This can shed some light on why the disposition effect varies with portfolio composition. If investors have a preference for realising a gain and a loss on the same day, on days when there is a low percentage of gains, the propensity to realise a gain will be high and the propensity to realise a loss will be low. This follows from the fact that, on those days, the investor can choose from a small pool of stocks at a gain, and a larger pool of losing stocks. PGR, as defined in Odean (1998) will have a very low denominator and PLR will have a high denominator. As the percentage of gains in the account increases, we expect the propensity to realise a loss to increase, and the propensity to realise a gain to decrease. This describes well the pattern we observe in Figure 2.1

Table 2.7: **Other loss indicator regression.** Linear probability model (given in (2.4)) where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Other loss realised indicator is a dummy which takes the value of 1 if, on a given account-day, a stock at a loss is realised (other than the stock whose propensity is being estimated).

	OLS	FE	FE
Gain dummy	0.00701***	0.00876***	0.0107***
	(0.000328)	(0.000416)	(0.000642)
Other loss realised indicator	0.488***	0.487***	0.486***
	(0.0291)	(0.0276)	(0.0275)
Gain dummy × Other loss realised indicator	-0.399***	-0.399***	-0.399***
	(0.0273)	(0.0263)	(0.0263)
Time FE	NO	NO	YES
N	7133537	7133537	7133537

Standard errors clustered at bank account level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.8: **Disposition Effect and other loss indicator.** Disposition effect when a loss is realised in the account on a given day or not. Disposition Effect is calculated as the difference between the propensity to realise a gain and the propensity to realise a loss. Out of sample predictions of a linear probability model (first column of Table 2.7) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level). Other loss realised refers to those day when, in a given account, a stock at a loss is realised (other than the stock whose propensity is being estimated).

Propensity to sell gain	Propensity to sell loss	Other loss realised	Disposition Effect
0.017	0.010	NO	0.007
0.105	0.497	YES	-0.392

Table 2.9: **Other gain indicator regression.** Linear probability model (given in (2.4)) where the dependent variable takes the value of 1 for sale days and 0 for hold days. Each observation is at account-stock-day level. Gain dummy is equal to 1 on those days when the stock is trading at a gain. Other gain realised indicator is a dummy which takes the value of 1 if, on a given account-day, a stock at a gain is realised (other than the stock whose propensity is being estimated).

	OLS	FE	FE
Gain dummy	0.00358***	0.00486***	0.00640***
	(0.000294)	(0.000349)	(0.000556)
Other gain realised indicator	0.0762***	0.0738***	0.0735***
	(0.00317)	(0.00306)	(0.00307)
Gain dummy × Other gain realised indicator	0.409***	0.407***	0.407***
	(0.0296)	(0.0287)	(0.0286)
Time FE	NO	NO	YES
N	7133537	7133537	7133537

Standard errors clustered at bank account level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.10: **Disposition Effect and other gain indicator.** Disposition effect when a gain is realised in the account on a given day or not. Disposition Effect is calculated as the difference between the propensity to realise a gain and the propensity to realise a loss. Out of sample predictions of a linear probability model (first column of Table 2.9) where the dependent variable takes the value of 1 for sale days and 0 for hold days (observations at account-stock-day level). Other gain realised refers to those day when, in a given account, a stock at a gain is realised (other than the stock whose propensity is being estimated).

Propensity to sell gain	Propensity to sell loss	Other gain realised	Disposition Effect
0.015	0.011	NO	0.004
0.500	0.087	YES	0.412

and leads the disposition effect to decrease as the percentage of stocks at a gain increases. The probability of realising a loss increases as the percentage of gains increases, while the probability of realising a gain follows a U-shape. It is lower in sextile 6 than in sextile 1 but it does reach the minimum in sextile 4. We are not suggesting that the preference for realising multiple stocks on the same day alone leads to the variation in the disposition effect that we observe, but it potentially contributes to it. Hence, the finding that investors tend to realise more than one stock on a given day, contributes to partially explain the mechanism which leads the disposition effect to change with the account composition.

The fact that the realisation of a gain (loss) has a dramatic impact on the propensity to realise another gain (loss) does not affect this explanation. Let's focus on the case where the percentage of gains is high. We know that realising a gain will increase the probability of realising another gain, and will also increase the probability of realising a loss, albeit to a lesser extent. Hence, there will be variation in the disposition effect due to changes in both PGR and PLR. However, since the denominator of PGR is high, the marginal (increasing) contribution that any realisation of gains has on the disposition effect, will be less than the marginal (decreasing) contribution that any loss has on the disposition effect, since the denominator of PLR is low.

2.7 A wide framing perspective on the disposition effect

These findings shed new light on the literature on narrow framing (Thaler and Johnson, 1990; Barberis et al., 2006). We suggest investigating investors' choices from a wide framing perspective, also in other domains. Choices might depend not only from the characteristics of the stock the investor is trading but also from the characteristics of other stocks in the bank account.

In his chapter we focused on a sample of relatively active traders (the 5% most active, who account for 35% of trades in the LDB dataset). We proposed a description of the disposition effect from a wide framing perspective. We looked at how the disposition effect changes when the percentage of stocks trading at a gain in a specific account-day changes. We estimated the propensity to realise gains and losses when more than one stock is realised on a given account-day.

We observed that when the percentage of stocks trading at a gain on a given account-day increases, the disposition effect is much lower and in some cases it disappears: the propensity to realise losses is higher than the propensity to realise gains. Our findings are similar to Sakaguchi et al. (2019) and An et al. (2019). However, Sakaguchi et al. (2019) impose some constraints on their data in order to fit a two-stage psychological model of sale. They restrict their analysis to those trading days when only one stock per account is realised. This influences their conclusions by construction and prevents them from observing the effect we find, that individuals have a preference for realising more than one stock at the same time. Moreover, Sakaguchi et al. (2019) found that the probability of realising a gain is independent of the number of stocks in the gain domain, while we found that the relationship between the propensity to realise gains and the percentage of stocks at a gain follows a U-shape and it is highest when the percentage of stocks trading at a gain is lowest. An et al. (2019) focused on the overall performance of the portfolio and how the disposition effect changes with it. The main conclusion is that the disposition effect is weaker when the portfolio as a whole is trading at a loss than when it is trading at a gain. We proposed some possible explanations, like mental accounting, reference point adaptation and disappointment. Our work has important implications for future research. First, we have shown the importance of a wide framing perspective. Taking such a perspective may lead to new findings in other settings. Second, given the prevalence and accessibility of financial trading across the economy, it is imperative to understand how portfolio composition shapes individual sale decisions. In particular, it would be of interest to see the extent to which our findings hold in other datasets which have been studied in relation to the disposition effect.

Our main conclusion represents an important advance in the literature on the disposition effect. It is already well known that the disposition effect is not necessarily the same for all types of investors (Grinblatt and Keloharju, 2001; Dhar and Zhu, 2006). However, we control for fixed effects at account and time level and we find that the disposition effect changes from period to period at the individual level. When the percentage of stocks trading at a gain in a given account-day is higher, the disposition effect is lower. That is almost counter-intuitive, since we observe that when the number of paper gains that the investor can choose to sell is relatively higher, the difference in the propensity to realise gains and losses is smaller. The disposition effect does not capture the behaviour of investors in all possible situations. In particular, it is more likely to occur in bad times than in good times.

Chapter 3

Reference Point and Disposition Effect

3.1 Introduction

The disposition effect has already been discussed in Chapter 2 from a wide framing perspective. There, we focused on how it changes as the portfolio composition changes. Here, we ask the question if the disposition effect changes if we change the reference point with respect to which we measure it. As we already pointed out, the disposition effect is the tendency to realise gains at a higher rate than losses (Shefrin and Statman, 1985; Odean, 1998; Barber and Odean, 2013). In measuring it, gains and losses are defined with respect to the purchase price. That is the most natural term of comparison and it is also the appropriate benchmark from an accounting point of view. However, we suggest that, at the psychological level, investors might not define gains and losses with respect to the purchase price but they might adopt an alternative reference point. The reference point is a vital component of Kahneman and Tversky Prospect Theory. Kahneman and Tversky (1979) introduced Prospect Theory as a descriptive alternative to the normative theory of Expected Utility. There are three main elements of Prospect Theory. First, people derive utility from gains and losses relative to a reference point, while traditional utility theory assumes that people derive utility from total wealth or consumption. Second, the value function is concave in the domain of gains and convex in the domain of losses (S-shaped utility). The shape of the function captures "dual risk attitudes": individuals tend to be risk averse in the gain domain but risk seeking in the loss domain. Third, the effect of a loss on utility is much larger than that of a gain of the same size ("loss aversion"). One possible explanation of the disposition effect is framed in terms of Prospect Theory where each of the S-shaped utility, loss aversion, and use of a reference point play a role (Barberis and Xiong, 2009; Henderson, 2012; Ingersoll and Jin, 2013). In this chapter, we focus on the formation of the reference point. We cannot elicit the reference point of investors, while they trade. However, it is natural to expect that investors would incorporate information unfolding since the purchase date of an investment, on the formation of their reference point. To make this point more clear, imagine that an investor buys a stock on day 1 at a price $p_1 = 100$ and she is considering the possibility of selling it on day 200. Will she evaluate the price on that day, p_{200} against the purchase price p_1 or will she compare it to some weighted average of the prices she experienced from day 1 to day 200. Imagine that the stock started decreasing in price from day 1 to day 100, reaching a minimum of $p_{100} = 90$, then it rebound and it started increasing in price, up to $p_{200} = 95$. Selling the stock at a price $p_{200} = 95$ is for sure a loss, from an accounting point of view. However, we suggest it might not be considered as a loss from a psychological point of view. If the investor puts more weight on recent prices, when forming her reference point, she might have a reference point which is lower than 95. Hence, she might consider the realisation of that stock as a gain, from a psychological point of view. This leads us to the three questions which we will try to address in this chapter:

- Is it possible that the disposition effect does not exist or it is attenuated, from a psychological point of view?
- Can we find a reasonable reference point formation rule which supports this statement?
- Are there different rules which attenuate the disposition effect for different investors' categories?

Our main conclusion is that, once we depart from the definition of the reference point as the purchase price, we can observe a lower disposition effect. Once we define gains and losses with respect to recent realisations of the trading price, we find that the disposition effect is strongly attenuated. The propensity to realise stocks which recently appreciated (local gains) and stocks which recently depreciated (local losses) is very similar. However, this is not true for any investors. As a general pattern we find that investors who trade less but for longer time tend to have a low disposition effect, when measured with respect to the purchase price. Investors who trade more have a lower disposition effect, when measured with respect to recent price realisations. We also test other possible reference point rules and produce a detailed comparison of two of them.

3.2 The quest for the reference point

In the early years of Prospect Theory, Tversky and Kahneman (1991) argued that "although the reference point usually corresponds to the decision maker's current position it can also be influenced by aspirations, expectations, norms, and social comparisons". Many years later Barberis (2013) claims that addressing the formation of the reference point is still a key challenge to apply Prospect Theory. Our hypothesis that the reference point might not be the purchase price and might stem from an adaptation process which incorporates intermediate prices, is backed up by both theoretical derivations and experimental observations of reference point adaptation.

Kőszegi and Rabin (2006, 2007) propose that the reference point does not need to be fixed exogenously but can be determined endogenously based on rational expectations about future outcomes. They develop a model where the reference point is determined endogenously by the economic environment. They assume that a person's reference point is her rational expectations held in the recent past about outcomes. The derivation of Kőszegi and Rabin (2006) stems from the idea that, in the presence of uncertainty, expectations change as the uncertainty is resolved. For example, in within-day labor-supply decisions, a worker is less likely to continue work if the income earned is unexpectedly high, but more likely to show up as well as continue work if expected income is high. Several theoretical models suggest an important role for the reference point in explaining the disposition effect (Shi et al., 2015; Meng and Weng, 2018; Andrikogiannopoulou and Papakonstantinou, 2019). Meng and Weng (2018) is an extension of the model proposed by Barberis and Xiong (2009). They show that an expectations-based reference point model can explain the disposition effect, under Prospect Theory preferences. In particular, a model based on loss aversion in Prospect Theory can explain the disposition effect under the Kőszegi and Rabin (2006) setting. Their model can explain the disposition effect by allowing the reference point to depend on the lagged values of the expected final wealth, only. They also predict that the disposition effect is more likely to be present when the reference point is not updated quickly enough, when the expected stock return is low, and when stock trading is infrequent. More generally, their model predicts that the quicker investors are able to adjust their reference points, the less conservative they are in initial purchase decisions. They do not commit to any specific mechanism of reference point formation but they suggest that "investors may linearly extrapolate from their past returns to form new expectations, or demonstrate overoptimistic beliefs and representative biases". Shi et al. (2015) as well propose to adopt a dynamic updating reference point, which is state and decision dependent, into a dynamic portfolio choice model. They model an asymmetric reference point adaptation, which causes the disposition effect. In their framework, investors update their reference point upwards after good news more than how they update it downwards after bad news since prior trading outcomes affect the reference point through its adaptation process. In turn, the shift in the reference point affects future trading actions. Although they use a partial and asymmetric adaptation in their specifications, their reference point model is rich enough to incorporate different patterns of reference point adaptation. Andrikogiannopoulou and Papakonstantinou (2019) propose a method to estimate a dynamic reference point and test it in the context of trading data from a sports wagering market. They find that if the reference point is not sticky to the first price, Prospect Theory can explain the prevalence of the disposition effect. They argue that betting data from people with a long story of trading are a good approximation of stock trading and go on to document that the disposition effect is explained, in that context, by a model where the reference point is a convex combination of the initial level and the intermediate levels of wealth. They structurally estimate a memory decay parameter and they conclude that investors take into account intermediate levels of wealth, since the memory decay is weaker than in the setting of Barberis and Xiong (2009), where memory decays immediately and the reference point is sticky to the initial level of wealth.

The formation of the reference point has been directly investigated in a series of experimental papers (Arkes et al., 2008, 2010; Baucells et al., 2011; Baillon et al., 2020) and in the context of financial investment (Quispe-Torreblanca et al., 2020). In an experimental setting, Arkes et al. (2008) show that investors tend to update their reference point upwards after a good outcome realises and downwards after a bad outcome realises. They find that the magnitude of reference point adaptation following a price change is not as large as the magnitude of the price change itself, and any adaptation is asymmetric with a greater adjustment after good, than after bad outcomes. This finding replicates in China, South Korea and the USA (Arkes et al., 2010). In the first treatment of their experiment Arkes et al. (2008) ask the two following questions.

- Two months ago, you bought a stock for \$30 per share. Last month, you were delighted to learn the stock was trading higher at \$36 per share. This month, you decide to check the stock's price again. At what price would the stock need to trade today to make you just as happy with the stock's price this month as you were when you learned the stock had risen from \$30 to \$36 last month? The average answer was \$40.24 with an implied adaptation of \$4.24.

- Two months ago, you bought a stock for \$30 per share. Last month, you were disappointed to learn the stock was trading lower at \$24 per share. This month, you decide to check the stock's price again. At what price would the stock need to trade today to make you just as sad with the stock's price this month as you were when you learned the stock had dropped from \$30 to \$24 last month? The average answer was \$21.49 with an implied adaptation of \$2.51.

Adaption was found to be greater after gains than after losses of the same size. The effect replicated, holding expectations constant, including the possibility of repurchasing the stock and introducing portfolio effect, by assuming that other stocks were present in the portfolio. Most importantly, the findings were replicated in a setting which involved financial incentives, adopting the Becker et al. (1964) procedure. They follow the same procedure we have just described, with a small change. At the beginning of the trading round, subjects are told that they purchased a stock at a certain price (p_0) and have held the stock for a week. They are then informed of the current price p_1, which is either higher or lower than their purchase price p_0. Also, they are informed of the two future possible prices of the stock in the next trading period (p_2). Before the realisation of the second period price p_2, subjects have a chance to sell the stock to the experimenter by stating their minimum selling price. Then, a buying price is randomly drawn between the two possible future prices. If the randomly drawn buying price exceeds or equals the subject's minimum selling price, the subject sells the stock at the randomly drawn buying price. If the buying price is less than the minimum selling price, the subject holds the stock and sells it at the next trading period's price p_2 which is determined by a coin flip. Under the Becker et al. (1964) procedure, it is optimal for the subjects to set their minimum selling price equal to their valuation of the gamble. Thus, the procedure reveals through subjects' minimum selling prices their valuations of risky gambles, which in turn helps us infer how their reference point changes after they experience gains or losses. The update of the reference point was still higher after gains than after losses. Starting from a stock price of $p_0 = \$20$, the reference point increased by \$5.75 after a \$6 increase and it decreased by \$5.13 after a \$6 dollar decrease.

In a lab experiment, Baucells et al. (2011) elicit the reference point after individuals experience a streak of payoffs and propose a recursive formula to derive the reference point. In their experiment, subjects were shown some streams of payoffs and they were subsequently asked the following question, to which we will refer as the "emotional neutrality question": At what selling price would you feel neutral about the sale of the stock, i.e., be neither happy nor unhappy about the sale? Values were obtained for 60 different streams of payoffs, which pairwise, had only one different characteristic. For example, take the sequence $s_2 = \{250, 200, 150, 200\}$ and the sequence $s_1 = \{150, 200, 250, 200\}$. They have different starting (purchase) prices but they have the same minimum, maximum, average and final value. Hence, the average difference that subjects give in the evaluation of the sequences s_1 and s_2 accounts for the causal effect of the purchase price on the reference point. If the subjects gave the same answer to the "emotional neutrality question" after looking at both sequence s_1 and s_2 the implications would be that the purchase price has no effect on the formation of the reference point. Baucells et al. (2011) find that the purchase price and the current price have a positive and significant correlation with the reference point. The average of the intermediate prices (200 and 250 in s_1) and the maximum price have a positive but weaker effect on the reference point and they find mixed evidence for the lowest price. Baucells et al. (2011) also test the impact of two other characteristics of the price path: dashed hope vs false alarms and early vs late. In the dashed hope case, an increase precedes a decrease; and in the false alarm, a decrease precedes an increase. The increases and decreases are of the same magnitude and the difference in reference points is found to be highly significant (higher in the dashed hope case). In the early vs late several combinations of two different patterns unfolded at an early or late stage of the payoff stream but no effect was found. Baucells et al. (2011) go on to estimate a recursive formula and a segregated formula to calculate the reference point, one of which we will refer to in Section 3.3. The formulas were tested, through out-of-sample predictions and revealed to have good external validity. In the context of static decisions, Baillon et al. (2020) discriminate amongst several alternative reference point rules. In a laboratory experiment, subjects were faced with the choice amongst several prospects and the reference point is elicited through a hierarchical Bayesian model. They find that three models explain around 80% of the choices of their participants. Around 30% used the so called "status quo"[1] as the reference point. Around 30% of the subjects were consistent with the MaxMin rule (use the highest of the minimal values of all prospects) and around 20% with the "prospect itself" as the reference point (Delquié and Cillo, 2006; Kőszegi and Rabin, 2006, 2007). If the prospect itself is the reference point, then the decision maker will, for example, re-frame the prospect (0.50, 100; 0.50, 0) as a 25% chance to gain 100 (if she wins 100 and 0 is the reference point, the probability of this happening is 0.50×0.50), a 25% chance to lose 100 (if she wins nothing and 100 is the reference point), and a 50% chance that she wins or loses nothing (if either she wins 100 and 100 is the reference point, or she wins nothing and nothing is the reference point). Finally, in the context of financial trading decisions Quispe-Torreblanca et al. (2020) measure the disposition effect with respect to the purchase price and with respect to the price of the last login, in a sample of British investors. Measuring the disposition effect with respect to the last login price means that stocks which appreciated since the last login of the investor are classified as a gain and stocks which depreciated are classified as a loss. Quispe-Torreblanca et al. (2020) find that investors realise a stock at a higher rate if the stock is in the gain domain with respect to both reference points. They also find that the disposition effect with respect to the purchase price is higher than the disposition effect calculated with respect to the last login price.

3.3 Alternative reference points for the disposition effect

We analyse the bank accounts in the LDB dataset where at least a stock for a gain and at least one for a loss were realised, at any point in time. As we did

[1] The equivalent of using the purchase price in our case

in the other chapters, the starting point of an investment is the first time an investor buys a stock or any time she buys it without the stock being present in the bank account at that time. The end point of an investment is the first sale date after that buy date (Shapira and Venezia, 2001; Brettschneider and Burgess, 2017). We define an episode as all the day-stock information between a buy and a sell date. An episode is classified as a gain if the selling price is higher or equal than the buy price. It is classified as a loss otherwise. The summary statistics of the sample are contained in Table 3.1.

Table 3.1: **Summary Statistics of the sample.**

Bank Accounts	29374
Episodes	371403
Episodes per bank account (mean)	12.64
Episodes per bank account (median)	7
Episode length in trading days (average)	227.95
Episode length in trading days (median)	113

To calculate the disposition effect we follow the procedure of Dhar and Zhu (2006). For each bank account, on any days where at least one stock is traded, we calculate the Proportion of Gains Realised, PGR, and the Proportion of Losses Realised, PLR. Then we average over all days at the account level, to obtain the average DE for any bank account. The proportion of gains realised is equal to the number of stocks sold for a gain divided by the number of stocks in the bank account which are trading at a gain on that day and equivalently for losses to define PLR (see Section 2.4 for a definition of PGR and PLR). There is a subtle but fundamental difference with what we did in Chapter 2. There, we stratified over bank account-gain percentage and then averaged over those two dimensions. Here, we only need to stratify at the bank account level, since we are not interested into within bank account variations of the disposition effect. To be more precise, we now calculate the average disposition effect at the account level. For each bank account A there is a sequence of days T_A where at least one stock is sold. For the number of days in this set we use $\#T_A$. On any day, $t \in T_A$, we obtain PGR_{At} as the proportion of gains realised on day t in account A and PLR_{At} as the proportion of losses realised on day t in account A. DE_{At} is defined as the difference between PGR_{At} and PLR_{At}. The disposition effect at the account level DE_A is constructed as follows. For each account A we obtain the average $\overline{PGR_A}$ and the average $\overline{PLR_A}$. These are temporal averages and can be expressed via the formula:

$$
\begin{aligned}
\overline{PGR_A} &= \frac{1}{\# T_A} \sum_{\text{all days } t \text{ in } T_A} \mathrm{PGR}_{At} \\
\overline{PLR_A} &= \frac{1}{\# T_A} \sum_{\text{all days } t \text{ in } T_A} \mathrm{PLR}_{At}
\end{aligned}
\tag{3.1}
$$

The disposition effect for a given account A is then

$$
DE_A = \overline{PGR_A} - \overline{PLR_A} \tag{3.2}
$$

Table 3.2: **Disposition Effect assuming that the reference point is the lagged price.** Disposition Effect calculated with respect to a lagged reference point. We defined gains and losses with respect to the price which realised n days before (given in the second column) and recalculated the DE. To give an example, in the first line of the column we report the DE calculated in the following way. We define all stocks whose price increased since the day before as gains (either paper or realised) and all stocks whose price decreased since the day before as losses (either paper or realised). We then calculated PGR, PLR and DE according to this figure. PP stands for Purchase Price. Hence, the last row reports the original disposition effect.

DE	Days
-0.008	1
0.003	2
0.022	3
0.028	4
0.035	5
0.057	10
0.068	15
0.068	20
0.071	30
0.073	40
0.075	50
0.089	PP

As we said in Section 3.1, we will focus on the calculation of the disposition effect with respect to alternative reference points. Our investigation is an "as if" analysis. We cannot elicit the actual reference point of the investors but we can assume they might have a different reference point from the purchase price. In our analysis, we look at how the disposition effect changes

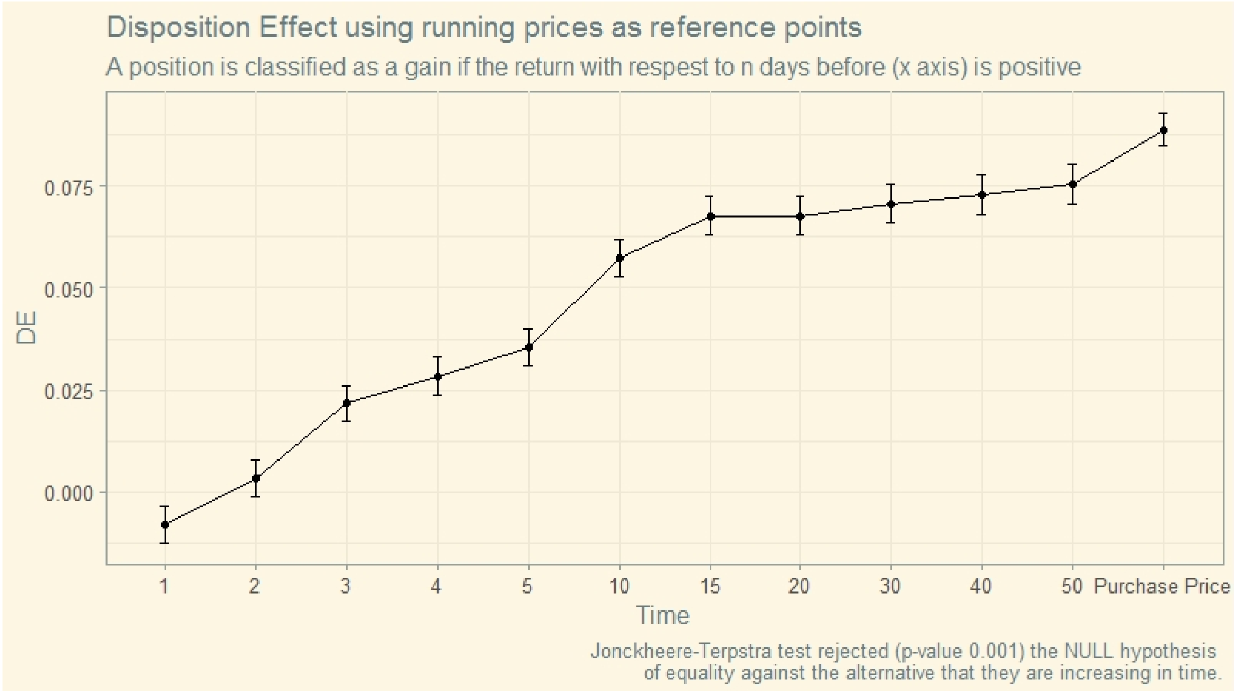

Figure 3.1: **Disposition Effect assuming that the reference point is the lagged price.** Disposition Effect calculated with respect to a lagged reference point. We defined gains and losses with respect to the price which realised n days before (given on the x axis) and recalculated the DE. To give an example, the first value on the left (1 day) reports the DE calculated in the following way. We define all stocks whose price increased since the day before as gains (either paper or realised) and all stocks whose price decreased since the day before as losses (either paper or realised). We then calculated PGR, PLR and DE according to this figure.

if we change the reference point. A preliminary analysis is reported in Figure 3.1 and in Table 3.2. There, we report the disposition effect calculated with respect to several alternative reference points. To make an example the disposition effect is equal to 0.035 if we assume that the reference point is the lagged price of a stock, with a lag of 5 trading days. This means that all the stocks which appreciated with respect to the closing price they had 5 days earlier, are classified as a gain and otherwise as a loss. We calculated it for several alternative reference points. In particular, we calculated it only if the reference point was included in the investment episode. To make it more clear, the DE calculated taking the 5 days lagged price is calculated only for those episodes which lasted at least 5 trading days.

What we see is a very clear and sharp pattern. The disposition effect is higher, the higher is the lag we assume for the reference point. In particular, if we assume that the investors adopt the previous day price as the reference point, we see that the disposition effect disappears (it is slightly negative). This means that the investors do not have a preference for realising stocks which appreciated with respect to stocks which depreciated from the previous day. In general, the disposition effect is attenuated for prices which are different from the purchase price and it is very low if recent prices (lagged price up to 5 tradings days) are adopted as the reference point. We find it reassuring that the trend is increasing as the lag of the reference point is increased. This makes us think that some psychological process might possibly be at work. Our investigation is limited from the fact that we do not actually know if the investors are shifting their attention to some alternative reference points, different from the purchase price. However, it is illuminating to observe that the disposition effect is extremely different, if we assume so. The experimental works we reviewed in Section 3.2 support the view that decision makers incorporate information dynamically in a dynamic decision (Arkes et al., 2008; Baucells et al., 2011). If traders incorporate information unfolding over the course of an investment episode, this means that the disposition effect is not so pronounced for them, from a psychological point of view. It is obviously the case that from an accounting perspective, investors sell their gains too early and keep their losses for too long. We are not saying that the disposition effect should not be defined as an investment bias. We are simply suggesting that from a psychological point of view, this might be a much more limited phenomenon. A decision maker, in this context might not be so prone to realise gains at a much higher rate than losses, it is just the case that she defines gains and losses with respect to a very specific and personal reference point rule. In Section 3.4 we are going to spell out possible differences in the disposition effect assuming that the investors adopt any of 4 possible reference point rules and we are going to investigate which rule minimises the disposition effect for which category of investors, defining the category based on the length and frequency of trading. Finally we will focus on two specific rules and see how investors' characteristics shape the disposition effect according to those two rules and which investors swap from a positive to a negative disposition effect from one rule to the other. Given that the starting point of an investment is day 1 and the purchase price is equal to p_1, the reference point on day n, r_n is defined according to any of the four following rules:

- The reference point is the purchase price (Purchase DE): $r_n = p_1 \ \forall n$;
- The reference point is the average of the last five trading days closing prices: $r_n = \sum_{i=n-5}^{n-1} p_i$ (Recent DE);
- The reference point is the average of all trading days closing prices since purchase: $r_n = \sum_{i=1}^{n-1} p_i$ (AvgAll);
- The reference point is obtained from one of the formulas proposed in Baucells et al. (2011): $r_n = 0.05p_1 + 0.26p_1 + 0.09pmedian_{n-1} + 0.49 * Xp_{n-1} + 0.15pmax_{n-1} - 0.01pmin_{n-1}$ where p_1 is the purchase price. We input the two weights separately to stress that 0.05 is the expected return, in line with Baucells et al. (2011) derivations, and 0.26 is the actual weight given to the purchase price. $pmedian_{n-1}$ is the median price from time 1 to time n-1, $pmax_{n-1}$ and $pmin_{n-1}$ are the maximum and minimum from time 1 to time n-1 respectively (Baucells DE).

They all have a psychological justification. The purchase price is the reference point usually adopted to calculate the disposition effect and it is the reference point from an accounting point of view. The Recent rule characterises an extreme case of updating, an investor who is only focused on the most recent realisations of the price. Recency effects are documented in the psychological and economic literature. Recent prices or wages easily come to mind since recent experiences are close to the current one on the time dimension, and influence judgment even if they are normatively irrelevant (DellaVigna et al., 2017). The psychological literature suggests that, in highly auto-correlated settings (the stock market is such a case), forgetting, and relying on small sets of the most recent experiences, can be very effective (Anderson and Schooler, 1991; Schooler and Hertwig, 2005). The AvgAll rule is inspired by the idea that investors might give the same weight to all the intermediate price of an investment, something similar to the context of Andrikogiannopoulou and Papakonstantinou (2019) but with a non decaying weight for past information. Finally, the rule inspired by Baucells et al. (2011) might look too complicated and a not very realistic description of investors' way of reasoning but it is just a different framing of the AvgAll rule. It is a rule where all the information which unfolded since the purchase date is taken into account, but different weights are given to different salient features of the price path. Before we move to a detailed discussion of our results, we would like to stress two practical points about the PGR and PLR definitions. First, we define a position as trading at a gain on a given day if the closing price on that day[2] is higher or equal than the reference point. Odean (1998) originally defined a stock as trading at a gain if the minimum price on a given day was higher than the purchase price. If the purchase price was between the minimum and the maximum on a given day, that stock was neither defined as a gain nor as a loss, on that day. We made our choice, to avoid a drastic reduction of stocks classified as gains and losses, when using the alternative rules. Take for example the Recent rule. If we stuck to the original definition of Odean (1998) we would have classified a stock as a gain, only if the minimum price on a given day was higher than the average of the closing prices in the five previous days. This would have excluded many observations. In any case, we measured the Purchase disposition effect by following Odean (1998) very closely and by adopting our approach and the difference between the two was negligible. Second, the number of bank accounts for which we are able to measure the disposition effect slightly changes from one rule to the other. The reason is easily explained. We analyse the bank accounts where at least one gain and one loss are realised. Imagine the extreme case of a bank account where only one gain and one loss are realised. When we switch the reference point from the Purchase rule to, say, the Recent rule, they might be both classified as gains. Hence PLR would not be defined and we would not be able to obtain the disposition effect according to the Recent rule. This happens only for a few bank accounts.

[2]The selling price on selling days.

3.4 Results

Table 3.3 and Figure 3.2 show that the disposition effect can change substantially if we assume alternative reference points for the investors. In particular, the Recent rule leads to the lowest disposition effect, while all the other rules do not lead to big changes. Given the pattern we observed in Figure 3.1, this is not surprising. There, we saw that assuming a lag in the reference point of a few days from the running price, led to a strong decrease in the disposition effect, with respect to the Purchase rule. This is reflected by the very small value for the Recent DE. However, assuming a longer lag in the reference point only led to a small decrease in the disposition effect. That is the case when we take into account the AvgAll disposition effect. The AvgAll is slightly smaller (not significantly smaller) than the Purchase DE. This reflects the preponderant effect that realisations of the price further in time have on the formation of this reference point. Finally, the Baucells inspired rule leads to a higher disposition effect than the Purchase rule. This is a consequence of the weight given to the maximum price in the derivation of the reference point, according to this rule. A weight of 15% given to the maximum price can push the reference point to a much higher level than all the other rules. This leads more observation to fall in the losses domain, *a fortiori*. Hence, if we believe that Baucells et al. (2011) give a representative description of the reference point formation, this means that the disposition effect represents a true preference that investors have for realising gains with respect to losses. Actually, this is even more pronounced than what we have so far observed by using the purchase price as the reference point. It should be noticed that the salient features of a series of prices might be more salient for a short series. Hence, the weights which were estimated by Baucells et al. (2011) in the lab are not easily transferable into the field. However, we believe that some salient features have a relevant impact on the decisions of investors. To make an example very close to our discussion, in Chapter 1 we highlighted how relevant the time and level of the past maximum price can be for the decision to realise a stock.

We go on to investigate the differences among investors, asking which rule minimises the disposition effect for them. We are not suggesting that the investor has the goal of minimising the disposition effect. However, we are interested in understanding the impact of the different reference point formation rules on the disposition effect. We checked which rule minimises the disposition effect for any investor and compared them based on the average

Table 3.3: **Disposition Effect with four different reference point rules.** We defined gains and losses with respect to four different reference point and calculated the DE accordingly. The reference point is: 1) Purchase: the purchase price; 2) Recent: the average of the last five trading days price; 3) AvgAll: the average of all prices since purchase; 4) Baucells, a weighted average of prices derived by Baucells et al. (2011): $0.31 * (purchase\, price) + 0.09 \times (median\, rice) + 0.49 \times (1\, day\, lagged\, price) + 0.15 \times (maximum\, price) - 0.01 \times (minimum\, price)$.

DE	Rule
0.089	Purchase
0.026	Recent
0.082	AvgAll
0.111	Baucells

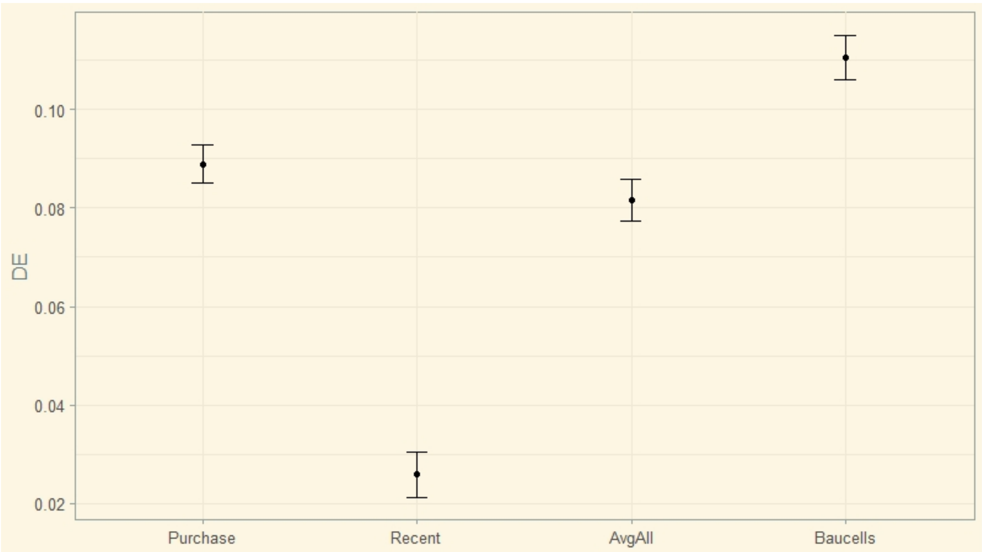

Figure 3.2: **Disposition Effect with four different reference point rules.** We defined gains and losses with respect to four different reference points and calculated the DE accordingly. The reference point is: 1) Purchase: the purchase price; 2) Recent: the average of the last five trading days price; 3) AvgAll: the average of all prices since purchase; 4) Baucells, a weighted average of prices derived by Baucells et al. (2011): $0.31 * (purchaseprice) + 0.09 * (medianprice) + 0.49 * (1daylaggedprice) + 0.15 * (maximumprice) - 0.01 * (minimumprice)$.

Table 3.4: **Reference point minimising rule for the Disposition Effect.** Number of bank accounts for which the disposition effect is minimised by a specific reference point rule. We only included bank accounts for which the disposition effect is minimised by a singles reference point rule. The reference point is: 1) Purchase: the purchase price; 2) Recent: the average of the last five trading days price; 3) AvgAll: the average of all prices since purchase; 4) Baucells, a weighted average of prices derived by Baucells et al. (2011): $0.31 * (purchaseprice) + 0.09 * (medianprice) + 0.49 * (1daylaggedprice) + 0.15 * (maximumprice) - 0.01 * (minimumprice)$.

Number	Rule
3422	Purchase
9528	Recent
3573	AvgAll
3922	Baucells

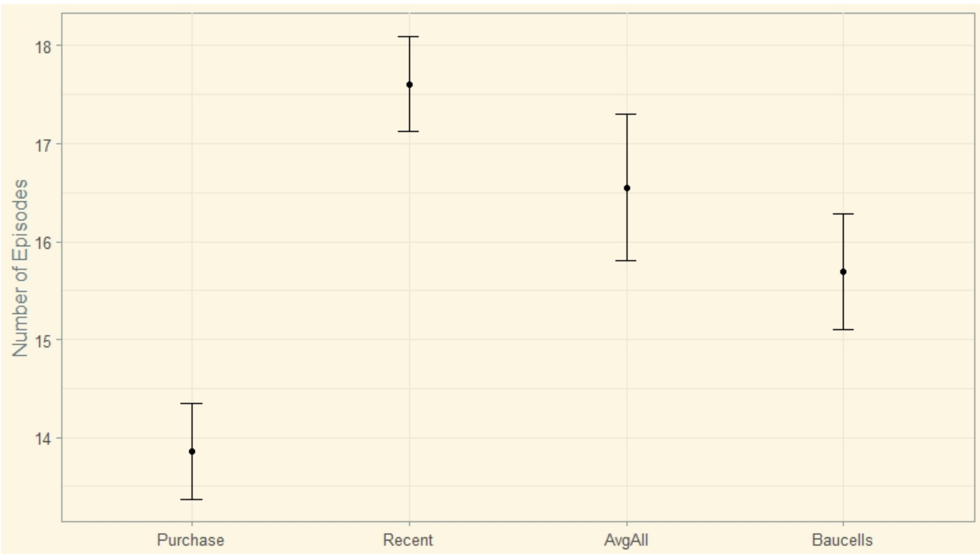

Figure 3.3: **Reference point minimising rule for the Disposition Effect: Average number of episodes.** Average number of episodes for each set of bank accounts for which the disposition effect is minimised by a specific reference point rule. We only included bank accounts for which the disposition effect is minimised by a singles reference point rule. The reference point is: 1) Purchase: the purchase price; 2) Recent: the average of the last five trading days price; 3) AvgAll: the average of all prices since purchase; 4) Baucells, a weighted average of prices derived by Baucells et al. (2011): $0.31 * (purchaseprice) + 0.09 * (medianprice) + 0.49 * (1daylaggedprice) + 0.15 * (maximumprice) - 0.01 * (minimumprice)$.

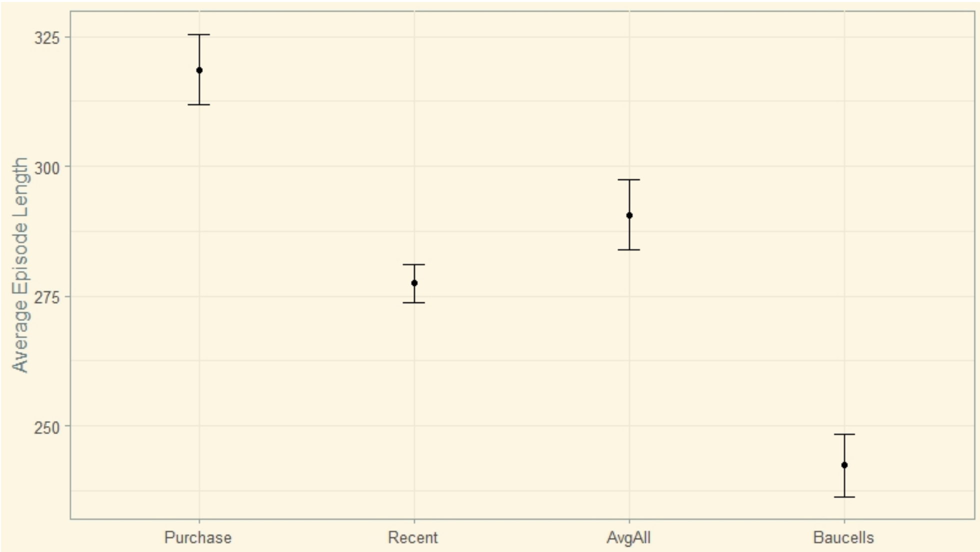

Figure 3.4: **Reference point minimising rule for the Disposition Effect: Average episode length in trading days.** Average episode length in trading days, for each set of bank accounts for which the disposition effect is minimised by a specific reference point rule. We only included bank accounts for which the disposition effect is minimised by a singles reference point rule. The reference point is: 1) Purchase: the purchase price; 2) Recent: the average of the last five trading days price; 3) AvgAll: the average of all prices since purchase; 4) Baucells, a weighted average of prices derived by Baucells et al. (2011): $0.31 * (purchaseprice) + 0.09 * (medianprice) + 0.49 * (1daylaggedprice) + 0.15 * (maximumprice) - 0.01 * (minimumprice)$.

Table 3.5: **Purchase DE and Recent DE comparison: Disposition Effect presence.** Percentage of bank accounts which show the disposition effect under Purchase or Recent rule. We defined gains and losses with respect to two different reference points and calculated the DE accordingly. The reference point is: 1) Purchase: the purchase price; 2) Recent: the average of the last five trading days price.

	NO Recent DE	YES Recent DE
NO Purchase DE	0.32	0.12
YES Purchase DE	0.20	0.35

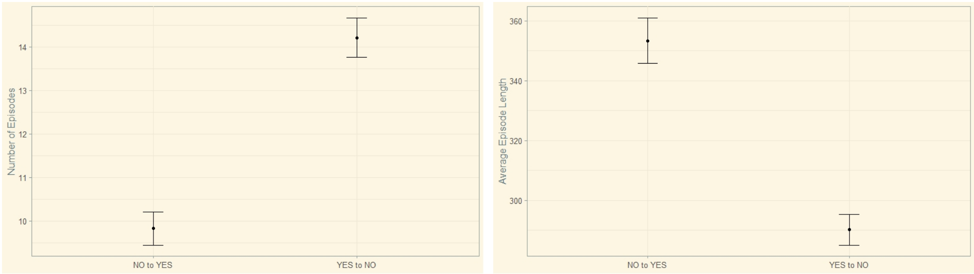

Figure 3.5: **Positive to negative Disposition Effect under two reference point rules: Number of episodes and Average episode length.** Left: Average number of episodes for bank accounts. Right: Average episode length for bank accounts. YES to NO is the set of bank accounts for which the disposition effect is strictly positive under the purchase reference point and zero or negative under the recent reference point. NO to YES is is the set of bank accounts for which the disposition effect is strictly positive under the recent reference point and zero or negative under the purchase reference point. Purchase reference point rule defines gains and losses w.r.t. the purchase price. Recent reference point rule defines gains and losses w.r.t. the average of the last five trading days price.

number of episodes and the average length of their trades. We take into account only bank accounts for which the disposition effect is minimised by a single rule. To make an example, if the disposition effect for a given bank account is 0.03 following the Purchase rule, 0.04 following the Recent rule, 0.05 following the AvgAll rule and 0.03 following Baucells rule, this account is not considered, since there is a tie between the Purchase rule and the Baucells rule. Most of the bank accounts (83%) for which we were able to obtain the disposition effects under all the four rules, have the disposition effect minimised by a single rule. From Table 3.4 we see that the number of bank accounts for which the Recent rule minimises the disposition effect is almost as big as the number of the bank accounts for which the other three rules minimise the disposition effect. For 9528 bank accounts the Recent rule leads to the lowest possible measure of the disposition effect. This was to be expected, given what we saw in Table 3.3. On average, assuming recent price realisations as the reference point induces a lower disposition effect. Now, we see that the Recent rule minimises the disposition effect for most of the bank accounts. We also checked differences of the bank account for which the disposition effect is minimised by a specific rule (Figure 3.3). Before discussing them, we would like to point out that in our discussion we focus on two characteristics of the bank accounts: number of trades and average trade length. We investigated differences induced by other demographic characteristics (Dhar and Zhu, 2006) but since we did not find significant differences and since demographics are only available for a limited sample of individuals, we decided to focus on a bigger sample and on trading frequency and length, only. We find that the group of bank accounts for which the disposition effect is minimised by the Purchase rule is characterised by a lower number of investment episodes. On the other hand, the group of bank account for which the disposition effect is minimised by the Recent rule is made of those bank account which registered the highest number of trades. In principle, we can expect investors with lower trading frequency (value investors) to rely more upon the purchase price as their reference point and traders with higher trading frequency to be more likely to incorporate recent price realisations in their reference point. This expectation is due to the fact that traders who trade more frequently are more likely to often log in their bank account. Hence, information unfolding over the course of an investment is more salient in their mind. We find that the purchase price, which is most likely to describe the reference point mechanism for value investors, leads to a lower disposition effect for that group. Recent price realisations, which are more likely to form the reference point of frequent traders, lead to a lower disposition effect for them. This is not conclusive evidence on the weakness of the disposition effect but it is somehow reassuring that the most likely reference point updating rule for each type of investors, also leads to a lower disposition effect for that group.

In Figure 3.4 we report the average length in trading days of the episodes contained in those bank accounts for which a specific rule minimises the disposition effect. This is an average of averages. We obtained the average length of trades for any bank account and then reported the average of that figure for any category. The bank accounts for which the Baucells rule leads to the minimum disposition effect are characterised by shorter trades, while the bank accounts for which the Purchase rule leads to the lowest possible disposition effect are characterised by longer trades. The Baucells rule is based on the salience of some features of the price process. We believe that those features are more likely to be salient in a shorter investment. What we find is that those investors who we believe are more likely to adopt the Baucells rule, are also those for whom the Baucells rule leads to the lowest possible disposition effect. A final thought on the fact that the Purchase rule is more likely to minimise the disposition effect for investors who trade less times for a longer number of days. We have already argued that we expect value investors to rely more upon the purchase price as their reference point. Value investors make less trades and their trades are longer. The Purchase price leads to the lowest possible measure of the disposition effect for them. We believe that value investors are able to develop some detachment from current price realisations and they might be less emotionally involved by ups and downs of the stocks. We are not surprised that, even when looking at the purchase price, this leads to a low disposition effect, for them.

We now restrict our focus to the comparison between the disposition effect induced by the Purchase rule and the disposition effect induced by the Recent rule. First of all we look at the so called "swappers". We started this chapter saying that, by assuming an alternative reference point rule to the purchase price, we could have observed a lower disposition effect. We already saw that the Recent rule induces, on average, a lower disposition effect. Here, we check for how many investors this is true. Table 3.5 reports the percentage of investors who show the disposition effect under the two rules. We say that the disposition effect is positive if the proportion of gains realised is strictly bigger than the proportion of losses realised. We observe that 32% of the bank accounts do not show a positive disposition effect under either rule, while 35% have a positive disposition effect under both rules. Later in our discussion, we will focus on those bank accounts for which the disposition effect is reduced by the Recent rule (without necessarily going from a positive to a negative disposition effect), with respect to the Purchase rule, but for now we restrict our attention to the set of the swappers. 20% of the bank accounts show a disposition effect under the Purchase rule but do not show it under the Recent rule, while 12% show the opposite pattern. Hence, the number of bank accounts where the disposition effect disappears as a consequence of the change in the reference point (from the purchase price to the average of recent prices) is higher than the number of bank accounts for which the reference point arises as a consequence of the change in the reference point. Figure 3.5 shows the differences in the characteristics of the two groups of swappers. Those who do not show the disposition effect under the Purchase rule but show it under the Recent rule, complete less trades but their trades are longer. Those who show the disposition effect under the Recent rule but do not show it under the Purchase rule, complete more trades and their trades are shorter.

We see a difference between those investors who can be defined as "buy and hold" (or value investors) and those who can be defined as "frequent traders". We appreciate the fact that probably not all investors in a group are "buy and hold" and vice-versa. We will give a much more fine grained analysis of the behaviour of investors based on their trading frequency, in a moment. For now, we can say that the most likely reference point updating rule for each type of investors also leads to a lower disposition effect for that group.

Finally, we compare the Purchase rule and the Recent rule from a detailed perspective. We will focus on four characteristics and see how they vary as the number of episodes in a bank account and the average length of trades in a bank account change:

- Purchase disposition effect;
- Recent disposition effect;
- Percentage of bank account for which the Purchase disposition effect is greater or equal than the Recent disposition effect;
- Average difference between the Purchase disposition effect and the Recent disposition effect. It is obtained as follows: for any bank account we take the difference of the two measures, obtained for that bank account, and we plot the average of the bank account level differences.

First, Figure 3.6 shows how these variables change, depending on the number of episodes in a bank account. We find that the Purchase disposition effect has an inverse-U shaped relationship with the number of trades. The impact of the number of trades on the disposition effect had been investigated by Dhar and Zhu (2006). They found that trading frequency is negatively correlated to the disposition effect. However, they did not take into account investors with few trades[3] and they only included the number of trades as a linear predictor of the disposition effect, hence they could not capture any non linear effects. Given this premise, we believe that our conclusion and theirs are consistent one with the other. This finding is consistent with the idea that trading frequency eliminates the endowment effect. The more investors trade, the lower is the disposition effect. The Recent disposition effect is constant for any level of trading frequency but it drops down sharply for investors who trade very frequently (more than 40 times in the 6 years period).

Investors who trade more are more likely to log in their account very frequently. Hence, we believe they are more likely to adopt the Recent rule

[3]They excluded those who traded less than once per year, hence all the investors who traded less than 6 times in the 6 year period and possibly some of the other groups as well.

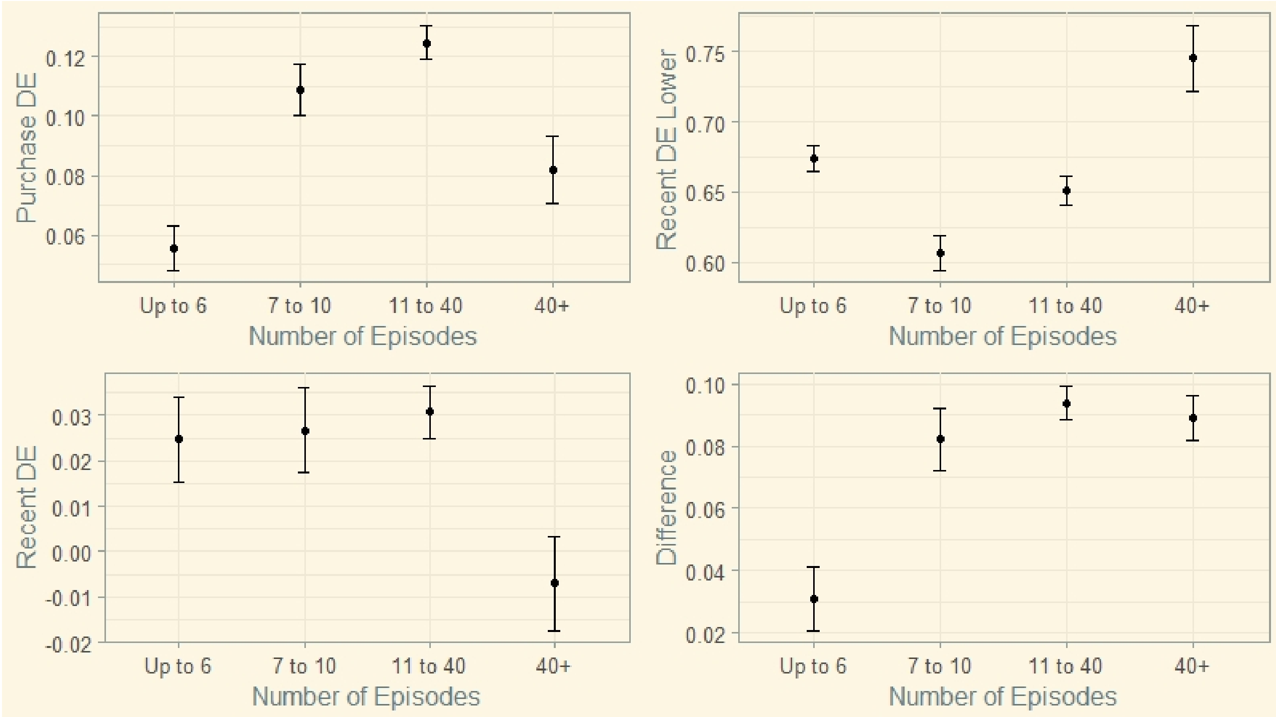

Figure 3.6: **Purchase DE and REcent DE comparison: Number of episodes.** Average number of episodes for bank accounts. Top left panel: Purchase DE, calculated defining gains and losses w.r.t. the purchase price. Bottom left panel: Recent DE, calculated defining gains and losses w.r.t. the average of the last 5 trading days prices. Top right panel: Percentage of bank accounts for which the Purchase DE is greater or equal than the Recent DE. Bottom right panel: difference between the Purchase DE and Recent DE.

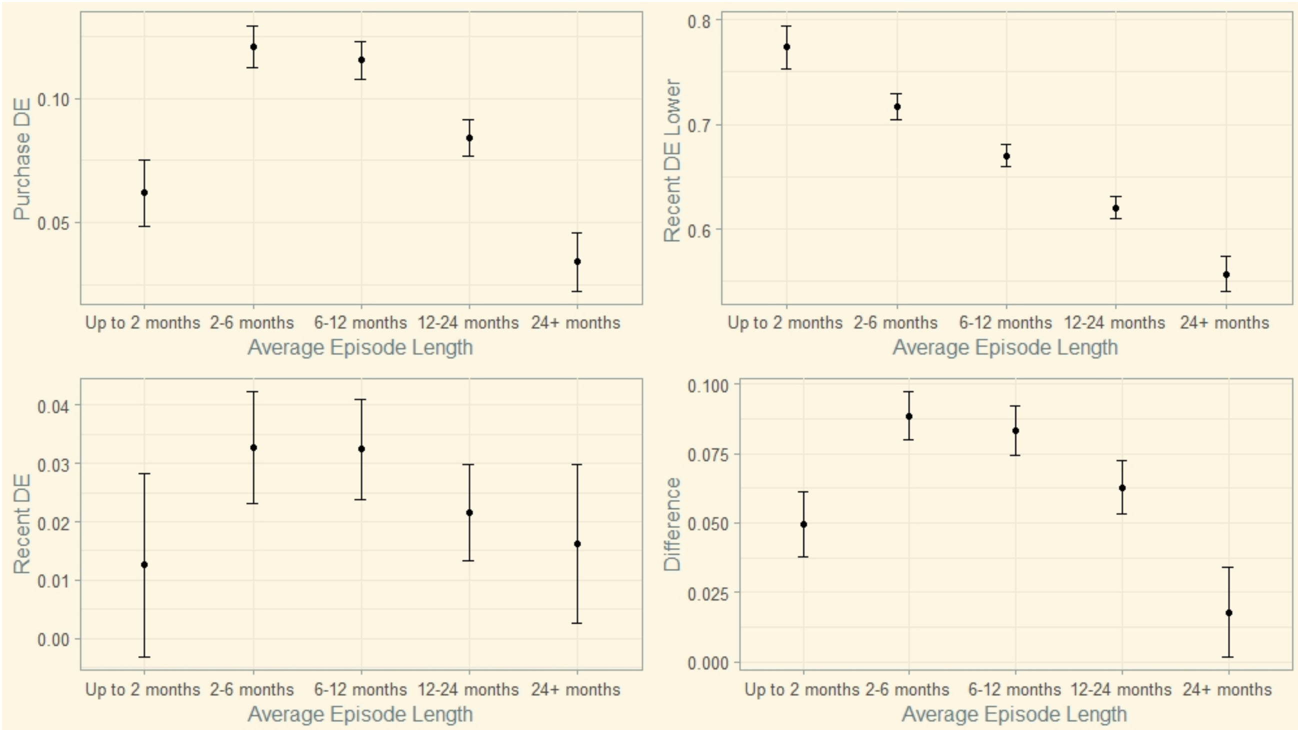

Figure 3.7: **Purchase DE and REcent DE comparison: Average episode length.** Average episode length in trading days for bank accounts. Top left panel: Purchase DE, calculated defining gains and losses w.r.t. the purchase price. Bottom left panel: Recent DE, calculated defining gains and losses w.r.t. the average of the last 5 trading days prices. Top right panel: Percentage of bank accounts for which the Purchase DE is greater or equal than the Recent DE. Bottom right panel: difference between the Purchase DE and Recent DE.

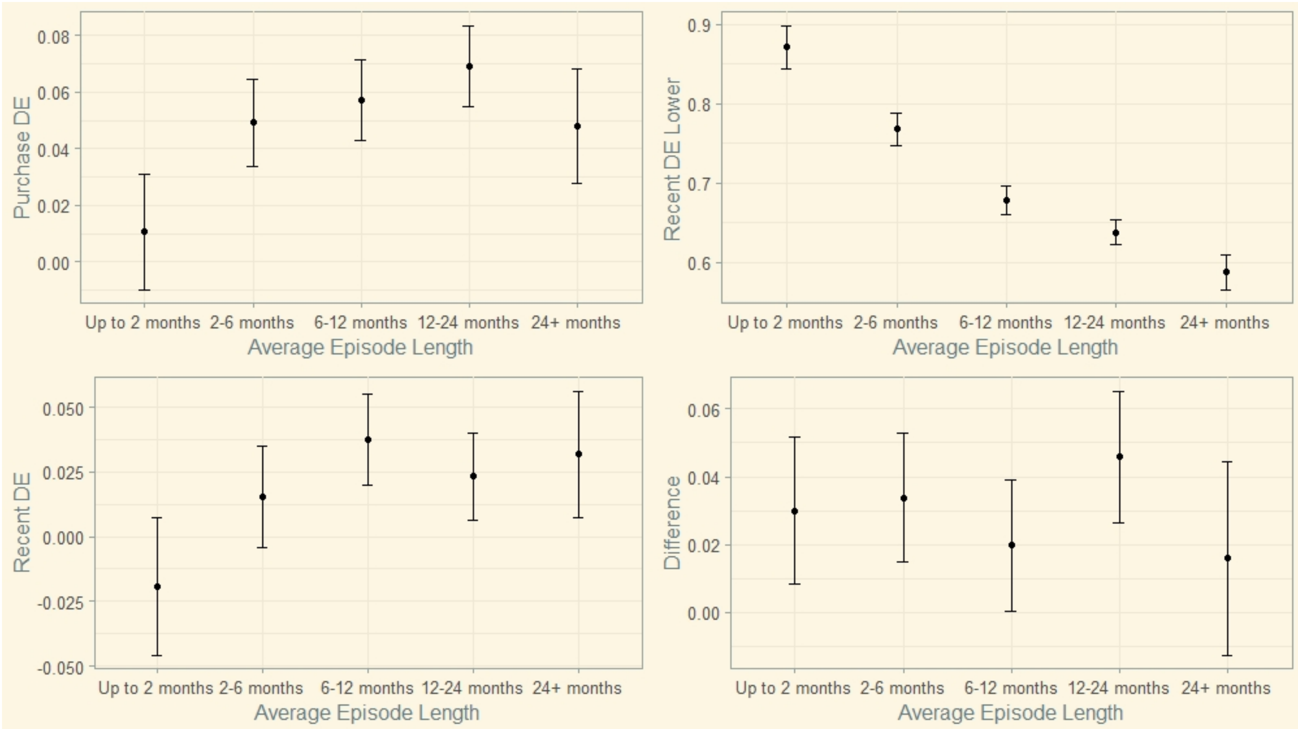

Figure 3.8: **Purchase DE and REcent DE comparison: Average episode length (up to 6 episodes).** Average episode length in trading days for bank accounts where up to 6 trading episodes were recorded. Top left panel: Purchase DE, calculated defining gains and losses w.r.t. the purchase price. Bottom left panel: Recent DE, calculated defining gains and losses w.r.t. the average of the last 5 trading days prices. Top right panel: Percentage of bank accounts for which the Purchase DE is greater or equal than the Recent DE. Bottom right panel: difference between the Purchase DE and Recent DE.

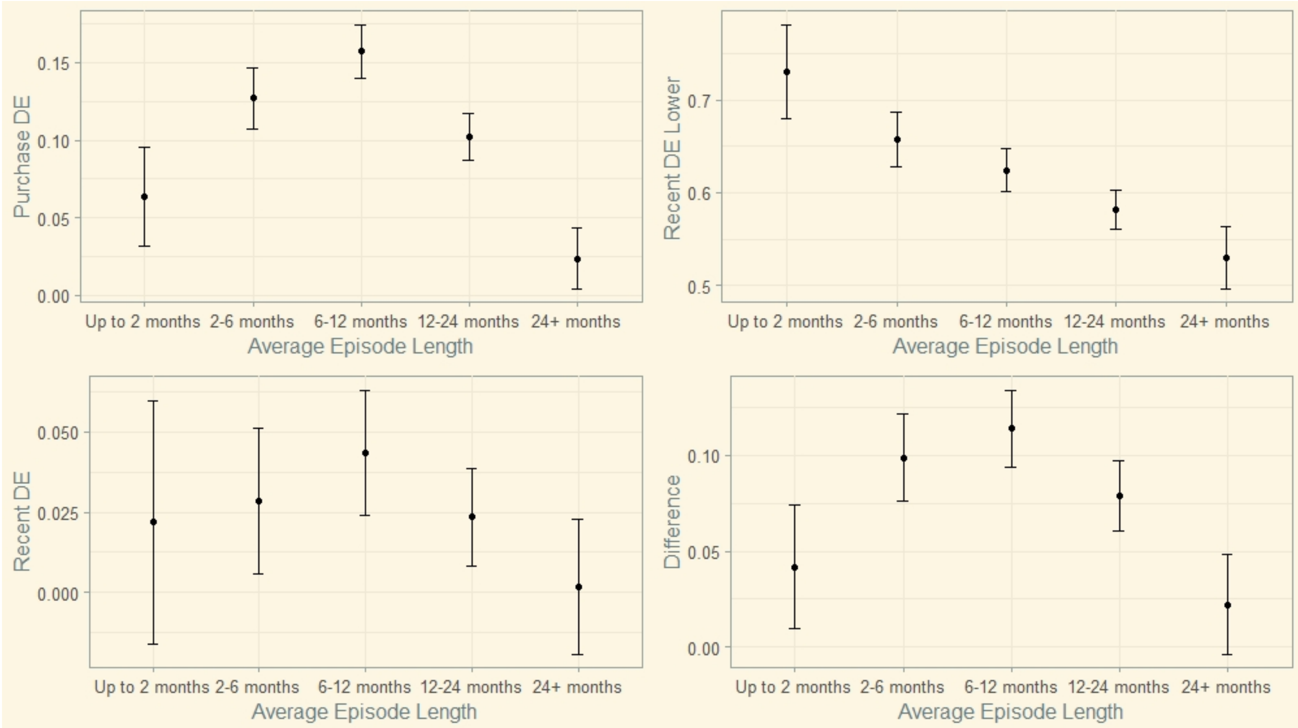

Figure 3.9: **Purchase DE and REcent DE comparison: Average episode length (7 to 10 episodes).** Average episode length in trading days for bank accounts where 7 to 10 trading episodes were recorded. Top left panel: Purchase DE, calculated defining gains and losses w.r.t. the purchase price. Bottom left panel: Recent DE, calculated defining gains and losses w.r.t. the average of the last 5 trading days prices. Top right panel: Percentage of bank accounts for which the Purchase DE is greater or equal than the Recent DE. Bottom right panel: difference between the Purchase DE and Recent DE.

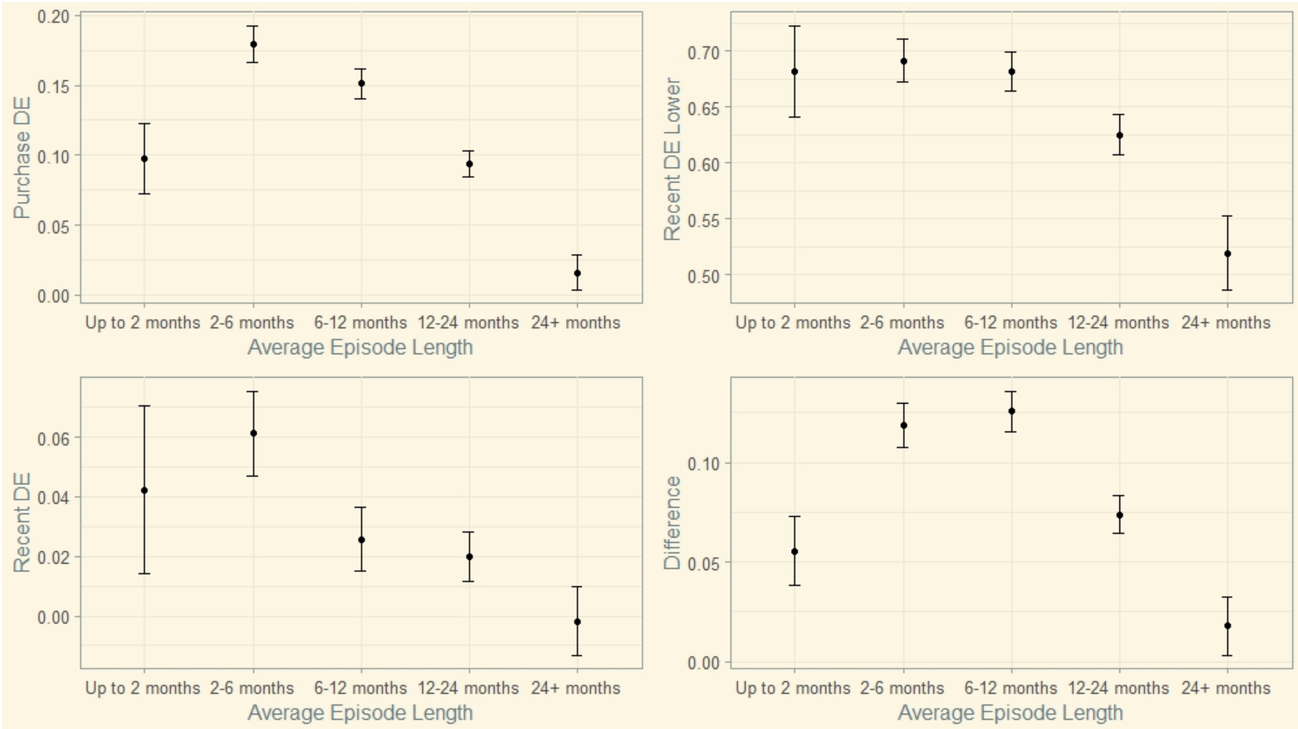

Figure 3.10: **Purchase DE and REcent DE comparison: Average episode length (11 to 40 episodes).** Average episode length in trading days for bank accounts where 11 to 40 trading episodes were recorded. Top left panel: Purchase DE, calculated defining gains and losses w.r.t. the purchase price. Bottom left panel: Recent DE, calculated defining gains and losses w.r.t. the average of the last 5 trading days prices. Top right panel: Percentage of bank accounts for which the Purchase DE is greater or equal than the Recent DE. Bottom right panel: difference between the Purchase DE and Recent DE.

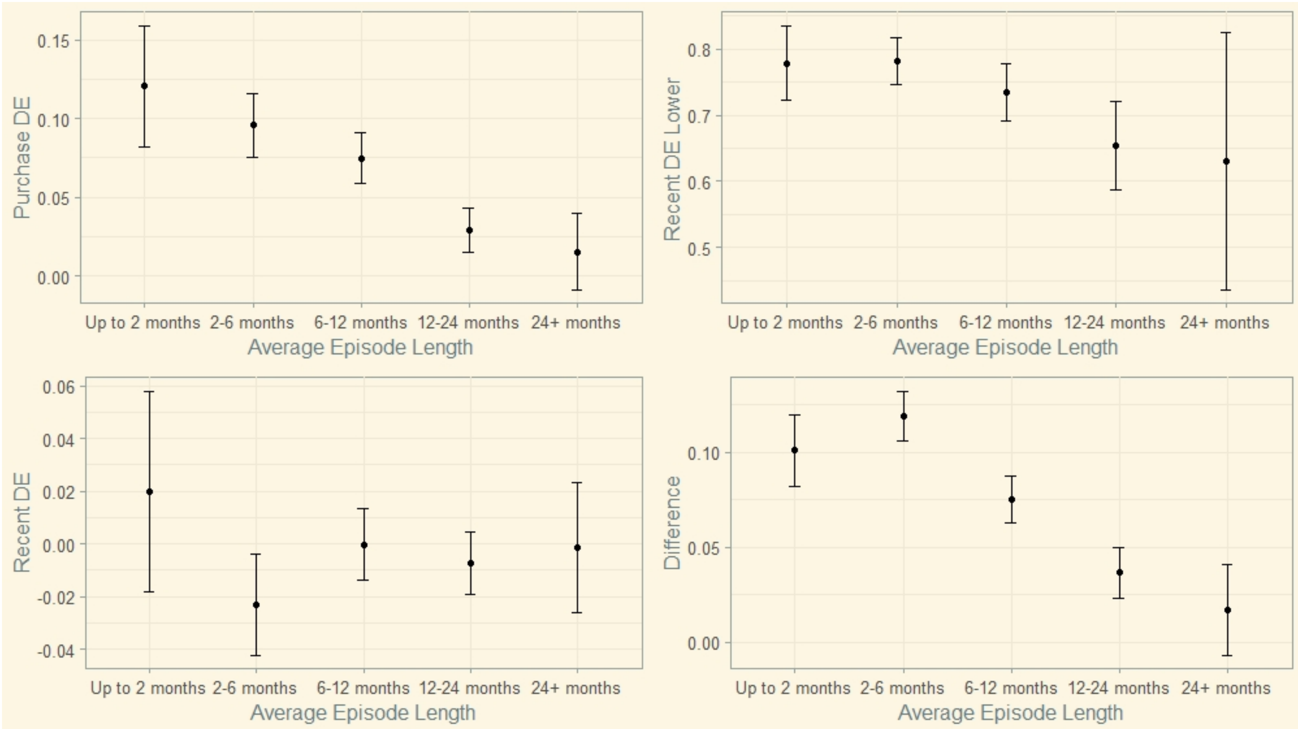

Figure 3.11: **Purchase DE and REcent DE comparison: Average episode length (more than 40 episodes).** Average episode length in trading days for bank accounts where more than 40 trading episodes were recorded. Top left panel: Purchase DE, calculated defining gains and losses w.r.t. the purchase price. Bottom left panel: Recent DE, calculated defining gains and losses w.r.t. the average of the last 5 trading days prices. Top right panel: Percentage of bank accounts for which the Purchase DE is greater or equal than the Recent DE. Bottom right panel: difference between the Purchase DE and Recent DE.

to form their reference point, since recent realisations of the price are more salient in their mind. We see that those investors have a lower disposition effect, according to the Recent rule. Turning our attention to the differences among the two measure we see that in the group of investors who trade more than 40 times the percentage of investors for which the Recent rule leads to a strictly lower disposition effect than the Purchase rule is as high as 75% and the absolute difference among the two is very high. For that group of investors, the two rules give two very different estimates of the disposition effect. This takes our reasoning to the extreme. Those investors trade very frequently and because of that they must log in their account very often. Hence, the Recent rule is probably a very good description of their reference point formation process. That rule also leads to a low disposition effect for many of them. One tentative explanation is that the disposition effect is lower, if we adopt the appropriate reference point rule.

Second, Figure 3.7 looks at the changes induced by the average trade length, measured in trading days. We remind that the disposition effect is always measured at the bank account level. Hence, when we refer, for example, to the average disposition effect when trading length is between 2 and 6 months, we refer to the average disposition effect for those bank account where the average length of trades, at the account level, is between 2 and 6 months. The Recent disposition effect does not change substantially as trading length changes. However, the Purchase disposition effect decreases for traders whose trades are longer. Investors whose trades are longer are "buy and hold" individuals. For them, the Purchase disposition effect is very low, confirming our preliminary estimates from the previous observations. As the average trading length increases, the percentage of traders for whom the Purchase disposition effect is higher than the Recent disposition effect decreases. If, again, we assume that value investors are more likely to use the purchase price as their reference point, we see that they have a lower disposition effect if we calculate it using that rule.

One relevant issue is the interaction between trading frequency and trades length. There might be traders who trade a lot and whose trades are short and traders who trade a lot and whose trades are very long. We now disentangle the differences due to the combination of these two characteristics. We look at the differences we investigated, based on trading length, but we split the analysis by number of episodes categories. From Figures 3.9 and 3.10 we see that in the group of subjects who completed 7 to 10 trades (11 to 40 trades) the general pattern we observed is replicated (almost) perfectly. In the group of traders who completed less than 6 trades (see Figure 3.8), we find a lower level of both measures of the disposition effect and we find that they both increase with the average trades length, but the increase is not strong. This is a departure from the general pattern, especially for the Purchase disposition effect. However, given that the measures are based on only a few observations (only a few selling days) we refrain from over-interpreting these findings. In the group of frequent traders (more than 40 trades in the 6 years window) we also see some departures from the general trend. In particular, the Purchase disposition effect is very high for investors whose trades are short.

Very active traders (see Figure 3.11), who possibly try to take advantage of short price movements, are more prone to the disposition effect. This complements the idea that high frequency in trading activity can increase investment biases (Barber and Odean, 2000). Most importantly, we see that the percentage of traders for whom the Recent rule is lower than the Purchase rule is always very high and does not decline steadily as trading length increases. We stress once more that the Recent rule might be a better description of reference point formation for very active traders. We see that this rule leads to a lower disposition effect for many of them, independently of the length of their trades. We have not found conclusive evidence on our question yet. However, the evidence suggests that traders who are more likely to adhere to a given reference point rule, also see a greater reduction in the disposition effect if that rule is adopted. Hence, there is the possibility that the disposition effect is a smaller effect than what has been so far hypothesised, from a psychological point of view.

3.5 Reference point and disposition effect: a new perspective

In this chapter we addressed three points:

- Is it possible that the disposition effect does not exist or it is very attenuated, from a psychological point of view?
- Can we find a reasonable reference point formation rule which supports this statement?
- Are there different rules which attenuate the disposition effect for different investors' categories?

First of all, we would like to stress the point that we do not have access to investors' belief and we can only hypothesise that they evaluate stocks with respect to some alternative reference point, other than the purchase price. Our hypothesis is supported by the experimental evidence (Arkes et al., 2008; Baucells et al., 2011) but we could not test it with our data. However, we reached one conclusion for sure: there is at least one alternative reference point rule which leads to a lower disposition effect. We took the, so called, Recent reference point rule to define the disposition effect. The Recent rule prescribes that the reference point in an investment is the average of the last five price realisations. Take for example an investment which started on day 1. The reference point on, say, day 18, is the average of the prices from day 13 to day 17. We defined gains and losses with respect to this rule and we found that this led to a decrease in the disposition effect of 70%. This is an advancement into the study of the relationship between reference point updating and the disposition effect, per se. We reached the conclusion that there is at least one rule which leads to a strong reduction of the disposition effect. In principle, it was possible that we could not find any rule which led to a decrease in the disposition effect. We cannot obviously claim causality but we are not the first to propose the idea that recent price realisations are salient in the mind of an investor (Arkes et al., 2008; DellaVigna et al., 2017; Quispe-Torreblanca et al., 2020). We also tested alternative reference point formation rules but those did not drastically impact the disposition effect. However, from that analysis we saw that some heterogeneity among investors might be present. Alternative rules lead to the minimisation of the disposition effect for different types of investors.

The main differences are linked to the number of trading episodes completed by the traders and the average trading length of the trading episodes. We detected several patterns but one was really decisive: the split among traders who trade less often for longer time and the traders who trade more but for shorter time. There are obviously several nuances in traders' behaviour but those are the two extremes. On the one hand, the set of value investors, the "buy and hold" investors who trade a few stocks and keep them for a long time. On the other hand, the set of frequent traders. We argued that, if we had to guess which reference point rule best describes reference point formation of the two groups, we would expect that the value investors would be more anchored to the purchase price and the frequent traders to recent price realisations. What we observe is that, on average, the disposition effect induced by the purchase price is linked to a lower disposition, especially for those who trade longer. On the other hand, the disposition effect induced by recent price realisations is linked to a lower disposition effect for those traders who trade more. The debate is not obviously concluded but this is the first evidence that some alternative reference point rules might lead to a sensible decline in the disposition effect. On top of that, the most likely reference point updating rule for each type of investors, also leads to a lower disposition effect for that group. More evidence is needed on the process of reference point formation for traders but this is a first step towards the conclusion that the disposition effect might be a weaker phenomenon, from a psychological point of view.

Chapter 4

Age, Income and Time Discounting

4.1 Introduction

A now-widespread critique of judgement and decision making research is that it focuses on a relatively small part of the human universe or what Henrich et al. (2010) call the WEIRD (Western Educated Industrialised Rich and Democratic) world. Researchers have responded to this critique by seeking to generalise findings beyond this group, and to investigate how factors which differ between the WEIRD world and the rest of the world matter. The importance of understanding individual and national differences and how they contribute to economic outcomes for individuals and nations can hardly be overstated. In this chapter we contribute to this project by investigating patience in intertemporal choices in a large sample of individuals all over the world, varying in age, education, income, religion and the nature of their national cultural, economic and political conditions.

Patience, or the willingness to defer current consumption in exchange for greater future consumption, may be one of the most important individual characteristics. Patience in childhood plays an important role in the development of successful and well-functioning adults (Mischel et al., 1989), and is also associated with a variety of factors in adulthood (Madden and Bickel, 2010). Patience has also been hypothesised to underpin vital pathways to growth and development. For instance, the willingness to invest in a long term project with larger overall rewards is one driver of the adoption of new technologies and hence the development and growth of economies (Ramsey, 1928). A population with more patient entrepreneurs will naturally invest in more long term projects. Many models of economic development such as Ramsey-Cass-Koopmans models or model of accumulation of the stocks of physical capital, human capital, or research intensity involve a key role for time preference (Becker, 1962; Ben-Porath, 1967; Doepke and Zilibotti, 2008; Galor and Özak, 2016; Sarid and Galor, 2017; Dohmen et al., 2018).

We investigate the role of patience at both an individual and collective level by means of a dataset that combines fine-grained individual level data with international coverage and representation. This is the Gallup End of Year Survey whose questions allow us to investigate the microeconomic and socio-demographic determinants of patience on an individual level. We consider how these relationships differ across different groups within and between countries and regions, and ask how macroeconomic variables such as GDP relate to the level of patience of members of the population. We included a simple measure of time preference designed to elicit individual time preference while controlling for differences in purchasing power across individuals and nations.

We emphasise what we can learn about individual characteristics and their universality, and especially how patience is related to age and income. As reviewed in the next section, these characteristics have previously been connected to patience, both theoretically and empirically, but the interaction between them has not been tested empirically. Moreover, our large international sample and substantial selection of individual characteristics enable us to test the robustness and generality of any observed relationships. Our main result is that our measure of patience shows a clear interaction with age and wealth. At a young age, people of all income groups show roughly the same likelihood of choosing a larger later over a smaller sooner option, but with age this changes. Richest older people are considerably more patient than poor older people; poor older people are considerably less patient than poor younger people, and younger people are just as patient, no matter what their income is.

We also discuss the relationship between patience and a host of other important individual characteristics, notably sex, employment, religion, economic optimism, education, and even attitudes toward vaccines. We report that women are more impatient than men, atheists more patient than protestants, who are more patient than other religious groups. Greater economic optimism, more education, and more positive attitudes toward vaccines' effectiveness are associated with greater patience. Employed people, students and housewives are more patient than unemployed and retired or disabled individuals. These analyses are apparently universal, since they hold even when the effects of country are accounted for by means of fixed effects models, or several alternative ways of taking into account within country correlations.

We then develop a simple and easily measurable index of country average patience and relate it to national characteristics. We find that, in order of relevance, higher GDP per capita, higher life expectancy, lower interest rates, higher Private Credit to GDP, higher distance from the Equator, higher level of Individualism, lower level of Uncertainty Avoidance (Hofstede and Bond, 1988; Hofstede, 2001) and lower level of inflation are positively and significantly correlated to our measure of patience. Countries whose main language is weakly future oriented (Chen, 2013) and countries whose Future Orientation Index (Preis et al., 2012) is higher show a higher level of patience, but the correlations we find are not statistically significant. We do not find any correlation with the Long Term Orientation index, debt to GDP rate, growth rate or gross savings rate. Most importantly, our measure of patience is highly and significantly correlated to the one proposed by Falk et al. (2018) and the one proposed by Wang et al. (2016), but it is much easier to elicit.

4.2 Some hypotheses on age, income and their effect on time discounting

Time discounting is a multifarious concept, but at its heart is the idea that, from the perspective of an agent deciding at a given time, consumption closer to that time is viewed as more valuable than consumption farther from that time. This specific claim is not generally the object of empirical investigation, which focuses on proxy measures, mostly on tradeoffs between money or goods over time. While these proxy measures can be objected to on theoretical grounds (Ramsey, 1928; Cubitt and Read, 2007), they nonetheless are associated with individual differences in patience-related outcomes, such as smoking, obesity and financial well-being (Chabris et al., 2008). Perhaps the main reason they do reflect individual differences is narrow bracketing, in that people can generally be relied upon to ignore opportunity costs and therefore to make intertemporal monetary tradeoffs much as they might make consumption or "utility" tradeoffs (Andreoni et al., 2018). It is therefore largely believed that intertemporal choices for money do reflect, at least to some degree, underlying time preferences for consumption (Andreoni et al., 2018).

One personal characteristic that has long been associated with discounting is wealth. Even the earliest economists who made time preference a special focus of study universally expected the poor would discount the future more than the wealthy (Loewenstein, 1992). Sometimes this expectation was based on the crushing effects of poverty itself (Fisher, 1930), sometimes on other correlates of poverty such as lack of education (Strotz, 1955), and sometimes impatience was expected to be the cause of poverty in itself (Ramsey, 1928). Fisher (1930) provided both rational and irrational explanations: "This influence of poverty is partly rational, because of the importance, by supplying present needs, of keeping up the continuity of life and thus maintaining the ability to cope with the future; and partly irrational, because the pressure of present needs blinds a person to the needs of the future." In line with the "rational" argument, Becker and Mulligan (1997) famously suggested that the poor should rationally discount more. They argued that discounting is inversely related to how much is invested in thinking about the future, and that the poor discount more because they have a bleak future which they do not want to spend time thinking about.

Empirical research has supported this prediction. Greater wealth is associated with a lower rate of time discounting. This is true in experimental or survey studies (Green et al., 1996; Poulos and Whittington, 2000; Meier and Sprenger, 2010; Tanaka et al., 2010), in estimates drawn from consumption data (Lawrance, 1991), and in field studies of choice behaviour (Hausman, 1979; Warner and Pleeter, 2001). Even experiments in which "wealth" is manipulated artificially show the same people discount the future more heavily when they are induced to think of themselves as poor rather than rich (Haushofer et al., 2013; Bickel et al., 2016).

Age is also widely believed to affect impatience. Unlike wealth, however, predictions concerning the effects of age differ widely because there are so many factors that might influence discounting over the lifespan, and these factors do not always work in the same direction. It was again Fisher who offered one of the earliest and most comprehensive accounts of the relationship. The following lengthy passage, provides a vivid portrait of how a single individual's time preference will change over the lifespan and the factors that influence it:

> Everyone at some time in his life doubtless changes his degree of impatience for income. In the course of an ordinary lifetime the changes in a man's degree of impatience are probably of the

> following general character: as a child he will have a high degree of impatience because of his lack of foresight and self-control; when he reaches the age of young manhood he may still have a high degree of impatience, but for a different reason, namely, because he then expects a large future income. He expects to get on in the world, and he will have a high degree of impatience because of the relative abundance of the imagined future as compared with the realised present. When he gets a little further along, and has a family, the result may be a low degree of impatience, because then the needs of the future rather than its endowment will appeal to him. He will not think that he is going to be so very rich; on the contrary, he will wonder how he is going to get along with so many mouths to feed. He looks forward to the future expenses of his wife and children with the idea of providing for them an idea which makes for a high relative regard for the future and a low relative regard for the present. Then when he gets a little older, if his children are married and have gone out into the world and are well able to take care of themselves, he may again have a high degree of impatience for income, because he expects to die, and he thinks, "Instead of piling up for the remote future, why shouldn't I enjoy myself during the few years that remain?" (Fisher, 1930)

Fisher emphasises *multiple* determinants of the age/discounting relationship. Foresight, self-control, expectations and the bequest motive all play a role to produce a "U-shaped" time course of discounting, with the greatest discounting amongst the young and the old. Other theoretical accounts also predict a U-shaped time course. These have a similar flavour to Fisher's although they differ in the details (Becker and Mulligan, 1997; Sozou and Seymour, 2003; Chu et al., 2010). In line with this, several studies have reported this U-shaped pattern, or at least data highly suggestive of it, using standard discounting tasks (Harrison et al., 2002; Read and Read, 2004; Bruderer Enzler et al., 2014; Falk et al., 2018; Richter and Mata, 2018).

The U-shaped pattern is by no means the only theoretical prediction available, nor the only empirical result in the literature. Rogers (1994) developed the idea that discounting is a function of evolutionary fitness, and argued (approximately) that since younger people can transform resources into children much more easily than can older ones, younger people will discount at a higher rate. This pattern of the observed discount rate declining with age has also been reported frequently (Green et al., 1996, 1997; Reimers et al., 2009; Lahav et al., 2010; Löckenhoff et al., 2011; Sparrow and Spaniol, 2018).

Another theoretical approach is that of Trostel and Taylor (2001) who proposed that discounting would be greater amongst the old than the young, because the ability to enjoy consumption decreased at an accelerating rate amongst the old. A pattern consistent with this has been reported by several researchers (Cropper et al., 1994; Kirby et al., 2002; Seaman et al., 2016; Eppinger et al., 2017). Moreover, to add to the diversity, some studies find no effect of age on discounting (Chao et al., 2009).

The diverse observed effects of age are what we would expect if, as already anticipated by Fisher (1930), there are many motives influencing discounting that can vary with age yet for different groups the different motives differ in their relative importance. For instance, Rogers (1994) evolutionary fitness argument combined with a bequest motive could suggest older people will discount at a very low rate – if your personal reproductive capacity is restricted, but you have children or grandchildren who can benefit from your support, then you might discount at a very low rate to increase the fitness of your offspring. But this might depend on the personal comfort of these older people. Someone who anticipates rapid decline in their ability to enjoy life might discount at a high rate, as suggested by Trostel and Taylor (2001) and in the passage by Irving Fisher, because they believe that now is their last opportunity to eke some pleasure from their life. The balance between these motives would produce a "net" discount rate that might decrease or increase or stay constant with age.

One opportunity we took with our study was to investigate the interaction between ageing, income, and discount rates. The possibility that the effect of age on discounting depends on financial circumstances has, with two exceptions we know of (Green et al., 1996; Epper et al., 2020), not previously been discussed. Green et al. (1996) investigated the wealth/income relationship but were unable to obtain the four cells of data needed to test for the age/income interaction. They did show a wealth effect, however, with older wealthier people discounting less than older poorer people. They did not locate a poor group of young people, but they did find that older wealthy people discounted at the same rate as younger wealthy people, suggesting that discounting might not change with age, at least for the well-off. It is natural, however, to imagine that age and poverty might interact. In particular, one reason not to expect big differences at younger age is the idea, suggested also by Fisher, that a young person is expected to be optimistic and forward looking, independently from the financial situation. In this study we are able to investigate the relationship between discounting and different levels of income. The literature has been mainly focused on the relation between discounting and wealth. However, we only have access to income information and we will use it as a proxy of wealth. The literature suggests we should find that discounting will decrease with wealth overall, and the one study by Green et al. (1996) suggests that for the wealthy, discounting will not change with age. There are many reasons to expect a specific interaction, in which the population of wealthy old people is more patient on average than poorer old people. This can occur both if greater patience "causes" wealth with age, as suggested by Ramsey (1928), or greater wealth "causes" greater patience with age, as suggested by Becker and Mulligan (1997). Unravelling the joint effect of income and age will be the main scopus of our work. Both Ramsey (1928) and Becker and Mulligan (1997) foster the expectation that the gap in patience between individuals in good financial conditions and individuals in bad financial conditions should increase with age, with patience being greater for individuals in good financial conditions. This claim is supported by the evidence presented by Epper et al. (2020). In their work, they measure discounting at one point in time and check where individuals ranked in the wealth distribution, over their lifespan. They find that those who are more patient are consistently wealthier. Epper et al. (2020) support the view that patience "causes" wealth with age and they attribute the effect to savings. In their sample, patience predicts big differences in the wealth ranking of individuals who are not credit constraint and can freely invest and borrow their money, only. This is in line with the explanation proposed by Ramsey (1928).

4.3 Discounting around the world

There have been other studies that measure discounting at the international level, allowing for comparison across countries, while examining individual, cultural, economic and geographic differences and how they are related to future oriented thinking.

Our closest predecessors are Wang et al. (2016) and Falk et al. (2018). Wang et al. (2016) collected data from 53 countries using a large-scale international survey on time preferences comprising almost 7000 undergraduate students in Economics, Finance or Business Administration. Time preferences were measured by asking three questions. First, their participants chose between "$3400 dollars this month" and "$3800 dollars next month". Then, they were asked to state the delayed payments which would make them indifferent between $100 now and that payment in one year, or in ten years. Wang et al. (2016) tested whether demographic variables, economic factors, and a range of individual differences predicted patience. They found a small effect of age, with older students more willing to choose the $3800 reward than younger ones. However, age differences in a sample of students are really small. Three of Hofstede's cultural dimensions (Hofstede, 2001), measured at the individual level, were found to have an impact on discounting. The three cultural factors were what Hofstede referred to as *Individualism*, *Uncertainty avoidance*, and *Long Term Orientation*[1]. Higher levels of uncertainty avoidance were associated with stronger hyperbolic discounting and higher present bias, whereas higher degrees of individualism and long term orientation were associated with a stronger tendency to wait for larger payoffs. GDP per capita as well, was positively associated with the tendency to wait for larger payoffs.

Falk et al. (2018) conducted a major study of global variation in economic preferences using their own proprietary Global Preferences Survey (GPS). As well as time preferences, they measured risk preference, positive and negative reciprocity, altruism, and trust from 80,000 respondents in 76 countries. Time preferences were measured by means of a quantitative and a qualitative measure (Falk et al., 2016). The quantitative measure involved five hypothetical binary choices between an immediate and delayed payment. The specific items asked depended on the respondents' answers to previous questions using a "staircase" method, and the monetary amounts were expressed in the respective local currency, scaled relative to the median household income in the given country. The qualitative measure was a self-assessment of the willingness to wait based on the statement "how willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?". Falk et al. (2018) combined the two measures to create a patience index. At the individual level, they found that patience varies with age, in a hump-shaped pattern: middle-aged individuals were the most patient, compared with the young and the elderly. Patience was also higher for individuals with

[1]The labels for Hofstede (2001) scales may be misleading taken on their own, so it is worth mentioning the specific measures. In Section 4.4 we carefully explain how these measures were taken and we spell out the differences between Wang et al. (2016) approach to measure Hofstede's cultural dimensions and the one followed by Hofstede, on which Falk et al. (2018) and we rely.

higher cognitive ability and individuals with higher subjective maths skills. Females were more impatient than males. Finally, they found patience to be positively related to savings and educational attainment of the respondents. Patience at the national level was correlated with: individualism and long-term orientation (Hofstede, 2001) measured at the national level; GDP per capita; geographic and biological variables that have previously been argued to be conducive for economic development (Diamond, 2005; Olsson and Hibbs, 2005; Spolaore and Wacziarg, 2013); distance from the equator; weak Future Time Reference (Chen, 2013); pronoun drop not allowed in the language of the country (Tabellini, 2008); share of protestants in the country (Weber, 1930; Doepke and Zilibotti, 2008) and risk taking. In addition, they found negative correlation of their index with the intensity of family ties (Alesina and Giuliano, 2014). They found that western European and English speaking countries were the most patient. In particular, when comparing the effect of the preferences they estimated, Falk et al. (2018) found that patience has a much higher explanatory power of GDP per capita of a country than the others (risk taking, positive and negative reciprocity, trust, altruism).

Other studies on cross-cultural differences in temporal discounting involved only two or three countries. Tan and Johnson (1996) studied Canadian undergraduates and foreign undergraduates of Chinese descents but they reported no difference in discount rates between the two groups. Du et al. (2002) studied American, Chinese, and Japanese graduate students on two tasks. In the delay discounting task, participants made choices between immediate and delayed hypothetical monetary rewards; in the probability discounting task, participants made choices between certain and probabilistic rewards. They found that the Americans and Chinese discounted delayed rewards more steeply than the Japanese. In addition, the Americans discounted probabilistic rewards the most, whereas the Chinese discounted probabilistic rewards the least. Mahajna et al. (2008) found that Israeli Jews, who are supposedly from a more individualistic society, are more patient than Israeli Arabs, who are supposedly from a more collectivistic society. They asked their participants to bid and ask prices for delayed fixed amounts and for lotteries and found that the subjective discount rate of Israeli Arabs were significantly higher than that of Israeli Jews.

4.4 Hofstede cultural dimension and measurement

Here, we spell out the details on how Hofstede's cultural dimensions (Hofstede and Bond, 1988; Hofstede, 2001) are measured. Most importantly, Wang et al. (2016) directly measured the cultural dimensions at the individual level, by asking some question inspired to the one used by Geert Hofstede, while Falk et al. (2018) and we compared our indices of patience at the national level to the values of the cultural dimension, as measured by Hofstede and available at Geert Hofstede's website. Wang et al. (2016) directly measured cultural factors at the individual level, in their survey. Individualism was measured by asking the participants to rate the importance of four features for an ideal job: having sufficient time for their personal or family life; good physical working conditions; security of employment and an element of variety and adventure in the job. Uncertainty Avoidance was derived from four questions. The first was "How often do you feel nervous or tense at work?" and the other three questions asked the participants to what extent they agreed with each of the following statements: "One can be a good manager without having precise answers to most questions that subordinates may raise about their work"; "Competition between employees usually does more harm than good" and "A company's or organisation's rules should not be broken – not even when the employee thinks it is in the company's best interest.". Finally, they measured Long Term Orientation by asking participants to rate the importance of two questions: "In your private life, how important is 'respect to tradition' for you?" and "How important is 'thrift' for you?". The questions used in the Hofstede's release on which Falk et al. (2018) and we relied upon are the following. Individualism was measured according to the answers to the following question: Please think of an ideal job, disregarding your present job, if you have one. In choosing an ideal job, how important would it be to you to (1) have sufficient time for your personal or home life (2) have security of employment (3) do work that is interesting (4) have a job respected by your family and friends? Uncertainty Avoidance was measured according to the answers to the following four questions: (1) How often do you feel nervous or tense? (2) All in all, how would you describe your state of health these days? (3) To what extent do you agree or disagree with each of the following statements? (3a) One can be a good manager without having a precise answer to every question that a subordinate may raise about his or her work. (3b) A company's or organisation's rules should not be broken, not even when the employee thinks breaking the rule would be in the organisation's best interest.

Long Term Orientation is measured according to the answers to the following four questions: (1) How important is doing a service to a friend? (2) How important is thrift (not spending more than needed)? (3) How proud are you to be a citizen of your country? (4) To what extent do you agree or disagree with the following statement: persistent efforts are the surest way to results?

4.5 Data and methodology

Our data come from the 2015 wave of the Gallup End of Year Survey. The survey was conducted in the autumn of 2015, from October to November, with 66040 interviewees across 68 countries. The survey was done via three ways: face-to-face interview, telephone and online interview. Data from one country could be collected from only one or more methods. Specifically, the face-to-face interview was the most commonly used method, done with 32172 subjects from 30 countries. The online survey was conducted with 22068 interviewees in 23 countries. 11800 subjects in 15 countries were interviewed via telephone (WIN/Gallup international, 2016). One advantage of the survey is that it spans the entire income distribution in each country and it also spans countries with very different characteristics and wealth. This enables us to control for income and age at the same time.

The dependent variable is the following question, which Gallup International permitted us to include:

Think about your current household income: which of the following choices would you choose if offered?

- Today you receive an extra payment which is equal to that of your normal monthly income.
- In exactly one year from now you receive an extra payment equal to twice that of your normal monthly income.

Participants had a right to refuse to answer this question. In particular, in three countries (Denmark, Israel and South Korea) no answer to our question were collected, which reduces the number of countries on which we have data to 65. This question enabled us to account for differences in income and currency within a single item and without using control questions. As we show later, it is highly correlated with other, typically more time consuming, measures. By convention, we use the abbreviations SS (smaller-sooner) for the first option, and LL (larger-later) for the second option, and when we refer to "patience" we are referring to choices of LL.

We obtained answers to the patience question from 55,939 from 65 countries. However, income information is available for 50,754 respondents. The number of participants in each country making each choice, along with the percentage of respondents choosing the LL option is reported in Table 4.2 and shown in Figure 4.1. We investigate the relationship between individual and personal characteristics and the individual choice of LL, and the relationship between country characteristics and the country choice of LL. Table 4.1 lists the variables from the survey that entered into our analysis. Note that we had no control over any measure other than our own.

Our analysis is structured into two parts. We start by investigating how individual characteristics are related to the choice of LL (patience). Our main focus will be on the influence that age and income have on patience, although we do include a number of potentially relevant individual measures in our analysis. In the second part we look at national characteristics.

4.5.1 Analysis of patience at the individual level

In Section 4.2, we discussed in great details that the main focus of our work is to investigate how income and age combined shape discounting. There are two competing explanations, both of which lead to the conclusion that the gap in patience between richer and poorer individuals increases with age. However, they differ in the mechanism which they advance. On the one hand, Ramsey (1928) suggests that greater patience leads to higher wealth with age. He suggests that patience is a driver of economic development and as a consequence patient individuals will accumulate higher levels of wealth throughout their lives. This is also consistent with the evidence presented by Epper et al. (2020), for Danish citizens. On the other hand, Becker and Mulligan (1997) propose that greater wealth leads to greater patience with age. They argue that the poor discount more because they have a bleak future which they do not want to spend time thinking about. Hence, poverty leads individuals not to invest energies into thinking about their future.

We included a wide range of factors from the survey. Several of these are already known to be associated with patience, or are associated with strong theoretical predictions, and so serve as "sense checks" for our measure of time preference, as well as providing further information on the generalisability of these earlier results. Others are novel or even exploratory.

Table 4.1: **List of variables included in the analysis of patience at the individual level.** Answers were collected in the WIN/Gallup End of Year (EoY) Survey 2015.

Income Quintile	Quintile of the income of the respondent in the distribution of the respondent's country. Ordered as poorest, second poorest, middle, second richest, richest.
Age	Age of the respondent.
University degree	A dummy equal to 1 if the respondent completed at least a university degree.
Employment	Employment of the respondent. Classified as Unemployed, Housewife, Retired/Disabled, Student, Working Part-time or Working full-time.
Next Year Outlook	A dummy equal to 1 if the respondent answered "Economic Prosperity" to the question "Compared to this year, in your opinion, will next year be a year of economic prosperity, economic difficulty or remain the same for your country?".
Happy	A dummy equal to 1 if the respondent answered either "Happy" or "Very Happy" to the question "In general, do you personally feel very happy, happy, neither happy nor unhappy, unhappy or very unhappy about your life?".
Confidence Vaccine Effectiveness	Rate of agreement with the statement "Overall I think vaccines are effective.".
Religion	Religion of the respondent. Possible answers were: Roman Catholic, Russian or Eastern Orthodox, Protestant, Other Christian, Hindu, Muslim, Jewish, Buddhist, Other, Atheist/Agnostic.
Change Soon	A dummy equal to 1 if the respondent answered either "In the short term" or "Right now" instead of "Never need to change", "In the medium term" or "In the long term" to the question "In your opinion, how soon does your country need to change to be a better place?".
Risk Averse	The question asked to elicit risk aversion was "Think about your current household income: which of the following choices would you choose if offered?" It is a dummy equal to 1 if the respondent answered " A guaranteed increase in your household income of 50%" instead of "A 50/50 chance to receive double your household income".

First, we check whether women or men are more patient. This is a subject about which there has been considerable discussion but no agreement. In several studies women have been found to display more patience than men (Silverman, 2003; Frederick, 2005; Bauer and Chytilová, 2013; Dittrich and Leipold, 2014), but others have reported no effect, or a reverse effect. Our immediate predecessors either found no effect Wang et al. (2016) or found women to be more impatient than men (Falk et al., 2018). It is not the goal of this work to give a definitive answer to this question, but the breadth of our sample can certainly help provide a definitive answer. Similarly, more education has been associated with more patience, as in Perez-Arce (2017) and Falk et al. (2018). We use the dummy University degree, equal to 1 if the respondent completed a University degree. We control for the employment status of the respondent with dummies corresponding to: Unemployed, Housewife, Retired/Disabled, Student, Working Part-time with Working full-time as the baseline. The Gallup End of Year survey does, indeed, include the category "Housewife". The survey also contained a question measuring risk attitude. Risk attitude has frequently been compared to intertemporal preference, and Ferecatu and Önçüler (2016) find participants willing to take risks are less willing to defer consumption. Also Anderhub et al. (2001); Tanaka et al. (2010) find that risk aversion is correlated to lower discounting. However, Falk et al. (2018) found patience to be correlated with the propensity to take risks. We included a dummy taking the value of 1 if the participant chose the risk averse option.

We check how the respondent felt about her current situation and the beliefs she had on the future of her country. First, we include a dummy equal to 1 if the respondent claimed to be happy or very happy about her life. Ifcher and Zarghamee (2011) found that people who are happier tend to discount the future less heavily. Second, participants were asked if their country needed to change soon to be a better place. Third, they were asked to evaluate the economic outlook for the country in the next year, resulting into two dummy variables indicating whether the respondent believed the economic outlook for the next year was neutral or positive (with negative as the baseline). These last two variables capture the possibility that individuals who are concerned about the future might be more wary of rewards which are distant in time. On top of that, economic uncertainty might raise doubts about the future value of money. Previous research indicated that an individual's tendency of temporal discounting is not only associated with the amount of money and the length of time, but also on how risky the future reward is perceived by the individual (Green and Myerson, 2004). If people consider the LL reward as less certain and riskier than the SS one, they might discount the future more.

Participants were also asked about their belief in the effectiveness of vaccines. While we know of no research comparing belief in vaccine effectiveness to patience, researchers have found that the *willingness* to vaccinate is associated with patience, with more patient people more willing to vaccinate (Nuscheler and Roeder, 2016). This belief was captured with three dummies ranking the degree of belief of the respondent in Vaccine Effectiveness, with strong agreement being the baseline. We control for the religion of the respondents, using Roman Catholic as the baseline. Weber (1930) proposed the idea of a "Protestant ethics" which, among other aspects, is believed to have made people more patient. Falk et al. (2018) found that the share of protestants in a given country is positively related to patience. Hence, we investigate the correlation between religious beliefs of the respondents and their propensity to delay the reward.

The first specification for our analysis, including only the effects of age and income, is:

$$y_i = \alpha + \beta a_i + \gamma_k I_{ki} + \delta_k a_i * I_{ki} \quad i \in I; \;\; k \in \{2, 3, 4, 5\} \tag{4.1}$$

where y_i takes the value of 1 if i respondent chose LL (was patient); I_k are four dummies for the four quintiles of the income distribution (the first is the baseline), and a_i is age (in decades) of subject i[2]. We model it as a Linear Probability Model, since interpretation of the marginal effect of the interactions is more straightforward (Ai and Norton, 2003).

We expect that all effects observed might vary from country to country. We accommodated this by including fixed effects at the country level[3]. In addition, we include the individual characteristics just summarised:

$$y_i = \alpha + \beta a_i + \gamma_k I_{ki} + \delta_k a_i * I_{ki} + \omega x_i + \lambda_j C_{ji} \quad i \in I; \;\; k \in \{2, 3, 4, 5\}; \;\; j \in J \tag{4.2}$$

[2]Age is reported in 6 bins in our data. We assigned the mid-point value to all individuals in a given bin and we treated age as a continuous variable. We did this to keep the interpretation simple. Having 4 dummies for the income quintile and 5 dummies for the age bins would have led to 20 interactions. We repeat the analysis using the bins for age and the results are virtually unchanged (see Table 4.10)

[3]Table 4.7 reports attempts to model heterogeneity among countries in different ways and results were robust across all specifications.

where C_{ji} is a dummy which refers to the country of the respondent. C_j are 64 dummies for the countries (J is the set of countries). The vector x_i refers to the individual characteristics.

4.5.2 Analysis of patience at the national level

The second part of our analysis is devoted to the study of heterogeneity of patience among countries. We take the percentage of respondents choosing LL in each country, as reported in Table 4.2, as an index of patience for that country. It is measured using answers of 55,939 individuals from 65 countries. We look at the correlation of our measure with those obtained by Falk et al. (2018) and Wang et al. (2016). For Falk et al. (2018), we use the index of patience available on the global perferences survey website. For Wang et al. (2016) we use the proportion of respondents choosing "$3800 dollars next month" over "$3400 dollars this month", in each country, as an index of patience. Moreover, we correlate the measure to several country characteristics (summarised in Table 4.3). We check the correlation of our measure of patience with both the 2014 and the 2015 release of the indices. Our subjects answered the patience question at the end of 2015, in the context of the Gallup End of Year 2015 survey. Hence, if we believe in a correlation which goes from patience to, say, economic development, it is worth looking at how patience measured in 2015 impacts any outcome (for example GDP per capita) at the end of that year. However, in some cases, the 2014 release is an appropriate comparison as well. Think of inflation, for example. When the subjects are answering the patience question, they are expected to take into account expected inflation. We expect them to incorporate information from the previous year (2014) which has already realised and information on the current year (2015) which had not yet been released at the time of the survey, but respondents were experiencing it in their every day consumption choices.

Since patience has historically been associated to economic development (Becker, 1962; Ben-Porath, 1967; Doepke and Zilibotti, 2008; Galor and Özak, 2016; Sarid and Galor, 2017; Dohmen et al., 2018), defined in a multifaceted way, we verify how our index correlate to some proxies of economic development. First, we consider the GDP per capita in 2014 and 2015 (World Bank). Second, we consider the growth rate in 2014 and 2015 (World Bank). On top of that, the growth rate is an index of how much individuals expect the economic environment to change. We mentioned that the uncertainty

Table 4.2: **Summary statistics on the patience question by country and region.**

Country/Region	SS	LL	LL (perc.)	Country/Region	SS	LL	LL (perc.)
Overall	28,439	27,500	0.49	Mongolia	488	459	0.48
Sweden	260	649	0.71	Argentina	433	403	0.48
Finland	314	708	0.69	Algeria	172	160	0.48
Netherlands	306	608	0.67	Mexico	498	460	0.48
Austria	300	596	0.67	Panama	565	501	0.47
Iceland	276	524	0.66	Slovenia	486	428	0.47
Canada	328	587	0.64	Palestine (W Bank Gaza)	459	393	0.46
Kosovo	247	441	0.64	Czech Republic	494	405	0.45
Bangladesh	282	493	0.64	South Africa	614	474	0.44
Saudi Arabia	206	352	0.63	Lebanon	542	382	0.41
Morocco	297	479	0.62	Russia	464	327	0.41
Germany	348	553	0.61	Ukraine	239	162	0.40
Colombia	379	587	0.61	Papua New Guinea	352	238	0.40
Japan	345	494	0.59	Congo	506	342	0.40
Macedonia	433	584	0.57	Armenia	524	352	0.40
United Kingdom	380	511	0.57	Ghana	534	357	0.40
India	446	587	0.57	Afghanistan	1,182	789	0.40
Australia	441	574	0.57	Nigeria	477	310	0.39
Belgium	380	493	0.56	Philippines	590	380	0.39
Bosnia Herzegovina	410	527	0.56	Serbia	539	344	0.39
Latvia	349	446	0.56	Ethiopia	605	334	0.36
United States	403	501	0.55	Greece	619	331	0.35
Hong Kong	191	233	0.55	Italy	547	292	0.35
Ecuador	379	450	0.54	Indonesia	313	167	0.35
Ireland	432	499	0.54	Bulgaria	568	300	0.35
Peru	426	481	0.53	Turkey	617	262	0.30
Portugal	471	481	0.51	Iraq	527	222	0.30
Tunisia	407	414	0.50	Brazil	1,351	523	0.28
Fiji	471	478	0.50	Azerbaijan	144	43	0.23
Thailand	181	182	0.50	North America	731	1,088	0.60
Poland	457	456	0.50	EU Europe	,7901	9,173	0.54
Pakistan	460	455	0.50	West South Asia	2,370	2,324	0.50
France	417	412	0.50	East Asia and Oceania	4,220	4,035	0.49
Vietnam	284	278	0.49	Eastern Europe	3,000	2,780	0.48
China	564	552	0.49	Latin America	4,031	3,405	0.46
Spain	497	481	0.49	MENA	3,450	2,878	0.45
Iran	223	214	0.49	Sub-Saharan African	2,736	1,817	0.40

Table 4.3: **List of variables included in the analysis of patience at country level.** We correlate them to the percentage of respondents choosing LL, as reported in Table 4.2, in each country as an index of Patience for that country. Sources of all variables are listed.

GDP per capita	In 2014 and 2015 (World Bank).
Growth Rate	In 2014 and 2015 (World Bank).
Distance from Equator	Absolute latitude of the country.
Private Credit to GDP	Ratio of domestic credit to the private sector over GDP in 2014 and 2015 (World Bank).
Debt to GDP Ratio	In 2014 and 2015 (IMF).
Gross savings to GDP	The difference between disposable income and consumption in 2014 and 2015 (World Bank).
Life Expectancy	Measured at birth in 2014 and 2015 (World Bank).
Real interest rate	The lending interest rate in 2014 and 2015 adjusted for inflation as measured by the GDP deflator (World Bank).
Inflation rate	In 2014 and 2015 (World Bank).
Future Time Reference (FTR)	Developed by Chen (2013). It assumes a value of 1 if a given language allows one to speak about the future in the present tense (Weak FTR), and 0 otherwise (Strong FTR).
Future Orientation Index (FOI)	Developed by Preis et al. (2012). Ratio of Google queries looking for information on 2016 w.r.t. queries looking for information on 2014.
Individualism (IDV)	It measures the degree to which the society reinforces individual or collective achievement, and the extent to which people are expected to stand up as an individual as compared to loyal affiliation to a life-long in-group (e.g., extended family, friends, etc.). Geert Hofstede's website ("2015 08 16" version, average value for each country).
Uncertainty Avoidance (UAI)	A high score of UAI indicates that a society is afraid of uncertain, unknown and unstructured situations. Geert Hofstede's website ("2015 08 16" version, average value for each country).
Long Term Orientation (LTO)	It captures the society's time horizon. It reflects to what extent a society has "a dynamic, future-oriented mentality". A higher score implies that the past is valued less than the future, and people may look more forward. Geert Hofstede's website ("2015 08 16" version, average value for each country).

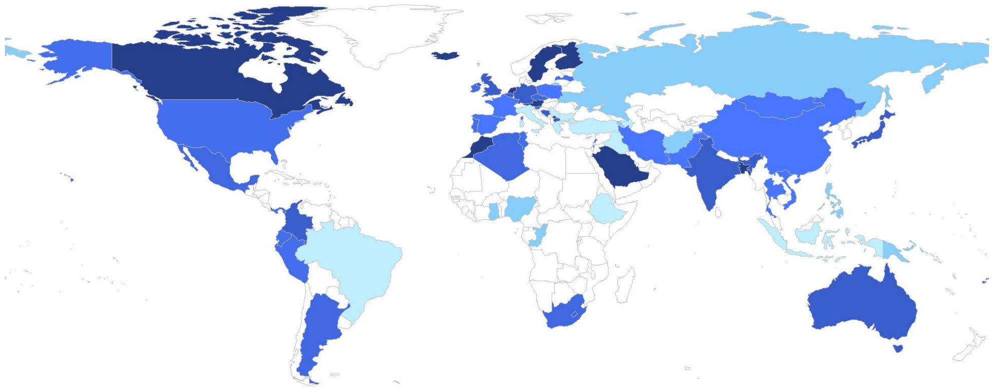

Figure 4.1: **Patience in the world.** Dark shaded countries show a higher level of Patience. Patience index in each country is measured as the percentage of respondents who chose the LL option. Based on 55,939 responses from 65 countries.

about the future reward can play a role on how individuals discount the future (Green and Myerson, 2004). Third, we consider the Distance from the Equator (absolute latitude). Geography has been hypothesised having an impact on economics development by several authors (Diamond, 2005; Spolaore and Wacziarg, 2013; Falk et al., 2018). We take into account three different indices which account for the degree of indebtedness and the tendency to save of a given country, in the public and in the private sector. We consider the Debt to GDP ratio in 2014 and 2015 (IMF). We expect countries which are more impatient to show higher levels of debt. We consider the Private credit to GDP in 2014 and 2015 (World Bank). This is the ratio of domestic credit to the private sector. However, it is true that these two indices do not only account for the tendency of individuals to subscribe debts but also for the degree of financial and economic development. Finally, we consider Gross National Savings to GDP, the difference between disposable income and consumption. Then, we correlate our measure of patience to three indices which account for uncertainty in the economic environment which pertains the reward, measured at the country level. First, life expectancy at birth in 2014 and 2015 (World Bank). We expect patience to be related to the probability of living long enough to enjoy potential future rewards. Second, the real interest rate in 2014 and 2015 (World Bank). This is the lending interest rate adjusted for inflation. Given that we propose a reward to be awarded in one year, the average interest rate the respondent might face is a natural term of comparison. Finally, inflation rate for 2014 (World Bank). Since the hypothetical reward we offer is due to be delivered in one year, expectations of inflation should have an impact on the propensity to accept it or not. We finally correlate our measure to some measures which refer to the sociological, linguistic and cultural approach to patience. We consider the Future Time Reference (FTR), as developed by Chen (2013) and slightly modified by Falk et al. (2018)[4]. Future Time Reference has attracted attention because it correlates with future-oriented decisions (Gudmestad and Edmonds, 2016). This variable assumes a value of 1 if a given language allows one to speak about the future in the present tense (Weak FTR), and 0 otherwise (Strong FTR). Chen (2013) suggested that languages with weak FTR would be associated with more patience because they treat the future as being just like the present and this is true for the sample of countries examined by Falk et al. (2018). We consider the Future Orientation Index, as developed by Preis et al. (2012). The FOI is an attempt to quantify how much people think about the future relative to the past. It is the ratio of the volume of internet searches for the next year to internet searches for the previous year. We take FOI for the period spanned by our study, looking at the ratio of searches for 2016 to searches for 2014[5]. The argument is that if the ratio of future over past searches is high, people in that group are devoting more resources to thinking about the future than the past. Preis et al. (2012) found that the index is highly correlated to the GDP of a country. Finally, we consider three of the Hofstede's cultural dimensions, which have been found to be related to patience by previous studies (Hofstede and Bond, 1988; Hofstede, 2001). Data were downloaded from Geert Hofstede's website ("2015 08 16" version, average value for each country). It is not always obvious how the questions used to derive the dimensions map onto those dimensions. However, this classification has been widely used, including by Wang et al. (2016) and Falk et al. (2018), so we follow it. We consider Individualism, which is intended to measure the degree to which the society reinforces individual or collective achievement, and the extent to which people are expected to stand up as an individual as compared to loyal affiliation to a life-long in-group (e.g., extended family, friends, etc.). We also consider Uncertainty Avoidance, which is intended to measure general fear of uncertain, unknown and unstructured situations. Higher scores indicate greater Uncertainty Avoidance. Finally, Long Term Orientation, or Confucian Dynamism,

[4]We follow Falk et al. (2018) classification. They set Farsi to "not classified" after corresponding with Chen (it was initially classified as "Strong") and classified Moroccan Arabic independently from Chen.

[5]We thank Merve Alanyali for conducting this analysis for us.

is intended to capture the society's time horizon. It reflects to what extent a society has "a dynamic, future-oriented mentality". Wang et al. (2016) found that higher levels of Uncertainty Avoidance to be associated with stronger hyperbolic discounting and higher present bias, whereas higher degrees of Individualism and Long Term Orientation predicted a stronger tendency to wait for larger payoffs. Falk et al. (2018) found a positive correlation of patience with individualism and long-term orientation.

4.6 Individual level discounting

Our main conclusion is already evident by looking at Table 4.4, where we report the raw percentages of respondents choosing the "Larger Later" option stratified for age and income. For the youngest group, the percentage of LL choices is approximately the same for all the income levels, ranging from 48% to 53%. The income groups however diverge as the respondents get older. Those in the poorest quintile of income are less patient, while those with high incomes become more patient. To put numbers on it, in the oldest group (those older than 65 years), the percentage choosing LL is 61% for the richest income quintile, but only 38% for the poorest income quintile. The other income groups are distributed in an orderly manner between these extremes. We will see that once we take into account country fixed effects, the gap in patience among the high and low income group will still arise as age increases but it will be solely driven by the decrease in patience of the lowest income group.

Table 4.5 reports the results of our regression analysis. The marginal effect of age for the poorest quintile is negative and fairly stable. For that group, every ten years the probability of choosing the "Large Later" option decreases by more than 2%, when we control for country fixed effects. The marginal effect for the other categories is given by the sum of the coefficient of age and the coefficient of age interacted with the appropriate category. From there, we can see that the marginal effect of age is virtually zero for the richest quintile of income. The coefficient of age interacted with the richest quintile is always positive, significant and comparable in magnitude to the coefficient of age. This means that the level of patience is constant, for any level of age, for the richest category. For the intermediate levels of income patience declines with age but the slope of the decline decreases as income increases. When we estimate patience taking into account age, income and country fixed effects

Table 4.4: **Summary statistics on the patience question by age and income group.** Age corresponds to the age group of the respondent and income corresponds to the position of the respondent in the income distribution in her country of origin. LL stands for "Larger Later" and SS for "Smaller Sooner".

Income Quintile	Age	LL (perc.)	LL	SS
Poorest	18 to 24	0.49	877	918
Poorest	25 to 34	0.43	974	1293
Poorest	35 to 44	0.39	712	1107
Poorest	45 to 54	0.40	654	977
Poorest	55 to 64	0.39	481	767
Poorest	65+	0.38	522	844
Second Poorest	18 to 24	0.49	858	902
Second Poorest	25 to 34	0.48	1389	1492
Second Poorest	35 to 44	0.47	1075	1219
Second Poorest	45 to 54	0.45	924	1117
Second Poorest	55 to 64	0.44	681	875
Second Poorest	65+	0.44	569	715
Middle	18 to 24	0.48	1001	1095
Middle	25 to 34	0.50	1666	1645
Middle	35 to 44	0.49	1423	1494
Middle	45 to 54	0.48	1125	1207
Middle	55 to 64	0.48	804	867
Middle	65+	0.49	527	545
Second Richest	18 to 24	0.53	696	628
Second Richest	25 to 34	0.53	1124	994
Second Richest	35 to 44	0.55	1052	871
Second Richest	45 to 54	0.53	904	791
Second Richest	55 to 64	0.55	661	532
Second Richest	65+	0.54	400	342
Richest	18 to 24	0.51	431	406
Richest	25 to 34	0.54	763	655
Richest	35 to 44	0.57	807	598
Richest	45 to 54	0.58	797	581
Richest	55 to 64	0.56	503	401
Richest	65+	0.61	288	188

only (column 2 in Table 4.5) patience declines at the following rates: for the lowest income quintile the probability of choosing LL decreases by 2.7% every ten years; for the second poorest it decreases at a similar rate; for the middle income quintile it decreases by 1.4% every ten years; for the second richest by 1% and for the richest quintile only by 0.02%. This is clearly visualised in Figure 4.2, where we plot the estimated probability of choosing LL for any combination of age and income in the United States. In a nutshell, patience is essentially constant for the richest quintile group, and strongly declining for the poorest quintile, with all other income groups falling in between. Falk et al. (2018) found that the relation between age and patience follows an inverse U-shaped pattern: middle-aged individuals are the most patient, compared with the young and the elderly. Wang et al. (2016) found that patience declines with age, but student participants in their experiment show limited variation in terms of age. To the best of our knowledge, we are the first to observe the relationship we describe between patience, income and age.

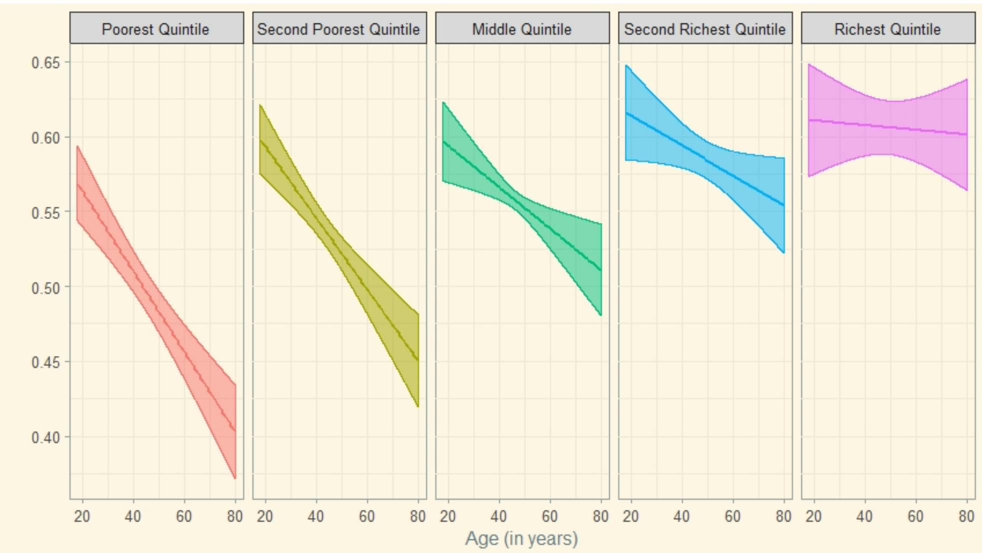

Figure 4.2: **Probability of choosing LL (age/income).** Estimated probability of choosing LL per each quintile of income. Predictions based on OLS regression model from column 2 of Table 4.5 with country fixed effects and clustered standard errors at country level. Country fixed to the United States of America.

As anticipated, we investigate how several individual characteristics influence patience. The effects of all the covariates are quite stable with respect to the inclusion of extra variables and the variance inflation factors of the models do not raise issues of collinearity. Women are around 3% less likely to

Table 4.5: **Individual level patience.** Linear Probability Model based on a sample of 65 countries.

Dep Var: Larger Later	(1)	(2)	(3)	(4)	(5)	(6)
Age (decades)	-0.018^{***}	-0.027^{***}	-0.024^{***}	-0.027^{***}	-0.023^{***}	-0.022^{***}
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Second Poorest Quintile	0.017	0.024	0.017	0.021	0.015	0.019
	(0.029)	(0.024)	(0.026)	(0.024)	(0.025)	(0.025)
Middle Quintile	-0.001	0.004	0.0004	-0.001	-0.007	-0.005
	(0.029)	(0.024)	(0.028)	(0.024)	(0.024)	(0.024)
Second Richest Quintile	0.028	0.017	0.025	0.009	0.0004	0.005
	(0.031)	(0.026)	(0.030)	(0.026)	(0.026)	(0.027)
Richest Quintile	0.007	-0.003	0.001	-0.016	-0.024	-0.016
	(0.038)	(0.031)	(0.035)	(0.030)	(0.030)	(0.029)
Age ∗Second Poorest Quintile	0.007	0.003	0.006	0.003	0.003	0.002
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age ∗Middle Quintile	0.017^{***}	0.013^{***}	0.015^{***}	0.013^{***}	0.012^{**}	0.011^{**}
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age ∗Second Richest Quintile	0.022^{***}	0.017^{***}	0.020^{***}	0.016^{***}	0.016^{***}	0.014^{**}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age ∗Richest Quintile	0.032^{***}	0.025^{***}	0.030^{***}	0.025^{***}	0.024^{***}	0.020^{***}
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Female				-0.030^{***}	-0.030^{***}	-0.031^{***}
				(0.006)	(0.006)	(0.006)
University Degree				0.028^{***}	0.029^{***}	0.028^{***}
				(0.007)	(0.007)	(0.007)
Employment (ref: Full-time work)						
Unemployed					-0.048^{***}	-0.043^{***}
					(0.009)	(0.010)
Housewife					-0.003	-0.002
					(0.014)	(0.014)
Retired/Disabled					-0.033^{***}	-0.031^{***}
					(0.012)	(0.012)
Student					-0.007	-0.009
					(0.018)	(0.019)
Working Part-time					-0.010	-0.007
					(0.010)	(0.010)
Next Yr Econ (ref: negative)						
Neutral						0.019^{**}
						(0.008)
Positive						0.024^{**}
						(0.009)
Happy						0.025^{***}
						(0.008)
Observations	50,754	50,754	50,754	50,565	49,766	47,255
Adjusted R^2	0.010	0.054	0.018	0.055	0.056	0.057
Country FE	NO	YES	NO	YES	YES	YES
Macro Area FE	NO	NO	YES	NO	NO	NO

Note: *p<0.1; **p<0.05; ***p<0.01; Clustered Standard Errors at Country Level.

Table 4.6: **Individual Level patience (extended).** Linear Probability Model. Religions not significant, not shown. Income not significant, not shown. Employment status not significant, not shown.

Dep Var: Larger Later	(1)	(2)	(3)
Age (decades)	−0.026***	−0.021***	−0.021***
	(0.004)	(0.004)	(0.005)
Age (decades) ∗Second Poorest Quintile	0.004	0.001	0.002
	(0.006)	(0.005)	(0.006)
Age (decades) ∗Middle Quintile	0.015***	0.011**	0.013**
	(0.005)	(0.006)	(0.006)
Age (decades) ∗Second Richest Quintile	0.017***	0.013**	0.014**
	(0.006)	(0.006)	(0.006)
Age (decades) ∗Richest Quintile	0.025***	0.016***	0.017**
	(0.006)	(0.006)	(0.007)
Risk Averse	0.084***		0.092***
	(0.021)		(0.023)
Happy		0.019**	0.020**
		(0.008)	(0.008)
Belief Country needs change soon		−0.036***	−0.042***
		(0.009)	(0.009)
Next Yr Econ (ref: negative)			
Neutral		0.012	0.013
		(0.008)	(0.009)
Positive		0.021**	0.023**
		(0.010)	(0.010)
Confidence Vaccine Effectiveness (ref: Strong agree.)			
Strong disagreement		−0.076***	−0.071***
		(0.023)	(0.023)
Moderate disagreement		−0.007	−0.003
		(0.013)	(0.013)
Moderate agreement		−0.012	−0.008
		(0.008)	(0.008)
Female		−0.026***	−0.027***
		(0.006)	(0.006)
University Degree		0.029***	0.027***
		(0.007)	(0.007)
Unemployed		−0.043***	−0.042***
		(0.011)	(0.011)
Retired/Disabled		−0.027**	−0.019
		(0.012)	(0.012)
Religion (ref: Catholic)			
Atheist/Agnostic		0.066***	0.065***
		(0.011)	(0.010)
Protestant		0.036***	0.033***
		(0.010)	(0.010)
Observations	48,451	39,965	38,407
Adjusted R^2	0.060	0.059	0.067
Country FE	YES	YES	YES
Countries number	65	60	60

Note: *p<0.1; **p<0.05; ***p<0.01; Clustered s. e. at country level.

choose LL, in line with the earlier paper by Falk et al. (2018). However, in the analysis of Falk et al. (2018) only 68% of countries have a coefficient indicating greater impatience for women, and only 32% have a statistically significant difference (p-value<0.1) in that direction. A closer analysis of our results, following the analysis of Falk et al. (2018) shows that in 48 of the 65 countries men were more patient than women (with 18 cases significant at p<0.1), and in 17 countries women were more patient with men (with 1 case significant at p<0.1). The overall gender effect appears quite robust for international survey data, although the diversity suggests that we should not be surprised by single country studies that find results in either direction. Educated people with at least a college degree are almost 3% more likely to choose LL, in line with recent well-controlled research focusing on the role of education in intertemporal choice (Perez-Arce, 2017; Dohmen et al., 2018). As expected, occupational status is very important. This holds after controlling for income. We see that including the employment conditions does not significantly impact the effect of income. Unemployed, retired or disabled people are less likely to choose LL. This may be due to financial constraints - for instance, it may be harder to get loans if you are unemployed - although it is also plausible that impatient individuals are more likely to end up unemployed. Our data do not allow us to distinguish between these possibilities. Individuals who believe their country is going to experience the same or better economic conditions in the future are more patient than those who believe conditions will be worse (around 2% for both groups). This is in line with the idea that the more uncertain are the conditions that the decision maker will experience in the future, the more she will discount it (Green and Myerson, 2004). A similar explanations applies to the result that individuals who are longing for changes in their country are around 4% less likely to choose LL than those who are satisfied with the status quo. That might be due to the pessimistic view they have of their own country. If they think their country needs to change they might fear, among other things, future severe economic conditions or they might be willing to leave the country soon. Hence, they are looking for an immediate reward since they perceive the future as risky and uncertain. Happy people are more patient. The probability of choosing LL increases by 2.5% for individuals who describe themselves as happy or very happy with respect to others. It looks like individuals who are unhappy look for some form of relief to their unhappiness by claiming the reward immediately. Happy individuals, on the other hand, are probably satisfied with the status quo and do not need some extra gratification.

This is in line with Ifcher and Zarghamee (2011). Individuals choosing the Risk Averse option in a risk question are around 9% more likely to choose LL. That is a huge effect and it backs up the evidence that Risk Aversion is correlated with patience (Anderhub et al., 2001; Tanaka et al., 2010). Individuals who strongly disagree that vaccines are effective are more than 7% less likely than others to choose LL. We believe that choices about vaccines are inherently related to discounting. The reward, namely being covered by the illness, comes in the future, while there is a (small) sacrifice in the present. This is in line with Nuscheler and Roeder (2016). We find that religion predicts patience. Atheists and Agnostic are 6.5% more likely than the baseline to choose LL. We could legitimately expect religious people to be more willing to delay the reward since religion is usually a matter of sacrificing today satisfaction for a future reward. On top of that, religion is usually forward looking being focused on the after life. Hence, we did not expect non religious people to score the highest on this metric. Protestants are around 3.5% more likely than the baseline to choose LL. That is somehow expected. From an institutional point of view, since patience is considered as a driver for development and wealth, we expected it to be correlated to Protestantism. Since Weber (1930), individual characteristics featured by Protestant ethics have been considered as beneficial for the prosperity of an economic environment and individualism is one of those characteristics. Here, Protestants score better with respect to other major religions but lower than non-religious people. Actually, it may be argued that individualism could be even stronger for an atheist than for a Protestant. For example, Caldwell-Harris (2012), argues that, among the other things, atheist are more individualistic than believers. Then, if individualism is a driver for economic prosperity and economic prosperity is linked both to patience and individualism, our results are sensible. In Section 4.10 we do find that our country level measure of patience is actually correlated to the average level of individualism in the country.

4.7 Alternative statistical models

When we model the answers of respondents from different countries, we need to take into account the possibility that the answers or the standard errors of the regressions, for individuals living in the same country, might be correlated. In Table 4.5 we relied upon a linear probability model with fixed effects. We chose that model because it gives a simple interpretation of the data but, at the same time, has enough sophistication to account for within country correlation of the answers. In Table 4.7 we explore several alternative specifications for country heterogeneity. We anticipate the take home message. As we have just said, our specification shown in Table 4.5 and expressed in Equation (4.2) gives an optimal approximation of the marginal effects and it accounts for within country correlations. However, we could only say that after attempting to model within country correlations by means of alternative models. The results are shown in Table 4.7 and we are now going to detail how those alternative models address the problem of the correlation of the answers at the country level.

In the first two columns of Table 4.7 we report the results of the linear probability models outlined in Equation (4.1) and Equation (4.2) (without x_i) and presented in columns 1 and 2 of Table 4.5. In column 1 of Table 4.7 we do not take into account the within countries correlations in our estimates. In column 2 we fit a fixed effects (or least squares dummy variables) model. In this way we estimate one time invariant intercept for any country. We observe a slight change in the estimate with respect to column 1. The general pattern remains true, patience decreases with age at a faster rate for the poorest quintile and the marginal effect of age increases as income increases. However, when we take into account country fixed effects, patience is basically stable, as age increases, for the richest quintiles of income and decreasing for the other quintiles. These will be our benchmark estimates, which we have exhaustively discussed in Section 4.6. Here, we will argue that they are robust and reliable. In column 3 of Table 4.7 we propose a mixed effects linear regression. In general, a linear mixed model for observations $y = (y_1, \ldots, y_n)$ has the general form $Y \sim \mathcal{N}(\mu, \Sigma)$, $\mu = X\beta + Zb, b \sim N(0, \Sigma_b)$ where X and Z are matrices containing values of the explanatory variables. Usually, $\Sigma = \sigma^2 I_n$. A typical example for clustered data might be

$$\begin{aligned} Y_{ij} &\sim \mathcal{N}(\mu_{ij}, \sigma^2) \ ind. \\ \mu_{ij} &= x_{ij}^T \beta + z_{ij}^T b_j \\ b_j &\sim \mathcal{N}(0, \Sigma_b) \ ind. \end{aligned} \tag{4.3}$$

where x_{ij} contains the explanatory data for cluster j, observation i and z_{ij} contains that sub-vector of x_{ij} which is allowed to exhibit extra between cluster variation in its relationship with Y. In the simplest (random intercept) case, $z_{ij} = \mathbf{1}$. In our case a cluster is a country. A plausible mixed model for

Table 4.7: **Alternative specifications.** Column (1): LPM with Clustered Standard Errors at Country Level. Column (2): LPM with Country FE and Clustered Standard Errors at Country Level. Column (3): Mixed effects (Country Level). Column (4): GLM Mixed Effects (Country Level). Column (5): Logistic Equation with Clustered Standard Errors at Country Level. Column (6): Conditional Logistic (strata are Countries) with Clustered Standard Errors at Country Level.

Dep Var: Larger Later	*LPM*	*LPM FE*	*Mixed Eff.*	*GLM Mixed Eff.*	*GEE*	*Conditional LogitLogit*
	(1)	(2)	(3)	(5)	(6)	(7)
Age (decades)	−0.018***	−0.027***	−0.026***	−0.114***	−0.086***	−0.075***
	(0.004)	(0.004)	(0.003)	(0.013)	(0.013)	(0.017)
Second Poorest Quintile	0.017	0.024	0.024	0.096	0.053	0.060
	(0.029)	(0.024)	(0.018)	(0.078)	(0.073)	(0.116)
Middle Quintile	−0.001	0.004	0.005	0.012	−0.004	−0.011
	(0.029)	(0.024)	(0.018)	(0.077)	(0.070)	(0.118)
Second Richest Quintile	0.028	0.017	0.017	0.062	0.019	0.104
	(0.031)	(0.026)	(0.020)	(0.086)	(0.072)	(0.123)
Richest Quintile	0.007	−0.003	−0.003	−0.027	−0.032	0.019
	(0.038)	(0.031)	(0.023)	(0.097)	(0.085)	(0.154)
Age (decades) ∗Second Poorest Q.	0.007	0.003	0.003	0.015	0.014	0.032
	(0.006)	(0.005)	(0.004)	(0.017)	(0.016)	(0.023)
Age (decades) ∗Middle Q.	0.017***	0.013***	0.013***	0.057***	0.044***	0.071***
	(0.006)	(0.005)	(0.004)	(0.017)	(0.015)	(0.023)
Age (decades) ∗Second Richest Q.	0.022***	0.017***	0.017***	0.074***	0.058***	0.091***
	(0.006)	(0.006)	(0.004)	(0.019)	(0.016)	(0.025)
Age (decades) ∗Richest Q.	0.032***	0.025***	0.025***	0.111***	0.079***	0.131***
	(0.007)	(0.006)	(0.005)	(0.022)	(0.017)	(0.030)
Observations	50,754	50,754	50,754	50,754	50,754	50,754
Adjusted R^2	0.010	0.054				
Note:						*p<0.1; **p<0.05; ***p<0.01

k clusters with $n_1, \ldots, n_k$ observations per cluster, and a single explanatory variable x is

$$\begin{aligned} y_{ij} &= \beta_0 + b_{0j} + (\beta_1)x_{ij} + \epsilon_{ij} \\ (b_{0j})^T &\sim \mathcal{N}(0, \Sigma_b)\ ind. \end{aligned} \tag{4.4}$$

where X and Z are defined as

$$\text{X} = \begin{pmatrix} 1 & x_{11} \\ \vdots & \vdots \\ 1 & x_{n_k k} \end{pmatrix} \quad \text{Z} = \begin{pmatrix} Z_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & Z_k \end{pmatrix} \quad Z_j = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}$$

In our case, we have more than a single explanatory variable since we have both age and income so the equation would be more similar to Equation (4.2). On top of that, we only allowed a random intercept for any country so we set $Z_j = (1, .., 1)\ \forall j$. Finally, the estimate of the mixed model are obtained through maximum likelihood and not through ordinary least squares. We can see that the estimate in column 3 of Table 4.7 are virtually unchanged from the estimate of column 2. Hence, we believe that adding random intercepts was an unnecessary complication. The other four models belong to the class of generalised linear models. Before we describe them, we'd like to add a caveat. The patience question proposes a binary choice. Hence, the reader might have expected we preferred a generalised linear model to perform our estimation. As we already pointed out in Section 4.5, we favoured the interpretability of the linear model. On top of that, since we did not have to deal with probabilities very close to 0 or 1 and since we had a great number of observations, we chose the linear model as our main specification. However, we will now describe our estimates for three different generalised linear models, all of the logit type. In general, for a logit model, the following is true. $y_1, \ldots, y_n$ are observations of response variables $Y_1, \ldots, Y_n$, assumed to be independently generated by a distribution of the same exponential family form, with means $\mu_i = E(Y_i)$ linked to explanatory variables $X_1, \ldots, X_n$ through

$$g(\mu_i) = \eta_i = x_i^T \beta \tag{4.5}$$

where, the $g(\cdot)$ function is called the link function and in the case of a logit it is equal to the logit function

$$logit(x) = \log \frac{x}{1-x} \tag{4.6}$$

In column 7 of Table 4.7 we present the estimate obtained with a logit model for the patience question

$$p_i = \alpha + \beta a_i + \gamma_k I_{ki} + \delta_k a_i * I_{ki} \quad i \in I; \;\; k \in \{2, 3, 4, 5\} \tag{4.7}$$

where $p_i = logit(y_i)$ and y_i takes the value of 1 if respondent i chose LL; I_k are four dummies for the four quintiles of the income distribution (the first is the baseline), and a_i is age (in decades) of the subject. Taking into account the caveat on the interpretation of interactions in a logit model (Ai and Norton, 2003), we see that the pattern observed for the linear model is replicated. We would like to point our that we obtained out of sample predictions for the logit model (not shown) and the pattern observed in Figure 4.2 was replicated for this model, as well.

In column 6 of Table 4.7 we report the result of a conditional logit regression approach. This is sometimes improperly referred to as "fixed effect logit". The intuition underlying this model is that both individual characteristics and group characteristics are taken into account for the estimation. The model allows us to stratify the data, based on the strata to which they belong, in our case the country. A nice description of the model is given in terms of underlying latent variable. Let's suppose that the (unobservable) utility derived by the choice of LL or SS is defined as:

$$y^*_{ir} = x_{ir}\beta + c_{ir} \quad r \in \{0, 1\} \tag{4.8}$$

where $r = 0$ refers to the choice of SS and $r = 1$ to LL. The vector x_{ir} contains the values of the variables which influence investor i to make choice r. The vector c_{ir} refers to country preferences regarding the choice of LL or SS. Estimating a conditional logit model we assume that the a_{ir} are independently distributed with a cdf $F(c) = \exp[-\exp(-c)]$. We do this in order to take into account the fact that the propensity to choose LL varies from a country to another, independently of the x. We are interested in estimating the probability that a respondent chooses LL

$$P(y_i = 1|x_i) = \frac{\exp(x_{i1}\beta)}{\exp(x_{i1}\beta) + \exp(x_{i0}\beta)} \tag{4.9}$$

The vector x_{ir} contains the same variables we have on the right-hand side of Equation (4.1). As we compare the estimate from column 7 and 6 in Table 4.7 we see the same "shrinkage" effect on the coefficients which we observed from column 1 to 2. Taking into account country specific characteristics reduces the spread in the probabilities of choosing LL, without eliminating the effect. In column 4 we fit the generalised linear model version of the mixed effects model we presented in column 3. This merges the formulation in Equation (4.5) and the one in Equation (4.4). The left-hand side of the equation is modeled as in Equation (4.5). The right-hand side of the equation as the right-hand side of Equation (4.4). In this way we model the relationship between the response variable and the covariates as a generalised linear model but we allow for random effects due to country characteristics. The coefficients shrink but less than the shrinkage observed going from a logit to a conditional logit. The usual pattern is respected.

Table 4.8: **Residuals regression.** Dependent variable is the residual of a Linear Probability Model regression of the answer to the patience question (1 if LL) on country dummies.

Dep Var	Res. Country Reg.
Age (decades)	-0.025^{***}
	(0.004)
Second Poorest Quintile	0.020
	(0.024)
Middle Quintile	0.0003
	(0.023)
Second Richest Quintile	0.007
	(0.026)
Richest Quintile	-0.013
	(0.029)
Age (decades) $*$Second Poorest Quintile	0.003
	(0.005)
Age (decades) $*$Middle Quintile	0.013^{***}
	(0.005)
Age (decades) $*$Second Richest Quintile	0.017^{***}
	(0.006)
Age (decades) $*$Richest Quintile	0.025^{***}
	(0.006)
Observations	50,754
R^2	0.007
Adjusted R^2	0.007

Note: *p<0.1; **p<0.05; ***p<0.01; Clustered s.e. at country level.

Finally, we show that the predictions are unchanged when we take the residuals of a regression of the LL variable on countries dummies and we

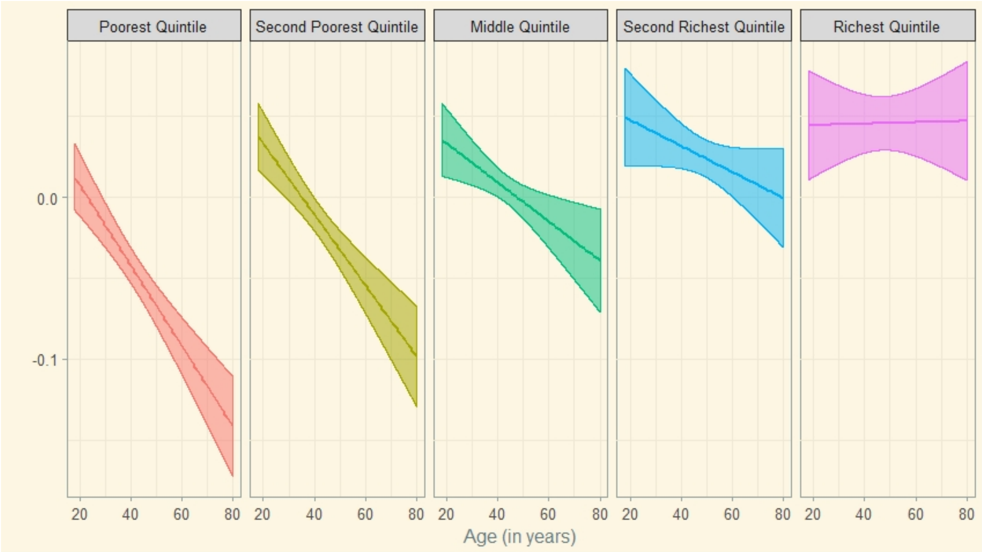

Figure 4.3: **Residuals regression predictions (age/income).** Predictions based on OLS regression model in Table 4.8. We regressed the answer to the patience question (1 if LL) on countries dummies. We then regressed the residuals from that regression on age, income and the interactions and obtained out of sample prediction for that model (clustered standard errors at country level).

regress them on age, income and their interactions (Table 4.8 and Figure 4.3). We proceeds as follows. First, we perform the following regression:

$$y_i = \lambda_j C_{ji} \quad i \in I; \;\; j \in J \tag{4.10}$$

where, y_i is the answer to the patience question by individual i (1 if LL), C_j are 65 dummies which refer to the country (j) of the respondent (i). We obtain the residuals of the regression performed in Equation (4.10), which are equal to

$$\begin{aligned} r_i &= y_i - \hat{y}_i \\ \hat{y}_i &= \hat{\lambda}_j C_{ji} \end{aligned} \tag{4.11}$$

with $\hat{\lambda}_j$ which represent the OLS estimate of the coefficients in Equation (4.10), and we regress them on age and income

$$r_i = \alpha + \beta a_i + \gamma_k I_{ki} + \delta_k a_i * I_{ki} \quad i \in I; \;\; k \in \{2, 3, 4, 5\} \tag{4.12}$$

where everything is defined as in Equation (4.1) apart from r_i. I_k are four dummies for the four quintiles of the income distribution (the first is the baseline), and a_i is age (in decades) of subject i. We first regressed the answers to the patience question on the country dummies. The residuals (Equation (4.11)) of this regression (Equation (4.10)) capture the variation in the patience question not due to country related variables. Hence, the marginal effects obtained in Equation (4.12) are the marginal effects of age and income, which are not due to country fixed characteristics but only to individual characteristics. The results are shown in Table 4.8 and in Figure 4.3. We cannot interpret the results as the probability of choosing LL, since the dependent variable does not have that meaning. We can interpret the results as the marginal effects that age and income have on the part of the probability of choosing LL, which is not explained by country characteristics. As we can see, the pattern observed in Figure 4.2 is perfectly replicated in Figure 4.3.

4.8 Robustness checks: sub-sample analysis, age as a categorical variable, missing answers

We replicate the main analysis (Equation (4.1) plus country fixed effects) in the four macro areas of the world: Europe, North and South America, Asia and Oceania, Middle East and North Africa and sub-Saharian Africa (Table 4.9). We see that, on average, patience is positively correlated with age for the richest category and it is negatively correlated with age for the poorest category. In particular, patience decreases with age for the poorest quintile in all areas, apart from Asia and Oceania. For the richest quintile of income, patience either decreases at a much lower rate (Europe) or it actually increases with age (Americas, Middle East and Africa). The area of Asia and Oceania is an exception. We do not find any significant effects for any interactions of age and income in that area. At least, the coefficient of age and that of age interacted with the second poorest quintile of income are negative, while the coefficients of the other three quintiles of income interacted with age are positive. In general, the effects for the intermediate categories of income are weaker than in the whole sample. However, as we said, when we focus on single areas of the world it is almost everywhere true that age means impatience for the poorest quintile and patience for the richest quintile.

We already pointed our that several studies have reported a U-shaped relation between age and discounting (Harrison et al., 2002; Read and Read,

Table 4.9: **Macro areas regressions.** Linear Probability Model. We re-estimate model from column (1) in Table 4.5 on four different subsets of the data. Robust standard errors in parenthesis

Dep Var: Larger Later	Europe	Americas	Asia Oceania	MENA Africa
	(1)	(2)	(3)	(4)
Age (decades)	-0.035^{***}	-0.016^{**}	-0.007	-0.025^{***}
	(0.004)	(0.007)	(0.007)	(0.006)
Second Poorest Quintile	0.048	0.048	0.085^{**}	-0.067^{*}
	(0.031)	(0.043)	(0.043)	(0.038)
Middle Quintile	0.048	0.027	0.020	-0.068^{*}
	(0.030)	(0.044)	(0.041)	(0.039)
Second Richest Quintile	0.065^{**}	0.037	-0.014	0.029
	(0.032)	(0.051)	(0.045)	(0.046)
Richest Quintile	0.054	-0.003	0.042	-0.120^{**}
	(0.036)	(0.058)	(0.049)	(0.061)
Age (decades) ∗Second Poorest Q.	-0.002	-0.0002	-0.010	0.022^{**}
	(0.006)	(0.009)	(0.010)	(0.009)
Age (decades) ∗Middle Q.	0.006	0.012	0.008	0.025^{***}
	(0.006)	(0.010)	(0.010)	(0.010)
Age (decades) ∗Second Richest Q.	0.013^{*}	0.011	0.017	0.009
	(0.007)	(0.011)	(0.011)	(0.011)
Age (decades) ∗Richest Q.	0.020^{***}	0.026^{**}	0.007	0.045^{***}
	(0.007)	(0.013)	(0.011)	(0.015)
Observations	20,236	8,657	11,772	10,089
R^2	0.072	0.062	0.025	0.039
Adjusted R^2	0.071	0.060	0.023	0.037
Country FE	YES	YES	YES	YES

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$; . Robust standard errors.

2004; Bruderer Enzler et al., 2014; Falk et al., 2018; Richter and Mata, 2018). The framework we proposed in Equation (4.1) does not allow us to document such a pattern, since we fit age as a linear predictor. Here, we show that analysing age as a categorical variables does not produce any non-linear pattern. In Table 4.10 we report the outcome of the following model:

$$\begin{aligned} y_i = \alpha + \beta_z a_{zi} + \gamma_k I_{ki} + \delta_{zk} a_{zi} * I_{ki} + \omega x_i + \lambda_j C_{ji} \\ i \in I; \ \ z \in \{2,3,4,5,6\}; \ \ k \in \{2,3,4,5\}; \ \ j \in J \end{aligned} \tag{4.13}$$

where y_i takes the value of 1 if i respondent chose LL; I_k are four dummies for the four quintiles of the income distribution (the first is the baseline), and a_z are five age dummies. The first group (the baseline) is 18 to 24 years, then 25 to 34, 35 to 44, 45 to 54, 55 to 64 and individuals above 65. Hence, there are 20 interactions for age and income categories. As before, C_j are 64 dummies for the countries (J is the set of countries) and the vector x_i refers to the individual characteristics. Table 4.10 reports the outcome of the regressions. Given that the effects of age and income depend on so many coefficients, it is much easier to visualise the relationship between patience, age and income by observing Figure 4.4. Figure 4.4 reports out of sample prediction for USA citizens, for a regression where age and income are considered as categorical variables and country fixed effects are added (hence the model reported in Equation (4.13) where no other x_i individual characteristics are considered). These are the equivalent predictions of Figure 4.2, where age was fitted as a continuous variable. We can see that the pattern observed in Figure 4.4 can be conveniently approximated by linear trends. Patience decreases with age for any income category and the marginal decrease is weaker, the higher is the income. The richest quintile of income shows constant patience for any level of income. This confirms that no U-shaped pattern is present in our data and we can rely upon the estimates presented in Section 4.6.

Finally, we check if our results are driven by the pattern of missing answers. It might be the case that the distribution of missing answers among income and age groups drives our results. Imagine that individuals who do not know if they want to answer the patience question are those who are more likely to choose SS, if only they answered the question. If the proportion of not respondent increases with age for the poorest quintile and it decreases with age for richer quintiles, this might bias our main result that age means patience to the rich and impatience to the poor. Hence, we perform the following

Table 4.10: **Age bins regression.** Linear Probability Model. Demographic controls in column (3) are the same of column (3) from Table 4.6

Dep Var: Larger Later	(1)	(2)	(3)
Age 25 to 34	−0.059***	−0.051***	−0.042*
	(0.021)	(0.018)	(0.025)
Age 35 to 44	−0.097***	−0.086***	−0.066**
	(0.026)	(0.021)	(0.027)
Age 45 to 54	−0.088***	−0.090***	−0.077***
	(0.024)	(0.023)	(0.027)
Age 55 to 64	−0.103***	−0.130***	−0.100***
	(0.025)	(0.023)	(0.028)
Age above 65	−0.106***	−0.145***	−0.112***
	(0.027)	(0.024)	(0.027)
Second Poorest Quintile	−0.001	0.002	0.001
	(0.027)	(0.022)	(0.026)
Middle Quintile	−0.011	−0.003	−0.010
	(0.024)	(0.019)	(0.021)
Second Richest Quintile	0.037	0.027	0.027
	(0.033)	(0.030)	(0.033)
Richest Quintile	0.026	0.014	0.006
	(0.039)	(0.032)	(0.037)
Age 25 to 34 ∗Second Poorest Quintile	0.054**	0.042*	0.045
	(0.024)	(0.023)	(0.029)
Age 35 to 44 ∗Second Poorest Quintile	0.078***	0.055**	0.038
	(0.030)	(0.026)	(0.029)
Age 45 to 54 ∗Second Poorest Quintile	0.053*	0.032	0.031
	(0.029)	(0.027)	(0.033)
Age 55 to 64 ∗Second Poorest Quintile	0.053	0.041	0.032
	(0.033)	(0.030)	(0.033)
Age above 65 ∗Second Poorest Quintile	0.062*	0.030	0.030
	(0.033)	(0.031)	(0.035)
Age 25 to 34 ∗Middle Quintile	0.085***	0.062***	0.054**
	(0.025)	(0.022)	(0.025)
Age 35 to 44 ∗Middle Quintile	0.107***	0.082***	0.065**
	(0.026)	(0.022)	(0.026)
Age 45 to 54 ∗Middle Quintile	0.092***	0.066***	0.058**
	(0.029)	(0.024)	(0.026)
Age 55 to 64 ∗Middle Quintile	0.107***	0.090***	0.081**
	(0.030)	(0.027)	(0.032)
Age above 65 ∗Middle Quintile	0.120***	0.081***	0.085**
	(0.033)	(0.030)	(0.037)
Age 25 to 34 ∗Second Richest Quintile	0.064*	0.046	0.027
	(0.036)	(0.034)	(0.039)
Age 35 to 44 ∗Second Richest Quintile	0.119***	0.086**	0.045
	(0.039)	(0.035)	(0.039)
Age 45 to 54 ∗Second Richest Quintile	0.095**	0.061*	0.043
	(0.039)	(0.037)	(0.042)
Age 55 to 64 ∗Second Richest Quintile	0.132***	0.110***	0.087**
	(0.038)	(0.036)	(0.042)
Age above 65 ∗Second Richest Quintile	0.120***	0.083**	0.062
	(0.042)	(0.039)	(0.043)
Age 25 to 34 ∗Richest Quintile	0.082**	0.066*	0.053
	(0.041)	(0.037)	(0.041)
Age 35 to 44 ∗Richest Quintile	0.157***	0.119***	0.077*
	(0.043)	(0.037)	(0.042)
Age 45 to 54 ∗Richest Quintile	0.151***	0.104***	0.080**
	(0.038)	(0.032)	(0.035)
Age 55 to 64 ∗Richest Quintile	0.145***	0.112***	0.063
	(0.040)	(0.034)	(0.039)
Age above 65 ∗Richest Quintile	0.197***	0.168***	0.126***
	(0.047)	(0.041)	(0.048)
Observations	50,754	50,754	38,407
Adjusted R^2	0.010	0.054	0.067
Demographic Controls	NO	NO	YES
Country FE	NO	YES	YES
Countries number	65	65	60

Note: *p<0.1; **p<0.05; ***p<0.01; Clustered standard errors at country level.

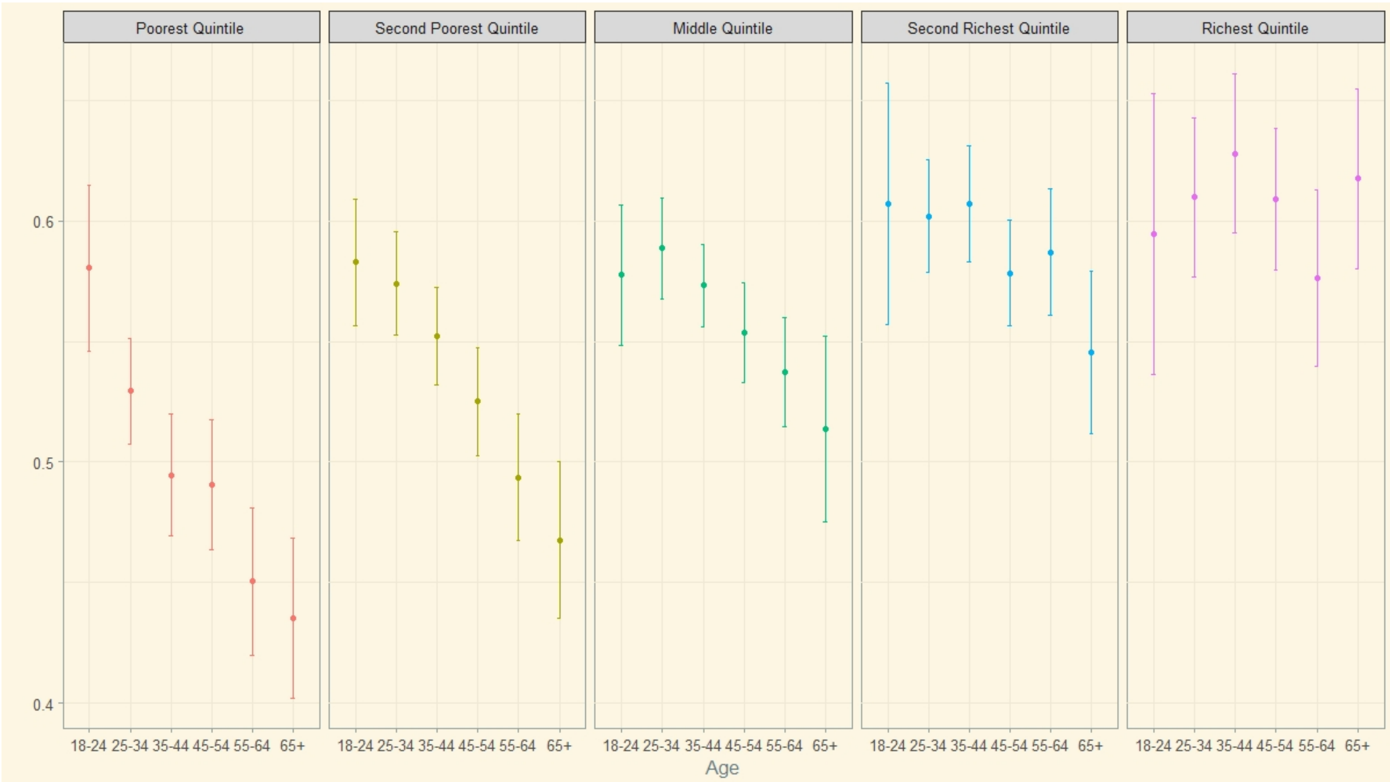

Figure 4.4: **Probability of choosing LL (age/income).** Estimated probability of choosing LL per each quintile of income. Predictions based on OLS regression model from column 2 of Table 4.10 with country fixed effects and clustered standard errors at country level. Country fixed to the United States of America. Age and income are both categorical variables.

Table 4.11: **No answer regression.** Dep. var. is 1 if the subject did not answer the Patience question. Logit Model based on a sample of 65 countries.

Dep Var: Not Resp	Coefficient	Odds Ratio
	(1)	(2)
Age (decades)	0.135***	1.14
	(0.034)	
Second Poorest Quintile	0.218	1.24
	(0.369)	
Middle Quintile	0.087	1.09
	(0.437)	
Second Richest Quintile	0.415	1.51
	(0.462)	
Richest Quintile	−0.482*	0.62
	(0.247)	
Age (decades) ∗Second Poorest Quintile	−0.086	0.92
	(0.054)	
Age (decades) ∗Middle Quintile	−0.076	0.93
	(0.062)	
Age (decades) ∗Second Richest Quintile	−0.142**	0.87
	(0.063)	
Age (decades) ∗Richest Quintile	−0.017	0.98
	(0.045)	
Observations	57,682	
McFadden Adj. R^2	0.182	
Note:	*p<0.1; **p<0.05; ***p<0.01; Clustered s. e. country level.	

Figure 4.5: **Probability not answering patience question (age/income).** Estimated probability of not answering the Patience question per each quintile of income. Predictions based on a logistic regression model with clustered standard errors at country level.

regression:

$$n_i = \alpha + \beta a_i + \gamma_k I_{ki} + \delta_k a_i * I_{ki} \quad i \in I; \;\; k \in \{2, 3, 4, 5\} \tag{4.14}$$

where $n_i = logit(m_i)$ and m_i takes the value of 1 if respondent i chose not to answer the patience question or answered "I don't know"; I_k are four dummies for the four quintiles of the income distribution (the first is the baseline), and a_i is age (in decades) of the subject. Since we have to deal with probabilities close to 0, we model it as a logit regression. Table 4.11 reports the outcome of the regression and Figure 4.5 reports out of sample predictions for the probability of not answering the patience question. We do not detect any remarkable pattern in our results. For any income category, older individuals are more likely to be non-respondents. The probability of not answering the question are quite small and quite stable across income groups, for any level of age. Very old individuals in the poorest quintile show the highest probability of not answering the question and very young individuals from the richest quintile show the lowest probability of not answering the question. However, these are not big departures from the other values and we firmly believe they are not strong enough to drive our main result.

4.9 Age means impatience to the poor and patience to the rich: a discussion

The first possible explanation for our results is that lower incomes lead to lower patience with age, while high incomes don't. Loibl (2017, p. 428) points out that poverty in older age can lead to serious difficulties: "Difficulties adjusting to the lower pension income in early retirement, higher health care expenses, increasing demands to pay towards the cost of care, and the need to modify the home to meet changing health needs are the reasons for tight financial situations in older age (Bucher-Koenen and Lusardi, 2011; van Rooij et al., 2011)." This suggests that poor people might end up discounting at a higher rate than the rich when they get older, because they will be more strongly affected by Fisher's "pressure of pressing needs". Along the same lines, Mani et al. (2013) suggested that poverty leads to lower cognitive functions and to worse financial choices. If worse financial choices worsen the financial situation of the individuals and lead to other wrong choices, we observe a never ending loop. This account is consistent with our findings, if we hypothesise that a preference for the “Smaller Sooner” option is the choice associated to lower cognitive functions. One possibility for the declining pattern of age, for lower income individuals, could be that persistent poverty reduces cognitive functions even more with time. Then, being persistently in the lowest quintile of income, can lead to have an always lower preference for the “Larger Later” option. Becker and Mulligan (1997) theory is also consistent with this notion: while people may not be born with different discount rates, those who are well off will find it worthwhile to invest more in thinking about the future, and will therefore become more patient because of this investment. So the rich will become more patient because they are rich. But, of course, this greater patience will lead them to get richer. The very poor, on the other hand, will find no reason to invest in thinking about the future. An alternative proposal about the relationship between ageing, poverty and discount reverses the causal arrow. Ramsey (1928), suggested that if discount rates differ among people, those who are more patient will become better off as they get older, while those who are less patient will become worse off. The logic is that if people start off with wealth “randomly distributed” over patience levels, those with lower discount rates will end life richer than those with higher rates. With age (measured cross-sectionally) those with the highest income when older would therefore have lower discount rates than those with the lowest income, while in their early years those with higher and lower income would not differ appreciably. These two accounts, for different reasons, suggest that a sample of poor elderly people will be less patient than a sample of wealthy elderly people, but this difference may not be observed for younger people.

Our evidence is consistent with the findings of Green et al. (1999) and Epper et al. (2020). We are able to “fill the gap” in the results of Green et al. (1999). They did show a wealth effect, with older wealthier people discounting less than older poorer people. Plus, they found that older wealthy people discounted at the same rate as younger wealthy people, suggesting that discounting might not change with age. We found that this is true for the well off, but it is not true for the worse off. Lower income individuals discount at a similar rate to higher income individuals when young and the difference arises only with age. Our results are perfectly consistent with the stereotype of a young person, poor or otherwise, as someone looking forward to the future and in most cases not constrained by current wealth but optimistic about future wealth, as suggested by Fisher. Our results are consistent with Epper et al.

(2020), as well. Epper et al. (2020) measured discounting at one point in time, for a sample of Danish citizens, and checked where individuals ranked in the wealth distribution, over their lifespan. They did find that individuals with relatively low time discounting were persistently positioned higher in the wealth distribution, throughout their lives. Their explanation, which is applicable to our case as well, is that patience affects individuals' positions in the wealth distribution through the savings channel. They claimed that those who are more patient tend to save more, during their life. To justify this claim, they showed that, for credit constraints individuals, patience did not predict their position in the wealth distribution. The explanation is that those individuals are not given free choice whether to borrow money or not. Hence, impatient individuals who are credit constraint do not rank much lower in the wealth distribution, than patient individuals who are credit constraint. In contrast, patience was found to be a strong predictor of wealth position for those who are not credit constraint. They saw that patience did not predict the wealth position for subjects who held liquid assets worth less than one month's disposable income, the credit constraint individuals. They found a strong predictive power of patience in the group of Danish citizen with liquid wealth corresponding to more than one month's disposable income. Moving from the lowest to the highest level of patience in this group increased the wealth rank position by 12 percentiles. In a nutshell, the explanation proposed by Epper et al. (2020) is that patience leads to higher wealth thanks to savings. We can only expect this effect to become stronger and stronger with age, leading the gap in wealth between patient and impatient people to increase over time. Although we presented data for income and not for wealth, income is by no doubt a good predictor of wealth. Plus, when considering household income, individuals should take into account also the cash flows coming from their investments, which are expected to be bigger the higher is the wealth available to the individual, to be saved and invested.

4.10 Patience around the world

If we look at the R^2 of the models in Table 4.5 we can see that country level fixed characteristics can explain most of the variation which we can describe, for our dependent variable. Hence, it is worth looking at how different national characteristics correlate with patience. We use as an index of national patience the percentage of respondents choosing "Larger Later" in each country. This is reported in Table 4.2 and shown in Figure 4.1. We start by comparing our measure to the measures of patience of Wang et al. (2016) and Falk et al. (2018). Table 4.12 shows the correlation of our patience index with these two alternative indices from the literature and some country characteristics. Table 4.13 shows the results of linear regressions where we regress our index of patience on the indices obtained by Falk et al. (2018) and Wang et al. (2016). They can both explain a lot of the variation in our index, but the Falk et al. (2018) is more correlated to our measure.

Table 4.12: **Patience correlation.** Correlation (Pearson) of our index of Patience (Proportion of respondents in a Country who chose LL) with other indices and country level variables.

	Corr. Patience	p-value	Countries
Patience Falk et al. (2018)	0.605	0.000	44
Patience Wang et al. (2016)	0.439	0.020	28
GDP per capita 2014	0.528	0.000	65
GDP per capita 2015	0.521	0.000	65
Life Expectancy 2015	0.435	0.000	65
Life Expectancy 2014	0.433	0.000	65
Real Interest Rate 2015	-0.496	0.001	43
Real Interest Rate 2014	-0.444	0.003	44
Private Credit to GDP 2014	0.329	0.009	63
Distance from Equator	0.320	0.009	65
Private Credit to GDP 2015	0.324	0.010	63
Uncertainty Avoidance (Hofstede)	-0.376	0.013	43
Individualism (Hofstede)	0.361	0.017	43
Inflation 2014	-0.271	0.030	64
Future Time Reference Weak	0.270	0.035	61
Inflation 2015	-0.256	0.041	64
Future Orientation Index	0.173	0.174	63
Gross Savings 2015	0.156	0.225	62
Debt to GDP Ratio 2014	0.113	0.376	63
Growth Rate 2015	0.095	0.451	65
Gross Savings 2014	0.082	0.526	62
Growth Rate 2014	-0.068	0.592	65
Debt to GDP Ratio 2015	0.066	0.605	63
Long Term Orientation (Hofstede)	-0.010	0.945	53

The correlation betwen our measure of patience and the one proposed by Falk et al. (2018) is 0.61 and it is highly significant. However, while their top 10 is made of

countries in the world [...] either located in the neo-European,

Table 4.13: **Patience comparison regression.** Dependent Variable is the Patience index calculated at Country level (percentage of LL replies). Robust Standard Errors reported.

Dep Var: Patience	(1)	(2)	(3)
Patience Falk et al. (2018)	0.174***		0.118**
	(0.030)		(0.049)
Patience Wang et al. (2016)		0.271***	0.144*
		(0.080)	(0.085)
Observations	44	28	23
Adjusted R^2	0.366	0.192	0.403
Note:			*p<0.1; **p<0.05; ***p<0.01

English-speaking world, or else in Western Europe, with the Scandinavian countries exhibiting particularly high levels of patience.

we observe some relevant exceptions. Apart from countries from the Western world (with Scandinavian ones at the very top) we see Bangladesh, Kosovo, Saudi Arabia and Morocco, popping in our top 10. In general, Latin American and African countries are less patient and Western countries are more patient. This is in line with Falk et al. (2018) and Wang et al. (2016). Our measure is highly correlated with the one developed by Wang et al. (2016), as well. Correlation is 0.44 and it is significant. We should take into account that the set of subjects surveyed in Wang et al. (2016) is not perfectly comparable to our set of subjects[6].

Turning our attention to country characteristics, we will look at them in order of relevance. The two most relevant factor to explain our index are GDP per capita and life expectancy in the country. Wealthier countries and countries where life expectancy is higher are more likely to delay the reward. GDP per capita in both 2014 an 2015 has a correlation higher than 0.5 with our measure of patience. This is in line with Falk et al. (2018) and in line with the thesis that development is linked to patience. Life expectancy at birth shows a correlation higher than 0.4 with our index, and highly significant. That was expected, since life expectancy should shape our future orientation, in terms of how sure the future rewards is perceived. The real interest rate is highly negatively correlated to our measure of patience. It is interesting

[6]We checked what is the correlation of Wang et al. (2016) measure with our measure calculated only using answers from young or young students and the correlation was actually lower.

to see that the interest rate individuals were experiencing at the time of the survey, in 2015, is a better predictor of patience (-0.496) than the interest rate from the previous year (-0.444). Since our question concerns a reward to be enjoyed in one year, it is discounted more in countries where available interest rates were higher. Private credit to the private sector is positively related to patience (more than 0.32 for both 2014 and 2015). This means that in countries where financial resources provided to the private sector by financial corporations are higher, have a higher level of patience. This proves that our index is linked to the financial development of countries. Our measure of patience increases in the distance from the equator, confirming ideas from Diamond (2005); Spolaore and Wacziarg (2013) and results in Falk et al. (2018). Countries with higher Uncertainty Avoidance are more present biased, in line with Wang et al. (2016). Individualism is positively related to our index of patience, in line with Wang et al. (2016) and Falk et al. (2018). The effect of individualism is consistent with Triandis (1971) in which participants from the more individualistic culture seemed to be more "willing to defer gratification". It is also in line with the findings by Mahajna et al. (2008), where the Israeli Jews (presumably from a more individualistic culture) exhibited higher patience for monetary incentives than Israeli Arabs (presumably from a more collectivistic culture). Inflation is negatively related to patience. The correlation is lower than -0.25 and significant for both 2014 and 2015. We can advance the same explanation we gave for the effect of the real interest rate. Since we propose an amount of money to be awarded in one year, it loses value as the expectations of inflation increase. Weak Future Time Reference (Chen, 2013) is positively and significantly, correlated with patience, consistently with Falk et al. (2018). In those countries where the linguistic distinction between present and future is not so strong, individuals are more patient and more likely to delay the reward.

Other variables are not significantly correlated but we can comment on the direction of correlation. We detect a weak positive relationship of the Future Orientation Index (Preis et al., 2012) with patience, although it is not significant. This respects our conjecture that countries which are more future oriented are more patient as well. The saving rate is positively correlated to patience (Epper et al., 2020). The growth rate in 2015 is positively correlated to patience, while the one in 2014 is negatively correlated to patience, hence we have no conclusive evidence on the degree of patience and the saving rate. Public debt to GDP ratio is surprisingly positively correlated to our index of patience. However, more developed countries, which show a higher level of patience, tend to have a higher debt to GDP ratio. On top of that, we already highlighted the fact that the correlation is very weak. Differently from Wang et al. (2016) and Falk et al. (2018), we do not find any correlation between Hofstede Long Term Orientation and our index. It is worth remembering that Falk et al. (2018) compared average value of Hofstede's cultural dimension for each country to their index of patience at the country level. Wang et al. (2016) measured Hofstede's cultural dimension at the individual level, alongside preference for intertemporal discounting. Falk et al. (2018) compared average level of Hofstede's cultural dimensions in each country to the patience index of each country, as we do. We believe that our measure does not correlate so well with LTO since LTO is measured looking at items that seem distant from time preferences (see Section 4.4). On top of that, the correlation between LTO and the measures of patience developed by Wang et al. (2016) or Falk et al. (2018) is actually stronger in those countries where our index of patience was not measured. The correlation between Hofstede's LTO index and our measure of patience rises from -0.01 on the entire set of countries which we considered, to 0.05 (not significant) on the set of countries which were involved in both our study and the one by Falk et al. (2018). The correlation between Hofstede's LTO index and Falk et al. (2018) measure of patience drops from 0.44, on the entire set of countries which they consider to 0.27 (significant only at 10% level) on the set of countries which were involved in both our study and their study. Hence, the discrepancy is much more attenuated in the set of common countries.

Although our main concern was focusing on individual differences in discounting rewards, and in particular the ones related to age and income, we believe that our unique dataset gave us a very nice opportunity to further investigate differences at the country level. We added more evidence that patience is correlated to economic development. On top of that, comparing our measure to the one derived in Falk et al. (2018), to the one in Wang et al. (2016) and to the country level indices widely believed to be linked to patience, strengthens the idea that our design is well calibrated and able to capture differences in patience.

4.11 Policy and academic implications

The policy implications of our results are wide and relevant. The patience of individuals changes based on the interaction of age and income. That affects decisions like borrowing money, saving for retirement and eventually how much to save towards a legacy. In particular, we would like to stress the fact that the older low income individuals are, the more likely they are to be impatient. That makes them particularly vulnerable, since older individuals are more likely to face financial troubles because of the increasing life expectancy all over the world and the increase in health related expenditures over the lifespan (Loibl, 2017). We suggest that those category should receive greater attention, when planning welfare interventions. On top of that, higher patience rates might be induced in those individuals.

The implications of our investigation on which individual characteristics are prognostic of patience are wider than that, though. Education, religious beliefs, gender and optimism are all correlated to our measure of patience. Although we cannot disentangle the direction of causality, we can for sure insist upon the fact that some behaviours should be encouraged to foster higher levels of individual patience and that some categories should be looked after, and might be nudged to make more patient choices, with more dedication than others. In particular, our work reminds us of the importance of expectations in shaping economic decisions. Having optimistic views towards the future increases patience. We are not advocating for governments and institutions misreporting information about the economic outlook of their countries. However, since we see that positive views about the future increase patience, we are speaking in favour of all those cases where institutional authorities and political leaders intervened to reassure the population. One of the best exemplifications of this point is the now famous "Whatever it takes" speech of the then president of the European Central Bank, Mario Draghi (Acharya et al., 2019).

Life satisfaction was found to be a good predictor of patience and this gives a hint to all policies which are now contemplating life satisfaction among the indices to take into account (Layard, 2020). Religious beliefs cannot be shaped by the regulators but they have a huge impact on patience. For example, both having no religious affiliation or being protestant increases patience with respect to being affiliated to any other religion, and in both cases the estimate of the increase is bigger than the increase induced by economic optimism. In particular, being non religious (atheist or agnostic) has three times the impact of positive economic expectations on patience. This contributes to the debate on the economic effects of religion (Iyer, 2016).

Finally, cultural variability, as captured by country differences, had the greatest explanatory power for our measure of patience. We were able to relate it to several indicators of economic development like GDP per capita, life expectancy, latitude and private credit to GDP. Most importantly, we developed a measure which correlated very well to the measure developed by Falk et al. (2018) and the one developed by Wang et al. (2016). Our measure has the advantage of being much easier to elicit and it overcomes all the issues due to having different currencies and different economic conditions from one country to another, and from one individual to another. It directly address the actual financial situation of the respondent and it is very easy to understand since it does not involve any demanding mathematical calculations. We introduced an exceedingly simple measure of intertemporal discounting which correlates very well with the main economic indicators and other more sophisticated measures. We suggest it can be easily added to the most relevant surveys which are routinely submitted to the world population, like the World Value Survey, the European Social Survey, the European Values Study and all their national or international equivalents.

Bibliography

Acharya, V. V., Eisert, T., Eufinger, C., and Hirsch, C. (2019). Whatever it takes: The real effects of unconventional monetary policy. *The Review of Financial Studies*, 32(9):3366–3411.

Ai, C. and Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, 80(1):123–129.

Alesina, A. and Giuliano, P. (2014). Family ties. In Aghion, P. and Durlauf, S. N., editors, *Handbook of Economic Growth*, volume 2 of *Handbook of Economic Growth*, pages 177 – 215. Elsevier.

An, L., Engelberg, J., Henriksson, M., Wang, B., and Williams, J. (2019). The portfolio-driven disposition effect. *Available at SSRN 3126997.*

Anderhub, V., Güth, W., Gneezy, U., and Sonsino, D. (2001). On the interaction of risk and time preferences: An experimental study. *German Economic Review*, 2(3):239–253.

Anderson, J. R. and Schooler, L. J. (1991). Reflections of the environment in memory. *Psychological Science*, 2(6):396–408.

Andreoni, J., Gravert, C., Kuhn, M. A., Saccardo, S., and Yang, Y. (2018). Arbitrage or narrow bracketing? on using money to measure intertemporal preferences. *National Bureau of Economic Research.*

Andrikogiannopoulou, A. and Papakonstantinou, F. (2019). History-dependent risk preferences: Evidence from individual choices and implications for the disposition effect. *The Review of Financial Studies.*

Arellano, M. (1987). Computing robust standard errors for within-group estimators. *Oxford Bulletin of Economics and Statistics*, 49(4):431–434.

Arkes, H. R., Hirshleifer, D., Jiang, D., and Lim, S. (2008). Reference point adaptation: Tests in the domain of security trading. *Organizational Behavior and Human Decision Processes*, 105(1):67–81.

Arkes, H. R., Hirshleifer, D., Jiang, D., and Lim, S. (2010). A cross-cultural study of reference point adaptation: Evidence from china, korea, and the us. *Organizational Behavior and Human Decision Processes*, 112(2):99–111.

Baillon, A., Bleichrodt, H., and Spinu, V. (2020). Searching for the reference point. *Management Science*, 66(1):93–112.

Barber, B. M. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The Journal of Finance*, 55(2):773–806.

Barber, B. M. and Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, 116(1):261–292.

Barber, B. M. and Odean, T. (2008). All that glitters: The effect of attention on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2):785–818.

Barber, B. M. and Odean, T. (2013). The behavior of individual investors. In Constantinides, G. M., Harris, M., and Stulz, R. M., editors, *Handbook of the Economics of Finance*, volume 2, chapter 22, pages 1533–1570. Elsevier.

Barberis, N., Huang, M., and Thaler, R. H. (2006). Individual preferences, monetary gambles, and stock market participation: A case for narrow framing. *American Economic Review*, 96(4):1069–1090.

Barberis, N., Huang, M., and Thaler, R. H. (2006). Individual preferences, monetary gambles, and stock market participation: A case for narrow framing. *American Economic Review*, 96(4):1069–1090.

Barberis, N. and Xiong, W. (2009). What drives the disposition effect? an analysis of a long-standing preference-based explanation. *The Journal of Finance*, 64(2):751–784.

Barberis, N. C. (2013). Thirty years of prospect theory in economics: A review and assessment. *Journal of Economic Perspectives*, 27(1):173–96.

Baucells, M., Weber, M., and Welfens, F. (2011). Reference-point formation and updating. *Management Science*, 57(3):506–519.

Bauer, M. and Chytilová, J. (2013). Women, children and patience: Experimental evidence from i ndian villages. *Review of Development Economics*, 17(4):662–675.

Becker, G. M., Degroot, M. H., and Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral Science*, 9(3):226–232.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy*, 70(5):9–49.

Becker, G. S. and Mulligan, C. B. (1997). The endogenous determination of time preference. *The Quarterly Journal of Economics*, 112(3):729–758.

Bell, D. E. (1985). Disappointment in decision making under uncertainty. *Operations Research*, 33(1):1–27.

Ben-David, I. and Hirshleifer, D. (2012). Are investors really reluctant to realize their losses? trading responses to past returns and the disposition effect. *The Review of Financial Studies*, 25(8):2485–2532.

Ben-Porath, Y. (1967). The production of human capital and the life cycle of earnings. *Journal of Political Economy*, 75(4):352–365.

Benartzi, S. and Thaler, R. H. (1995). Myopic loss aversion and the equity premium puzzle. *The Quarterly Journal of Economics*, 110(1):73–92.

Benartzi, S. and Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. *American Economic Review*, 91(1):79–98.

Bickel, W. K., Moody, L. N., and Higgins, S. T. (2016). Some current dimensions of the behavioral economics of health-related behavior change. *Preventive medicine*, 92:16–23.

Birru, J. (2015). Confusion of confusions: A test of the disposition effect and momentum. *The Review of Financial Studies*, 28(7):1849–1873.

Bleichrodt, H. and Wakker, P. P. (2015). Regret theory: A bold alternative to the alternatives. *The Economic Journal*, 125(583):493–532.

Bordalo, P., Gennaioli, N., La Porta, R., and Shleifer, A. (2019). Diagnostic expectations and stock returns. *The Journal of Finance*, 74(6):2839–2874.

Braun, M. and Muermann, A. (2004). The impact of regret on the demand for insurance. *Journal of Risk & Insurance*, 71(4):737–767.

Brettschneider, J. and Burgess, M. (2017). Using a frailty model to measure the effect of covariates on the disposition effect. *CRISM Working Paper Series*, 17(5).

Bruderer Enzler, H., Diekmann, A., and Meyer, R. (2014). Subjective discount rates in the general population and their predictive power for energy saving behavior. *Energy Policy*, 65(C):524–540.

Bruine De Bruin, W. (2017). Ageing and economic decision-making. In Ranyard, B., editor, *Economic Psychology*, chapter 23, pages 371–386. John Wiley & Sons, Ltd.

Bucher-Koenen, T. and Lusardi, A. (2011). Financial literacy and retirement planning in germany. *Journal of Pension Economics and Finance*, 10(4):565–584.

Caldwell-Harris, C. L. (2012). Understanding atheism/non-belief as an expected individual-differences variable. *Religion, Brain* & *Behavior*, 2(1):4–23.

Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., and Taubinsky, D. (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of risk and uncertainty*, 37(2-3):237.

Chang, T. Y., Solomon, D. H., and Westerfield, M. M. (2016). Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect. *The Journal of Finance*, 71(1):267–302.

Chao, L.-W., Szrek, H., Sousa Pereira, N., and Pauly, M. V. (2009). Time preference and its relationship with age, health, and survival probability. *Judgment and Decision Making*, 4(1):1–19.

Chen, M. K. (2013). The effect of language on economic behavior: Evidence from savings rates, health behaviors, and retirement assets. *American Economic Review*, 103(2):690—-731.

Chiyachantana, C. N. and Yang, Z. (2013). Reference point adaptation and disposition effect. *Research Collection Lee Kong Chian School Of Business.*

Chu, C. C., Chien, H.-K., and Lee, R. D. (2010). The evolutionary theory of time preferences and intergenerational transfers. *Journal of Economic Behavior & Organization*, 76(3):451–464.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2):187–220.

Cropper, M. L., Aydede, S. K., and Portney, P. R. (1994). Preferences for life saving programs: How the public discounts time and age. *Journal of Risk and Uncertainty*, 8(3):243–265.

Cubitt, R. P. and Read, D. (2007). Can intertemporal choice experiments elicit time preferences for consumption? *Experimental Economics*, 10(4):369–389.

DellaVigna, S., Lindner, A., Reizer, B., and Schmieder, J. F. (2017). Reference-dependent job search: Evidence from hungary. *The Quarterly Journal of Economics*, 132(4):1969–2018.

Delquié, P. and Cillo, A. (2006). Disappointment without prior expectation: A unifying perspective on decision under risk. *Journal of Risk and Uncertainty*, 33(3):197–215.

Descamps, A., Massoni, S., and Page, L. (2016). Knowing when to stop and make a choice, an experiment on optimal sequential sampling. Technical report, Available at SSRN 2883847.

Deville, L. and Riva, F. (2007). Liquidity and arbitrage in options markets: A survival analysis approach. *Review of Finance*, 11(3):497–525.

Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5):726–740.

Diamond, J. M. (2005). *Guns, germs and steel: a short history of everybody for the last 13,000 years.* National Geographic, Washington, D.C.

Dierick, N., Heyman, D., Inghelbrecht, K., and Stieperaere, H. (2019). Financial attention and the disposition effect. *Journal of Economic Behavior & Organization*, 163:190–217.

Dittrich, M. and Leipold, K. (2014). Gender differences in time preferences. *Economics Letters*, 122(3):413–415.

Doepke, M. and Zilibotti, F. (2008). Occupational choice and the spirit of capitalism. *The Quarterly Journal of Economics*, 123(2):747–793.

Dohmen, T., Enke, B., Falk, A., Huffman, D., and Sunde, U. (2018). Patience and comparative development. *Working Paper*.

Du, W., Green, L., and Myerson, J. (2002). Cross-cultural comparisons of discounting delayed and probabilistic rewards. *The Psychological Record*, 52(4):479–492.

Epper, T., Fehr, E., Fehr-Duda, H., Kreiner, C. T., Lassen, D. D., Leth-Petersen, S., and Rasmussen, G. N. (2020). Time discounting and wealth inequality. *American Economic Review*.

Eppinger, B., Heekeren, H. R., and Li, S.-C. (2017). Age differences in the neural mechanisms of intertemporal choice under subjective decision conflict. *Cerebral Cortex*, 28(11):3764–3774.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., and Sunde, U. (2018). Global evidence on economic preferences. *The Quarterly Journal of Economics*, 133(4):1645–1692.

Falk, A., Becker, A., Dohmen, T., Huffman, D., and Sunde, U. (2016). The preference survey module: A validated instrument for measuring risk, time, and social preferences. *IZA Discussion Paper No. 9674*.

Feng, H. and Hobson, D. (2016). Gambling in contests with regret. *Mathematical Finance*, 26(3):674–695.

Feng, L. and Seasholes, M. S. (2005). Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance*, 9(3):305–351.

Ferecatu, A. and Önçüler, A. (2016). Heterogeneous risk and time preferences. *Journal of Risk and Uncertainty*, 53(1):1–28.

Fioretti, M., Vostroknutov, A., and Coricelli, G. (2018). Dynamic regret avoidance. Technical report, USC-INET Research Paper.

Firth, D. (2003). Overcoming the reference category problem in the presentation of statistical models. *Sociological Methodology*, 33(1):1–18.

Firth, D. and De Menezes, R. X. (2004). Quasi-variances. *Biometrika*, 91(1):65–80.

Fisher, I. (1930). *Theory of interest: as determined by impatience to spend income and opportunity to invest it.* Augustusm Kelly Publishers, Clifton.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic perspectives*, 19(4):25–42.

Galor, O. and Özak, Ö. (2016). The agricultural origins of time preference. *American Economic Review*, 106(10):3064–3103.

Gathergood, J., Hirshleifer, D. A., Leake, D., Sakaguchi, H., and Stewart, N. (2019). Naive buying diversification and narrow framing by individual investors. *Available at SSRN 3056254*.

Gollier, C. and Salanié, B. (2006). Individual decisions under risk, risk sharing and asset prices with regret. Technical report, Working paper, University of Toulouse.

Green, L. and Myerson, J. (2004). A discounting framework for choice with delayed and probabilistic rewards. *Psychological Bulletin*, 130(5):769–792.

Green, L., Myerson, J., Lichtman, D., Rosen, S., and Fry, A. (1996). Temporal discounting in choice between delayed rewards: the role of age and income. *Psychology and aging*, 11(1):79–84.

Green, L., Myerson, J., and Mcfadden, E. (1997). Rate of temporal discounting decreases with amount of reward. *Memory and Cognition*, 25:715–723.

Green, L., Myerson, J., and Ostaszewski, P. (1999). Discounting of delayed rewards across the life span: age differences in individual discounting functions. *Behavioural Processes*, 46(1):89–96.

Grinblatt, M. and Keloharju, M. (2001). What makes investors trade? *The Journal of Finance*, 56(2):589–616.

Gudmestad, A. and Edmonds, A. (2016). Variable future-time reference in french: A comparison of learners in a study-abroad and a foreign-language context. *Canadian Journal of Linguistics/Revue canadienne de linguistique*, 61(3):259–285.

Harrison, G. W., Lau, M. I., and Williams, M. B. (2002). Estimating individual discount rates in denmark: A field experiment. *American Economic Review*, 92(5):1606–1617.

Haushofer, J., Schunk, D., and Fehr, E. (2013). Negative income shocks increase discount rates. *University of Zurich Working Paper*.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *Bell Journal of Economics*, 10(1):33–54.

Heath, C., Huddart, S., and Lang, M. (1999). Psychological factors and stock option exercise. *The Quarterly Journal of Economics*, 114(2):601–627.

Henderson, V. (2012). Prospect theory, liquidation, and the disposition effect. *Management Science*, 58(2):445–460.

Henrich, J., Heine, S. J., and Norenzayan, A. (2010). Beyond weird: Towards a broad-based behavioral science. *Behavioral and Brain Sciences*, 33(2-3):111.

Hofstede, G. (2001). *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations*. Sage, Thousand Oaks, CA.

Hofstede, G. and Bond, M. H. (1988). The confucius connection: From cultural roots to economic growth. *Organizational dynamics*, 16(4):5–21.

Huddart, S., Lang, M., and Yetman, M. H. (2009). Volume and price patterns around a stock's 52-week highs and lows: Theory and evidence. *Management Science*, 55(1):16–31.

Ifcher, J. and Zarghamee, H. (2011). Happiness and time preference: The effect of positive affect in a random-assignment experiment. *American Economic Review*, 101(7):3109–29.

Ingersoll, J. E. and Jin, L. J. (2013). Realization utility with reference-dependent preferences. *Review of Financial Studies*, 26(3):723–767.

Ivković, Z., Poterba, J., and Weisbenner, S. (2005). Tax-motivated trading by individual investors. *The American Economic Review*, 95(5):1605–1630.

Ivković, Z. and Weisbenner, S. (2005). Local does as local is: Information content of the geography of individual investors' common stock investments. *The Journal of Finance*, 60(1):267–306.

Iyer, S. (2016). The new economics of religion. *Journal of Economic Literature*, 54(2):395–441.

Jia, J., Dyer, J. S., and Butler, J. C. (2001). Generalized disappointment models. *Journal of Risk and Uncertainty*, 22(1):59–78.

Jiao, P. (2015). Losing from naive reinforcement learning: A survival analysis of individual repurchase decisions. Technical report, Available at SSRN 2574141.

Kahneman, D. and Lovello, D. (1993). Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science*, 39:17–31.

Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–91.

Kent, J. T. and O'Quigley, J. (1988). Measures of dependence for censored survival data. *Biometrika*, 75(3):525–534.

Kirby, K. N., Godoy, R., Reyes-García, V., Byron, E., Apaza, L., Leonard, W., Pérez, E., Vadez, V., and Wilkie, D. (2002). Correlates of delay-discount rates: Evidence from tsimane' amerindians of the bolivian rain forest. *Journal of Economic Psychology*, 23(3):291–316.

Korniotis, G. M. and Kumar, A. (2011). Do older investors make better investment decisions? *The Review of Economics and Statistics*, 93(1):244–265.

Korniotis, G. M. and Kumar, A. (2013). Do portfolio distortions reflect superior information or psychological biases? *Journal of Financial and Quantitative Analysis*, 48(1):1–45.

Kőszegi, B. and Rabin, M. (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics*, 121(4):1133–1165.

Kőszegi, B. and Rabin, M. (2007). Reference-dependent risk attitudes. *American Economic Review*, 97(4):1047–1073.

Lahav, E., Benzion, U., and Shavit, T. (2010). Subjective time discount rates among teenagers and adults: Evidence from israel. *The Journal of Socio-Economics*, 39(4):458–465.

Lawrance, E. C. (1991). Poverty and the rate of time preference: Evidence from panel data. *Journal of Political Economy*, 99(1):54–77.

Layard, R. (2020). *Can We Be Happier? Evidence and Ethics*. Pelican Books.

Löckenhoff, C. E., O'Donoghue, T., and Dunning, D. (2011). Age differences in temporal discounting: The role of dispositional affect and anticipated emotions. *Psychology and Aging*, 26(2):274–284.

Loewenstein, G. (1992). othe fall and rise of psychological explanations in the economics of intertemporal choice. *Choice over Time, New York: Russel Sage Foundation*, 3034.

Loibl, C. (2017). *Living in Poverty: Understanding the Financial Behaviour of Vulnerable Groups*, chapter 26, pages 421–434. John Wiley & Sons, Ltd.

Loomes, G. and Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The Economic Journal*, 92(368):805–824.

Loomes, G. and Sugden, R. (1986). Disappointment and dynamic consistency in choice under uncertainty. *The Review of Economic Studies*, 53(2):271–282.

Madden, G. J. and Bickel, W. K. (2010). *Impulsivity: The behavioral and neurological science of discounting.* American Psychological Association.

Maglio, S. J., Trope, Y., and Liberman, N. (2013). Distance from a distance: Psychological distance reduces sensitivity to any further psychological distance. *Journal of Experimental Psychology: General*, 142(3):644–657.

Mahajna, A., Benzion, U., Bogaire, R., and Shavit, T. (2008). Subjective discount rates among israeli arabs and israeli jews. *The Journal of Socio-Economics*, 37(6):2513–2522.

Mani, A., Mullainathan, S., Shafir, E., and Zhao, J. (2013). Poverty impedes cognitive function. *Science (New York, N.Y.)*, 341:976–80.

Meier, S. and Sprenger, C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, 2(1):193–210.

Meng, J. and Weng, X. (2018). Can prospect theory explain the disposition effect? A new perspective on reference points. *Management Science*, 64(7):3331–3351.

Michenaud, S. and Solnik, B. (2008). Applying regret theory to investment choices: Currency hedging decisions. *Journal of International Money and Finance*, 27(5):677–694.

Mischel, W., Shoda, Y., and Rodriguez, M. I. (1989). Delay of gratification in children. *Science*, 244(4907):933–938.

Muermann, A., Mitchell, O., and Volkman, J. (2006). Regret, portfolio choice, and guarantees in defined contribution schemes. *Insurance: Mathematics and Economics*, 39(2):219–229.

Muermann, A. and Volkman, J. M. (2006). Regret, pride, and the disposition effect. Technical report, PARC Working Paper Series.

Nuscheler, R. and Roeder, K. (2016). To vaccinate or to procrastinate? that is the prevention question. *Health economics*, 25(12):1560–1581.

Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance*, 53(5):1775–1798.

Odean, T. (1999). Do investors trade too much? *American Economic Review*, 89(5):1279–1298.

Olsson, O. and Hibbs, D. (2005). Biogeography and long-run economic development. *European Economic Review*, 49(4):909–938.

O'Quigley, J., Xu, R., and Stare, J. (2005). Explained randomness in proportional hazards models. *Statistics in Medicine*, 24(3):479–489.

Perez-Arce, F. (2017). The effect of education on time preferences. *Economics of Education Review*, 56:52–64.

Poulos, C. and Whittington, D. (2000). Time preferences for life-saving programs: Evidence from six less developed countries. *Environmental Science & Technology*, 34(8):1445–1455.

Preis, T., Moat, H. S., Stanley, H. E., and Bishop, S. R. (2012). Quantifying the advantage of looking forward. *Scientific reports*, 2:350.

Quispe-Torreblanca, E., Gathergood, J., Loewenstein, G. F., and Stewart, N. (2020). Investor attention, reference points and the disposition effect. *Available at SSRN 3422790*.

Ramsey, F. P. (1928). A mathematical theory of saving. *The Economic Journal*, 38(152):543–559.

Read, D. and Loewenstein, G. (1995). Diversification bias: Explaining the discrepancy in variety seeking between combined and separated choices. *Journal of Experimental Psychology: Applied*, 1(1):34–49.

Read, D., Loewenstein, G., and Rabin, M. (1999). Choice bracketing. *Journal of Risk and Uncertainty*, 19(171):171–197.

Read, D. and Read, N. (2004). Time discounting over the lifespan. *Organizational Behavior and Human Decision Processes*, 94(1):22–32.

Reimers, S., Maylor, E. A., Stewart, N., and Chater, N. (2009). Associations between a one-shot delay discounting measure and age, income, education and real-world impulsive behavior. *Personality and Individual Differences*, 47(8):973–978.

Richards, D. W. and Willows, G. D. (2018). Who trades profusely? The characteristics of individual investors who trade frequently. *Global Finance Journal*, 35:1–11.

Richter, D. and Mata, R. (2018). Age differences in intertemporal choice: U-shaped associations in a probability sample of german households. *Psychology and aging*, 33(5):782.

Rogers, A. R. (1994). Evolution of time preference by natural selection. *The American Economic Review*, pages 460–481.

Sakaguchi, H., Stewart, N., and Walasek, L. (2019). The disposition effect varies with portfolio composition because people take gain-loss-domain-level sell decisions. *Available at SSRN 3053331.*

Sarid, A. and Galor, O. (2017). Geographical origins and economic consequences of language structures. *Working Papers.*

Schooler, L. J. and Hertwig, R. (2005). How forgetting aids heuristic inference. *Psychological Review*, 112(3):610–628.

Seaman, K., Gorlick, M., Vekaria, K., Hsu, M., Zald, D., and Samanez-Larkin, G. (2016). Adult age differences in decision making across domains: Increased discounting of social and health-related rewards. *Psychology and Aging*, 31:737–746.

Seasholes, M. S. and Zhu, N. (2010). Individual investors and local bias. *The Journal of Finance*, 65(5):1987–2010.

Shapira, Z. and Venezia, I. (2001). Patterns of behavior of professionally managed and independent investors. *Journal of Banking & Finance*, 25(8):1573–1587.

Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of Finance*, 40(3):777–790.

Shi, Y., Cui, X., Yao, J., and Li, D. (2015). Dynamic trading with reference point adaptation *Operations Research*, 63(4):789–806.

Silverman, I. W. (2003). Gender differences in delay of gratification: A meta-analysis. *Sex roles*, 49(9-10):451–463.

Sozou, P. D. and Seymour, R. M. (2003). Augmented discounting: Interaction between ageing and time-preference behaviour. *Proceedings: Biological Sciences*, 270(1519):1047–1053.

Sparrow, E. P. and Spaniol, J. (2018). Aging and altruism in intertemporal choice. *Psychology and Aging*, 33(2):315–324.

Spolaore, E. and Wacziarg, R. (2013). How deep are the roots of economic development? *Journal of Economic Literature*, 51(2):325–369.

Strack, P. and Viefers, P. (2019). Too proud to stop: Regret in dynamic decisions. *Journal of the European Economic Association.*

Strotz, R. H. (1955). Myopia and inconsistency in dynamic utility maximization. *The Review of Economic Studies*, 23(3):165–180.

Tabellini, G. (2008). Institutions and culture. *Journal of the European Economic Association*, 6(2-3):255–294.

Tan, C. T. and Johnson, R. D. (1996). To wait or not to wait: The influence of culture on discounting behavior. *Perspectives on judgment and decision making*, pages 297–305.

Tanaka, T., Camerer, C. F., and Nguyen, Q. (2010). Risk and time preferences: Linking experimental and household survey data from vietnam. *American Economic Review*, 100(1):557–71.

Thaler, R. H. and Johnson, E. J. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science*, 36(6):643–660.

Trautmann, S. T. (2019). Distance from a distance: the robustness of psychological distance effects. *Theory and Decision*, 87(1):1–15.

Triandis, H. C. (1971). Some psychological dimensions of modernization. *Proceedings of the 17th International Congress of Applied Psychology (Vol. II)*.

Trostel, P. A. and Taylor, G. A. (2001). A theory of time preference. *Economic inquiry*, 39(3):379–395.

Tversky, A. and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, 211:453–458.

Tversky, A. and Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics*, 106(4):1039–1061.

Tversky, A. and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and uncertainty*, 5(4):297–323.

van Rooij, M., Lusardi, A., and Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, 101(2):449–472.

Wang, M., Rieger, M. O., and Hens, T. (2016). How time preferences differ: Evidence from 53 countries. *Journal of Economic Psychology*, 52:115–135.

Warner, J. T. and Pleeter, S. (2001). The personal discount rate: Evidence from military downsizing programs. *American Economic Review*, 91(1):33–53.

Weber, M. (1930). *The Protestant Ethic and the "Spirit" of Capitalism.* Scribner's, New York.

Xu, R. and O'Quigley, J. (1999). A r2 type measure of dependence for proportional hazards models. *Journal of Nonparametric Statistics*, 12(1):83–107.