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Essays on Behavioral Finance

Proefschrift

Proefschrift ter verkrijging van de graad van doctor aan Tilburg University op gezag van prof. dr. G.M. Duijsters, als tijdelijk waarnemer van de functie rector magnificus en uit dien hoofde vervangend voorzitter van het college voor promoties, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Aula van de Universiteit op woensdag 9 oktober 2019 om 13.30 uur door

Gábor Neszveda

geboren op 6 november 1985 te Boedapest, Hongarije.

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One of the essences of a Ph.D. program is going out of the comfort zone, where Ph.D. candidates need to find new topics, new approaches, new aspects yielding new and original research. However, going out of the comfort zone is always challenging and overcoming these challenges would not be possible without the support of others.

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Gábor Neszveda

Budapest, June 2019

Contents

Introduction

One of the cornerstones of most economic and asset pricing models is how decision-makers evaluate risk. Despite the fact that almost everyone faces risk in their lives and it is a crucial ingredient in economic models including asset pricing models, it is still an open debate how decision-makers or even investors evaluate risk. A large body of research assumes the standard expected utility framework to model the risk attitude of people and investors. However, experimental and empirical evidence shows that the standard expected utility theory falls short of explaining many economic and asset pricing phenomena. Behavioral finance provides alternative conceptual frameworks to explain these phenomena.

In Chapter 1, I investigate the potential impacts of the expected utility theory with an aspiration level on stock returns. Expected utility theory with an aspiration level departs from the standard expected utility theory. It assumes that achieving a given aspiration level generates an additional utility for the decision-maker yielding several implications different from those of the standard expected utility theory. For instance, marathon runners set a target time as an aspiration level, cabdrivers set a daily target for their income as an aspiration level, and investors might set an aspiration level return for a given time period which could explain why stocks have much higher expected returns than bonds (equity premium puzzle).

Motivated by this evidence, I investigate whether this conceptual framework can also shed light on predicting the cross-section of expected stock returns. I hypothesize that stocks that have higher probability of achieving the aspiration level return are more preferred, yielding a lower expected return. I find a significant negative relation between the probability of success and the expected stock return consistent with the hypothesis.

In Chapter 2, I investigate the impact of the law of small numbers on stock returns. According to the law of small numbers, people tend to infer too much from a small sample. For instance, people tend to believe that prior signals predict immediate reversal, while they also seem to believe that an unlikely long streak is a sign for continuation. The first phenomenon is known as the gambler's fallacy, while the second phenomenon is known as the hot-hand fallacy.

I assume that these phenomena might have an impact on stock returns as well and I test how these errors in the perception of risk can influence the risk-return trade-off. I find a significant and robust relation between the risk-return trade-off and prior signals of stocks consistent with these behavioral phenomena.

In Chapter 3, we investigate the relation between time discounting and risk taking in an experiment. Standard expected utility theory assumes independence between risk taking and time discounting yielding puzzling experimental and empirical results in behavioral finance literature. We test a model in an experiment that provides a theoretical framework for explaining these puzzling results. We also find evidence on the relation between risk taking and time discounting and we find supporting evidence for the model.

Chapter 1

Aspiration Level Theory and Stock Returns: An Empirical Test

1.1 Introduction

Imagine an investor who sets a target return in his mind which makes any opportunity more appealing for him which achieves that target. For instance, managers might disregard investment opportunities which don't achieve a certain target return with high probability (Payne et al., 1980;1981).

Several researches find that the decision-maker usually focuses on achieving an aspiration level in several different fields of economic decisions to simplify complex decisions (Brandstätter, Gigerenzer, and Hertwig, 2006). Farmers seem to minimize the probability of falling below an aspiration level (Lopes, 1987), cabdrivers set a daily target as an aspiration level (Camerer et al., 1997), marathon runners set an aspiration level for finishing time (Allen et al., 2016), or even in experiments, decision-makers try to achieve a target mean return or a specific aspiration level (Payne et al., 1980; Baucells and Heukamp, 2006). This approach is even used in financial regulations when the probability of "failure" is required to be less than a certain level (Value-at-Risk, VaR) (Dowd, 1998).

Building on this intuition, I assume that investors also pay attention to aspiration level returns. For instance, it might be important for an investor to beat the market return or the industry average return. I define the measure of the probability of success as the probability of achieving the aspiration level. As a consequence, I construct the measure of the probability of success as the percentage of the daily returns in the last month that achieved the aspiration level return. The motivation of achieving the aspiration level return could play an important role for more sophisticated investors as well. Their performances at a trader level and also at an institutional level are usually benchmarked to a certain index. Nevertheless, this approach of aspiration level theory does not reject the expected utility framework (Diecidue and Van De Ven, 2008). Thus, it shouldn't be considered as irrational behavior to aim for an aspiration level. These arguments suggest that the results of the probability of success measure might not be only driven by naive investors and not more pronounced among stocks with large limits to arbitrage.

Although the intuition that investors have an aspiration level might be realistic and supported by several experiments, identifying such an aspiration level in an empirical setting for stock returns presents a serious challenge. Survey results or ownership data would provide only indirect evidence on any aspiration level. Additionally, the aspiration level could be also market-wide or individual stock specific and it may also differ for each investor. All these challenges make it impossible to provide a clear identification strategy for the aspiration level. As a consequence, in this study, I can not provide a clear identification for aspiration level returns. Thus, this approach can only provide an imperfect measure. I only provide explorative analyses in which I investigate the effect of four different aspiration levels such as a zero return, the risk-free rate, the market return, and the industry average return.

I find evidence for the prediction of aspiration level theory. Stocks with a higher probability of success have a lower expected return, while stocks with a lower probability of success have a higher expected return in the cross-section of U.S. stock returns. It remains both economically and statistically significant for stocks with small arbitrage costs and even among stocks with high institutional ownership. It all suggests that the implication of an aspiration level is not only valid for retail investors and stocks with high limits to arbitrage. Finally, the measure is similar to several other known variables that are usually considered to be related to microstructure effects. Additional tests show that the results of the probability of success is not related to these potential microstructure effects.

The assumption that investors might pay attention to an aspiration level has a large literature. Beyond experimental and empirical evidence, there is an ongoing debate about defining risk in both theory and practice. The definition of risk as not achieving the aspiration level is already documented for a long time by both scholars and practitioners (Mao, 1970). This literature inspired Diecidue and Van De Ven (2008) to establish the conceptual framework of aspiration level theory as the probability of failure and success. Levy and Levy (2009) propose a similar model to Diecidue and Van De Ven (2008) but in their model there is only the probability of failure. Levy and Levy (2009) interpret their model as a weighted average of a standard expected utility and a safety first model. According to the safety first approach (Roy, 1952), the investor considers some outcomes below a certain level as an unacceptable disaster which he prefers to avoid at all costs. In the approach of Levy and Levy (2009), an outcome below the aspiration level is not unacceptable but provides a fixed substantial loss. This approach provides an explanation for the equity premium puzzle (Levy and Levy, 2009).

Using the aspiration level that the decision-maker would like to achieve is a similar concept to the use of a reference-point such as in prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Suffering a fixed loss by failing the aspiration level (or gaining the fixed utility by achieving the aspiration level) is similar to the property of loss-aversion in prospect theory. However, aspiration level theory is different from prospect theory in several aspects. First, in aspiration level theory, if an outcome is below the aspiration level then the decision-maker suffers a fixed utility loss (not gaining a fixed utility) independently from the distance from the aspiration level. In contrast, in prospect theory the value depends on the distance from the reference point. For instance, in aspiration level theory, there is no difference if the realized return is 1% below the target return or 15% below the target return. In contrast, the loss-aversion property of prospect theory implies that there is a difference between realizing a 1% or a 15% lower return than the reference point. Second, aspiration level theory can be rationalized in the expected utility framework (Diecidue and Van De Ven, 2008). Third, aspiration level theory does not necessarily imply risk-seeking behavior if all outcomes are below the aspiration level, while prospect theory implies risk-seeking behavior if all outcomes are below the reference point.

An aspiration level already defines the probability of success in a theoretical framework where all the possible states of the world and their payoffs are well-defined. In each decision, the decision-maker benefits from an additional fixed utility if the payoff achieves the aspiration level in a given realization. Thus, the decision-maker considers the total probability of the sates in which she can achieve the aspiration level because in these states she can derive the additional fixed utility. As a consequence, this total probability is the probability of success for her.

Theoretical works find that, for instance, prospect theory can explain higher volatility or predictability (Barberis, Huang, and Santos 2001), preference for skewness (Barberis and Huang, 2008), or the role of heterogeneity in asset prices (Easley and Yang, 2015), while empirical works find that, for instance, prospect theory can be a reason why stocks with potential high upsides are overpriced (Bali, Cakici, and Whitelaw, 2011), the idiosyncratic volatility puzzle could be related to gain and loss asymmetry proposed by prospect theory (Bhootra and Hur, 2015), and prospect theory has implications for the cross-section of stock-returns (Barberis, Mukherjee, and Wang, 2016). Barberis (2013) provides an overview of the applications of prospect theory to economics and finance.

Prospect theory and its possible impacts on asset prices have been investigated in the literature of behavioral finance, while the influence of the aspiration level theory on asset prices and its descriptive validity in the data hasn't been investigated so far, despite its appealing and simple features.

Proposing a new factor raises concerns of data mining in the literature. Harvey, Liu, and Zhu (2016) propose two additional requirements for testing new factors. First, there should be a conceptual framework behind the new factor. Second, the absolute value of t-statistics should be above 3. Although my measure is imperfect for identifying the aspiration level and the probability of success, there is a theoretical motivation (e.g., Diecidue and Van De Ven (2008) and Levy and

Levy (2009)) for such a measure. Second, the results for the probability of success measure have a substantially larger absolute values than 3 as the tables report in the firm-level regressions and portfolio-level analyses.

The remainder of the paper is organized as follows. Section 2 discusses the conceptual framework of the aspiration level theory and experimental results that highlight the main differences compared to other theories. Section 3 describes a model with an aspiration level and its implication. Section 4 describes the construction of measure. Section 5 discusses the data and the results of the empirical tests and robustness tests of the implication on the probability of success in the cross-section of stock returns. Finally, section 6 concludes.

1.2 Conceptual Framework

In this section, I present the conceptual framework of the aspiration level theory and I also discuss the evidence and application for narrow framing in asset prices. Narrow framing implies that the investor evaluates each choice separately when he faces several concurrent choices such as in an asset pricing setting.

To present the conceptual framework of Diecidue and Van De Ven (2008), there are S states of nature, $s = 1 \dots S$ each occurring with probability π_s, where $\sum_s \pi_s = 1$. Imagine that there are risky lotteries with a discrete payoff distribution X which pays x_s in state s. There is also an aspiration level payoff $\bar{x}$ which the decision-maker would like to achieve. This aspiration level payoff divides the outcomes into two groups, namely, the outcomes below the aspiration level payoff and the outcomes above or equal to the aspiration level payoff[1]. The

[1]Diecidue and Van De Ven (2008) defines the set of outcomes which are below the aspiration

probability of success is given for a lottery j with payoff distribution X_j by $PS_j(\bar{x}) = 1 - P(X_j < \bar{x})$. This approach provides the following specification of the expected utility function with a loading of $\lambda > 0$ on the utility gain of achieving the aspiration level:

$$V(X) = E(u(X)) + \lambda PS(\bar{x}) = E(u(X) + \lambda 1_{[\bar{x},\infty)}(X)) \tag{1.1}$$

where $1_{[\bar{x},-\infty,)}(X)$ is the usual indicator function of achieving the aspiration level. This indicator function has a value of zero when the outcome is strictly below the aspiration level, while the value of the indicator function is one when the outcome is above or equal to the aspiration level. Incorporating such an aspiration level into a utility function still leads to an expected utility representation (see for more details Diecidue and Van De Ven (2008) and Levy and Levy (2009)).

To demonstrate the explanatory power of aspiration level theory, consider the experiment of Payne (2005) where a five-outcome gamble was presented to the subjects. The outcomes of the gamble were \$100, \$50, \$0, −\$25, −\$50 each with equal chance. In the first case, the subjects could choose between adding \$38 to the outcome of \$100 or to the outcome of \$0. The majority chose to add the \$38 to the outcome of \$0. In the second case, the subjects could choose between adding the same \$38 to the outcome of \$100 or to the outcome of \$50. In the second case, there was no significant difference between choosing the different options. Payne (2005) concludes that standard expected utility theory (without discontinuity) does not offer a description for such a choice pattern (Diecidue and Van De Ven, 2008),

level and the probability of failure $P(x < \bar{x})$ and the set of outcomes that are above the aspiration level. I use a simplified version where only achieving the aspiration level generates a positive value. Levy and Levy (2009) use a similar approach but in their asset pricing application and experimental tests only the probability of failure plays a role.

while aspiration level theory explains this behavior by increasing the possibility to achieve the aspiration level of \$0 in the first case, while it is not possible anymore in the second case. Prospect theory does not offer an explanation for this behavior either. Prospect theory would imply that the subjects should have preferred to increase the payoff of the best outcome (\$100) compared to the outcome of \$0.

In another experiment (Levy and Levy, 2009), subjects could choose between a gamble with the payoffs of -\$80,000, \$10,000, \$20,000, \$150,000 with equal chance and a gamble with the payoffs of −\$30,000,−\$10,000, −\$5,000, \$145,000 with equal chance. The majority of the subjects (74.7%) chose the first gamble even though a decision-maker with mean-variance preferences would choose the second gamble and a decision-maker with prospect theory preferences also would choose the second gamble. There is no such a large loss-aversion parameter which would explain this experimental result (Levy and Levy, 2009). However, the aspiration level theory provides an explanation for this pattern by assuming that the decision-maker has an aspiration level at zero. Furthermore, using the estimated parameter in the experiment, the aspiration level theory can account for the equity premium puzzle as well (Levy and Levy, 2009). Although their estimated parameter for $\lambda = 0.1$ might seem to be small, it generates a large equity premium reconciling the problem that standard expected utility theory (without discontinuity) alone can not account for the observation that decision-makers reject small stake gambles, while they accept large stake gambles (Rabin, 2000).

To provide an even more direct relationship between the choices and the probability of success, Venkatraman, Payne, and Huettel (2014) used eye-tracking technology to observe the behavior of the decision-makers in experiments. They also find supporting evidence that decision-makers use the probability of success as an important aspect in their risky decisions.

Finally, to differentiate the probability of success, prospect theory, salience theory (Bordalo, Gennaioli, and Shleifer, 2013), and preference for positive skewness, Zeisberger (2016) provides a series of experiments in which the subjects played an investment game. He finds consistently that subjects preferred the investment which had a higher probability of success compared to the investment which had a lower probability of success but a more positively skewed distribution, a higher expected return, a lower volatility, and a higher prospect theory value. Thus, the first investment was worse in all these aspects except in the probability of success and it was still the preferred investment option (see Table 1.1). This result is robust for several different specifications. He finds the same results for repeated games, one-shot games, experience based probabilities, known probabilities, and several other specifications. In addition, the results remain significant even after allowing for performance feedback. It suggests that the decision-makers pay attention to the overall probability of success in risky decisions even in experiments very similar to real investment problems.

These experimental results are also in line with the characteristics of the stocks. To present similar comparisons among stocks, I sort stocks based on the probability of success in each month based on the last month daily returns. I form a portfolio of stocks based on the highest 20% of the probability of success in each month, while I form another portfolio of stocks that are among the 40% lowest probability of success in each month and with a higher value of cumulative prospect theory value of -0.0065 based on the last month daily returns.

Table 1.2 presents the characteristics of the two portfolios. It demonstrates that stocks exhibit similar patterns as observed in experiments. Stocks in portfolio

Table 1.1: This Table presents one of the investment games in the series of experiments of Zeisberger (2016). It demonstrates that subjects invests in the option which has a lower expected return, a higher variance, a less positively skewed distribution, and a lower cumulative prospect theory value (with Tversky and Kahneman (1992) specification and parameters) but a higher probability of success (defined as the probability of achieving a positive outcome). All outcomes had equal chance to occur.

	High Success	Low Success
Outcomes	−12%, 0.5%, 1%, 14%	−9%, −1%, −0.5%, 15%
Probability of Success	75%	25%
Expected Return	0.88%	1.13%
Variance	0.85%	0.76%
Skewness	0.07	1.07
CPT value	−0.047	−0.035

A are overvalued (by having lower expected return) with a high probability of success even though they have a lower cumulative prospect theory value and a lower skewness than stocks with a low probability of success but a higher CPT value and skewness. Portfolio A earns 0.54% return per month on average (6.68% per year) with a volatility of 2.8% (44.45% annualized volatility), while portfolio B earns 1.16% per month on average (14.84% per year) with a volatility of 2.6% (41.27% annualized volatility). In the results section, I investigate the relationship between the measure of probability of success and several known characteristics including CPT value and skewness in more detail.

Table 1.2: This Table presents the average values of the characteristics of two portfolios. Portfolio A consists the stocks with the 20% highest probability of success in each month based on the last month daily returns, while portfolio B consists the stocks with the 40% lowest probability of success but a higher cumulative prospect theory value (with Tversky and Kahneman (1992) specification and parameters) than -0.0065. It demonstrates that stocks with a less positively skewed distribution, and a lower cumulative prospect theory value (with Tversky and Kahneman (1992) specification and parameters) but a higher probability of success yields a lower expected return (these stocks are overvalued) than stocks with a more positively skewed distribution, and a higher cumulative prospect theory value. Thus, these stocks suggest that experimental results are in line with asset pricing data. The average probability of success, volatility, skewness, and CPT value based on the last month daily returns are reported for both portfolios and their differences with the corresponding t-statistic in parentheses. N denotes the number of observations.

	A High Success	B Low Success	Diff
Probability of Success	62%	40%	22% (1000)
Volatility	0.028%	0.026%	0.002% (14.03)
Skewness	0.13	0.65	−0.52 (−151.58)
CPT Value	−0.0065	−0.0003	−0.0062 (−129.51)
Expected Return	0.54%	1.16%	−0.62% (−11.38)
N	305,511	62,902	

The application of the results of experimental studies to asset pricing usually raises some questions. One of the most crucial questions is how to define the non-consumption source of utility. For instance, in the application of the loss-aversion property of prospect theory, there is the question whether loss-aversion should be defined over wealth, over a portfolio, or over individual stocks (Barberis and Huang, 2001). In the case of aspiration level theory, this question is also relevant. Should the aspiration level be defined over the portfolio or over each stock separately? According to mental accounting theory (Thaler, 1980), the investor could evaluate his investment "broadly" when he considers the total effect of his investments as a portfolio or "narrowly" when he evaluates the individual stocks separately. The results of experimental studies (e.g., Kahneman and Tverksy, 1981; Redelmeier and Tversky,1992; Kahneman and Lovallo, 1993; Gneezy and Potters, 1997; Thaler et al. 1997; Benartzi and Thaler 1999; Rabin and Thaler, 2001) suggest that decision-makers apply narrow-framing.

Furthermore, assuming narrow framing in several different models in asset prices can shed light on the stock market participation puzzle (Barberis, Huang, and Thaler, 2006), the equity premium puzzle (Barberis and Huang, 2006), the stock investment decisions (Kumar and Lim, 2008), the taste for skewness, the growth-value puzzle, and the time varying risk premia (Bordalo, Gennaioli, and Shleifer, 2013).

Following these approaches, I also assume narrow framing and I define aspiration level over individual stocks.

1.3 Asset Prices and Aspiration Level

In this section, I consider a one-period model in which there is a price taking representative investor with two sources of utility. Following Barberis and Huang (2001), the investor derives utility from consumption and from a non-consumption source. The non-consumption source of utility can be interpreted in different ways. Barberis and Huang (2001) argue that the investor may experience a sense of regret over his decisions, or it might hurt his ego which makes him suffer in the case of loss-aversion. Similarly, this non-consumption source of utility might also be interpreted as a potential humiliation in front of friends or family. In my approach, achieving the aspiration level could be interpreted as a utility from an experience of a good decision or a potential opportunity to use as an argument in a discussion in front of a colleague or friend. In this model, the investor formulates a probability of success value for each asset j based on the past returns (PS_j). Although several researches use the assumption that investors use a forward-looking representation of stock returns in this paper I follow the approach of Barberis, Mukherjee, and Wang (2016)[2]. I also assume that the representative agent forms a mental representation of the stock by the distribution of its past returns and he formulates the probability of success based on this representation of an asset j (PS_j). In this specification, I assume that the probability of success

[2]Barberis, Mukherjee, and Wand (2016) provide a model for incorporating prospect theory value based on the stocks' past returns into a traditional mean-variance framework. They assume that some investors hold the tangency portfolio, while other investors hold the tangency portfolio by tilting their holdings towards stocks with higher prospect theory value based on historical returns. Thus, they assume that the investors use backward-looking representation of the stock returns. Their model could be also applied in this case by assuming that some of the investors hold the tangency portfolio by tilting their holding towards stocks with higher probability of success based on past returns. This approach yields the same implication compared to the implication presented in this section.

for the risk-free rate is zero.

In the model, there are two time periods $t = 0, 1$ and I assume that the investor derives utility from consumption in the two time periods and he can derive an additional utility gain from achieving the aspiration level for an asset. The price of each available asset $j = 1 \ldots J$ is p_j. I assume that there is no discounting and the utility is time separable, additive, monotonically increasing in consumption, the first order derivative exists and it is positive, and the second order derivative exists and it is non-positive. At $t = 0$, the investor has an endowment of e_0 of the consumption good and one unit from each of the J available assets. At $t = 1$, there are S states of nature $s = 1 \ldots S$ with the probability of π_s for state s. At $t = 1$, the investor receives the payoffs of the assets. An asset j has a payoff X_j that pays $x_{j,s}$ in state s.

I assume that an investor trades an amount h_j of each asset j and the investor expects a probability of success PS_j for an asset j in the second time period. Assuming narrow framing implies that the investor evaluates each asset separately. The investor derives utility from the consumption in the two time periods and additionally he derives a possible utility gain of $\lambda \geq 0$ from achieving the aspiration level. In this model, there is no aspiration level for consumption but only for each stock. Thus, the problem of maximizing the investors' utility is continuous in consumption. It is also important that in this approach the probability of success is exogenous in the model since the probability of success is based on the past returns which is given at $t = 0$ in this model.

Thus, in this model the investor chooses c_0, c_1, and h_j $(j = 1 \ldots J)$ to optimize his expected utility at $t = 0$:

$$\max_{h_j, c_0, c_1} \quad u(c_0) + E(u(c_1)) + \lambda \sum_j (h_j + 1) PS_j \qquad \lambda \geq 0$$

$$\text{subject to} \quad 0 \leq c_0 \leq e_0 - \sum_j h_j p_j \tag{1.2}$$

$$0 \leq c_1 \leq \sum_j (h_j + 1) X_j$$

The first-order condition when the investor maximizes his utility by choosing the optimal trading behavior is the following for each asset j:

$$0 = -u'(c_0) p_j + E(u'(c_1) X_j) + \lambda PS_j \tag{1.3}$$

$$p_j = E(\frac{u'(c_1)}{u'(c_0)} X_j) + \frac{\lambda PS_j}{u'(c_0)} \tag{1.4}$$

I define an equilibrium that consists of optimal trading decisions h_j by the investor based on equation (1.2) and all markets clear, $h_j = 0$ for all j (since there is only one representative agent). As a result, it is an equilibrium if $h_j = 0$ for all j, $c_0 = e_0$, $c_1 = \sum_j X_j$, and the price for an asset j is

$$p_j = E(\frac{u'(\sum_j X_j)}{u'(e_0)} X_j) + \frac{\lambda PS_j}{u'(e_0)} \tag{1.5}$$

According to equation (1.5), the price of an asset is an increasing function of the probability of success, i.e., the investors are willing to pay a higher price for an asset with a higher probability of success when $\lambda > 0$. If $\lambda = 0$, the probability of success does not play a role and equation (1.5) can be simplified to the standard expression, where the price of an asset j is $p_j = E(\frac{u'(\sum_j X_j)}{u'(e_0)} X_j)$.

To describe the relationship between the expected return of an asset j and the probability of success, I consider the marginal effect of the probability of success on the expected return of an asset j.

$$\frac{\partial E(R_j)}{\partial PS_j} = \frac{\partial \frac{E(X_j)}{p_j}}{\partial PS_j} = E(X_j) \frac{\partial \frac{1}{p_j}}{\partial p_j} \frac{\partial p_j}{\partial PS_j} = -E(X_j) \frac{1}{p_j^2} \frac{\lambda}{u'(e_0)} < 0 \tag{1.6}$$

The marginal effect of the probability of success on the expected return is negative because the expected payoff $E(X_j)$, the price, λ, and $u'(e_0)$ are all positive. Thus, equation (1.6) describes my main hypothesis that there is a negative relationship between the expected return of an asset j and its probability of success. This relationship also holds for excess return above the risk-free rate of an asset j since the return of the risk-free asset is unaffected by PS_j ($PS = 0$ for the risk-free rate).

1.4 Construction of Probability of Success Measure

In this section, I state my hypothesis and I also describe and discuss the assumptions that I use to construct the empirical measure for the probability of success.

Hypothesis: Stocks with a higher probability of success earn a lower subsequent return. Conversely, stocks with a lower probability of success earn a higher subsequent return.

To test this hypothesis, I need to make several assumptions in the empirical settings since there is no possibility to observe the characteristics of an asset from this perspective. To define the probability of success, I make the following assumptions:

Assumption 1: Investors incorporate the probability of success of an asset into their utility functions described in equation (1.2). I assume four different aspiration level returns: zero return, risk-free rate, market return, and the industry average return.
Assumption 2: Investors use the daily observations of the last month to construct their estimated probability of success.
Assumption 3: Investors assume that each trading day occurred with the same probability.

Assumption 1 means that investors aim to achieve the aspiration level return. I investigate several different specifications for aspiration level return such as zero return, risk-free return, market return (value-weighted market return), and the industry average return (based on the Fama-French 49 industry classification[3]). First, I investigate the specification when the aspiration level return is zero or the risk-free rate because the investors might prefer to avoid negative net returns or returns that are lower than the risk-free rate. It would imply that they only consider an outcome to be successful if it does not underperform a strategy in which the investor does not invest into stocks. Second, I investigate the specification of

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html

the aspiration level return when it is the market return or the industry average return because it is natural to expect that the investors use a benchmark return to evaluate their decisions.

Assumption 2 means that investors use daily window length for aspiration levels. Using the daily returns seems to be an appropriate window length because of the easy availability of the daily returns for the investors and the daily returns present a recent experience for the investors which might influence them more. My second assumption also implies that the investors use past information to predict future characteristics which is a standard assumption for being able to create an estimate for future values. Although several characteristics of a stock are not stable over time (e.g., Bondt & Thaler, 1985) it has been shown that investors might use extrapolation more often than it is rational (Barberis et al., 2015).

An alternative interpretation of the assumption of using the past information to construct the probability of success measure is that the investors try to maximize the probability of success of their portfolio because they use it as an argument to prove their skills and to defend against a critique of their decisions. If they prefer stocks that achieved the aspiration level return recently then it is easier to interpret that recent success as part of their decisions. For instance, an investor can defend easier a choice of a stock that has performed poorly in a month if it has a better performance based on the last two months.

Finally, following Barberis, Mukherjee, and Wang (2016), assumption 3 that each observation occurs with the same probability provides a clear approach to calculate the probabilities based on the past information.

Based on these assumptions, I construct my measure as the percentage of the daily returns that achieved the aspiration level return in the last month.

$$PS_{j,t} = \frac{\sum_{s_t} 1_{[\bar{r}_{j,t},\infty)}(R_{j,s_t})}{S_t} \tag{1.7}$$

where $PS_{j,t}$ is the probability of success measure for an asset j in the month t, $s_t = 1, \ldots, S_t$ represents the trading days in month t, S_t is the number of trading days in the current month t, $\bar{r}_{j,t}$ is the aspiration level return for an asset j in month t, and $1_{(\bar{r}_{j,t},\infty)}(R_{j,s_t})$ is an indicator function which has the value of one if the daily return on the day s is above or equal to the aspiration level return and zero otherwise.

1.5 The Probability of Success in the Cross-section of Stock Returns

In this section, I describe the data and I present the empirical tests of the hypothesis of the model with an aspiration level. Namely, I test whether stocks with a high probability of success measure earn a lower return than the stocks with a low probability of success measure. I also investigate the effect of choosing different aspiration levels such as zero return, risk-free return, market return, and the industry average return.

First, I describe the data that I use to test the hypothesis. Second, I run univariate portfolio analyses to present the strength of the probability of success measure. Third, I run bivariate portfolio level analyses and Fama-MacBeth regressions to control for a set of different variables. Fourth, I present the characteristics of portfolio quintiles based on the probability of success measure to investigate the similarities and differences between the probability of success measure and the control variables. Fifth, I investigate the effect of arbitrage costs and sophistication on my measure. Sixth, I present additional evidence that the results of the measure is not driven by liquidity or microstucutre effect. Finally, I present additional sensitivity analyses with different aspiration levels in Fama-MacBeth regressions including all control variables.

1.5.1 Data

Data come from CRSP and COMPUSTAT and consists of the monthly and daily stock prices, share volume, holding period returns, number of shares outstanding, SIC code and value-weighted market return from CRSP and book value for total assets from COMPUSTAT. The sample covers the period from July 1962 to December 2016 for all stocks from CRSP. Following Fama and French (1992), I measure firm size by the market value of equity and book-to-market as the ratio of the book and market value of equity. I calculate book-to-market using accounting data from COMPUSTAT as of December of the previous year and exclude firms for a given month t with negative book-to-market equity. I extend the book equity data from Kenneth French's website[4] for those observations which are not covered by COMPUSTAT. I exclude stock-month observations if any of the two following requirements does not hold. First, a stock-month observation must have all control variables available. Second, the stock must be traded on each day in the month. My control variables for month t are calculated in the following way:

- Size: the logarithm of the number of shares outstanding in month t times

[4] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

the price in month t (in million dollars).

- BTM: the logarithm of the firm's book value divided by its market value where these values were calculated following Fama and French (1992).
- MOM: the stock's cumulative return from month $t-11$ to the end of month $t-1$.
- REV: the stocks' return in month t.
- ILLIQ: the Amihud (2002) measure using daily return and volume data in month t.
- Beta: market beta based on the last month daily returns.
- IVOL: the volatility of the stocks' daily idiosyncratic volatility in month t (Ang, Hodrick, Xing, and Zhang 2006).
- MAX: the stock's maximum daily return in month t (Bali, Cakici, and Whitelaw, 2011).
- MIN: the stock's minimum daily return in month t (Bali, Cakici, and Whitelaw, 2011).
- SKEW: Skewness of the stock's daily return in month t.
- PT: Cumulative Prospect Theory value of a stock based on the stock's daily returns in month t (Barberis, Mukherjee, and Wang, 2016).

I winsorize size, book-to-market ratio, momentum, short-term reversal, illiquidity, beta, idiosyncratic volatility, skewness, and the subsequent monthly return at the 1% level in each month.

1.5.2 Expected Return and the Probability of Success

In this section, I use the percentage of the daily returns that achieved the aspiration level return in the last month as the probability of success measure (PS) to test the main prediction of the aspiration level theory. I form quintile portfolios based on the probability of success measure in each month. To provide an equal number of observations in each portfolio quintile, if there are many observations at the cutting value then I assign stocks with the same values randomly[5] to one of the portfolio quintiles. However, I also present the results of the Fama-MacBeth regressions which mitigate any concern that this approach would affect my results significantly.

Univariate Portfolio Level Analyses

I form quintile portfolios in each month by sorting on the probability of success (PS) measure. The stocks with the smallest probability of success are in portfolio 1 and the stocks with the highest probability of success are in portfolio 5. The aspiration level theory predicts that there is a monotone decrease in the time-series average of the subsequent monthly portfolio returns of the quintiles.

Table 1.3 reports the time-series average of the equal-weighted subsequent excess portfolio return and the equal-weighted returns obtained from the four factor Carhart (1997) model (market, size, book-to-market, momentum). Table 1.4 reports the time-series average of the value-weighted subsequent monthly excess return and the value-weighted subsequent monthly excess returns obtained from the four factor Carhart (1997) model.

[5] Using unequal number of observations in each quintile to avoid randomization leads to the same conclusions.

Table 1.3: Quintile portfolios are formed every month from July 1962 to November 2016 by sorting on the probability of success (PS) for four different specifications when the aspiration level return ($\bar{r}$) is equal to zero, the risk-free rate (r_{rf}), the value-weighted market return (r_m), and the industry average return (r_{ind}). Portfolio 1 is the portfolio with smallest probability of success (PS) stocks over the current month. The Table reports for each quintile the average subsequent monthly excess returns of the portfolios in the case of equal-weighted (EW) portfolios and the equal-weighted returns obtained from the four factor Carhart (1997) model (market, size, book-to-market, momentum). "Return difference" is the average difference in the portfolio subsequent monthly excess returns between the stocks with the highest and lowest probability of success (the Newey-West corrected t-statistic with 12 lags in parentheses). N denotes the number of observations.

	Excess returns				4F Alpha			
Quintile	$\bar{r}=0$	$\bar{r}=r_{rf}$	$\bar{r}=r_m$	$\bar{r}=r_{ind}$	$\bar{r}=0$	$\bar{r}=r_{rf}$	$\bar{r}=r_m$	$\bar{r}=r_{ind}$
Lowest	1.05	1.27	1.15	1.38	0.47	0.67	0.56	0.74
2	0.86	0.84	0.93	0.97	0.22	0.21	0.29	0.30
3	0.79	0.70	0.70	0.73	0.11	0.03	0.02	0.06
4	0.68	0.56	0.59	0.52	−0.04	−0.14	−0.12	−0.16
Highest	0.39	0.39	0.39	0.16	−0.34	−0.34	−0.31	−0.51
Difference	−0.66	−0.88	−0.76	−1.21	−0.81	−1.01	−0.87	−1.25
t-stat	(−6.61)	(−5.68)	(−6.63)	(−10.61)	(−5.85)	(−6.76)	(−5.61)	(−8.42)
N	653	653	653	653	653	653	653	653

Table 1.4: Quintile portfolios are formed every month from July 1962 to November 2016 by sorting on the probability of success (PS) for four different specifications when the aspiration level return ($\bar{r}$) is equal to zero, the risk-free rate (r_{rf}), the value-weighted market return (r_m), and the industry average return (r_{ind}). Portfolio 1 is the portfolio with smallest probability of success (PS) stocks over the current month. The Table reports for each quintile the average subsequent monthly excess returns of the portfolios in the case of value-weighted (VW) portfolios and the value-weighted returns obtained from the four factor Carhart (1997) model (market, size, book-to-market, momentum). "Return difference" is the average difference in the portfolio subsequent monthly excess returns between the stocks with the highest and lowest probability of success (the Newey-West corrected t-statistic with 12 lags in parentheses). N denotes the number of observations.

	Excess returns				4F Alpha			
Quintile	$\bar{r}=0$	$\bar{r}=r_{rf}$	$\bar{r}=r_m$	$\bar{r}=r_{ind}$	$\bar{r}=0$	$\bar{r}=r_{rf}$	$\bar{r}=r_m$	$\bar{r}=r_{ind}$
Lowest	0.78	0.93	0.85	0.94	0.27	0.39	0.33	0.35
2	0.64	0.83	0.68	0.77	0.09	0.33	0.14	0.20
3	0.60	0.66	0.62	0.65	0.05	0.12	0.08	0.09
4	0.52	0.55	0.54	0.48	−0.10	−0.01	−0.03	−0.08
Highest	0.20	0.38	0.32	0.20	−0.41	−0.23	−0.26	−0.35
Difference	−0.59	−0.55	−0.52	−0.74	−0.68	−0.61	−0.59	−0.69
t-stat	(−6.02)	(−4.24)	(−5.24)	(−7.46)	(−5.77)	(−5.48)	(−4.56)	(−5.70)
N	653	653	653	653	653	653	653	653

In line with the theoretical prediction, the lowest quintile's average return is higher than the highest quintile's average return and there is a monotone decrease in the time-series average of the subsequent excess monthly average returns from the portfolio of stocks with the lowest probability of success to the portfolio of stocks with the highest probability of success. The time-series average of the equal-weighted portfolio returns of the stocks in the lowest quintile earn 1.05% per month excess return on average, while the portfolio with the stocks in the highest quintile earn 0.39% excess return per month on average if the aspiration level return is equal to zero according to Table 1.3. Setting the aspiration level return equal to the risk-free rate or the market return provides similar results, while setting the aspiration level return equal to the industry average return increases the average excess return for the lowest quintile and decreases the average excess return for the highest quintile yielding an even stronger effect.

According to Table 1.3, the equal-weighted average excess return difference per month between portfolio 5 (highest probability of success) and portfolio 1 (lowest probability of success) is −0.66% when the aspiration level return is equal to zero. This difference is economically and statistically significant (t=−6.61) at all conventional significance levels. This difference is even increasing for all other specifications. However, only setting the aspiration level return equal to the industry average provides a convincingly higher average return difference with a much stronger t-statistic (−10.61).

These results get stronger when the equal-weighted portfolio average returns are obtained from the four factor (market, small-minus-big, high-minus-low, momentum) Carhart (1997) model. The average return difference for the portfolio quintiles with the highest and lowest probability of success increases to 0.81% average excess return per month when the aspiration level return is equal to zero. However, the statistical significance does not increase with the return difference because the Newey-West corrected t-statistic is -5.85 in this case compared to the -6.61 in the case of average raw excess returns. Thus, controlling for the four factors does not change the results substantially.

Table 1.4 reports the value-weighted average excess returns and the value-weighted average returns obtained from the four factor Carhart (1997) model. These results exhibit similar patterns to the equal-weighted portfolios. Although there is a slightly smaller average return difference in each case for the value-weighted portfolio average returns there are large and both economically and statistically significant results. For instance, the average difference between the average raw excess returns of the portfolio quintiles with the highest and lowest probability of success is -0.59% per month with a t-statistic of -6.02 when the aspiration level return is equal to zero. Average returns obtaining from the four factor model do not change the results substantially in the case of value-weighted portfolios. All average differences are highly significant with at least a t-statistic of -4.56. Finally, the specification of setting the aspiration level return equal to the industry average provides the largest average return difference between the average returns of the portfolio quintiles with the highest and lowest probability of success.

Although all specifications provide large and statistically significant average return differences I report the results of the specification when the aspiration level return is equal to the industry average return in the following sections. I choose to report this specification because it provides the strongest results for both equal-weighted and value-weighted portfolios. However, I also discuss the effect if several different specifications of the aspiration levels in the sensitivity analysis.

As a conclusion, univariate sorts suggest that there is a strong negative relationship between the expected return and the probability of success measure even after controlling for the standard risk factors. However, these results might be driven by another characteristic of the stocks that has an already documented negative relationship with the expected return. In the next section, I control for several known characteristics in bivariate sorts to differentiate the probability of success measure from them.

Bivariate Portfolio Level Analyses

In this section, I investigate the relationship between the probability of success and the subsequent monthly average excess return after controlling for a set of several different variables such as short-term reversal, skewness, illiquidity, size, book-to-market, momentum, MAX effect, idiosyncratic volatility, market beta, and PT value. To control for a variable, first I sort stocks into quintiles based on the control variable. Then within each quintile I sort stocks into quintiles based on the probability of success. Thus, I form five times five portfolios based on the control variable and the probability of success. Finally, I take the average returns across the five control variable quintiles. For brevity, Tables 1.5 and 1.6 present the results of the time-series averages of the equal-weighted and value-weighted returns for each double sorted quintile of the probability of success. This procedure generates high dispersion in the probability of success and low dispersion in the control variable across the portfolio quintiles.

Table 1.5: Double sorted, equal-weighted quintile portfolios are formed every month from July 1962 to November 2016 by sorting stocks based on the probability of success (PS) after controlling for REV, skewness (Skew), Illiquidity (Illiq), Size, BTM, MOM, MAX, idiosyncratic volatility (IVOL), market beta, and PT value. In each case, I first sort stocks into quintiles using the control variable then within each quintile I sort stocks into quintile portfolios based on the probability of success over the current month so quintile 1 contains the stocks with the lowest probability of success across the portfolio quintiles of the control variable. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1. (the Newey-West corrected t-statistic with 12 lags are reported in parentheses.) N denotes the number of observations.

					EW					
Quintile	REV	Skew	Illiq	Size	BTM	MOM	MAX	IVOL	Beta	PT
Lowest	1.12	1.42	1.34	1.34	1.37	1.40	1.41	1.42	1.38	1.19
2	0.93	0.96	0.96	0.97	0.97	0.97	0.99	0.99	0.98	0.92
3	0.81	0.73	0.73	0.72	0.71	0.75	0.71	0.73	0.72	0.73
4	0.71	0.49	0.54	0.54	0.53	0.50	0.51	0.50	0.53	0.56
Highest	0.50	0.15	0.18	0.20	0.18	0.12	0.14	0.11	0.16	0.36
Difference	−0.62	−1.27	−1.16	−1.14	−1.19	−1.28	−1.27	−1.31	−1.22	−0.83
t-stat	(−10.03)	(−10.99)	(−11.15)	(−11.63)	(−11.50)	(−11.82)	(−11.35)	(−12.39)	(−10.65)	(−11.17)
CAPM α	−0.55	−1.14	−1.03	−1.03	−1.06	−1.16	−1.13	−1.20	−1.10	−0.82
t-stat	(−9.49)	(−9.60)	(−9.68)	(−10.13)	(−9.83)	(−10.52)	(−9.90)	(−11.22)	(−9.48)	(−11.05)
4F α	−0.54	−1.31	−1.16	−1.13	−1.20	−1.30	−1.28	−1.31	−1.26	−0.83
t-stat	(−9.79)	(−8.61)	(−9.26)	(−9.83)	(−9.71)	(−11.09)	(−9.81)	(−11.02)	(−8.86)	(−10.45)
N	653	653	653	653	653	653	653	653	653	653

Table 1.6: Double sorted, value-weighted quintile portfolios are formed every month from July 1962 to November 2016 by sorting stocks based on the probability of success (PS) after controlling for REV, skewness (Skew), Illiquidity (Illiq), Size, BTM, MOM, MAX, idiosyncratic volatility (IVOL), and market beta. In each case, I first sort stocks into quintiles using the control variable then within each quintile I sort stocks into quintile portfolios based on the probability of success over the current month so quintile 1 contains the stocks with the lowest probability of success across the portfolio quintiles of the control variable. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1. (the Newey-West corrected t-statistic with 12 lags are reported in parentheses.) N denotes the number of observations.

VW

Quintile	REV	Skew	Illiq	Size	BTM	MOM	MAX	IVOL	Beta	PT
Lowest	0.86	0.95	0.93	0.93	0.96	0.98	0.98	0.96	0.96	0.84
2	0.74	0.75	0.74	0.74	0.76	0.74	0.75	0.78	0.75	0.67
3	0.57	0.66	0.63	0.62	0.62	0.65	0.66	0.63	0.65	0.55
4	0.49	0.45	0.44	0.43	0.48	0.46	0.45	0.44	0.45	0.50
Highest	0.29	0.21	0.20	0.20	0.19	0.18	0.20	0.17	0.21	0.31
Difference	−0.58	−0.74	−0.72	−0.72	−0.77	−0.79	−0.78	−0.79	−0.75	−0.54
t-stat	(−6.21)	(−7.98)	(−7.54)	(−7.72)	(−8.29)	(−8.31)	(−7.99)	(−8.32)	(−7.95)	(−6.29)
CAPM α	−0.54	−0.65	−0.64	−0.64	−0.68	−0.71	−0.68	−0.72	−0.67	−0.53
t-stat	(−5.95)	(−7.04)	(−6.60)	(−6.80)	(−7.32)	(−7.52)	(−7.03)	(−7.62)	(−7.09)	(−6.38)
4F α	−0.51	−0.70	−0.69	−0.69	−0.73	−0.76	−0.75	−0.76	−0.71	−0.49
t-stat	(−5.47)	(−6.06)	(−5.69)	(−5.88)	(−6.54)	(−6.99)	(−6.44)	(−6.54)	(−6.38)	(−4.98)
N	653	653	653	653	653	653	653	653	653	653

The average return differences for equal-weighted portfolios range from −1.14% per month to −1.31% per month except for the short-term reversal. It means that none of the control variables changes the average return difference substantially compared to the result of the univariate sort but the short-term reversal. However, the average return difference remains both economically and statistically significant even after controlling for the short-term reversal. The average return difference is −0.62% per month with a highly significant t-statistic of −10.03. This t-statistic is not only highly significant but close to the t-statistics of the other bivariate sorts return differences. It suggests that none of the used control variables can largely reduce the magnitude of the average return or its statistical power in the bivariate sorts for the equal-weighted average return differences.

Table 1.6 reports the value-weighted portfolio bivariate sorts providing similar results to the equal weighted case. It reports the largest reduction in average return difference for the short-term reversal compared to the univariate sorts. However, it is again both economically and statistically highly significant with an average return difference of −0.58% and the t-statistic of −6.21. After controlling for the rest of the control variables does not change the average return difference and its significance level extensively.

All these results are robust for controlling for the market factor or the four factor model. Both for equal-weighted and value-weighted portfolios, the average return spread between the high and low probability of success quintiles are highly significant and these average return spreads are close to the average raw excess return differences. It suggests that these common factors have limited impact on the results of the probability of success.

Finally, both the equal-weighted and value-weighted portfolio average returns decrease monotonically in each case. It mitigates any concern that the results are driven by only a few stocks concentrated in one of the extreme quintiles.

The advantage of sorting is that it does not require any assumption of the functional form of the relationship. On the other side, one of the biggest critiques against sorting is that the control might not be sufficient enough. Addressing this concern, I also run cross-sectional regressions which could control for all variables at the same time.

Firm-level Cross-sectional Regressions

I examine the cross-sectional relation between the probability of success and expected return at the firm level using Fama-MacBeth (1973) regressions. I present the time-series average of the slope coefficients from the regressions of excess stock returns on the probability of success (PS), market beta (Beta), log market capitalization (Size), log book-to-market ratio (BTM), momentum (MOM), short-term reversal (REV), illiquidity (Illiq), idiosyncratic volatility (IVOL), maximum daily return (MAX), minimum daily return (MIN), and skewness (Skew). I normalize all variables in each month to make the coefficients comparable. I include beta, size, and book-to-market ratio as the standard control variables and I also include short-term reversal and momentum to show that my measure captures something that is different from the returns of the last few months. I also include MAX and MIN to differentiate my measure from them (Bali et al., 2011). Furthermore, one could argue that my measure is quite close to several already known variables such as the idiosyncratic volatility (e.g., Ang et al, 2006) or skewness. Thus, I include the idiosyncratic volatility and skewness of the last month daily returns as control variables. I also include illiquidity to show that my measure remains a strong predictor even after controlling for it. As a result, I run cross-sectional regressions with the following specification and nested versions thereof:

$$\begin{aligned} R_{i,t+1} =& \gamma_{0,t} + \gamma_{1,t} PS_{i,t} + \gamma_{2,t} Beta_{i,t} + \gamma_{3,t} Size_{i,t} + \gamma_{4,t} BTM_{i,t} \\ &+ \gamma_{5,t} MOM_{i,t} + \gamma_{6,t} REV_{i,t} + \gamma_{7,t} Illiq_{i,t} + \gamma_{8,t} IVOL_{i,t} \\ &+ \gamma_{9,t} MAX_{i,t} + \gamma_{10,t} MIN_{i,t} + \gamma_{11,t} Skew_{i,t} + \epsilon_{i,t+1}, \end{aligned} \tag{1.8}$$

where $R_{i,t+1}$ is the realized excess return on stock i in month $t+1$. The predictive cross-sectional regressions are run on the month t values of PS, Beta, logarithm of the market value (size), logarithm of BTM, MOM, REV, Illiq, IVOL, MAX, MIN, and Skewness. The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables, on average, have non-zero premiums.

Table 1.7: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including probability of success (PS) in the current month which is defined as the percentage of the daily returns that achieved the aspiration level return in the current month and ten control variables. I normalize each variable at the monthly level to make the coefficients comparable. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics with 12 lags (in parentheses). N denotes the number of observations.

	(1)	(2)	(3)
PS	−0.42	−0.43	−0.27
	(−10.75)	(−12.83)	(−10.41)
Beta		−0.09	0.02
		(−2.03)	(0.44)
Size		−0.02	−0.26
		(−0.19)	(−4.18)
BTM		0.33	0.23
		(5.32)	(4.18)
MOM			0.44
			(6.84)
REV			−0.34
			(−5.67)
MAX			−0.12
			(−2.38)
MIN			0.07
			(1.51)
IVOL			−0.35
			(−3.14)
Illiq			0.11
			(3.95)
Skew			0.00
			(0.10)
N	653	653	653

Table 2.6 reports the result of the Fama-MacBeth regressions. The measure of the probability of success is priced in each regression. I run a regression when it stands alone to show that it is a highly significant predictor of the subsequent monthly excess return. I also run a regression in which I include the four most typical control variables: market beta, book-to-market ratio, size, and momentum. In this specification, my measure gets even stronger. This result is in line with the results of the univariate sorts, where the return difference even increased after controlling for these variables. Finally, I run a regression in which I control for ten different measures to show that none of them makes my measure insignificant even if I control for them at the same time.

In each case, the coefficient on my measure of probability of success is negative which means that a higher probability of success leads to a lower expected return as the theory predicts.

The time-series average of the coefficients of the probability of success measure is still -0.27 even in the inclusion of all the ten control variables. It means that one standard deviation increase in the probability of success measure yields a 0.27% lower expected return per month in the subsequent monthly return. It means that the probability of success measure is not only highly significant statistically with a t-statistic of 10.41 but it also provides an economically significant predictive power in the cross-section of stock returns.

Understanding the Characteristics of the Probability of Success

Table 1.8 reports the summary statistics for various characteristics of the stocks in quintiles sorted on the percentage of the daily returns that achieved the aspiration level return in the last month as a probability of success (PS) measure to provide an overview of the relationship between the PS measure and several important variables. I present the average across months of the average values for my probability of success measure (PS), market beta (Beta), logarithm of book-to-market ratio (BTM), logarithm of market capitalization (Size), momentum (MOM) following Jegadeesh and Lehmann (1993), short-term reversal (REV) following Jegadeesh and Lehmann (1990), the maximum daily return (MAX), the minimum daily return (MIN), idiosyncratic volatility (IVOL), a measure of illiquidity, and skewness of the daily returns of the last month in each month for the stocks in each quintile.

Table 1.8: Quintile portfolios are formed every month from July 1962 to November 2016 by sorting on the probability of success (PS) in the last month. Portfolio 1 contains the stocks with the lowest probability of success over the current month. The Table reports for each quintile the averages of the average values within each month of various characteristics for the stocks: probability of success (PS), market beta (Beta), logarithm of book-to-market ratio (BTM), logarithm of market capitalization (Size), momentum (MOM) following Jegadeesh and Lehmann (1993), short-term reversal (REV) following Jegadeesh and Lehmann (1990), the maximum daily return (MAX), the minimum daily return (MIN), idiosyncratic volatility (IVOL), a measure of illiquidity (Amihud, 2002), and skewness of the last month's returns. N denotes the number of observations.

	PS	Beta	BTM	Size	MOM	REV	MAX	MIN	IVOL	Illiq	Skew
1	0.33	0.95	−0.54	19.09	0.15	−0.07	0.06	−0.06	2.58	7.92	0.31
2	0.42	0.96	−0.57	19.12	0.14	−0.02	0.07	−0.06	2.63	8.74	0.27
3	0.47	0.96	−0.59	19.19	0.14	0.01	0.07	−0.05	2.59	8.51	0.22
4	0.52	0.96	−0.63	19.29	0.15	0.05	0.06	−0.05	2.53	7.90	0.18
5	0.62	0.95	−0.70	19.47	0.17	0.11	0.06	−0.05	2.39	6.09	0.13
N	653	653	653	653	653	653	653	653	653	653	653

There are some interesting patterns in the characteristics of the portfolio quintiles based on the probability of success. First of all, there is no relationship between the probability of success and beta, size, momentum, MAX, MIN, idiosyncratic volatility or illiquidity. It means that none of the quintiles is concentrated among small and illiquid stocks or stocks with high idiosyncratic volatility.

Second, there is a negative correlation between the logarithm of the book-to-market ratio and the probability of success. Thus, stocks with low probability of success tend to have a higher book-to-market ratio. This might be driven by the fact that the prices of the stocks with a low probability of success are more likely to fall in the past which could raise the book-to-market ratio. However, the variation in the logarithm of the book-to-market ratio across the portfolio quintiles are quite small (from -0.54 to -0.70).

Third, the short-term reversal has a positive correlation with the probability of success measure. The portfolio quintile with the smallest probability of success has an average of 7% return per month drop in the last month, while the portfolio with the highest probability of success has an average of 11% return per month. This correlation is intuitively based on the construction of the probability of success measure. To differentiate the measure of the probability of success from the short-term reversal, I present bivariate sorts and Fama-MacBeth regressions but I also perform additional tests in a following section to control for potential microstructure effects. Finally, there is a negative correlation between the skewness of the daily returns and the probability of success measure. It is also intuitive since a stock with a lot of small positive returns but one large drop is more likely to end up in the high probability of success quintile, while a stock with lot of small negative returns with a large positive outlier return is more like to end up in the low probability of success quintile by construction. However, skewness has the opposite prediction compared to the probability of success. According to preference for skewness, stocks with a positive skewness should earn a lower subsequent monthly average excess return on average, while the low probability of success predicts a higher subsequent monthly average excess return on average.

Table 1.8 also provides an explanation why there was only very limited impact of the control variables on the probability of success measure in bivariate sorts since the values of most of the control variables are the same across the portfolio quintiles of the probability of success. This Table also confirms that short-term reversal is the only control variable which could have a substantial impact on the probability of success measure.

To mitigate any concern that my measure would capture any of the effects of the book-to-market ratio or the short-term reversal, I present the equal- and value-weighted bivariate sorts and the firm-level regressions.

1.5.3 Robustness of the Probability of Success

In this section, I investigate the effect of arbitrage cost and sophistication on the probability of success measure.

Arbitrage is more costly for stocks with small market capitalization, with higher illiquidity and with higher idiosyncratic volatility (Brav, Heaton, and Li, 2010). Thus, I use size, idiosyncratic volatility, and illiquidity to create sub-samples with high and low arbitrage costs. I use the institutional ownership ratio to approximate the effect of sophistication. If the probability of success is priced only because of mispricing then the probability of success should not be priced among stocks with low arbitrage costs. Furthermore, if the probability of success is more important for less sophisticated retail investors then the effect of the probability of success is supposed to disappear with higher concentration of the institutional ownership.

Institutional ownership (IO) is calculated as the percentage of the shares held by institutional investors lagged by one quarter based on the Thomson Reuters Institutional Holdings (13F) database.

However, I find that the probability of success is still priced among stocks with low arbitrage cost and high institutional ownership. It suggests that the probability of success is not a consequence of mispricing. The return spread between the highest and lowest probability of success quintile is large and highly significant among large and liquid stocks as well. In addition, the value-weighted portfolio return difference is even higher and stronger for low idiosyncratic volatility stocks than for high idiosyncratic volatility stocks. It suggests that the results of the probability of success is not only driven by small and illiquid stocks with high arbitrage costs. This results also mitigates the concern that the return spread between the high and low probability of success quintiles are driven by capturing some microstructure effects.

Increasing the institutional ownership makes the results even stronger which indicates that the low level of sophistication does not drive the results either. The value-weighted average portfolio return difference increases from -0.51% per month to -0.73% per month by increasing the institutional ownership. This also suggests that the probability of success is not a consequence of mispricing which persists because of high arbitrage costs or low sophistication.

Table 1.9 reports the time-series averages of the subsequent monthly excess returns for each quintile sorted based on the probability of success into two sub-samples based on size, liquidity, and idiosyncratic volatility. In each month, I use the median value of the control variable to split the sample into two sub-samples. Within each sample in each month, I sort the stocks into portfolio quintiles based on the probability of success. Finally, I generate the average return difference between the quintile with the highest probability of success and the quintile with the lowest probability of success (t-statistics are in parentheses). Both the equal- and value-weighted average return differences are highly significant for small and large stocks and liquid and illiquid stocks. Thus, the effect of the probability of success is significant irrespective of the sub-samples. The value-weighted portfolio average return difference is -0.73% per month with a t-statistic of -7.71 for large firms and -0.71% per month with a t-statistic of -7.47 for the liquid firms. These average return differences are highly significant, both economically and statistically.

Furthermore, the average return difference is even stronger for stocks with low idiosyncratic volatility than for stocks with high idiosyncratic volatility. The value-weighted average portfolio return difference is -0.86% per month with a t-statistic of -8.94, while the value-weighted average portfolio return difference is -0.63% per month with a t-statistic of -4.99. These results suggest that the average return differences for the probability of success is not driven by stocks with high transaction costs which would prevent the sophisticated investors from arbitrage.

Table 1.9: Double sorted, equal- and value-weighted quintile portfolios are formed every month from July 1962 to November 2016. In each case, I first sort the stocks into two sub-samples based on their median size (small and large), based on their median illiquidity measure, and based on their median idiosyncratic volatility then within each sub-sample I sort stocks into quintile portfolios based on the probability of success over the current month so quintile 1 contains the stocks with the lowest probability of success. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1. (the Newey-West corrected t-statistics with 12 lags are reported in parentheses.) N denotes the number of observations.

	Small		Large		Illiquid		Liquid	
Quintile	EW	VW	EW	VW	EW	VW	EW	VW
Lowest	1.59	1.45	1.14	0.92	1.57	1.34	1.16	0.92
2	1.03	1.00	0.91	0.75	1.02	0.94	0.91	0.75
3	0.76	0.79	0.68	0.60	0.73	0.73	0.73	0.60
4	0.55	0.67	0.53	0.43	0.48	0.43	0.59	0.46
Highest	0.13	0.30	0.21	0.19	0.02	0.07	0.30	0.21
Difference	−1.46	−1.15	−0.93	−0.73	−1.54	−1.28	−0.85	−0.71
t-stat	(−11.63)	(−11.34)	(−9.49)	(−7.71)	(−11.47)	(−11.24)	(−8.26)	(−7.47)
N	653	653	653	653	653	653	653	653

	High IVOL		Low IVOL	
Quintile	EW	VW	EW	VW
Lowest	1.33	0.81	1.51	1.07
2	0.81	0.53	1.14	0.82
3	0.57	0.50	0.88	0.69
4	0.38	0.49	0.64	0.45
Highest	−0.03	0.18	0.28	0.21
Difference	−1.36	−0.63	−1.23	−0.86
t-stat	(−10.38)	(−4.99)	(−12.29)	(−8.94)
N	653	653	653	653

Table 1.10 reports the average returns for each quintile sorted based on the probability of success for two sub-samples based on the institutional ownership. In each month, I use the 67th percentile[6] of the control variable to split the sample into two sub-samples. Within each sample in each month, I sort the stocks into portfolio quintiles based on the probability of success. Finally, I generate the average return difference between the quintile with the highest probability of success and the quintile with the lowest probability of success (t-statistics are in parentheses). The average return differences are significant for both sub-samples. Furthermore, both the equal-weighted and value-weighted average return differences are not smaller for stocks with high institutional ownership but even larger. The value-weighted average portfolio return difference is -0.73% per month with a t-statistic of -6.02 for the stocks with high institutional ownership, while the value-weighted portfolio return difference is -0.51% per month with a t-statistic of -3.96 for the stocks with low institutional ownership. It means that the probability of success does not get less important for more sophisticated investors. It suggests that the probability of success might be even more important for sophisticated investors than for retail investors.

[6] I use the 67th percentile instead of the median to mitigate the problem that in the beginning of the institutional ownership data there are only few stocks with higher ownership ratio than 0 (following Barberis et al., 2016).

Table 1.10: Double sorted, equal- and value-weighted quintile portfolios are formed every month from January 1980 to November 2015 because of the data availability of the institutional ownership data. In each case, I first sort the stocks into two sub-samples based on their one quarter lagged institutional ownership with a breaking point at the 67th percentile then within each sub-sample I sort stocks into quintile portfolios based on the probability of success over the current month so quintile 1 contains the stocks with the lowest probability of success. "Return difference" is the average monthly return difference between portfolio 5 and 1. (Newey-West corrected t-statistics with 12 lags are reported in parentheses.) N denotes the number of observations.

	Low IO		High IO	
Quintile	EW	VW	EW	VW
Lowest	1.21	0.82	1.50	1.17
2	0.77	0.77	1.20	0.92
3	0.60	0.69	0.96	0.92
4	0.45	0.48	0.78	0.80
Highest	0.16	0.31	0.40	0.44
Difference	−1.05	−0.51	−1.10	−0.73
t-stat	(−7.37)	(−3.96)	(−8.49)	(−6.02)
N	419	419	419	419

To investigate the effect of arbitrage costs and sophistication on the measure of the probability of success, I also run Fama-MacBeth regressions including all control variables that are mentioned in equation (2.7) and, additionally, the interaction terms between the probability of success and the control variable for approximating the arbitrage costs or the sophistication in the given specification.

Table 1.11 reports the time-series average coefficients of the probability of success and its interaction terms with the variable for arbitrage costs or sophistication. All variables are standardized to make the coefficients more comparable. According to Table 1.11, increasing the size of a stock or increasing the illiquidity of a stock yield a lower effect for the probability of success. This is in line with the results of Table 1.9 where the measure of the probability of success generates a significant and large average return difference in the sub-sample of small firms and in the sub sample of illiquid stocks. However, the interaction term between the idiosyncratic volatility and the probability of success is not significant. It means that increasing the idiosyncratic volatility does not increase the strength of the probability of success. The Fama-MacBeth approach evaluates each observation equally important, which might be the reason why there is no positive sign on the average coefficients of the interaction term between the idiosyncratic volatility and the probability of success as Table 1.9 suggests, based on the value-weighted portfolios. According to Table 1.9, the equal-weighted portfolios generate a larger average return difference for high volatility stocks than for low volatility stocks but this pattern changes for the value-weighted portfolios.

The results are very similar for the institutional ownership. The interaction term between the institutional ownership and the probability of success is not significant. However, the negative average coefficients indicate that increasing the sophistication (institutional ownership) yields an even stronger effect for the probability of success. This pattern is even stronger in Table 1.10 for the value-weighted portfolios.

These results suggest that there is no strong evidence that the measure of the probability of success would be a result of mispricing. Although the size and illiquidity seem to have an effect on the magnitude of the effect of the probability of success idiosyncratic volatility and institutional ownership does not confirm this pattern. In addition, the probability of success is highly significant among small and illiquid stocks as well.

Finally, I investigate the effect of the sentiment index (Baker and Wurgler, 2006) on the probability of success. High sentiment index values indicate optimism on the market and higher participation of naive investors. It would suggests that the measure of the probability of success should generate lower average return differences in low sentiment time periods than in high sentiment time periods if it is driven by unsophisticated investors. For instance, Stambaugh, Yu, and Yuan (2012) shows that anomalies that capture overpricing certain stocks is more pronounced during high sentiment time periods. However, Table 1.12 reports that the probability of success generates an even larger average return difference in the low sentiment time periods. This result and the results of the tests with the institutional ownership suggest that the measure of the probability of success is an important aspect for all investors.

Table 1.11: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly return on subsets of predictor variables including probability of success (PS) in the current month which is defined as the percentage of the number of daily returns that achieved the industry average and ten control variables including market beta, size, book-to-market ratio, momentum, short-term reversal, MAX, MIN, idiosyncratic volatility, illiquidity, and skewness. I also include the interaction between the probability of success and size, illiquidity, idiosyncratic volatility, and the institutional ownership (logarithm of the measure plus 1 following Barberis et al. (2016)). The sample covers from January 1980 to December 2015 in the case of the institutional ownership because of data availability. For brevity, this Table only reports the coefficients of the probability of success, the variables which interacts, and the interaction terms. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics with 12 lags (in parentheses). N denotes the number of observations.

	Size	Illiq	IVOL	IO
PS	−0.29	−0.29	−0.28	−0.25
	(−10.56)	(−10.60)	(−9.42)	(−6.53)
PS×Size	0.10			
	(5.03)			
PS×Illiq		−0.16		
		(−6.60)		
PS×IVOL			−0.03	
			(−1.40)	
PS×IO				−0.13
				(−0.70)
Size	−0.26			
	(−4.22)			
Illiq		0.11		
		(3.23)		
IVOL			−0.36	
			(−3.22)	
IO				0.34
				(3.79)
Controls	Yes	Yes	Yes	Yes
N	653	653	653	419

Table 1.12: Double sorted, equal- and value-weighted quintile portfolios are formed every month from July 1965 to November 2014. In each case, I first sort the stocks into two sub-samples based on sentiment index value with a breaking point at the 50th percentile then within each sub-sample I sort stocks into quintile portfolios based on the probability of success over the current month so quintile 1 contains the stocks with the lowest probability of success. "Return difference" is the average monthly return difference between portfolio 5 and 1. (Newey-West corrected t-statistics with 12 lags are reported in parentheses.) N denotes the number of observations.

	Low sentiment		High sentiment	
Quintile	EW	VW	EW	VW
Lowest	1.80	1.02	1.00	0.80
2	1.37	0.87	0.59	0.62
3	1.11	0.71	0.36	0.55
4	0.81	0.52	0.19	0.34
Highest	0.40	0.25	−0.15	0.07
Difference	−1.40	−0.78	−1.15	−0.73
t-stat	(−8.34)	(−4.59)	(−7.39)	(−6.62)
N	581	581	581	581

1.5.4 Alternative Explanations

In this section, I provide additional tests to show that the probability of success measure is different from a potential microstructure effect.

First, short-term reversals are sensitive to bid-ask bounces. To investigate the effect of the bid-ask bounces, I exclude the first day return of the subsequent monthly return to mitigate the potential concern that the results are driven by these bounces, similarly to Jegadeesh (1990). I find there is no substantial change in the probability of success measure in the Fama-MacBeth regressions.

Second, short-term reversals and several other known variables related to liquidity are the strongest in January. Thus, I additionally report the results for January and non-January months to explore the January-effect on the probability of success measure.

Third, the short-term reversal can be decomposed into an inter-industry momentum and an intra-industry reversal (Hameed and Mian, 2015). The intra-industry reversal is quite similar to the probability of success measure in my main specification when the aspiration level return is equal to the industry average return. Thus, I perform additional bivariate sorts with intra-industry reversal and Fama-MacBeth regression including the inter-industry momentum and the intra-industry reversal instead of the short-term reversal.

Finally, I analyze the time variation of the coefficient loading on the probability of success. According to the literature, liquidity-related strategies such as the short-term reversals are stronger in the time of strong liquidity constraints. As a results, the coefficient of the probability of success should vary with the market uncertainty (using the VIX index), the month of January, and it should be stronger in the pre-decimalization (before April 2001) time period. I find that the coefficient of the probability of success does not depend on any of these variables, while the intra-industry reversal does. These results also suggest that the probability of success measure can not be explained by microstructure effects.

Table 1.13: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly return on subsets of predictor variables including probability of success (PS) in the current month which is defined as the percentage of the number of daily returns that achieved the industry average and ten control variables including market beta, size, book-to-market ratio, momentum, short-term reversal, MAX, MIN, idiosyncratic volatility, illiquidity, and skewness. These coefficients are reported in the first column. This Table in the second column also reports the time-series average coefficients when the first day return of the subsequent monthly return is excluded. Finally, the third and fourth column report the time-series average coefficients for the January effect. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics with 12 lags (in parentheses). N denotes the number of observations.

	Excluding the first day		January effect	
	No	Yes	January	Non-January
PS	−0.27	−0.27	−0.23	−0.28
	(−10.75)	(−10.73)	(−4.06)	(−11.03)
Beta	0.02	0.02	−0.00	0.02
	(0.44)	(0.65)	−(0.03)	(0.45)
Size	−0.26	−0.27	−1.82	−0.12
	(−4.18)	(−4.15)	(−5.44)	(−1.99)
BTM	0.23	0.19	0.79	0.18
	(4.18)	(3.62)	(2.91)	(3.37)
MOM	0.44	0.42	−0.27	0.50
	(6.84)	(7.10)	(−2.00)	(7.52)
REV	−0.34	−0.12	−1.74	−0.21
	(−5.67)	(−2.45)	(−8.13)	(−3.85)
MAX	−0.12	−0.13	−0.35	−0.10
	(−2.38)	(−2.68)	(−1.64)	(−1.99)
MIN	0.07	0.07	0.71	0.02
	(1.51)	(1.38)	(6.00)	(0.32)
IVOL	−0.35	−0.36	1.71	−0.54
	(−3.14)	(−3.52)	(4.95)	(−4.44)
Illiq	0.11	0.12	0.65	0.06
	(3.95)	(4.50)	(8.68)	(2.21)
Skew	0.00	−0.01	−0.07	0.01
	(0.10)	(−0.62)	(−1.47)	(0.36)
N	653	653	653	653

Table 1.13 reports the time-series averages of the coefficients of the regressions for the two tests. The first and second column reports the time-series averages of the coefficients when the subsequent monthly excess returns include the first day of the month return and when they exclude the first day of the month return. The average coefficient of the short-term reversal suffers a large drop both in its size and in its significance by excluding the first day return. This is in line with the literature that the short-term reversal is sensitive to the bid-ask bounces as a microstructure effect. However, the probability of success is not affected by excluding the first day return. Both the magnitude and the significance of the time-series average of the coefficients remain the same. It suggests that the measure is not driven by the bid-ask bounce.

The third and fourth columns of Table 1.13 report the time-series averages of the coefficients for January and the non-January months. There are several variables which are sensitive to the January-effect such as the short-term reversal, size, or book-to-market ratio. However, the probability of success is not affected by the January-effect. It remains both economically and statistically significant. The probability of success is even a bit stronger among the non-January months. This also supports the hypothesis that this measure is different from the known variables, especially from the short-term reversal.

Table 1.14 reports the equal-weighted and value-weighted time-series averages of the subsequent excess returns of the bivariate sorts controlling for the intra-industry reversal. In this case, I sort stocks into portfolio quintiles based on the return of the current month within each industry in each month. In this approach portfolio quintiles are generated in which the first quintile consists of the industry losers of the last month and the fifth quintile consists of the industry winners of

Table 1.14: Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2016 by sorting stocks based on the probability of success (PS) after controlling for intra-industry reversal. In each case, I first sort the stocks into quintiles based on the current monthly return in each month in each industry then within each quintile I sort stocks into quintile portfolios based on probability of success over the current month so quintile 1 contains the stocks with the lowest probability of success across the portfolio quintiles of the control variable. The Table reports for each quintile the average subsequent excess monthly return of the portfolios in the case of equal-weighted (EW) and value-weighted (VW) portfolios and the equal-weighted returns and value-weighted (VW) returns obtained from the four factor Carhart (1997) model (market, size, book-to-market, momentum)."Return difference" is the average monthly return difference between portfolio 5 and 1. (the Newey-West corrected t-statistic with 12 lags are reported in parentheses.) N denotes the number of observations.

	Raw Excess Return		4F Alpha	
Quintile	EW	VW	EW	VW
Lowest	0.89	0.77	0.21	0.19
2	0.85	0.72	0.18	0.18
3	0.76	0.58	0.09	0.02
4	0.72	0.52	0.04	−0.06
Highest	0.54	0.37	−0.10	−0.17
Difference	−0.35	−0.40	−0.31	−0.36
t-stat	(−6.06)	(−6.07)	(−5.83)	(−5.57)
N	653	653	653	653

the last month. Then, within each portfolio quintile, I sort stocks into portfolio quintiles based on their probability of success.

According to Table 1.14, the average return difference between the highest and lowest quintile's returns become smaller than in the univariate sorts. However, with −0.35% per month for equal-weighted portfolios and −0.40% per month for value-weighted portfolios, the results remain highly significant with a t-statistic of −6.06 and −6.07. These results are both economically and statistically significant and the four factor (Carhart, 1997) model provides similar results. It mitigates the concern that my measure would only be driven by the intra-industry reversal.

However, the probability of success measure might capture the combination of the intra-industry reversal and some other known variables. I also perform Fama-MacBeth regressions in which I include inter-momentum (Ind-MOM) using the variable of the industry average return in the last month for a stock and the intra-industry reversal (Ind-REV) using the variable of the difference between the stock return and the industry average return. These two variables are created by decomposing short-term reversal because they capture two significantly different parts of the short-term reversal (Hameed and Mian, 2015).

The first column of the Table 1.15 reports the time-series averages of the coefficients of the Fama-Macbeth regressions including inter-industry and intra-industry decomposition of the short-term reversal. The time-series average of the probability of success measure becomes smaller by decomposing short-term reversal which means that intra-industry reversal can explain part of the results of the probability of success measure. However, similarly to the results of the bivariate sorts, the time-series average of the coefficients of PS also remains both economically and statistically significant with a t-statistic of -7.62 after controlling for all control variables.

In the following, I present the results of the tests to show that the probability of success measure is not driven by a microstructure effect after controlling for intra-industry reversal. The second column of Table 1.15 reports the time-series averages of the coefficients of the Fama-Macbeth regressions including an inter-industry and intra-industry decomposition of the short-term reversal when the first day return is excluded from the subsequent monthly returns. This method controls for the potential effect of bid-ask bounces. Intra-industry reversal suffer a large reduce in the magnitude of the time-series average coefficient similarly to the short-term reversal. However, the time-series average coefficient for the probability of success does not decrease in this case either. It suggests that short-term reversal and intra-industry reversal variables are sensitive to the microstructure effects such as bid-ask bounces, while the probability of success measure is insensitive to bid-ask bounces.

The third and fourth column of Table 1.15 reports the time-series averages of the coefficients of the Fama-Macbeth regressions including inter-industry and intra-industry decomposition of the short-term reversal for the January months and the non-January months. Several known variables that are related to microstructure effects are known to be stronger for the month of January. In line with the literature, the magnitude of the intra-industry reversal has a stronger effect in the month of January than in the non-January months. However, the time-series average of the probability of success is not even significant in the month of January but it is highly significant in the non-January months with a t-statistic of -8.25.

Finally, I test whether the coefficient on the probability of success varies with the liquidity constraints. The profitability of a strategy that are related to microstructure effects depend on liquidity constraints. For instance, short-term reversal or intra-industry reversal profitability is higher during high uncertainty time periods when it is harder to fund liquidity. In addition, these factors are more profitable in the month of January and in the pre-decimalization time (before April 2001) (Hameed and Mian, 2015). To investigate the relationship between the probability of success and the microstructure effects, I run a regression of the coefficient of the probability of success from the Fama-MacBeth regressions on the VIX index as an approximation for the market uncertainty, the January dummy, and the dummy variable on pre-decimalization months. Table 1.16 reports the coefficients of the regression and their t-statistics. Table 1.16 also reports the same regressions of the intra-industry reversal coefficient to compare the results with a factor which is known to be related to microstucture effects (Hameed and Mian, 2015).

According to Table 1.16, none of the variables alone or together is a significant predictor of the profitability of the probability of success measure. However, all of these variables are a strong predictor of the profitability of the intra-industry reversal coefficient (short-term reversal coefficients exhibit similar results). Higher market uncertainty (higher VIX) leads to a lower coefficient (stronger reversal) on the intra-industry reversal and both the month of January and the months in pre-decimalization time periods provide a lower coefficient (stronger reversal).

As a conslusion, in this section I find that the probability of success measure is independent from microstructure effects. It mitigates the concern that the results of the probability of success could have an alternative microstructure explanation.

Table 1.15: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly return on subsets of predictor variables including probability of success (PS) in the current month which is defined as the percentage of the number of daily returns that achieved the industry average and nine control variables including market beta, size, book-to-market ratio, momentum, MAX, MIN, idiosyncratic volatility, illiquidity, and skewness plus the intra-industry reversal and the inter-industry momentum instead of the short-term reversal. These coefficients are reported in the first column. This Table in the second column also reports the time-series average coefficients when the first day return of the subsequent monthly return is excluded. Finally, the third and fourth column report the time-series average coefficients for the January effect. In each row, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics with 12 lags (in parentheses). N denotes the number of observations.

	Excluding the first day		January effect	
	No	Yes	January	Non-January
PS	−0.12	−0.12	−0.02	−0.13
	(−7.62)	(−8.35)	(−0.51)	(−8.25)
Beta	0.02	0.03	−0.01	0.03
	(0.61)	(0.92)	(−0.06)	(0.64)
Size	−0.25	−0.26	−1.81	−0.11
	(−4.28)	(−4.69)	(−5.37)	(−1.99)
BTM	0.24	0.19	0.83	0.19
	(4.72)	(4.10)	(3.19)	(3.72)
MOM	0.42	0.40	−0.31	0.48
	(6.74)	(7.00)	(−2.45)	(7.47)
Ind−REV	−0.56	−0.30	−1.97	−0.43
	(−9.43)	(−6.35)	(−9.75)	(−7.93)
Ind-MOM	0.31	0.30	0.08	0.33
	(6.88)	(6.33)	(0.46)	(7.60)
MAX	−0.08	−0.10	−0.28	−0.06
	(−1.61)	(−2.09)	(−1.31)	(−1.26)
MIN	0.14	0.12	0.77	0.08
	(2.78)	(2.42)	(6.58)	(1.50)
IVOL	−0.33	−0.34	1.72	−0.51
	(−2.99)	(−3.36)	(5.21)	(−4.37)
Illiq	0.11	0.11	0.62	0.06
	(3.71)	(4.28)	(8.64)	(1.99)
Skew	0.02	0.01	−0.04	0.03
	(1.01)	(0.37)	(−0.81)	(1.29)
N	653	653	653	653

Table 1.16: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly return on subsets of predictor variables including probability of success (PS) in the current month which is defined as the percentage of the number of daily returns that achieved the industry average and nine control variables including market beta, size, book-to-market ratio, momentum, MAX, MIN, idiosyncratic volatility, illiquidity, and skewness plus the intra-industry reversal and the inter-industry momentum instead of the short-term reversal. Obtaining these coefficients, I regress the coefficient of the probability of success or the coefficient of the intra-industry reversal on VIX (from January 1990 to November 2016), the dummy of the January month (which is one in the month of January and zero otherwise), and on the dummy of pre-decimalization (which is one before April 2001 and zero otherwise). These new coefficients are capturing the sensitivity of the coefficient of a variable to the liquidity constraint time variation. In each row, the Table reports the slope of the coefficients and their Newey-West corrected t-statistics with 12 lags (in parentheses). N denotes the number of observations.

	γ_{PS}				$\gamma_{Ind-REV}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VIX	−0.00			−0.00	−0.05			−0.05
	(−0.83)			(−0.89)	(−4.78)			(−5.30)
January		0.11		0.04		−1.54		−1.69
		(1.37)		(0.30)		(−5.86)		(−3.70)
Pre-decimalization			−0.03	−0.02			−0.50	−0.51
			(−0.89)	(−0.47)			(−4.78)	(−4.05)
N	323	653	653	323	323	653	653	323

1.5.5 Aspiration Level Sensitivity

In this section, I investigate the sensitivity of the results for different aspiration levels. I use the zero return, the risk-free rate, the market return, and the industry average return as a specification for an aspiration level. I run Fama-MacBeth regressions for each specification in which I control for all alternative measures at the same time. Table 1.17 reports the time-series averages of the coefficients on the probability of success measure for different specifications after controlling for a set of variables. Setting the aspiration level as zero return generates significant results with a t-statistic of -2.96, while setting the aspiration level return to the risk-free rate leads to an insignificant average coefficient.

Using the market return as an aspiration level return yields a significant result with a t-statistic of -2.49. However, the strength of the result is quite similar to the zero return aspiration level. Although the zero return and the market return aspiration level are both significant, they are much weaker than setting the aspiration level return to the industry average return. One standard deviation change in the measure generates an approximately four times higher average return difference for the aspiration level as the industry average return than for the other two specifications. This result indicates that setting the aspiration level to zero or to the market return generates significant results only because of partly capturing the effect of the specification when the aspiration level return is equal to the industry average.

Table 1.17: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly return on subsets of predictor variables including probability of success (PS) in the current month and ten control variables including MAX, MIN, idiosyncratic volatility, market beta, size, book-to-market ratio, momentum, short-term reversal, illiquidity, and skewness. For brevity, the Table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics with 12 lags (in parentheses). N denotes the number of observations.

	$\bar{r}=0$	$\bar{r}=r_{rf}$	$\bar{r}=r_m$	$\bar{r}=r_{ind}$
PS	−0.07	−0.03	−0.05	−0.27
	(−2.96)	(−1.12)	(−2.49)	(−10.41)
Beta	0.01	0.01	0.02	0.02
	(0.36)	(0.36)	(0.51)	(0.44)
Size	−0.28	−0.26	−0.26	−0.26
	(−4.45)	(−4.37)	(−4.21)	(−4.18)
BTM	0.24	0.23	0.24	0.23
	(4.19)	(4.14)	(4.13)	(4.18)
MOM	0.44	0.44	0.44	0.44
	(6.85)	(6.89)	(6.88)	(6.84)
REV	−0.49	−0.51	−0.49	−0.34
	(−8.03)	(−8.14)	(−7.77)	(−5.67)
MAX	−0.10	−0.10	−0.11	−0.12
	(−1.94)	(−1.81)	(−2.11)	(−2.38)
MIN	0.11	0.11	0.11	0.07
	(2.20)	(2.18)	(2.20)	(1.51)
IVOL	−0.33	−0.35	−0.33	−0.35
	(−2.75)	(−3.09)	(−2.88)	(−3.14)
Illiq	0.11	0.10	0.10	0.11
	(3.90)	(3.72)	(3.70)	(3.95)
Skew	0.04	0.06	0.05	0.00
	(1.64)	(2.37)	(2.29)	(0.10)
N	653	653	653	653

1.6 Conclusion

In this paper, I investigate the implications of incorporating an aspiration level into asset prices on the cross−section of stock returns. Aspiration level theory has been tested in the laboratory and in economic decisions. However, it hasn't been applied for the cross-section of stock returns so far. Aspiration level in this paper is defined as a target return that the investors want to achieve on each stock (narrow framing) they invest in. In this framework, investors are willing to accept a low expected return (higher price) for a stock if it has a high probability of success.

I provide empirical evidence for this implication. First, univariate portfolio level analyses present convincing average return spreads between the portfolios with the highest and lowest probability of success for both equal-weighted and value-weighted portfolios. This average return spread remains both economically and statistically significant, even after for controlling for a set of variables in bivariate portfolio analyses and Fama-MacBeth regressions.

The zero-cost long-short trading strategy based on the portfolios with high and low probability of success remains significant among large and liquid stocks with low idiosyncratic volatility. It suggests that the measure of the probability of success is not only pronounced among stocks with high arbitrage costs. The impact of the probability of success is even stronger among stocks with higher institutional ownership as an approximation for sophistication. These results indicate that the probability of success plays an important role in asset pricing.

Aspiration level theory might also have interesting implications for option pricing, dynamic asset allocation, or corporate finance because of its appealing features, clear intuitions, and strong explanatory power in decision making, and in the cross-section of stock returns. Investigating these questions could be a promising exercise for future work.

Chapter 2

Prior experience and the risk-return trade-off

2.1 Introduction

There is a well-documented negative risk-return relation in the empirical asset pricing literature. For instance, there is a negative relation between the expected return and the idiosyncratic volatility (Ang et al., 2006), between the expected return and the market beta (Baker et al., 2011), and between the expected return and the analyst forecast dispersion (Diether et al., 2002). This negative relation is puzzling because standard asset pricing models in finance, for instance, Capital Asset Pricing Model (CAPM) of Sharpe (1964) or Lintner (1965) would predict no relation or positive relation between the idiosyncratic volatility and the expected stock returns (Merton, 1987) and a positive relation between the market beta and the expected stock returns. In these models, for instance, Merton (1987) assumes risk-averse investors with a concave utility function of wealth.

My main contribution is to present a new empirical fact that the risk-return relation in the cross-section of stock returns depends on prior experience. Namely, there is a negative risk-return relation among stocks owned by investors face more prior negative experience and there is a positive or no relation among stocks owned by investors facing more positive experience. The reason I study the risk-return relation among stocks with different prior experience is motivated in section 2. The basic idea is that the investors might be influenced by the gambler‘s fallacy modeled by Rabin (2002). The model of Rabin (2002) has already provided explanations for several phenomena and has been also tested in the finance literature (e.g., Loh and Warachka, 2012). The crucial element of the model is that people mistakenly believe that less frequent prior signals are more likely to occur. Thus, the model predicts that most individuals tend to overweight the probability of a signal that has been observed less often than its expected rate. Expecting a strong mean reversion yielding an overweight of the probabilities of the positive outcomes for stocks with more prior negative experience and the overweight of the probabilities of the negative outcomes for stocks with more prior positive experience. This can lead to both negative and positive risk-return relation that is the main interest of my empirical tests.

The definition of prior experience is a challenge in empirical studies and there are several possibilities for examining this for the stock returns. This paper presents an explorative study in which I investigate several different approaches to define prior experience such as streaks or ratio of prior signals. I also investigate several alternative specifications of these approaches to explore the potential effects of these different approaches and specifications.

To demonstrate how the model of Rabin (2002) building on the gamblers' fallacy challenges the traditional positive risk-return trade-off, consider the following example. Assume that investors hold two assets purchased five time periods ago, stock A and B. Now, the price of both stocks A and B are \$40. The price of stock A can go up by \$1 or go down by \$1 with equal chance. The price of stock B can go up by \$10 or go down by \$10 with equal chance. Thus, both stocks have the same expected payoff but stock B has higher volatility (riskier) than stock A. The price of both stocks A and B went down four times and went up once during the last five time periods. The investors know that the rate for a positive (up) and negative (down) signal is 50-50%. Under the influence of the gambler's fallacy, they expect that the probability of a price increase is higher than the probability of a price decrease because they predict that the future signals should balance out the deviation from the underlying rate. Therefore, the demand for stock B for investors influenced by the gambler's fallacy is larger than the demand for stock A. In equilibrium, if the demand by rational investors is not perfectly elastic, the price of stock B could be higher than that of stock A, yielding to a lower expected return for stock B. Thus, there is a negative risk-return relation in this scenario.

The model of Rabin and Vayanos (2010) also builds on the assumption of the gambler's and the hot-hand fallacies similarly to the model of Rabin (2002). Although the model of Rabin and Vayanos (2010) has several appealing features and can be considered as a more advanced version of the model of Rabin (2002), it also presents several additional challenges for empirical applications. To empirically test the model of Rabin (2002), several assumptions must be made but empirically testing the model of Rabin and Vayanos (2010) would require even more assumptions on the values of several additional parameters of the model (e.g., σ_ϵ,σ_η,α,δ). Thus, I use the model of Rabin (2002) to motivate my empirical tests in this study to limit the number of assumptions that are needed to be made.

Although the gambler's fallacy based on prior experience can potentially account for both negative and positive risk–return trade-off based on the previous logic, I acknowledge that, in a dynamic setting, it might not lead to the same conclusion. However, developing a formal dynamic model is beyond the scope of this study. My focus is on showing that the risk–return trade-off depends strongly on the sign of the prior outcomes of the stocks and that the gambler's fallacy may play a role in this. Thus, the sign of the risk–return trade-off should depend on stocks' prior performances.

To generate a measure based on the model of Rabin (2002), I need to make several assumption on the belief formation. First, I estimate the purchase date with a similar method to Grinblatt and Han (2005) to specify the first experience. Second, I generate the ratio of the positive and negative experience during the holding time period. I consider several measures motivated the model of Rabin (2002). According to the model of Rabin (2002), the investors influenced by the gambler's fallacy expect a reversal and overweight the probability of the less frequent prior experience.

Based on this new measure, I sort stocks into portfolios and within each portfolio, I sort stocks based on the idiosyncratic volatility as a measure of risk. Using the idiosyncratic volatility as a risk measure, I find that high risk firms earn higher returns among firms with more prior positive experience, while I find a significant and negative risk-return relation among firms with more prior negative experience. For instance, the value-weighted returns of the high-risk firms are 1.95% lower per month than those of low-risk firms among firms with more prior negative experience. On the contrary, I find that the value-weighted returns of high-risk firms are 0.35% higher per month than those of low-risk firms among firms with more prior positive experience.

To investigate the robustness of this empirical evidence, I use several alternative measures of risk beyond the idiosyncratic volatility including the CAPM beta based on the last five years' monthly returns, the return volatility of the last five years' monthly returns, the cash-flow volatility following Zhang (2006), firm age, and analyst forecast dispersion following Wang et al. (2017). All of these different measures of risk try to capture the riskiness of a firm with different approaches using different data. As a result, these measures of risk are probably correlated with the perceived risk by the investors. I find that the prior experience are important determinant of the risk-return relation for all of these risk measures. There is a negative risk-return relation among stocks with more prior negative experience and there is a positive risk-return relation among stocks with more prior positive experience for all of these risk measures. In the results section, I use the idiosyncratic volatility as the measure of risk but I also provide additional information on the results using alternative risk measures in the section of sensitivity analyses.

An alternative possible explanation for my finding is that the negative and positive risk-return relation is only due to reference-dependent preferences. According to prior research (Wang et al., 2017; Bhootra and Hur, 2015), there is a negative risk-return relation among stocks with low capital gain overhang values and there is a positive relation among stocks with high capital gain overhang measure. They provide a similar static argument but using the reference-dependent preferences known from prospect theory. Under their explanation, the key driving factor is that investor exhibit risk-seeking behavior facing prior losses and risk-averting behavior facing prior gains according to prospect theory.

The conceptual framework of this study is different from the conceptual framework of Bhootra and Hur (2015) and Wang, Yan, and Yu (2017). They test the relation between prior gains or losses and the risk-return trade-off building on the gain-loss asymmetry property of prospect theory, while I test the relation between the series of prior experience and the risk-return trade-off. Naturally, there are some similarities between the two measures since a series of prior negative (positive) outcomes of a stock implies a higher chance for prior loss (gain) in total. However, these two concepts are different in many cases. The average monthly R^2 of the regressions of the capital gain overhang (CGO) measure on the prior experience measure (PE) is 0.22 and there is a 0.44 average cross-sectional monthly correlation between the two measures. These results suggest that there is a link between the two measures as expected but the variation of one of the variables does not explain the variation of the other variable to a great extent. To mitigate any concern that the two measures capture the same effect, first, I control for the capital gain overhang measure in bivariate sorts and the results remain both economically and statistically significant. Second, I control for the capital gain overhang measure and its interaction term with the risk measures in Fama-MacBeth regressions. I find that the interaction term between the prior experience and risk still predicts future returns significantly for each risk measures. These results suggest that the relation between the prior experience and the risk-return trade-off is not driven by the relation between the capital gain overhang measure and the risk-return trade-off.

In additional tests, I show that the documented effect is present in both January and non-January months, in high and low sentiment time periods. I also show that the interaction between prior experience and risk remains strong predictor of future returns even if the prior experience are calculated based on monthly observations instead of daily observations.

Many studies provide explanations for the negative risk-return relation puzzle. One of the explanations argue that low volatility stocks might be preferred because of their more positively skewed return distribution (Baker, Bradley, and Wurgler, 2011; Bali et al., 2011). An alternative explanation for the negative risk-return relation puzzle that, for instance, stocks with high idiosyncratic volatility have higher limits to arbitrage which yields that they have lower expected returns if the dispersion of opinions on their expected returns is higher. Barberis and Xiong (2012) even consider the case when the investors only derive utility from realizing their gains and losses which can shed new light on why investors can prefer high volatility stocks. However, these explanations provide a mechanism which can yield a lower expected return for stocks with high risk but it does not make a prediction on the cross-section of stock returns. These explanations does not predict that the negative risk-return relation puzzle would be more pronounced among certain stocks. By contrast, this research focuses on the risk–return trade-off in the cross section of stock returns. Building on prospect theory, Bhootra and Hur (2015) and Wang, Yan, and Yu (2017) provide an explanation for the negative risk-return relation puzzle with a prediction on the cross-section of stock returns. According to their results, the negative risk-return relation puzzle is concentrated among stocks owned by investors facing prior losses since these investors become risk-seeking in line with prospect theory. I contribute to these results with providing an additional aspect that can shape the investors' risk attitude. I test whether the signs of prior outcomes also matter in shaping the investors' risk attitude as suggested by the model of Rabin (2002). I find that the effect of the gambler's fallacy can additionally increase the risk-seeking behavior yielding an additional insight into the negative risk-return relation puzzle.

Loh and Warachka (2012) also use the model of Rabin (2002) as a motivation to study the role of prior outcomes in asset pricing. They investigate the effect of streaks and the ratio of the signs of prior earnings surprises using the I/B/E/S database of analyst estimates on the returns using the CRSP database. I investigate the effect of streaks and the ratio of the signs of prior returns using the CRSP database on the risk-return trade-off using the same CRSP database. Although there is some predictability in earnings surprises (e.g., Chan et al., 2007), Loh and Warachka (2012) consider these signals to be a good proxy to test a theoretical model on gambler's and hot-hand fallacies. Similarly, there is some predictability in returns in my empirical setting, I consider them to be a good proxy for random sequences where decision-makers might be influenced by the gambler's or hot-hand fallacies. Loh and Warachka (2012) build on the motivation of the model of Rabin (2002) to explain the post-earnings-announcement drift, while, in this paper, I use the same motivation to explore and contribute to a better understanding of the puzzling negative risk-return relationship. I also contribute to the literature by providing a novel empirical evidence on the role of the gambler's and hot-hand fallacies in empirical asset pricing.

The remainder of the paper is organized as follows. Section 2 discusses the hypotheses development and construction of measures. Section 3 describes the data and the characteristics of the prior experience measure. Section 4 discusses the results of the empirical tests and the robustness tests. Finally, Section 5 concludes.

2.2 Hypotheses Development and Construction of Measures

People usually overestimate the likelihood how a sample resembles the parent population from which it is drawn (Tverksy and Kahneman, 1971). This error in judgments is labeled as the "law of small numbers". Consistent with the "law of small numbers", people usually think that prior signals predict immediate reversal by future signals. For instance, if early coin flips are disproportionately heads, then people tend to exaggerate how likely the next flip to be tail. This phenomenon is labeled as the gambler's fallacy. The gambler's fallacy has been documented in gambling or laboratory settings (e.g., Bar-Hillel and Wagenaar, 1991; Rapoport and Budescu, 1997; Terrell, 1994; Croson and Sundali, 2005; Asparouhova, Hertzel, and Lemmon, 2009; Suetens, Galbo-Jorgensen, and Tyran, 2015), in several high-stakes field-settings (Chen, et al., 2016), and in empirical asset pricing exploring the effect of the signs of prior earnings surprises (Loh and Warachka, 2012). Furthermore, prior experience seem to influence people's belief formation on future expectations (Malmendier and Nagel, 2015).

Rabin (2002) presents the model of the "law of small numbers" assuming that people believe that the sequences of random binary outcomes are generated from an "urn" of size N without replacement, while they are made with replacement. This captures belief in the "law of small numbers", since it means that the people believe that the proportion of signals must balance out to the underlying rate. Thus, this model yields the gambler's fallacy. In the model of Rabin (2002), the decision-maker also believes that the urn is renewed every K draws ($K \leq N$) to reconcile the conflict between observing a very long sequence and assuming that the "urn" is finite.

Assuming that there are positive and negative signals and the decision-makers have an informative prior regarding their likelihood, the model of Rabin (2002) implies that the probability of a positive signal is overweighted when there are disproportionately more prior negative signals, while the probability of a negative signal is overweighted when there are disproportionately more prior positive signals.

Overweighting the probability of the positive signal contributes to a more risk-seeking behavior since the higher volatility leads to a higher positive deviation from the expected outcome, while overweighting the probability of the negative signal contributes to a more risk-averse behavior since the higher volatility leads to a stronger negative deviation from the expected outcome. To present the earlier example again within the framework of the model of Rabin (2002), consider again that investors hold two assets purchased five time periods ago, stock A and B. The price of both stocks A and B are \$40 now. The price of stock A can go up by \$1 or go down by \$1 with equal chance. The price of stock B can go up by \$10 or go down by \$10 with equal chance. Thus, both stocks have the same expected payoff but stock B has higher volatility (riskier) than stock A. The price of both stocks A and B went down four times and went up once during the last five time periods. The investors know that the probability of a positive (up) or a negative (down) signal is 50-50% and they assume that the "urn" has 10 balls. Thus, they expect that the probability of a price increase is higher than the probability of a price decrease because they predict that the future signals should balance out the deviation from the underlying rate. The distorted probability for the price increase is 80% and the distorted probability for the price decrease is 20%. As a result, the expected payoff of stock A is \$40.6 and the expected payoff of stock B is \$46. Therefore, the demand for stock B for investors influenced by the gambler's fallacy is larger than the demand for stock A. Assuming that the demand by rational investors is not perfectly elastic, a negative risk-return relation emerges in this case.

Thus, I hypothesize that (1) there is a negative risk-return relation among stocks with disproportionately more prior negative signals, (2) there is a positive risk-return relation among stocks with disproportionately more prior positive signals, and (3) the return difference between stocks with high risk and stocks with low risk should be greater among firms with more prior positive experience than among firms with more prior negative experience.

I need to make several assumptions on how I construct a measure based on the model of Rabin (2002). First, I need to define the signals. Second, I need to specify N as the size of the "urn". Third, I need to define when the first signal arrives. Fourth, I need to specify the renewal rate of the "urn". Fifth, I need to make an assumption on the likelihood of positive and negative signals.

In this study, I need to make several assumptions to create a measure. However, these assumptions could be sometimes strong. To explore the effect of prior experience and its effect on the risk-return trade-off, I explore several approaches and alternative specifications of my measures following the model of Rabin (2002) and the empirical study of Loh and Warachka (2012).

My first assumption is that the investors consider the sign of each daily return of a stock as a signal. I also perform additional tests to show that using monthly returns as signals yields the same conclusion. In this approach, the investors care only about the sign of a return and ignore its magnitude similarly to the study of Loh and Warachka (2012). This assumption also contains the implicit assumption that the decision-makers mentally frame each asset as belonging to individual accounts ignoring possible interactions among these assets according to the mental accounting theory (Thaler, 1980,1985). Mental accounting is assumed in many asset pricing studies (e.g., Grinblatt and Han, 2005; Bhootra and Hur, 2015; Wang, Yan, and Yu, 2017). My second assumption is that $N<\infty$ but larger than any holding time period in the empirical data. Thus, there is always an additional ball in the urn but it is still less than infinity. My third assumption is that the investors consider the first observation after the purchase of a stock as the first signal. My fourth assumption is that $K = N$. This means that there is no renewal of the "urn" during the holding time period. To relax this assumption, I also consider the case in which the urn is renewed in each time period with a given probability. Finally, I assume that the investors consider the likelihood of positive and negative signals to be the same for each stock to make them comparable.

Grinblatt and Han (2005) estimate the expected purchase price for each stock using the turnover as a relative probability for purchasing the stocks for a price on a given date. I also use the turnover as a relative probability for purchasing the stocks on a given date. As a result, I can estimate the expected date when the investors bought the stocks of a firm. Afterwards, I generate the prior experience measure as the number of positive returns minus the number of negative returns divided by the number of all returns since the estimated purchase date. This measure represents the ratio of positive and negative prior experience.

According to my final assumption, the investors know the underlying rate for the likelihood of positive and negative signals. This assumption is an important one in the model of Rabin (2002) to predict that investors expect a reversal as a result of the gambler's fallacy. However, Rabin (2002) also investigates the effect of assuming that investors do not know the underlying rate. Under this new assumption, the model of Rabin (2002) implies the hot-hand fallacy in the long-term after an extremely unlikely long sequence of the same signal. In his model, the investors expect a continuation after an extremely unlikely long sequence of the same signals because they update mistakenly their beliefs about the underlying rate. To investigate this implication of the model, I use streaks and several alternative definitions of the prior experience measure similarly to Loh and Warachka (2012). The model of Rabin (2002) implies reversal for short-term as a result of the gambler's fallacy but it is undermined by the hot-hand fallacy for the long term even implying continuation in the case of unlikely long sequence of the same signal.

In the next sections, I present the construction of the capital gain overhang measure, the prior experience measure, the weighted prior experience measure, the measure of streaks and trends following Loh and Warachka (2012), and the measure of trends following Grinblatt and Moskowitz (2004).

2.2.1 Measure of Capital Gain Overhang

In this section, I present the capital gain overhang (CGO) (Grinblatt and Han, 2005) measure which defines a reference point price for a stock and the change between the reference point price and the current price. According to prior research (Grinblatt and Han, 2005), CGO provides a measure for prior losses and gains for each stock that the investors have to face. Assuming reference-dependent preferences, prior loss can imply a risk-seeking behavior yielding a negative risk-return relation among certain stocks (Bhootra and Hur, 2015; Wang, Yan, and Yu, 2017). First of all, the CGO measure is important for my analyses because, similarly to the CGO measure, I also use the turnover as a relative probability of purchasing the stocks on a given date. Second, I need to distinguish the prior experience (PE) measure from the CGO measure since they are both based on prior outcomes, although they capture conceptually different feature of prior outcomes. CGO estimates the prior loss or gain for each stock that the investors have to face, while the PE measure estimates the ratio of prior negative and positive experience that the investors have to face.

The capital gain overhang (CGO) for an asset j on a day t is:

$$CGO_{j,t} = \frac{P_{j,t} - RP_{j,t}}{P_{j,t}} \tag{2.1}$$

where $P_{j,t}$ is the price of an asset j on day t and $RP_{j,t}$ is the reference point price for an asset j on day t. The reference point price $RP_{j,t}$ is calculated with the following recursive formula:

$$RP_{j,t} = V_{j,t-1}P_{j,t-1} + (1 - V_{j,t-1})RP_{j,t-1} \tag{2.2}$$

where, $V_{j,t-1}$ is the turnover of asset j on day $t-1$. The reference point price can be interpreted as the expected purchase price for an asset j assuming that the daily turnover represents a relative probability of buying the stocks on that day. Thus, the capital gain overhang measure (CGO) represents the percentage change between the estimated purchase price and the current price. I use daily data to calculate the capital gain overhang measure for each stock for each day. I update each price and shares outstanding with dividend payments and stock splits. If there is no data for the volume, then I do not take that observation into account for my measure, I use the last available price data. I use the first available price of the stock as the first reference price and I start to calculate the reference price formula from the second available price observation. Finally, in equation 2.1, I use the ten trading days (two weeks) delayed price to mitigate any concern that this measure would pick up a micro-strucutre effect. I also winsorize the measure at the 1% level in each month.

A positive value for the capital gain overhang measure indicates that the owners of a firm bought the firm's stocks at a lower price than the current price. Conversely, a negative capital gain overhang measure indicates that the owners of a firm bought the firm's stocks at a higher price than the current price.

2.2.2 Measure of Prior Experience

In this section, I define the measure of prior experience (PE) which estimates the ratio of prior negative and positive experience.

I define the measure of PE as the number of trading days with positive returns minus the number of trading days with negative returns divided by the total number of trading days since the estimated date of the purchase. Thus, a high value of this measure indicates that the investors face more prior positive experience than negative during the holding time period, while a low value of this measure indicates that the investors face more prior negative experience than positive during the holding time period. This measure has a range between -1 and 1, $PE \in [-1, 1]$.

Formally, $(PE_{j,t})$ for a stock j on a day t is:

$$PE_{j,t} = \frac{\sum_{(s_{j,t})} sign(R_{j,t-s_{j,t}})}{ND_{j,t}} \tag{2.3}$$

where $sign(R_{j,t-s_{j,t}})$ is an indicator function with a value of 1 if the return of stock j on day $t - s_{j,t}$ is positive, -1 if the return is negative, and zero if the return equals to zero. $s_{j,t} = 0, 1, \ldots, ND_{j,t} - 1$ is an index running from zero to $ND_{j,t} - 1$ and $ND_{j,t}$ is the number of trading days between day t and the estimated purchase date $(RD_{j,t})$ for an asset j on day t. $ND_{j,t}$ and $RD_{j,t}$ are defined in the following way:

$$ND_{j,t} = t - RD_{j,t} \tag{2.4}$$

$$RD_{j,t} = V_{j,t-1}(t-1) + (1 - V_{j,t-1})RD_{j,t-1} \tag{2.5}$$

where $V_{j,t-1}$ is the turnover of asset j on day $t - 1$. Similarly to the capital gain overhang measure, $V_{j,t-1}$ presents a relative probability that the stocks were purchased on that day. If there is no data, then I do not take that observation into account for my measure. I start the recursive formula from the second available observation for a stock taking the first observation as the reference date. I also winsorize the PE measure at the 1% level in each month. To provide more insights into to the PE measure, I provide summary statistics of the PE measure in a following section.

2.2.3 Measure of Weighted Prior experience

In this section, I relax the assumption that $K = N$. I assume that the "urn" is renewed in each time period with a probability of $(1 - \lambda)$. Thus, the investors know that the process can restart with a probability of $(1 - \lambda)$. In other words, the "urn" can be renewed but the investors do not know when it happens. The chance that the "urn" was not renewed between today and t signals ago is $(\lambda)^t$. Thus, the relative probability that the signal t periods ago still matters is $(\lambda)^t$. As a result, using these relative probabilities as weights, the weighted prior experience (WPE) measure becomes an exponentially decaying weighted average of the prior experience.

Formally, $(WPE_{j,t})$ for a stock j on day t is:

$$WPE_{j,t} = \frac{\sum_{s_{j,t}} \lambda^{s_{j,t}+1} sign(R_{j,t-s_{j,t}})}{\sum_{s_{j,t}} \lambda^{s_{j,t}+1}} \tag{2.6}$$

where $sign(R_{j,s_{j,t}})$ is an indicator function with a value of 1 if the return of stock j on day $s_{j,t}$ is positive, -1 if the return is negative, and zero if the return equals to zero. $s_{j,t} = 0, 1, \ldots, ND_{j,t} - 1$ is an index running from zero to $ND_{j,t} - 1$ and $ND_{j,t}$ is the number of trading days between day t and the estimated purchase date $(RD_{j,t})$ for an asset j on day t. Finally, $0 \leq (1 - \lambda) \leq 1$ represents the probability that the "urn" is renewed after one time period. In the case of $\lambda = 1$, the formula provides the definition of PE. I also winsorize the measure at the 1% level in each month. To explore the change in the λ weight, I investigate the effect of several different λ specifications including $\lambda = 0.999; 0.995; 0.99; 0.975; 0.95$. In the case of $\lambda = 0.999$, a daily signal one year ago (200 trading days ago) has the relative weight of 0.819 compared to the most recent daily signal, while in the case of $\lambda = 0.99$ this weight is 0.14, and in the case of $\lambda = 0.95$ this weight becomes 0.000 which is almost negligible. I find that the results become stronger and stronger by decreasing the λ from 1 to 0.99.

2.2.4 Measure of Streaks and Trends

In this section, I define streaks and trends for returns following Loh and Warachka (2012) because these measures are also motivated by the model of Rabin (2002) even though streaks and trends are only special cases when the gambler's fallacy predict probability distortion. A streak is defined by returns having the same sign in consecutive time periods. A return that equals to zero is classified as being negative. Missing values for the return variable are considered as the end of a streak (neither positive nor negative). The streak variable is defined as the number of consecutive positive monthly returns if the portfolio formation monthly return is positive and the number of consecutive negative monthly returns multiplied by minus one if the portfolio formation monthly return is negative.

A trend is defined as the sign of the majority of prior returns. Following Loh and Warachka (2012), I define the $trend_{LW}$ variable equaling 1 (-1) if a stock's monthly returns are positive (negative) in at least six of the one-year horizon's 11 months and the most recent monthly return is also positive (negative). I also define a similar $trend_{GM}$ variable but following Grinblatt and Moskowitz (2004) in which the variable is 1 (-1) if a stock's monthly returns are positive (negative) in at least eight of the one-year horizon's 11 months skipping the portfolio formation month to eliminate a potential market micro-structure bias and otherwise 0. Although this measure was not created to test the model of Rabin (2002), it is consistent with the prediction of the gambler's fallacy implied by the model of Rabin (2002).

To construct these measures, I use monthly returns as signals for both streaks and trends. I use monthly returns for streaks because using daily returns would raise several concerns about capturing micro-structure effects and I use monthly returns and the one-year window for defining trends because Grinblatt and Moskowitz (2004) already defined a similar measure.

2.3 Data

Data comes from CRSP and COMPUSTAT and consists of the monthly stock prices, share volume, holding period returns, number of shares outstanding, value-weighted market return and daily holding period returns, price, share volume, dividends, and adjusting factors for number of shares from CRSP for common stocks (share code 10 and 11) listed on NYSE, AMEX, NYSE and book value for total assets from COMPUSTAT. I update the book values with the information from the website of Kenneth French for all firms. The sample covers the period from December 1925 to December 2016 for all stocks from CRSP. Following Fama and French (1992), I measure firm size by the market value of equity and book-to-market as the ratio of the book and market value of equity. I calculate book-to-market using accounting data from COMPUSTAT as of December of the previous year and exclude firms for a given month t with negative book-to-market equity. I extend the book equity data from Kenneth French's website for those observations which are not covered by COMPUSTAT. I exclude penny stocks (stocks with price lower than \$5). Although I calculate all variables from December 1925 to use all available information to construct my measure to be as accurate as possible I report the results from July 1962 to make it more comparable with the literature on the cross-section of stock returns following Bali, Cakici, and Whitelaw (2011). This approach also provides enough time periods to estimate more accurately the variables based on past information.

My control variables for month t are calculated in the following way:

- Size: the logarithm of the number of shares outstanding in month t times the price in month t (in million dollars).
- BTM: the logarithm of the firm's book value divided by its market value where these values were calculated following Fama and French (1992).
- MOM: the stock's cumulative return from month $t-11$ to the end of month $t-1$.
- REV: the stocks' return in month t.
- ILLIQ: the Amihud (2002) measure using daily return and volume data in month t.
- Beta: market beta based on the last month daily returns.
- IVOL: the volatility of the stocks' daily idiosyncratic volatility in month t (Ang, Hodrick, Xing, and Zhang 2006).
- MAX: the stock's maximum daily return in month t (Bali, Cakici, and Whitelaw, 2011).
- MIN: the stock's minimum daily return in month t (Bali, Cakici, and Whitelaw, 2011).

- SKEW: Skewness of the stock's daily return in the last month.

I winsorize size, book-to-market ratio, momentum, short-term reversal, illiquidity, beta, idiosyncratic volatility, skewness, and the subsequent monthly return at the 1% level in each month.

2.3.1 Characteristics of Prior Experience Measure

In this section, I provide more detailed information on the characteristics of the PE measure and its relation to other known measures. I sort stocks into portfolio quintiles in each month and I compute the means of the characteristics in each portfolio quintile in each month. Table 2.1 reports the time series averages of the monthly means.

First of all, the time series average of the monthly means of the PE measure for the portfolio quintile consisting the stocks with the lowest PE values is -0.09 and it is 0.07 for the portfolio quintile consisting stocks with the highest PE values. The PE measure also considers zero returns which yields that the value of -0.09 of the PE measure indicates an approximately 25% more prior negative experience than prior positive experience on average[1], while the value of 0.07 of the PE measure indicates a 20% more prior positive experience than prior negative experience on average.

Second, there is a clear correlation between the PE measure and the CGO measure. It is not surprising since the PE measure estimates the ratio of the prior negative and positive experience and the CGO measure captures the return change between the current and the estimated purchase price. This correlation

[1] These numbers are based on additional calculations when I recalculate each measure excluding days with zero return.

only shows that stocks with more prior negative experience have a lower return relative to its purchase price. Although there is a clear correlation between the PE measure and the CGO measure these two measures are different. Performing a linear regression of the PE measure on the CGO measure in each month generates only a 0.22 R^2 on average. This suggests that the variation of the CGO measure only explains a relatively small part of the variation of the PE measure. To mitigate any additional concern that the PE measure only captures the effect of the CGO measure, I perform several tests including bivariate sorts and Fama-MacBeth regressions in the following sections. I find consistently both economically and statistically significant results for the relationship between the PE measure and the idiosyncratic volatility even after controlling for the CGO measure. The negative risk-return relation remains significant for all alternative risk measures such as the market beta based on the las five years' monthly observations, volatility of the last five years monthly observations, cash-flow volatility, age of the firm, and the dispersion of the analyst forecasts.

Third, stocks with high or low PE measure values tend to be riskier. Both the average Beta and BTM values for portfolio quintiles exhibit a U-shape indicating that stocks in the lowest and highest portfolio quintiles tend to be riskier compared to the other stocks. Thus, there is no clear relationship between these variables and the PE measure.

Fourth, there is a small correlation between size and the PE measure which probably comes from the definition since stocks with high PE values tend to increase their price which yields higher market capitalization.

Fifth, there is a strong link between the PE measure and momentum. Stocks with the lowest PE measure value have 1.46% momentum return, while stocks with the highest PE measure values have 36.20% momentum return. It raises a concern since one could argue that my measure captures something similar to news underreaction, while idiosyncratic volatility might capture information uncertainty. In this case, it would mean that I only replicate the results of Zhang (2006). To mitigate any concern, I also control for this in a later section. All conclusions remain the same after controlling for possible underreaction and information uncertainty.

Sixth, there is also a clear but weaker link between the short-term reversal and the PE measure. It is less direct how this relationship would affect my results since the last few trading days can only have limited impact on the PE measure. The average number of experience is at least almost two years according to the last column of Table 2.1. However, I also perform the tests with a modified PE measure in which I do not use the last two weeks trading days to mitigate any concern. I find the same relations and conclusions with this measure as well[2].

Seventh, according to Table 2.1, stocks with low PE values tend to have more volatile returns in the last month since these stocks have the highest idiosyncratic volatility, MAX returns and the absolute value of MIN returns. This is in line with the results of Wang, Yan, and Yu (2017). They find even stronger difference in idiosyncratic volatility between the portfolio quintiles sorted based on the CGO measure.

Eighth, there is no clear link between the PE measure and the illiquidity measure. The stocks with the highest PE measure values are the most liquid but the stocks with the lowest PE measure values are not the most illiquid stocks.

Finally, Table 2.1 reports the average number of trading days since the estimated

[2] These results are available upon request

date of purchase. It shows that the stocks are typically bought quite long ago on average according to this measure. Stocks with the lowest PE measure values are bought the most recently, approximately two years passed for these stocks since their purchase, while stocks with high PE measure values have even longer history with 788 trading days on average.

Table 2.1: Quintile portfolios are formed every month from July 1962 to November 2016 by sorting on the prior experience measure (PE) in the current month. Portfolio 1 contains the stocks with the lowest PE values over the current month. The table reports, for each quintile, the averages of the average monthly values of various characteristics of the stocks: the prior experience (PE), the market beta (Beta), the logarithm of book-to-market ratio (BTM), the logarithm of market capitalization (Size), the momentum (MOM) following Jegadeesh and Lehmann (1993), the short-term reversal (REV) following Jegadeesh and Lehmann (1990), the maximum daily return (MAX), the minimum daily return (MIN), the idiosyncratic volatility (IVOL), the illiquidity (Amihud, 2002), and the estimated number of trading days since the investors hold a given stock (ND). N denotes the number of observations.

	PE	CGO	Beta	BTM	Size	MOM	REV	MAX	MIN	IVOL	Illiq	ND
1	-0.09	-0.29	1.07	-0.50	18.79	1.46	-0.70	6.97	-5.61	2.71	8.90	392
2	-0.03	-0.11	0.85	-0.43	18.73	11.41	1.23	5.93	-4.81	2.35	12.81	611
3	-0.00	0.02	0.77	-0.48	18.92	17.53	1.77	5.36	-4.43	2.15	13.21	767
4	0.02	0.12	0.74	-0.60	19.36	22.29	2.15	4.80	-4.05	1.93	8.71	880
5	0.07	0.19	0.88	-0.90	19.99	36.20	3.74	4.82	-4.04	1.89	3.07	788
N	653	653	653	653	653	653	653	653	653	653	653	653

2.4 Results

In this section, I present the results of the tests of my hypotheses. First, I replicate the results of the idiosyncratic volatility puzzle (Ang., et al., 2006) in my sample. Sorting stocks based on their idiosyncratic volatility in each month into portfolio quintiles generates a substantial and statistically significant average subsequent monthly return difference between the high idiosyncratic volatility and low idiosyncratic volatility quintiles.

Second, I replicate the results of the relationship between the capital gain overhang measure and the idiosyncratic volatility. Both equal-weighted and value-weighted portfolios are formed and the negative relation between the idiosyncratic volatility and the subsequent monthly return is concentrated among stocks with low capital gain overhang values. There are no significant results for the average subsequent monthly return difference between quintiles with high and low idiosyncratic volatility for stocks with high capital gain overhang values. This is in line with previous results in the literature (Bhootra and Hur, 2015; Wang, Yan, and Yu, 2017).

Third, I present the results of my main hypothesis. I sort stocks into portfolio quintiles based on their PE values in each month, then, within each portfolio quintile, I sort stocks into portfolio quintiles based on their idiosyncratic volatility. Thus, I form 5 times 5 portfolios in each month. Both equal-weighted and value-weighted portfolio subsequent monthly returns are formed for each portfolio in each month. I find that there is a negative relation between the idiosyncratic volatility and the subsequent monthly return for stocks with low PE values but there is no such a relation among stocks with high PE values. It means that the idiosyncratic volatility puzzle is concentrated among stocks owned by investors facing prior negative experience. To mitigate any concern that these results might be driven by the similarity between the CGO and PE measures, I perform several additional tests.

Fourth, I present test results on a triple sort where I sort stocks into portfolio quintiles based on their CGO values in each month, then, within each portfolio, I sort stocks into portfolio quintiles based on their PE values. I form portfolio quintiles based on the PE quintiles across the CGO quintiles. For instance, the new portfolio quintile with the highest PE values is formed from the portfolio quintiles with the highest PE values within each CGO portfolio quintiles. This method generates portfolio quintiles that have high variation in the PE measures but low variation in the CGO measures. Finally, I sort stocks into portfolio quintiles within this five double sorted portfolio quintiles based on their idiosyncratic volatility measure. I test the average subsequent monthly return difference between the high and low idiosyncratic volatility portfolios for the stocks with low PE values across CGO portfolio quintiles and I also perform the same test for stocks with high PE values across CGO portfolio quintiles.

This method shows that the variation of the PE values within each CGO quintile is large enough to generate a negative relation between the idiosyncratic volatility and the average subsequent monthly return among stocks with low PE values. Thus, my measure does not simply capture something similar to the CGO measure.

Finally, I perform several Fama-MacBeth regressions (1973) and I find that the interaction term between the PE measure and the idiosyncratic volatility is positive and significant even after controlling for the interaction between the CGO measure and the idiosyncratic volatility and several additional known factors.

2.4.1 Idiosyncratic Volatility and the Capital Gain Overhang Measure

First, I present the idiosyncratic volatility puzzle (Ang, etal., 2006) in Table 2.2 which reports the average subsequent monthly returns of portfolio quintiloes sorted based on idiosyncratic volatility. Stocks with high idiosyncratic volatility earn a lower subsequent monthly return on average than stocks with low idiosyncratic volatility. In my sample, the quintile portfolio with the highest idiosyncratic volatility earn a value-weighted 0.57% per month return lower than the quintile portfolio with stocks with the lowest idiosyncratic volatility. This puzzle has gained a lot of attention and one of the potential explanations is provided by reference-dependent preferences (Bhootra and Hur, 2015; Wang, Yan, and Yu, 2017). This approach argues that investors exhibit risk-seeking behavior if they are in the loss domain according to cumulative prospect theory. Bhootra and Hur (2015) and Wang, Yan, and Yu (2017) find that idiosyncratic volatility puzzle is more pronounced among stocks where the investors face prior loss which is in line with the gain-loss asymmetry property of cumulative prospect theory.

Table 2.3 yields the same conclusions and similar results in my sample. First, I sort stocks into portfolio quintiles based on their capital gain overhang measure in each month, then, within in each portfolio quintile, I sort stocks into portfolio quintiles based on their idiosyncratic volatility. Table 2.3 presents the average subsequent monthly returns of the double sorted portfolios. There is a -1.87% return difference between the high and low idiosyncratic volatility quintiles with a t-statistic of -9.64 for equal-weighted portfolios when the investors face prior losses and there is a similar result for value-weighted portfolios. The Fama-French

(1993) three factor alphas yield the same conclusions. There is a positive but not significant return difference between the high and low idiosyncratic volatility quintiles when the investors face prior gains. The value-weighted return difference controlling for the Fama-French three factor model is 0.21% per month with a t-statistic of 1.25.

Table 2.2: Equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2016. I sort stocks into quintiles using the idiosyncratic volatility variable over the current month so quintile 1 contains the stocks with the lowest idiosyncratic volatility. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1 and the corresponding Fama-French alphas are also reported. (The Newey-West corrected t-statistic are reported in parentheses.) N denotes the number of observations.

IVOL	EW	VW
Lowest	0.74	0.60
2	0.92	0.65
3	0.98	0.71
4	0.82	0.54
Highest	0.17	0.03
Difference	-0.57	-0.57
t-stat	(-4.97)	(-4.18)
3F α	-0.86	-0.84
t-stat	(-7.28)	(-5.09)
N	653	653

2.4.2 The Effect of Prior Experience

In this section, I test my main hypotheses. I sort stocks into portfolio quintiles based on their PE values in each month then in each PE portfolio quintile I sort stocks into portfolio quintiles based on their idiosyncratic volatility. Table 2.4 reports the equal-weighted and value-weighted average subsequent monthly returns for the portfolio quintiles. The equal-weighted average subsequent monthly

Table 2.3: Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2016. In each case, I first sort stocks into quintiles using the capital gain overhang variable (CGO) then within each quintile I sort stocks into quintile portfolios based on the idiosyncratic volatility variable over the current month so quintile 1 contains the stocks with the lowest idiosyncratic volatility. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1 and the corresponding Fama-French alphas are also reported. (The Newey-West corrected t-statistic are reported in parentheses.) N denotes the number of observations.

	EW			VW		
IVOL	CGO1	CGO3	CGO5	CGO1	CGO3	CGO5
Lowest	0.96	0.75	0.73	0.86	0.66	0.61
2	0.91	0.88	0.90	0.57	0.68	0.61
3	0.53	0.90	1.05	0.09	0.75	0.76
4	0.19	0.86	1.15	-0.19	0.49	0.89
Highest	-0.91	0.42	1.21	-1.08	1.68	0.96
Difference	-1.87	-0.33	0.48	-1.95	-0.49	0.35
t-stat	(-9.64)	(-1.49)	(2.54)	(-7.32)	(-1.90)	(1.86)
3F α	-1.93	-0.53	0.30	-2.06	-0.64	0.21
t-stat	(-13.93)	(-3.49)	(1.74)	(-9.11)	(-3.41)	(1.25)
N	653	653	653	653	653	653

return difference between the high and low idiosyncratic volatility stocks is -1.52% per month with a t-statistic of -7.81 among the stocks owned by investors facing more prior negative experience, while equal-weighted average subsequent monthly return difference between the high and low idiosyncratic volatility stocks is 0.14% per month with a t-statistic of 0.61 among the stocks owned by investors facing prior positive experience. The value-weighted average subsequent monthly return difference between the high and low idiosyncratic volatility stocks is -1.50% per month with a t-statistic of -5.63 among the stocks owned by investors facing more prior negative experience, while value-weighted average subsequent monthly return difference between the high and low idiosyncratic volatility stocks is 0.10% per month with a t-statistic of 0.40 among the stocks owned by investors facing more prior positive experience. Thus, I find supporting evidence that prior negative experience can increase the risk-seeking behavior yielding a lower expected return for high idiosyncratic volatility stocks. This confirms my first hypothesis that the idiosyncratic volatility puzzle is concentrated among stocks with low PE values. Second, there is no evidence for the second hypothesis and there is no clear positive risk-return relation among stocks with high PE values. Third, these results support my third hypothesis that the spread between the high and low idiosyncratic volatility stocks increases in the PE values. The Fama-French three factor alphas yield the same conclusions.

Table 2.4: Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2016. In each case, I first sort stocks into quintiles using the prior experience measure (PE) then within each quintile I sort stocks into quintile portfolios based on the idiosyncratic volatility variable over the current month so quintile 1 contains the stocks with the lowest idiosyncratic volatility. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1 and the corresponding Fama-French alphas are also reported. (The Newey-West corrected t-statistic are reported in parentheses.) N denotes the number of observations.

	EW				VW			
IVOL	PE1	PE3	PE5	Diff	PE1	PE3	PE5	Diff
Lowest	0.95	0.77	0.63		0.85	0.65	0.47	
2	0.94	0.98	0.76		0.57	0.70	0.59	
3	0.79	0.96	0.90		0.36	0.66	0.71	
4	0.35	0.96	0.93		0.10	0.69	0.78	
Highest	-0.57	0.38	0.78		-0.65	0.20	0.57	
Difference	-1.52	-0.39	0.14	1.66	-1.50	-0.45	0.10	1.61
t-stat	(-7.81)	(-2.42)	(0.61)	(9.00)	(-5.63)	(-2.02)	(0.40)	(7.69)
3F α	-1.66	-0.61	-0.10	1.56	-1.69	-0.67	-0.05	1.64
t-stat	(-10.93)	(-5.50)	(-0.55)	(9.07)	(-7.66)	(-4.26)	(-0.26)	(7.51)
N	653	653	653	653	653	653	653	653

To mitigate any concern that these results are driven by the similarity between the PE and CGO measure, I also perform bivariate sort analyses in the next section.

2.4.3 Controlling for the Capital Gain Overhang Measure in Bivariate Sorts

In this section, I test whether my main results remain significant after controlling for the CGO measure in a bivariate sort. The PE measure quantifies the ratio between the prior negative and positive experience, while the CGO quantifies the prior loss or gain for a stock. Although these measures define two different concepts these might coincide in the empirical data. To test it, I sort stocks into portfolio quintiles based on their CGO values in each month, then, within each portfolio quintile, I sort stocks into portfolio quintiles based on their PE values. I form portfolio quintiles based on the PE portfolio quintiles across the CGO quintiles. For instance, the new portfolio quintile with the highest PE value is formed from the portfolio quintiles with the highest PE values within each CGO portfolio quintiles. It generates portfolio quintiles with high variation in PE but low variation in CGO. In this case, the portfolio quintile with the lowest PE values contains the stocks that have the lowest PE values in each CGO quintile. Finally, I sort stocks into portfolio quintiles based on their idiosyncratic volatility within each new portfolio quintile.

Table 2.5 reports the average monthly subsequent monthly returns for each idiosyncratic portfolio quintile within the double sorted portfolios. There is a 0.88% average equal-weighted subsequent monthly return difference per month between the portfolio quintiles with the highest and the lowest idiosyncratic volatility with a t-statistic of -4.86 among the stocks with the lowest PE values across the CGO quintiles. This difference is even larger and stronger for the Fama-French three factor alpha. Nevertheless, there is only a -0.26% average equal-weighted subsequent monthly return difference per month between the portfolio quintiles with the highest and the lowest idiosyncratic volatility with a t-statistic of -1.20 among the stocks with the highest PE values across the CGO quintiles. Thus, even after controlling for the CGO measure, the idiosyncratic volatility puzzle strongly appears among stocks with low PE values, while there is no significant relation between the idiosyncratic volatility and the subsequent monthly returns among the stocks with high PE values across the CGO quintiles. This suggests that the relation between the PE and the idiosyncratic volatility is robust even after controlling for the CGO measure.

I also test whether the difference between the differences is significant. The difference between the high and low idiosyncratic volatility portfolio quintiles is on average 0.62% higher for the low PE value stocks across the CGO quintiles compared to the difference between the portfolio quintiles with the highest and lowest idiosyncratic volatility for the high PE value stocks across the CGO quintiles. This difference for the equal-weighted portfolios is significant with a t-statistic of 4.53. This difference is also large and highly significant for the value-weighted portfolio quintiles as well reported in Table 2.5.

These highly significant results suggest that the results of the PE measure is not driven by the similarity between the CGO measure and the PE measure. To investigate the effect of prior experience in the presence of the capital gain overhang measure and its interaction with idiosyncratic volatility, I also perform several Fama-MacBeth regressions in the next section. In these additional tests, I also control for other known variables in the analyses.

Table 2.5: Triple sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2016. In each case, I first sort stocks into quintiles using the CGO measure then within each quintile I sort stocks into quintile portfolios based on the PE measure over the current month. I form portfolio quintiles of the PE portfolio quintiles across the CGO portfolio quintiles. Thus, the new PE portfolio quintiles with stocks with the highest PE values consists the stocks with the highest PE values within each CGO quintiles in each month. Finally, I sort stocks into portfolio quintiles based on their idiosyncratic volatility within each double sorted portfolio quintile. So quintile 1 contains the stocks with the lowest idiosyncratic volatility. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1 and the corresponding Fama-French alphas are also reported. This table also reports the difference between the differences between the high and low idiosyncratic portfolio quintiles. (The Newey-West corrected t-statistic are reported in parentheses.) N denotes the number of observations.

		EW				VW		
IVOL	PE1	PE3	PE5	Diff	PE1	PE3	PE5	Diff
Lowest	0.88	0.84	0.71		0.68	0.73	0.56	
2	0.91	0.84	0.80		0.51	0.47	0.62	
3	0.89	0.84	0.84		0.73	0.61	0.73	
4	0.71	0.78	0.64		0.49	0.50	0.57	
Highest	-0.00	0.34	0.45		-0.11	0.23	0.53	
Difference	-0.88	-0.50	-0.26	0.62	-0.79	-0.49	-0.04	0.75
t-stat	(-4.86)	(-3.24)	(-1.20)	(4.53)	(-3.25)	(-2.56)	(-0.16)	(4.41)
3F α	-1.00	-0.64	-0.43	0.57	-0.97	-0.61	-0.16	0.81
t-stat	(-6.38)	(-6.23)	(-2.83)	(4.32)	(-4.73)	(-3.56)	(-0.81)	(4.58)
N	653	653	653	653	653	653	653	653

2.4.4 Fama-MacBeth Regressions

In this section, I perform several Fama-MacBeth (1973) regressions to investigate the relationship among the PE measure, the capital gain overhang measure, and the idiosyncratic volatility. It has been documented that there is a positive interaction between the capital gain overhang and the idiosyncratic volatility. My previous results suggest that there is also a positive interaction term between the PE measure and the idiosyncratic volatility measure. In these tests, I show that there is a positive and significant relationship between the PE measure and idiosyncratic volatility as expected and this positive interaction remains significant after controlling for the interaction between the CGO and the idiosyncratic volatility and controlling for several other known variables.

The results of the regressions are summarized in Table 2.6. I present the time-series average of the slope coefficients from the regressions of excess stock returns on the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the PE measure (PE), the interaction between the capital gain overhang and the idiosyncratic volatility(CGO×IVOL), the interaction between the PE measure and the idiosyncratic measure (PE×IVOL), market beta (Beta), log market capitalization (Size), log book-to-market ratio (BTM), momentum (MOM), short-term reversal (REV), illiquidity (Illiq), maximum daily return in the portfolio formation month (MAX), minimum daily return in the portfolio formation month (MIN), and skewness (Skew) in Table 2.6. I normalize all variables in each month to make the coefficients comparable.

As a result, I run cross-sectional regressions with the following specification and nested versions thereof:

$$
\begin{aligned}
R_{i,t+1} = {} & \gamma_{0,t} + \gamma_{1,t} IVOL_{i,t} + \gamma_{2,t} CGO_{i,t} IVOL_{i,t} + \gamma_{3,t} PE_{i,t} IVOL_{i,t} + \\
& + \gamma_{4,t} CGO_{i,t} + \gamma_{5,t} PE_{i,t} + \gamma_{6,t} Beta_{i,t} + \gamma_{7,t} Size_{i,t} + \gamma_{8,t} BTM_{i,t} \\
& + \gamma_{9,t} MOM_{i,t} + \gamma_{10,t} REV_{i,t} + \gamma_{11,t} Illiq_{i,t} + \gamma_{12,t} IVOL_{i,t} \\
& + \gamma_{13,t} MAX_{i,t} + \gamma_{14,t} MIN_{i,t} + \gamma_{15,t} Skew_{i,t} + \epsilon_{i,t+1},
\end{aligned}
\tag{2.7}
$$

where $R_{i,t+1}$ is the realized excess return on stock i in month $t+1$, $\gamma_{i,t}$ is the coefficient on variable i in month t and ϵ is the error term. The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables, on average, have non-zero premiums. The predictive cross-sectional regressions are run on the month t values of IVOL, CGO, PE, CGO×IVOL, PE×IVOL, Beta, Size, BTM, MOM, REV, Illiq, MAX, MIN, and Skew.

Table 2.6: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the prior experience measure(PE), the interaction between the capital gain overhang and the idiosyncratic volatility(CGO×IVOL), the interaction between the PE measure and the idiosyncratic measure (PE×IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	(1)	(2)	(3)	(4)	(5)
IVOL	-0.47	-0.38	-0.42	-0.37	-0.01
	(-4.61)	(-3.88)	(-4.37)	(-3.75)	(-0.11)
CGO×IVOL		0.25		0.18	0.14
		(6.43)		(5.21)	(4.73)
PE×IVOL			0.27	0.18	0.16
			(6.85)	(4.92)	(4.86)
CGO		0.15		0.14	0.11
		(3.35)		(3.41)	(3.50)
PE			0.09	0.03	0.08
			(2.19)	(1.00)	(3.00)
Beta					0.03
					(0.67)
Size					-0.20
					(-3.36)
BTM					0.25
					(3.66)
MOM					0.37
					(5.92)
REV					-0.63
					(-11.33)
MAX					0.06
					(0.81)
MIN					0.43
					(6.49)
Illiq					-0.74
					(-3.72)
Skew					-0.04
					(-1.97)
N	653	653	653	653	653

Table 2.6 shows five different specifications of the Fama-MacBeth regressions. The first column presents the idiosyncratic volatility puzzle. This result is similar to the result in the univariate sorts. I also find a strong negative relationship between the idiosyncratic volatility and the subsequent monthly return.

In the second column, I replicate the previous results in the literature between the CGO measure and the idiosyncratic volatility. I also find that there is a strong and positive relationship between the CGO measure and the idiosyncratic volatility. The interaction term between the CGO measure and the idiosyncratic volatility has a 0.25 coefficients on average with a t-statistic of 6.43.

In the third column, I provide an additional test for my main hypothesis. I find similar results to the results of sorting in the previous sections. I find a positive and highly significant interaction term between the PE measure and the idiosyncratic volatility. The average coefficient of the interaction term is 0.27 which also suggests that the effect is as high as the interaction between the CGO measure and the idiosyncratic volatility.

In the fourth column, I replicate the test between the PE measure and the idiosyncratic volatility with controlling for the known relationship between the CGO measure and the idiosyncratic volatility. The average coefficients for both interaction terms decrease but both of them remain highly significant and positive. Both interaction terms have an average coefficient of 0.18. It suggests that there is an overlap between the information that both measures contain but together they explain more than only one of them. These results are in line with the results of the bivariate sorts where the PE measure could provide significant results even after controlling for the CGO measure.

Finally, in the fifth column, I run a test including several known variables that might have an impact on the results. Including these additional variables slightly decreases the average coefficients of the interaction terms but they remain highly significant both economically and statistically. These results provide additional support for the relationship between the PE measure and the idiosyncratic volatility. This relationship is robust for these tests as well. In the next section, I perform several additional tests to show that this relationship remains significant even among liquid and illiquid stocks and different time periods. Finally, I also provide evidence that this relationship remains significant even if I assume that the investors do not use the daily returns for prior experience but the monthly returns which might be more reasonable for most of the investors.

2.4.5 Sensitivity of the Results

In this section, I investigate the robustness of the results. First, I create sub-samples based on liquidity to investigate whether these results are driven by illiquid stocks. Second, I investigate the robustness of the results in the time series. I create sub-samples based on the sentiment index (Baker and Wurgler, 2006) and the January effect. Third, I investigate the robustness of the measure construction by changing the evaluation periods. In an alternative measure, I use the monthly returns as an approximation of the prior negative and positive experience instead of the daily returns. Fourth, I use the alternative measure of weighted prior experience (WPE). Fifth, I use the alternative measures of streaks and trends to explore the robustness of the measure.

First, Table 2.7 presents the results of the double sort in a sample consisting of only the illiquid stocks. I create a sub-sample of stocks that are less liquid than the median liquidity in each month based on the Amihud (2002) measure. Then, I sort stocks into portfolio quintiles based on their PE values and within each portfolio quintile I sort stocks into portfolio quintiles based on their idiosyncratic volatility. I find the same pattern for the illiquid stocks as for the full sample. The idiosyncratic volatility is concentrated among the stocks with low PE values, while it is non-existing among stocks with high PE values.

Table 2.8 presents the results of the double sort in a sample consisting only the liquid stocks. In this sub-sample, there are only stocks which are more liquid than the median in each month. I find the same pattern again as in the full sample. The idiosyncratic volatility is more pronounced among the stocks with low PE values, while it is non-existing among stocks with high PE values.

Table 2.7: Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2016 in a sub-sample only consisting of stocks that are less liquid than the median illiquidity in each month. In each case, I first sort stocks into quintiles using the prior experience measure (PE) then within each quintile I sort stocks into quintile portfolios based on the idiosyncratic volatility variable over the current month so quintile 1 contains the stocks with the lowest idiosyncratic volatility. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1 and the corresponding Fama-French alphas are also reported. (The Newey-West corrected t-statistic are reported in parentheses.) N denotes the number of observations.

	EW			VW		
IVOL	PE1	PE3	PE5	PE1	PE3	PE5
Lowest	0.98	0.96	0.90	0.96	0.80	0.81
2	1.04	1.13	0.95	0.84	0.95	0.80
3	0.65	0.99	0.95	0.54	0.87	0.74
4	0.11	0.89	0.97	-0.02	0.77	0.68
Highest	-0.93	0.10	0.66	-0.95	0.13	0.47
Difference	-1.91	-0.85	-0.24	-1.91	-0.66	-0.34
t-stat	(-9.80)	(-5.34)	(-1.12)	(-8.05)	(-3.04)	(-1.63)
3F α	-2.03	-0.99	-0.50	-2.00	-0.83	-0.58
t-stat	(-11.63)	(-7.64)	(-3.07)	(-9.79)	(-4.62)	(-3.55)
N	653	653	653	653	653	653

Table 2.8: Double sorted, equal-weighted and value-weighted quintile portfolios are formed every month from July 1962 to November 2016 in a sub-sample only consisting of stocks that are more liquid than the median illiquidity in each month. In each case, I first sort stocks into quintiles using the prior experience measure (PE) then within each quintile I sort stocks into quintile portfolios based on the idiosyncratic volatility variable over the current month so quintile 1 contains the stocks with the lowest idiosyncratic volatility. "Return difference" is the average subsequent monthly excess return difference between portfolio 5 and 1 and the corresponding Fama-French alphas are also reported. (The Newey-West corrected t-statistic are reported in parentheses.) N denotes the number of observations.

	EW			VW		
IVOL	PE1	PE3	PE5	PE1	PE3	PE5
Lowest	0.86	0.72	0.55	0.78	0.61	0.48
2	0.83	0.81	0.68	0.62	0.63	0.61
3	0.69	0.88	0.91	0.45	0.77	0.72
4	0.47	0.88	0.94	0.20	0.61	0.79
Highest	-0.30	0.60	0.78	-0.37	0.39	0.51
Difference	-1.16	-0.12	0.23	-1.15	-0.22	0.04
t-stat	(-5.19)	(-0.61)	(0.93)	(-4.31)	(-1.14)	(0.15)
3F α	-1.31	-0.31	0.07	-1.33	-0.40	-0.09
t-stat	(-7.60)	(-2.54)	(0.35)	(-6.12)	(-3.05)	(-0.42)
N	653	653	653	653	653	653

I also perform time-series tests to investigate the nature of the relationship between the PE measure and the idiosyncratic volatility. Table 2.9 presents the results of robustness in the Fama-MacBeth regressions including all control variables.

The first and second column of Table 2.9 present the time-series average coefficients for each variable in the month of January and for all other months, respectively. The month of January is known to be related to micro-structure effects. The interaction term between the PE values and the idiosyncratic volatility is positive for both January and non-January months. In the month of January, it is even higher, however, because of the lower sample size it is only weakly significant. This suggests that this relationship is not driven by the January effect.

The third and fourth column of Table 2.9 present the time-series average coefficients for high sentiment periods and low sentiment periods defined by Baker and Wurgler (2006). The interaction term between the PE values and the idiosyncratic volatility is positive and significant for both time periods. Surprisingly, this interaction term has a lower average coefficient for high sentiment periods than for low sentiment periods. This suggests that this relationship is not only driven by naive investors in the time periods of high sentiment.

The fifth column of Table 2.9 presents the time-series average coefficients when I use an alternative measure for the PE values. One could argue that most of the investors do not experience the effect of daily returns since they do not follow their investments that carefully. Thus, I created the same measure based on monthly returns. I used the estimated purchase date and I calculated the new monthly measure based on the number of negative and positive monthly returns compared to the number of all months since the estimated purchase date. The time-series average of the coefficients is a bit lower compared to the measure with daily returns, however, it is still highly significant with a t-statistic of 3.82. This suggests that the PE measure is not sensitive to the definition of the prior experience time periods. Using the daily or monthly time periods yield the same conclusions.

Finally, I also control for the potential alternative explanation of my results that my PE measure is similar to the momentum and as a result it captures news underreaction, while the idiosyncratic volatility is similar to information uncertainty measure. In this case, I would only replicate the findings of Zhang (2006). To mitigate any concern related to this, the last column of Table 2.9 reports the time series average of the coefficients when I also add the interaction term of momentum and the idiosyncratic volatility. It does not affect any of my results.

All of these results suggest that the documented relationship between the PE measure and the idiosyncratic volatility is not driven by a few extreme cases. It is not driven by the January effect or high sentiment time periods. The relationship is not sensitive to the evaluation periods of the measure. Creating the PE measure using prior monthly returns generates similar results. Furthermore, I could exclude a potential alternative explanation for my results that the documented relationship would be driven by the news underreaction and information uncertainty (Zhang, 2006).

Table 2.9: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the prior experience measure (PE), the interaction between the capital gain overhang and the idiosyncratic volatility(CGO×IVOL), the interaction between the PE measure and the idiosyncratic measure (PE×IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), the skewness (Skew), and the interaction term between the momentum and the idiosyncratic volatility (MOM×IVOL). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	January		Sentiment		Monthly Experience	Underreaction
	Yes	No	High	Low	$PE_{Monthly}$	
IVOL	0.90	-0.10	-0.22	0.35	-0.03	-0.00
	(1.86)	(-0.79)	(-1.29)	(1.86)	(-0.24)	(-0.04)
CGO×IVOL	0.21	0.13	0.18	0.12	0.16	0.14
	(1.81)	(4.53)	(4.18)	(2.85)	(5.53)	(4.78)
PE×IVOL	0.29	0.15	0.10	0.21	0.10	0.16
	(1.81)	(4.44)	(2.18)	(3.99)	(3.82)	(4.94)
CGO	-0.76	0.19	0.17	0.04	0.12	0.11
	(-3.72)	(6.14)	(4.00)	(0.91)	(3.80)	(3.38)
PE	-0.20	0.11	0.13	-0.00	0.03	0.08
	(-2.51)	(3.82)	(3.46)	(-0.02)	(1.46)	(3.00)
Beta	-0.00	0.04	-0.04	0.14	0.03	0.02
	(-0.03)	(0.68)	(-0.55)	(1.74)	(0.58)	(0.62)
Size	-1.16	-0.12	-0.12	-0.32	-0.20	-0.20
	(-3.87)	(-1.92)	(-1.76)	(-2.80)	(-3.09)	(-3.34)
BTM	0.53	0.22	0.36	0.11	0.25	0.25
	(2.65)	(3.31)	(3.69)	(1.05)	(3.70)	(3.74)
MOM	0.34	0.37	0.40	0.38	0.38	0.40
	(2.65)	(5.94)	(5.65)	(3.31)	(6.14)	(6.09)
REV	1.50	-0.55	-0.62	-0.68	-0.61	-0.63
	(8.80)	(-10.73)	(-8.62)	(-7.36)	(-10.89)	(-11.35)
MAX	0.25	0.05	0.20	-0.13	0.01	0.07
	(0.74)	(0.61)	(2.09)	(-1.14)	(0.17)	(0.88)
MIN	1.37	0.35	0.46	0.47	0.40	0.44
	(4.14)	(5.36)	(4.87)	(5.15)	(6.18)	(6.49)
Illiq	-0.48	-0.76	-0.36	-1.39	-0.69	-0.74
	(-1.23)	(-3.71)	(-2.34)	(-3.65)	(-3.44)	(-3.74)
Skew	-0.34	-0.02	-0.07	-0.02	-0.04	-0.05
	(-2.31)	(-0.71)	(-2.63)	(-0.69)	(-1.70)	(-2.20)
MOM×IVOL						-0.04
						(-1.28)
N	653	653	653	653	653	653

2.4.6 Weighted Prior Experience Measure

In this section, I investigate the effect of using the weighted prior experience measure. In this case, I assume that there is a probability of $(1-\lambda)$ that the "urn" is updated which means that the process restarts and outcomes before that date are not relevant anymore. For instance, $\lambda = 1$ means that the "urn" is never updated yielding the original prior experience measure.

To explore the change in the λ weight I run Fama-MacBeth regressions with several different λ specifications. I use $\lambda = 0.999; 0.995; 0.99; 0.975; 0.95$ specifications. In the case of $\lambda = 0.999$, a negative or positive experience one year ago (200 trading days ago) has the relative weight of 0.819 compared to the most recent experience, while in the case of $\lambda = 0.99$ this weight is 0.14, and in the case of $\lambda = 0.95$ this weight becomes 0.000 which is almost negligible.

Table 2.10 reports the average coefficients of the Fama-Macbeth regressions including several different specifications of the weighted PE measures. The positive relationship between the PE measure and the idiosyncratic volatility gets stronger when λ is slightly lower than one. However, when λ gets lower than 0.99 the positive relationship between the PE measure and the idiosyncratic volatility starts to diminish and there is no significant effect anymore when λ is 0.95.

2.4.7 Streak and Trend Measures

In this section, I use several alternative measures for prior experience to explore the robustness the definition of prior experience. I use the measure of streaks with monthly returns, I use the measure of trend of prior experience following the consistency measure of Grinblatt and Moskowitz (2004), and the measure of trend

Table 2.10: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the weighted prior experience measure (WPE) with several different specifications of λ, the interaction between the capital gain overhang and the idiosyncratic volatility(CGO$\times$IVOL), the interaction between the weighted PE measure and the idiosyncratic volatility measure (WPE$\times$IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	0.999	0.995	0.99	0.975	0.95
IVOL	-0.01	0.00	-0.00	-0.07	-0.17
	(-0.08)	(0.03)	(-0.04)	(-0.54)	(-1.26)
CGO$\times$IVOL	0.13	0.13	0.13	0.16	0.18
	(4.55)	(4.54)	(4.82)	(5.65)	(6.14)
WPE$\times$IVOL	0.18	0.23	0.24	0.16	-0.01
	(5.12)	(6.12)	(6.52)	(5.38)	(-0.44)
CGO	0.11	0.10	0.11	0.13	0.13
	(3.35)	(3.24)	(3.49)	(3.92)	(3.80)
WPE	0.10	0.13	0.12	-0.02	-0.23
	(3.51)	(4.73)	(4.11)	(-0.65)	(-8.53)
Controls	Yes	Yes	Yes	Yes	Yes
N	653	653	653	653	653

following Loh and Warachka (2012) with monthly returns.

Table 2.11 reports the average coefficients of the Fama-Macbeth regressions including the measure of streak, the measure of $trend_{LW}$ following Loh and Warachka (2012), and the measure of $trend_{GM}$ following Grinblatt and Moskowitz (2004). In each case, there is a positive interaction term between the alternative prior experience measure and the idiosyncratic volatility. It presents that there is a robust relation between prior experience and the risk-return trade-off.

Table 2.11: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the alternative prior experience measure (PE) with several different specifications including the *streak* measure, the $Trend_{LW}$ measure following Loh and Warachka (2012), and the $Trend_{GM}$ measure following Grinblatt and Moskowitz (2004), the interaction between the capital gain overhang and the idiosyncratic volatility(CGO×IVOL), the interaction between the alternative PE measure and the idiosyncratic volatility measure (PE×IVOL), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	Streak	$Trend_{GM}$	$Trend_{LW}$
IVOL	-0.01	-0.01	-0.01
	(-0.91)	(-0.54)	(-0.74)
CGO×IVOL	0.13	0.12	0.12
	(3.50)	(3.34)	(3.33)
PE×IVOL	0.12	0.11	0.26
	(4.32)	(2.55)	(5.76)
CGO	0.13	0.12	0.12
	(3.50)	(3.34)	(3.33)
PE	-0.00	0.08	0.13
	(-1.44)	(2.40)	(3.84)
Controls	Yes	Yes	Yes
N	653	653	653

Streaks

In this section, I create several new streak measures to explore their effects on the risk-return trade-off. Streaks have at least two advantages to examine in terms of prior experience. First, streaks provide an intuitive and strong example by which decision-makers are influenced according to the model of Rabin (2002). Second, it also provides a possibility to have a clear test of the different implications of the model of Rabin (2002) for the short-term and the long-term.

To explore the effects of different specifications of streaks, I use 18 different streak measures to be able to explore the different effects. First, I created the monthly return streaks and the monthly excess return (above the market) streaks. Second, I created the quarterly return streaks and the quarterly excess return streaks. Finally, I created the annual return streaks and the annual excess return streaks. The firm-level regression results are reported in Table 2.12, Table 2.13, and Table 2.14. In each table, the first and the fourth column report the time-series averages of the coefficients when the streak measure is the signed length of the streak, for instance, -5 means five negative consecutive returns. The second and fifth column report the time-series averages of the coefficients when the streak measure is 1 for positive streaks, -1 for negative streaks, and 0 for no streaks. The third and the sixth column of these tables report the time-series averages of the coefficients when the streak measure is 1 for positive streaks, -1 for negative streaks, and 0 for no streaks and the long streak measure is 1 for at least four positive consecutive returns, -1 for at least four negative consecutive returns, and 0 otherwise. In additional unreported tests, I investigate the effect of defining long streak as at least eight consecutive returns with the same sign instead of at least four consecutive returns with the same sign. Both definitions yield the same conclusions.

Table 2.12 reports the time-series averages of the coefficients of the firm-level regressions including streaks based on monthly returns. In the first and the fourth column, Table 2.12 reports the results when streak is defined as the signed length of the streak of monthly returns and excess monthly returns. The interaction terms between the measure of streak and the idiosyncratic volatility are positive and statistically highly significant with a t-statistic of 4.31 and 3.77 even after controlling for a set of characteristics of stocks and the interaction term between the CGO measure and the idiosyncratic volatility. As reported in the second and fifth column, these results become even stronger both economically and statistically when the measure of streak can only have the values of 1,-1, and 0 based on the sign of the streak. To test the different implications of the model of Rabin (2002) for short-term and long-term, in the third and sixth column, Table 2.12 reports the time-series averages of the coefficients when both the measure of streak with values of 1,-1, and 0 is included and the measure of long streak with values of 1,-1, and 0. I find that the interaction term between the measure of streak and the idiosyncratic volatility is still positive and significant, while the interaction term between the long streak and the idiosyncratic volatility is not significant.

Table 2.13 reports the time-series averages of the coefficients of the firm-level regressions including streaks based on quarterly returns. In the first and the fourth column, Table 2.13 reports the results when streak is defined as the signed length of the streak of quarterly returns and excess quarterly returns. The interaction terms between the measure of streak and the idiosyncratic volatility are positive and statistically highly significant with a t-statistic of 4.16 and 3.25 even after controlling for a set of characteristics of stocks and the interaction term between the CGO measure and the idiosyncratic volatility. Similarly to the results of the monthly streaks, these results become even stronger both economically and statistically when the measure of streak can only have the values of 1,-1, and 0 based on the sign of the streak, as reported in the second and fifth column in Table 2.13. To test the different implications of the model of Rabin (2002) for short-term and long-term, in the third and sixth column, Table 2.13 reports the time-series averages of the coefficients when both the measure of streak with values of 1,-1, and 0 is included and the measure of long streak with values of 1,-1, and 0. In this case, I find different results compared to the monthly returns. I find that the interaction term between the measure of streak and the idiosyncratic volatility is still positive and significant, while the interaction term between the long streak and the idiosyncratic volatility is negative in both cases and it is even significant for excess quarterly returns. These results are in line with the prediction of the model of Rabin (2002). Investors seem to exhibit the gambler's fallacy for short streaks, while, after experiencing an extremely long streak, the hot-hand fallacy undermines the effect of the gambler's fallacy.

To investigate the effect of a longer time horizon and different lengths of the streaks, I also define streaks based on annual returns. Table 2.14 reports the time-series averages of the coefficients of the firm-level regressions including streaks based on annual returns. In the first and the fourth column, Table 2.14 reports the results when streak is defined as the signed length of the streak of annual returns and excess annual returns. The interaction terms between the measure of streak and the idiosyncratic volatility are negative and statistically highly significant with a t-statistic of -3.29 and -4.09 even after controlling for a set of characteristics of stocks and the interaction term between the CGO measure and the idiosyncratic volatility. As reported in the second and fifth column, these results do not change substantially when the measure of streak can only have the values of 1,-1, and 0 based on the sign of the streak. These results are different from the previous results. It suggests that using longer time horizon yields results that are more in line with the hot-hand fallacy. To test the different implications of the model of Rabin (2002) for short-term and long-term, in the third and sixth column, Table 2.14 reports the time-series averages of the coefficients when both the measure of streak with values of 1,-1, and 0 is included and the measure of long streak with values of 1,-1, and 0. I find that the interaction term between the measure of streak and the idiosyncratic volatility is still negative and significant, while the interaction term between the long streak and the idiosyncratic volatility is not significant.

These results suggest that the time horizon influences the results the most. Investors seem to exhibit the gambler's fallacy for short-term such as monthly streaks and short streaks of quarterly returns, while they seem to follow the hot-hand fallacy for long quarterly streaks and for annual streaks. This is in line with the concept that investors think that they know the underlying rate for short-term, thus, they expect a reversal as a consequence of the gambler's fallacy, while the investors do not know the underlying rate for long-term, thus, they expect continuation.

These results also suggest that approximately one year or less can be considered as short-term and longer time horizon can be considered as long-term. This is consistent with the literature and it seems that prior experience measure has a link with momentum (e.g., Jegadeesh and Titman, 1993). To control for the effect of momentum on these results, I perform several additional tests in a following section.

Table 2.12: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the Streak measure (Streak) with several specifications (1), (4) signed length of the streak, (2),(3),(4),(6) sign of the streak (-1,1,0), and (3),(6) long streak (Long Streak) with the values -1,0,1 if there is at least four consecutive returns with the same sign, the interaction between the capital gain overhang and the idiosyncratic volatility (CGO×IVOL), the interaction between the Streak measure and the idiosyncratic measure (Streak×IVOL), and the control variables I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

Streaks Based on Monthly (Raw or Excess) Returns

	Raw Returns			Excess Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
IVOL	-0.07	-0.07	-0.07	-0.07	-0.06	-0.06
	(-0.82)	(-0.75)	(-0.77)	(-0.81)	(-0.67)	(-0.67)
CGO×IVOL	0.10	0.09	0.09	0.11	0.11	0.11
	(5.85)	(3.70)	(3.52)	(5.93)	(6.00)	(6.04)
Streak×IVOL	0.07	0.19	0.18	0.06	0.10	0.10
	(4.31)	(5.33)	(4.81)	(3.77)	(4.34)	(3.84)
Long Streak×IVOL			0.07			0.01
			(1.54)			(0.19)
CGO	0.08	0.04	0.04	0.08	0.08	0.08
	(2.09)	(0.96)	(1.11)	(2.11)	(2.16)	(2.26)
Streak	-0.06	0.03	0.05	-0.10	-0.17	-0.15
	(-3.47)	(0.62)	(1.16)	(-5.21)	(-4.75)	(-3.97)
Long Streak			-0.09			-0.08
			(-1.86)			(-1.85)
Beta	0.02	-0.00	-0.01	0.02	0.02	0.01
	(0.51)	(-0.14)	(-0.20)	(0.48)	(0.44)	(0.43)
Size	-0.19	-0.20	-0.20	-0.19	-0.19	-0.19
	(-3.31)	(-3.66)	(-3.63)	(-3.33)	(-3.30)	(-3.26)
BTM	0.21	0.18	0.18	0.21	0.21	0.21
	(3.69)	(3.26)	(3.27)	(3.66)	(3.69)	(3.70)
MOM	0.37	0.39	0.40	0.38	0.38	0.39
	(6.28)	(6.60)	(6.67)	(6.34)	(6.37)	(6.35)
REV	-0.45	-0.54	-0.55	-0.43	-0.44	-0.44
	(-9.99)	(-9.90)	(-9.85)	(-9.91)	(-10.35)	(-10.34)
MAX	-0.00	-0.01	-0.01	-0.00	0.00	-0.00
	(-0.00)	(-0.21)	(-0.21)	(-0.06)	(0.05)	(-0.00)
MIN	0.20	0.11	0.11	0.19	0.20	0.20
	(5.06)	(1.98)	(1.89)	(4.85)	(5.02)	(4.98)
Illiq	-0.06	-0.07	-0.07	-0.06	-0.06	-0.06
	(-2.14)	(-2.26)	(-2.24)	(-2.21)	(-2.24)	(-2.17)
Skew	-0.01	0.01	0.01	-0.01	-0.02	-0.02
	(-0.70)	(0.23)	(0.21)	(-0.68)	(-0.84)	(-0.81)
N	653	653	653	653	653	653

Table 2.13: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the Streak measure (Streak) with several specifications (1), (4) signed length of the streak, (2),(3),(4),(6) sign of the streak (-1,1,0), and (3),(6) long streak (Long Streak) with the values -1,0,1 if there is at least four consecutive returns with the same sign, the interaction between the capital gain overhang and the idiosyncratic volatility (CGO×IVOL), the interaction between the Streak measure and the idiosyncratic measure (Streak×IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	Streaks Based on Quarterly (Raw or Excess) Returns					
	Raw Returns			Excess Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
IVOL	-0.03	-0.06	-0.06	-0.04	-0.05	-0.05
	(-0.37)	(-0.65)	(-0.67)	(-0.50)	(-0.58)	(-0.55)
CGO×IVOL	0.10	0.10	0.10	0.10	0.10	0.11
	(5.88)	(5.73)	(5.76)	(5.80)	(5.89)	(6.00)
Streak×IVOL	0.07	0.12	0.12	0.05	0.09	0.12
	(4.16)	(4.65)	(4.27)	(3.25)	(3.78)	(4.30)
Long Streak×IVOL			-0.02			-0.12
			(-0.57)			(-3.10)
CGO	0.07	0.07	0.07	0.07	0.07	0.07
	(1.91)	(1.82)	(1.87)	(1.98)	(1.92)	(1.95)
Streak	0.03	0.06	0.06	0.01	0.03	0.04
	(1.39)	(1.84)	(1.75)	(0.33)	(0.99)	(1.15)
Long Streak			-0.03			-0.05
			(-0.69)			(-1.24)
Beta	0.02	0.02	0.02	0.02	0.02	0.02
	(0.53)	(0.55)	(0.56)	(0.49)	(0.46)	(0.49)
Size	-0.19	-0.19	-0.19	-0.19	-0.19	-0.19
	(-3.39)	(-3.41)	(-3.43)	(-3.36)	(-3.38)	(-3.41)
BTM	0.21	0.20	0.20	0.21	0.21	0.21
	(3.71)	(3.69)	(3.69)	(3.72)	(3.74)	(3.74)
MOM	0.35	0.35	0.35	0.36	0.36	0.36
	(5.95)	(5.80)	(5.82)	(6.03)	(5.91)	(5.98)
REV	-0.49	-0.49	-0.49	-0.49	-0.49	-0.49
	(-10.55)	(-10.59)	(-10.62)	(-10.50)	(-10.57)	(-10.60)
MAX	0.04	0.04	0.04	0.04	0.05	0.04
	(0.89)	(0.99)	(0.90)	(0.90)	(1.18)	(1.05)
MIN	0.24	0.24	0.24	0.24	0.24	0.24
	(5.92)	(5.85)	(5.89)	(5.87)	(5.93)	(6.03)
Illiq	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06
	(-2.24)	(-2.17)	(-2.16)	(-2.17)	(-2.15)	(-2.16)
Skew	-0.05	-0.05	-0.05	-0.05	-0.05	-0.05
	(-2.32)	(-2.33)	(-2.32)	(-2.26)	(-2.44)	(-2.38)
N	653	653	653	653	653	653

Table 2.14: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the Streak measure (Streak) with several specifications (1), (4) signed length of the streak, (2),(3),(4),(6) sign of the streak (-1,1,0), and (3),(6) long streak (Long Streak) with the values -1,0,1 if there is at least four consecutive returns with the same sign, the interaction between the capital gain overhang and the idiosyncratic volatility (CGO×IVOL), the interaction between the Streak measure and the idiosyncratic measure (Streak×IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	Streaks Based on Annual (Raw or Excess) Returns					
	Raw Returns			Excess Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
IVOL	-0.05	-0.04	-0.04	-0.06	-0.06	-0.06
	(-0.62)	(-0.41)	(-0.47)	(-0.64)	(-0.73)	(-0.74)
CGO×IVOL	0.13	0.13	0.13	0.13	0.13	0.13
	(7.21)	(7.26)	(7.46)	(7.24)	(7.32)	(7.47)
Streak×IVOL	-0.05	-0.09	-0.09	-0.07	-0.10	-0.08
	(-3.29)	(-3.26)	(-2.92)	(-4.09)	(-3.76)	(-2.93)
Long Streak×IVOL			-0.00			0.09
			(-0.08)			(-1.92)
CGO	0.07	0.07	0.07	0.07	0.07	0.07
	(1.98)	(2.09)	(2.06)	(2.06)	(2.05)	(2.10)
Streak	-0.01	-0.02	-0.03	-0.04	-0.05	-0.04
	(-0.56)	(-0.51)	(-0.73)	(-1.51)	(-1.25)	(-1.06)
Long Streak			0.02			-0.05
			(0.30)			(-1.12)
Beta	0.03	0.02	0.03	0.02	0.02	0.02
	(0.61)	(0.58)	(0.59)	(0.50)	(0.49)	(0.47)
Size	-0.20	-0.20	-0.20	-0.20	-0.20	-0.20
	(-3.50)	(-3.53)	(-3.57)	(-3.49)	(-3.49)	(-3.48)
BTM	0.20	0.20	0.20	0.19	0.19	0.19
	(3.56)	(3.55)	(3.56)	(3.44)	(3.42)	(3.41)
MOM	0.36	0.36	0.36	0.36	0.36	0.36
	(6.20)	(6.16)	(6.18)	(6.31)	(6.18)	(6.18)
REV	-0.49	-0.49	-0.49	-0.49	-0.49	-0.49
	(-10.48)	(-10.50)	(-10.55)	(-10.57)	(-10.58)	(-10.59)
MAX	0.02	0.02	0.02	0.03	0.03	0.02
	(0.53)	(0.50)	(0.46)	(0.70)	(0.64)	(0.53)
MIN	0.23	0.23	0.23	0.23	0.23	0.23
	(5.78)	(5.73)	(5.73)	(5.88)	(5.73)	(5.63)
Illiq	-0.06	-0.06	-0.06	-0.06	-0.06	-0.06
	(-2.23)	(-2.25)	(-2.27)	(-2.29)	(-2.32)	(-2.32)
Skew	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04
	(-1.81)	(-1.81)	(-1.72)	(-2.00)	(-1.97)	(-1.85)
N	653	653	653	653	653	653

2.4.8 Alternative Starting Point for Prior Experience Measures

In this section, I investigate the effect of choosing different starting points of the prior experience measure. I consider the observation one year ago, five years ago, and the first appears in the database as a starting point. I also consider both daily and monthly returns to explore the robustness of the results.

Table 2.15 reports the time-series averages of the coefficients of the firm-level regressions where the prior experience measure has six different specifications. First, the first and fourth column of the table report the time-series averages of the coefficients when the first signal considered is the observation one year ago. This measure provides a possibility to test the short-term horizon since the last one year is usually considered to be a short-term similarly to the momentum effect. Using the last one year observations also makes this measure more comparable to momentum. If the results are driven by the momentum effect, then this measure is supposed to be to the closest to momentum. Second, the second and fifth column of the table report the time-series averages of the coefficients when the first signal is considered to be the observation five years ago. This measure provides a possibility to explore a potential long-term effect since five year horizon is usually considered to be long-term. Finally, the third and sixth column of the table report the time-series averages of the coefficients when the first signal is considered to be the first observation available in the database. This measure can be interpreted as an extremely long-term effect.

I find that the interaction terms between any of the prior experience measures based on daily returns and the idiosyncratic volatility are positive and significant. The predictive power of the interaction term gets weaker as the time-horizon gets longer but they are all significant. I find, similarly, positive interaction terms when the measures are based on monthly returns, however, it is only significant for the measure which is based on the last one year monthly observations.

These results suggest that investors exhibit the gambler's fallacy when the ratio of the prior experience is considered. Although the results are getting weaker for long time horizons, I find no clear evidence for a long-term effect. The absence of empirical support for the long-term effect might be the result of the specification of this measure. Perhaps, the ratio of the daily or monthly returns can not capture the extreme cases when the investors update their beliefs about the underlying rate.

Table 2.15: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the prior experience measure (PE), the interaction between the capital gain overhang and the idiosyncratic volatility(CGO×IVOL), the interaction between the Streak measure and the idiosyncratic measure (PE×IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	Daily			Monthly		
	1 year	5 year	All	1 year	5 year	All
IVOL	0.00	0.00	-0.05	-0.02	0.01	-0.04
	(0.03)	(0.04)	(-0.59)	(-0.26)	(0.08)	(-0.52)
CGO×IVOL	0.08	0.09	0.10	0.09	0.11	0.11
	(4.68)	(4.78)	(5.64)	(5.17)	(5.61)	(6.05)
PE×IVOL	0.15	0.08	0.05	0.10	0.01	0.03
	(7.04)	(3.82)	(2.62)	(6.01)	(0.68)	(1.68)
CGO	0.06	0.07	0.08	0.07	0.06	0.08
	(1.78)	(1.98)	(2.54)	(1.87)	(1.70)	(2.41)
PE	0.14	-0.01	-0.04	0.08	-0.02	-0.03
	(5.25)	(-0.20)	(-0.95)	(3.47)	(-0.88)	(-1.42)
Beta	0.03	0.02	0.01	0.02	0.03	0.02
	(0.67)	(0.55)	(0.28)	(0.58)	(0.72)	(0.46)
Size	-0.21	-0.17	-0.18	-0.20	-0.17	-0.18
	(-3.71)	(-3.26)	(-3.40)	(-3.47)	(-3.19)	(-3.37)
BTM	0.20	0.18	0.21	0.21	0.17	0.21
	(3.66)	(3.65)	(3.74)	(3.70)	(3.51)	(3.65)
MOM	0.28	0.28	0.36	0.31	0.28	0.37
	(4.78)	(4.90)	(6.10)	(5.53)	(4.88)	(6.12)
REV	-0.53	-0.50	-0.50	-0.51	-0.50	-0.49
	(-11.24)	(-11.98)	(-10.63)	(-10.92)	(-11.90)	(-10.52)
MAX	0.06	0.07	0.07	0.03	0.04	0.04
	(1.39)	(1.46)	(1.70)	(0.63)	(0.88)	(1.02)
MIN	0.26	0.24	0.25	0.23	0.23	0.24
	(6.32)	(6.25)	(6.37)	(5.83)	(6.01)	(5.96)
Illiq	-0.08	-0.06	-0.06	-0.06	-0.06	-0.06
	(-3.06)	(-2.27)	(-2.27)	(-2.14)	(-2.29)	(-2.31)
Skew	-0.04	-0.05	-0.06	-0.04	-0.04)	-0.05
	(-1.89)	(-2.35)	(-2.93)	(-2.02)	(-1.93)	(-2.32)
N	653	653	653	653	653	653

2.4.9 Alternative Risk Measures

In this section, I perform Fama-MacBeth regressions using alternative risk measures instead of the idiosyncratic volatility to mitigate any concern about idiosyncratic volatility as a measure of risk. I use five alternative measures for risk.

First, I use market beta based on monthly observations of the last five years. This measure also mitigates the concern that the results are driven by the returns of the last month.

Second, I use the volatility of the last five years' monthly return.

Third, I use the cash-flow volatility as an alternative risk measure. This measure mitigates any concern that the negative risk-return relation only hold for risk measures based on past returns.

Fourth, I use the age of the firm as an alternative risk measure.

Finally, I use the dispersion of the analyst forecasts as an alternative risk measure. This measure mitigates any concern that these results only hold for observed past information since this measure captures risk based on the dispersion of beliefs.

Table 2.16 reports the time series average of the coefficients for each regressions. The interaction terms between the prior experience measure and the risk measure are always significant and positive yielding that the results are robust independently from which risk measure I use. These relations gets even stronger by using the weighted PE measure with the specification of $\lambda = 0.99$.

Table 2.16: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including several risk measure (IVOL, Beta, RetVol, CFVol, Age, and Dispersion), the capital gain overhang measure (CGO), the PE measure (PE), the interaction between the capital gain overhang and the risk measure (CGO×Risk), the interaction between the PE measure and the risk measure (PE×Risk), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew. I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected t-statistics (in parentheses). N denotes the number of observations.

	IVOL	Beta	RetVol	CFVol	Age	Disp
CGO×Risk	0.14	0.04	0.05	0.02	0.08	-0.03
	(4.49)	(1.68)	(2.20)	(0.74)	(4.81)	(-0.79)
PE×Risk	0.17	0.04	0.07	0.07	0.03	0.08
	(4.89)	(2.00)	(3.41)	(4.28)	(2.21)	(2.07)
CGO	0.11	0.14	0.11	0.12	0.14	0.08
	(3.36)	(4.24)	(3.33)	(3.70)	(4.25)	(1.41)
PE	0.07	0.02	-0.00	-0.01	0.02	-0.04
	(2.40)	(0.88)	(-0.14)	(-0.18)	(0.63)	(-1.05)
Risk	-0.05	0.08	0.01	-0.05	-0.00	-0.23
	(-0.40)	(1.40)	(0.14)	(-1.64)	(-0.22)	(-4.89)
Size	-0.22	-0.22	-0.21	-0.24	-0.23	-0.21
	(-3.74)	(-4.17)	(-3.90)	(-3.97)	(-4.03)	(-2.07)
BTM	0.25	0.26	0.22	0.24	0.26	0.26
	(3.52)	(4.22)	(3.81)	(3.67)	(3.74)	(2.12)
MOM	0.38	0.33	0.31	0.35	0.37	0.33
	(5.76)	(5.18)	(4.73)	(5.28)	(5.49)	(2.60)
REV	-0.61	-0.69	-0.68	-0.60	-0.59	-0.45
	(-11.10)	(-11.85)	(-12.29)	(-10.41)	(-10.22)	(-4.15)
MAX	0.12	0.04	0.07	0.02	-0.05	0.35
	(1.90)	(0.70)	(1.06)	(0.53)	(-0.89)	(1.41)
MIN	0.41	0.43	0.41	0.41	0.42	0.36
	(6.02)	(7.72)	(7.66)	(6.23)	(6.97)	(2.13)
Illiq	-0.75	-0.71	-0.78	-1.02	-0.78	-20.25
	(-3.52)	(-3.80)	(-3.91)	(-3.77)	(-3.65)	(-1.52)
Skew	-0.05	-0.04	-0.04	-0.03	-0.03	00.04
	(-2.01)	(-1.54)	(-1.48)	(-1.07)	(-1.18)	(-0.50)
N	653	653	653	653	653	653

2.4.10 Control for Momentum

In this section, I investigate the role of momentum in the results. High (low) momentum value indicates that the overall return in the last one year is high (low) which increases the probability to have a streak of positive (negative) returns or to have a high number of positive (negative) returns in the past. Although there could be such a link between the momentum and the prior experience measure, it is not necessarily true that the results are driven by the momentum effect instead of the prior experience measure. For instance, there could be a high momentum with having a high return in the last one year, while this high return comes from only few high positive days or months and during the rest of the days there could be small negative returns.

The times-series averages of the monthly correlation between the momentum and the prior experience measures are relatively high in certain cases which could raise a serious concern. There is a 0.51 time-series average monthly correlation between the momentum and the prior experience measure based on the last one year's daily return and it is 0.59 based on the monthly returns. This is not surprisingly high since these prior experience measures were created to make prior experience measure more similarly to the momentum. There are a 0.31 and 0.35 time-series average monthly correlation between the momentum and prior experience measure based on the daily and monthly returns since the estimated purchase price. These values are substantially smaller but they could be still concerning. The rest of the prior experience measures based on the last five years or all available observations are less correlated with the momentum effect (in each case, it is positive but smaller than 0.14).

Similarly, there are substantial 0.48 and 0.52 time-series average monthly correlations between the momentum effect and the streaks based on the quarterly returns. However, there are only weak correlations ranging between 0.18 and 0.28 between the momentum effect and the rest of the streak measures.

To explore the role of momentum and its relation with prior experience measures and streaks, I perform several additional tests in which I control for the effect of momentum. Specifically, I regress a given prior experience measure on momentum and a constant in each month and I take the residuals as a new measure. Thus, these new measures are orthogonal to momentum. If the predictive power of the prior experience measures disappears, then it is probable that the results were only driven by the momentum effect. However, if these results remain substantial and both statistically and economically significant, then the predictive power of the prior experience measures seems to be independent from the momentum effect.

Table 2.17 reports the time-series averages of the coefficients of the firm-level regressions in which the residuals of the prior experience measures are included after regressing a given prior experience measure on the momentum effect and a constant in each month. Using the residuals do not have any impact on any of the previous results. I find positive and significant interaction terms between the prior experience measure residuals and the idiosyncratic volatility for all measures based on daily returns and I find positive and significant interaction term for the prior experience measures based on the monthly returns when it is based on the last one year and on the observations since the estimated purchase date.

Residuals of the prior experience measure based on the last one year provide even a slightly stronger predictive power than the original prior experience measure. This suggests that momentum does not have any impact on these results. None of the other prior experience measures yields different conclusion either after controlling for the momentum effect which also suggests that momentum has no significant role in explaining any of the previous results.

One might consider that streaks are more related to the momentum effect and the streak measures based on the quarterly returns have strong correlation with the momentum effect as well. To explore the role of the momentum effect in those results, I also perform several additional firm-level regressions to control for the effect of momentum. Specifically, I regress, again, a given streak measure based on quarterly returns on momentum and a constant in each month and I take the residuals as a new measure.

Table 2.18 reports the time-series averages of the coefficients of the firm-level regressions in which the residuals of the streaks based on quarterly returns are included after regressing streaks based on quarterly returns on the momentum effect and a constant in each month. Using the residuals do not have any impact on any of my previous results. Similarly to the prior experience measure, I find an even slightly stronger predictive power. It suggests that the predictive power of streak measures are also independent from the momentum effect.

Table 2.17: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the residuals of prior experience measure (PE) orthogonal to momentum, the interaction between the capital gain overhang and the idiosyncratic volatility(CGO×IVOL), the interaction between the residuals of prior experience measure (PE) orthogonal to momentum and the idiosyncratic measure (PE×IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected *t*-statistics (in parentheses). *N* denotes the number of observations.

	Orthogonal to MOM							
	Daily				Monthly			
	1 year	5 year	All	Purchase	1 year	5 year	All	Purchase
IVOL	0.01	0.00	-0.05	-0.02	-0.02	0.01	-0.04	-0.04
	(0.15)	(0.03)	(-0.60)	(-0.29)	(-0.19)	(0.09)	(-0.51)	(-0.45)
CGO×IVOL	0.11	0.10	0.10	0.10	0.11	0.12	0.11	0.10
	(6.33)	(4.92)	(5.71)	(5.36)	(6.14)	(5.60)	(6.10)	(5.96)
PE×IVOL	0.15	0.08	0.05	0.09	0.11	0.01	0.02	0.07
	(7.90)	(3.82)	(2.52)	(4.91)	(7.16)	(0.75)	(1.61)	(4.33)
CGO	0.05	0.08	0.08	0.07	0.06	0.08	0.08	0.07
	(1.50)	(2.25)	(2.53)	(1.95)	(1.63)	(2.05)	(2.39)	(2.06)
PE	0.11	0.00	-0.03	0.03	0.06	-0.02	-0.03	-0.00
	(4.91)	(0.01)	(-0.96)	(1.08)	(3.22)	(-0.80)	(-1.41)	(-0.21)
Beta	0.03	0.02	0.01	0.04	0.02	0.03	0.02	0.02
	(0.62)	(0.59)	(0.30)	(0.55)	(0.52)	(0.76)	(0.47)	(0.45)
Size	-0.20	-0.17	-0.18	-0.20	-0.19	-0.17	-0.18	-0.19
	(-3.67)	(-3.29)	(-3.41)	(-3.63)	(-3.42)	(-3.23)	(-3.39)	(-3.36)
BTM	0.21	0.19	0.21	0.21	0.21	0.19	0.21	0.21
	(3.69)	(3.64)	(3.75)	(3.70)	(3.73)	(3.51)	(3.65)	(3.73)
MOM	0.40	0.31	0.37	0.38	0.39	0.30	0.37	0.38
	(6.54)	(5.08)	(6.27)	(6.35)	(6.40)	(4.94)	(6.19)	(6.24)
REV	-0.53	-0.53	-0.50	-0.51	-0.51	-0.53	-0.49	-0.49
	(-11.26)	(-11.96)	(-10.63)	(-11.29)	(-10.93)	(-11.87)	(-10.53)	(-10.80)
MAX	0.06	0.06	0.07	0.05	0.02	0.04	0.04	0.03
	(1.37)	(1.26)	(1.62)	(1.32)	(0.46)	(0.73)	(1.00)	(0.56)
MIN	0.26	0.25	0.24	0.25	0.23	0.24	0.24	0.22
	(6.43)	(6.13)	(6.39)	(6.21)	(5.71)	(5.93)	(6.02)	(5.84)
Illiq	-0.08	-0.06	-0.06	-0.07	-0.06	-0.06	-0.06	-0.06
	(-3.05)	(-2.31)	(-2.26)	(-2.69)	(-2.14)	(-2.40)	(-2.31)	(-2.25)
Skew	-0.04	-0.05	-0.06	-0.05	-0.04	-0.04	-0.05	-0.04
	(-2.00)	(-2.34)	(-2.87)	(-2.19)	(-1.88)	(-1.95)	(-2.32)	(-1.85)
N	653	653	653	653	653	653	653	653

Table 2.18: Each month from July 1962 to November 2016 I run a firm-level cross-sectional regression of the subsequent monthly excess return on subsets of predictor variables including the idiosyncratic volatility (IVOL), capital gain overhang measure (CGO), the residuals of streaks (Streak) orthogonal to momentum, the interaction between the capital gain overhang and the idiosyncratic volatility(CGO×IVOL), the interaction between the residuals of streaks (Streak) orthogonal to momentum and the idiosyncratic measure (Streak×IVOL), the market beta (Beta), the log market capitalization (Size), the log book-to-market ratio (BTM), the momentum (MOM), the short-term reversal (REV), the illiquidity (Illiq), the maximum daily return (MAX), the minimum daily return (MIN), and the skewness (Skew). I normalize all variables in each month to make the coefficients comparable. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their Newey-West corrected *t*-statistics (in parentheses). *N* denotes the number of observations.

	Orthognal to MOM Streaks Based on Quarterly Returns	
	Raw Returns	Excess Returns
IVOL	-0.03	-0.04
	(-0.35)	(-0.47)
CGO×IVOL	0.11	0.11
	(6.32)	(6.39)
Streak×IVOL	0.08	0.06
	(5.47)	(4.38)
CGO	0.06	0.07
	(1.76)	(1.85)
Streak	0.02	0.00
	(1.42)	(0.27)
Beta	0.02	0.02
	(0.50)	(0.48)
Size	-0.19	-0.19
	(-3.35)	(-3.34)
BTM	0.21	0.21
	(3.72)	(3.74)
MOM	0.38	0.38
	(6.27)	(6.31)
REV	-0.49	-0.49
	(-10.57)	(-10.50)
MAX	0.04	0.03
	(0.84)	(0.80)
MIN	0.24	0.24
	(5.89)	(5.90)
Illiq	-0.06	-0.06
	(-2.25)	(-2.17)
Skew	-0.05	-0.05
	(-2.29)	(-2.22)
N	653	653

2.5 Conclusion

I document a relation between the prior experience and the risk-return trade-off motivated by the model of Rabin (2002). I assume that investors become more risk-seeking for stocks in which they face prior negative experience. To create a measure for prior experience, I estimate the purchase date of a stock and I calculate the number of positive experience minus the number of negative experience divided by the number of all prior experience since that date.

According to my hypotheses, I find that the negative risk-return relation is concentrated among stocks owned by investors facing prior negative experience and it is non-existing among stocks owned by investors facing prior positive experience.

These results contribute to a better understanding of the negative risk-return relation and its variation in the cross-section of stock returns. The measure of prior experience is quite similar to the capital gain overhang measure which estimates the prior loss or gain that investors face for a stock. However, these two measures capture two different concepts since the capital gain overhang measure is for the total gain or loss, while the prior experience measure is about the number of prior negative and positive changes that the investors face. I run several tests to mitigate any concern that the results of the prior experience measure would be driven by the capital gain overhang measure. I run double sorts to control for the capital gain overhang measure and I find that the results remain highly significant. I also perform several Fama-MacBeth regressions to control for the capital gain overhang measure, its interaction with risk measures, and several other known variables. I still find a highly significant relation between the prior experience and the risk-return trade-off.

Finally, I perform several test to explore the robustness of the results. I find that the results remain significant for liquid and illiquid stocks, for the January and non-January months, and for high and low sentiment time periods. I also use several alternative measures for prior experience and I always find significant results.

Prior experience and the gambler's fallacy might have interesting implications for option pricing, dynamic asset allocations or corporate finance because of its well documented effect. Exploring these fields could be a promising exercise for future research. I document a relation between the prior experience and the risk-return trade-off motivated by the model of Rabin (2002). I assume that investors become more risk-seeking for stocks in which they face prior negative experience. To create a measure for prior experience, I estimate the purchase date of a stock and I calculate the number of positive experience minus the number of negative experience divided by the number of all prior experience since that date.

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Chapter 3

Unifying Risk Taking and Time Discounting: An Experimental Study

Co-author: Bertrand Melenberg

3.1 Introduction

Almost in every economic decision we have to take into account uncertainty and delay in outcomes. Discounted expected utility as a normative theory prescribes how to make these decisions. However, several violations of the descriptive validity of discounted expected utility have been documented in both time and risk preferences and even in their interactions. Time preferences exhibit immediacy, decreasing discount rates (for example, hyperbolic discounting, Strotz, 1955; Loewenstein and Thaler, 1989; Ainslie, 1991) and subproportionality (Read and Roelofsma, 2003). At the same time, abundant experiments found several deviations from expected utility which have been formalized by rank dependent utility (Quiggin, 1982), probability weighting (Gonzalez and Wu, 1999), and cumulative prospect theory (Tversky and Kahneman, 1992). Furthermore, a series of violations have been observed about the interaction of time and risk which couldn't be explained even by cumulative prospect theory or a decreasing discount rate. First, risk tolerance increases with delay and for late uncertainty resolution (Ahlbrecht and Weber, 1996; Noussair and Wu, 2006). Second, risk tolerance is lower for frequent feedback than for one shot evaluation (Gneezy and Potters, 1997). Third, the order of discounting and taking expected values influences the evaluation of future prospects (Öncüler and Onay, 2009).

Although standard models in the field of economics have the implicit assumption that time discounting and risk taking are independent, this assumption has been challenged by empirical works. As a consequence, several studies attempt to understand the relation between time discounting and risk taking in many different economic problems.

For instance, people tolerate risk more in the distant future than in the short-term, thus, the level of risk-aversion depends on the time horizon. Specifically, Maronick (2007) finds that short-term insurance market is highly profitable for retailers because of the high risk-aversion for short-term, while insurance in general is less popular among consumers. It is also related to the economic problem why people are willing to buy warranties for home appliances at a high price (Cicchetti and Dubin, 1994) but spend too little on health insurance (Schoen, Hayes, Collins, Lippa, and Radley, 2014) or why people seem to be strongly risk-averse in the field of investing in the short-term (Mehra and Prescott, 2003), while they do not protect themselves financially against natural disasters which usually occur in the long-term (Viscusi, 2010). In asset pricing, van Binsbergen, Brandt, and Koijen (2012) find that the price of near-term risk is higher than the price of long-term risk. Motivated by this empirical evidence, Eisenbach and Schmalz (2016) suggest a theory that relaxes the restriction of constant risk-aversion across time horizons. However, this theory only focuses on the application of this single form of the relation between time discounting and risk taking.

Another form of the relation between time discounting and risk taking when people prefer uncertainty to resolve later than sooner (e.g., Lovallo and Kahneman, 2000). For instance, people tend to avoid information about the outcome of their medical tests (Ganguly and Tasoff, 2016). This contradicts the standard models of choice under risk which predict that people always prefer uncertainty to resolve as early as possible to gain information.

In addition, impatience is higher for short-term than long-term which is usually explained by the relation between risk taking and time discounting (e.g., Dasgupta and Maskin, 2005). This phenomenon is also known as hyperbolic discounting that is used to explain the decline in U.S. saving rates (Laibson, 1997) or certain human behaviors such as addictions (Vuchinich and Simpson, 1998).

Understanding the relation between time discounting and risk taking can contribute to better understanding of these economic problems.

There is a new trend in unifying time and risk preferences in a parsimonious theoretical model to explain these anomalies based on an extension of prospect theory (Halevy, 2008; Baucells and Heukamp, 2012; Epper and Fehr-Duda, 2015). In particular, we consider the model of Epper and Fehr-Duda (2015).

The aim of this paper is to investigate the descriptive validity of this model in an experiment on a random sample of the subject pool consisting of a representative sample of the Dutch population. The model of Epper and Fehr-Duda (2015) incorporates survival probabilities of delayed outcomes as an additional source of risk into prospect theory. This model provides a unified model to explain several anomalies in the field of risk and time preferences, even in their interactions. Assuming the model of Epper and Fehr-Duda (2015), the estimated probability weighting function should be the same for both risk and time preferences since the model argues that there is one unified model which describes both behaviors. In other words, subjects distort probabilities in a similar way when they face a gamble or a survival risk with delayed outcomes. Thus, our main hypothesis is that the probability weighting parameter is the same when estimated in risk or time preferences.

To test this hypothesis, an experiment was run on a random sample of the DNB Household Survey subject pool which consists of a representative sample of the Dutch population. In the first part of the experiment, subjects valued gambles to measure their risk preferences. In the second part, subjects valued the present value of future payments to measure their time preference. Estimating the model of Epper and Fehr-Duda (2015) for risk and time preferences separately, we find that the estimated parameters from the two fields are positively correlated across individuals and we can't reject the hypothesis that they are the same.

The idea that future outcomes are inherently risky goes back to the nineteenth century (Rae, 1834). Following the idea of a risky future, people could apply discounting, for instance, because of the risk of death. As a consequence of this case, discounting also reflects risk. For instance, Fuchs (1982) found a relationship between health of an individual and the individual's discounting rate. Becker and Mulligan (1997) argue that people with better health will have lower mortality and that is why these people could afford to apply lower discount rates. Furthermore, there are plenty of similarities between risk and time preferences (e.g., Prelec and Loewenstein, 1991; Keren and Roelofsma, 1995).

Our contribution is at least two-fold even though there is some indirect evidence for the relationship between time and risk preferences (Keren and Roelofsma, 1995) even for the relationship between the probability weighting function and time preferences (Epper, Fehr-Duda and Bruhin, 2011). First, Karen and Roelofsma (1995) and Epper, Fehr-Duda, and Bruhin (2011) recruited students for their experiments. We contribute to this literature by recruiting subjects from a representative sample of the Dutch population. Second, prior researches find only indirect evidence for the relationship between time and risk preference. We provide a direct evidence on the relationship between time and risk preference in a representative sample of the Dutch population by showing that the parsimonious model of Epper and Fehr-Duda can account for both time and risk preferences in a unified model.

Although there is some indirect evidence on the link between risk taking and time discounting, studies (e.g., Andreoni and Sprenger, 2012) did not find any specification which could provide a direct link. Thus, testing the model of Epper and Fehr-Duda (2015) not only might provide evidence on the link between risk taking and time discounting but it could also provide the underlying mechanism that links risk taking and time discounting.

Section 2 describes the model of Epper and Fehr-Duda (2015) and our main hypothesis. Section 3 describes our experimental method and measures of preferences. Section 4 describes the descriptive statistics of the data, while Section 5 describes our results and robustness checks. Finally, Section 6 concludes.

3.2 The Model

We follow the model of Epper and Fehr-Duda (2015) who consider binary gain prospects $P = (x_1, p, x_2)$ with payoffs $x_1 > x_2 \geq 0$, where p is the probability of the larger payoff and $(1 - p)$ is the probability of the smaller payoff. Following cumulative prospect theory (Kahneman and Tverksy, 1992), when the payoffs are played out and paid out immediately the value of such a prospect can be described as:

$$V(P) = w(p)u(x_1) + [1 - w(p)]u(x_2) \tag{3.1}$$

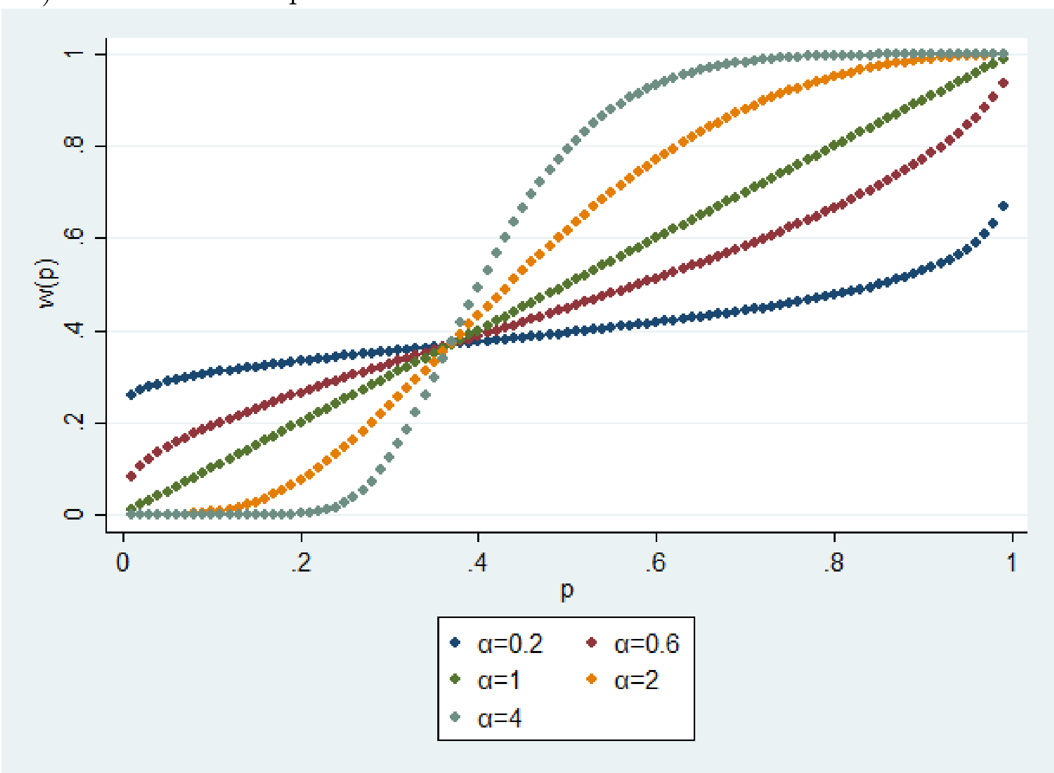
where u measures the utility of monetary outcomes x, with $u(0)$ normalized to 0, and w is the subjective probability function of p. Following the usual assumptions, u and w are both monotonically increasing and w is twice differentiable with $w(0) = 0$ and $w(1) = 1$. We apply the functional form of the subjective probability weighting $w(p) = e^{-(-\ln(p))^{\alpha}}$ of Prelec (1998).[1] When the survival probability s is equal to one we get the standard model in which risk taking and time discounting are independent from each other.

Probability weighting is a key concept in the model of Epper and Fehr-Duda. We use the functional form of the subjective probability weighting of Prelec (1998)

[1]Deriving their results, Epper and Fehr-Duda require subproportionality from the subjective probability function w. Subproportionality holds for $w(\cdot)$ if and only if $1 \geq p > q > 0$ and $1 > \lambda > 0$ imply the following inequality $\frac{w(p)}{w(q)} > \frac{w(\lambda p)}{w(\lambda q)}$. The subjective probability weighting function proposed by Prelec (1998) is globally subproportional (for more details about subjective probability weighting and subproportionality see Fehr-Duda and Epper (2012); Epper and Fehr-Duda (2015))

with an α parameter $w(p) = e^{-(-\ln(p))^{\alpha}}$. This α parameter is non-negative ($\alpha \in [0, \infty)$) and there is no probability distortion if $\alpha = 1$. In the case of $\alpha \in [0, 1)$, the decision-maker overweights small probabilities and underweights large probabilities, while in the case of $\alpha \in (1, \infty]$, the decision-maker underweights small probabilities and overweights large probabilities. To illustrate the probability weighting function, Figure 3.1 presents probability weighting functions for different α parameters. According to the literature, in most of the cases, $\alpha < 1$ which implies the overweight of small probabilities and the underweight of large probabilities.

Figure 3.1: Subjective probability weighting functions $w(p) = e^{-(-\ln(p))^{\alpha}}$ (Prelec, 1998) with different α parameters.



If the prospects are paid out in the future at time $t > 0$ then two more factors are incorporated in the model of Epper and Fehr-Duda (2015). The first factor is a discount weight $\rho(t) = e^{-\mu t}$ where $\mu \geq 0$ expresses a constant rate for delaying a monetary payoff with time length t. The value of a prospect at present (indicated by the subscript 0) when the payoffs are paid out in the future time t is

$$V_0(P) = [w(p)u(x_1) + [1 - w(p)]u(x_2)]\rho(t) \tag{3.2}$$

Following the model of Epper and Fehr-Duda, the second factor is the survival probability. Let $0 < s \leq 1$ denote the probability of survival per period, which we assume to be constant. This is the subject's perceived probability that she will actually receive the promised payoff by the end of the time period. Therefore, the two-outcome prospect is perceived as a three-outcome prospect by the decision-maker, described by $\overline{P} = (x_1, ps^t; x_2, (1-p)s^t; 0)$, with a probability of ps^t to receive the payoff of x_1, a probability of $(1-p)s^t$ to receive the payoff of x_2, and the zero outcome is the payoff when "something goes wrong" with a probability of $1 - s^t$.[2]

Now, the value of the prospect at $t = 0$, when the payoffs are paid out in the future at time t, using $u(0) = 0$, is

$$\begin{aligned} V_0(\overline{P}) &= (w(ps^t)u(x_1) + [w(ps^t + (1-p)s^t) - w(ps^t)]u(x_2))\rho(t) \\ &= (w(ps^t)u(x_1) + [w(s^t) - w(ps^t)]u(x_2))\rho(t) \\ &= \left(\frac{w(ps^t)}{w(s^t)}[u(x_1) - u(x_2)] + u(x_2)\right)w(s^t)\rho(t) \end{aligned} \tag{3.3}$$

This model provides a description of risk, time preferences, and their interaction. To investigate the descriptive validity of the model, we separately estimate it for

[2]The model can be generalized to $n > 2$ outcomes (Epper and Ferh-Duda, 2015).

time and risk preferences. According to the model, we should get similar parameter estimates for $w(p)$ in the time and risk domains. The subjective probability weighting function is postulated to be $w(p) = e^{-(-ln(p))^{\alpha}}$ (Prelec, 1998), where α is the probability weighting parameter and the utility function is a power utility function $u(x) = x^r$, where $r > 0$ is the risk attitude parameter (see the discussion by Wakker, 2008 p. 1335). In this specification, $1 > r > 0$ means a risk-averse attitude, $r = 1$ refers to a risk-neutral attitude, and $r > 1$ describes a risk-seeking attitude.

To eliminate the effect of time preference, we set $t = 0$. Thus, the payoffs are paid out instantaneously and the value of the prospect simplifies to equation (1). According to the model of Epper and Fehr-Duda (2015), the certainty equivalents for different gambles can be described as follows, using $x_2 = 0$,

$$u(CE_{i,j}) = w(p_j)u(x_1) \tag{3.4}$$

where $CE_{i,j}$ is the certainty equivalent value provided by the individual i for the gamble j, $\alpha_{risk,i}$ is the probability weighting parameter for individual i, and r_i is the utility curvature for individual i. Substituting the functional forms for the probability weighting, and the utility, we get the following specification for the certainty equivalents in the domain of risk

$$(CE_{i,j})^{r_i} = e^{-(-\ln(p_j))^{\alpha_{risk,i}}} x_1^{r_i} \tag{3.5}$$

or

$$\frac{CE_{i,j}}{x_1} = e^{-(1/r_i)(-\ln(p_j))^{\alpha_{risk,i}}} \tag{3.6}$$

This specification might contain errors which lead to the following econometric specification, where $\epsilon_{i,j,risk}$ is the error term for individual i in gamble j which is assumed to be independent and identically distributed with zero mean:

$$\frac{CE_{i,j}}{x_1} = e^{-(1/r_i)(-\ln(p_j))^{\alpha_{risk,i}}} + \epsilon_{i,j,risk} \tag{3.7}$$

To eliminate the effect of risk, we set $p = 1$. In this case, the payoffs are delayed sure amounts and their value is

$$V_0(\overline{P}) = u(x_1)w(s^t)\rho(t) \tag{3.8}$$

According to Epper and Fehr-Duda (2015), assuming $\mu = 0$ doesn't affect any of their conclusions about the existence of the link between time and risk preference via the probability weighting and decreasing impatience (Epper and Fehr-Duda, 2015, page 11). We will use the equation with setting $\mu = 0$ to simplify the estimation and reducing the number of parameters. Although it doesn't affect the existence of the link (Epper and Fehr-Duda, 2015) it might affect our parameter estimates in the time preference. This simplification might add additional noise to our estimate but the link seems to be strong enough even in this approach. Estimating the model for time preference, we also apply Prelec's subjective probability weighting function (1998) and the power utility function which yields the following equation

$$CE_{i,t} = [e^{-(-\ln(s_i^t))^{\alpha_{i,time}}}(x_1)^{r_i}]^{(1/r_i)}, \tag{3.9}$$

or

$$CE_{i,t}/x_1 = e^{(-(-(1/r_i)^{1/\alpha_{i,time}} \times t \times \ln(s))^{\alpha_{i,time}})} = e^{(-(-t \times \ln(s^{1/r_i}{}^{1/\alpha_{i,time}}))^{\alpha_{i,time}})} \tag{3.10}$$

In this equation we can only estimate $s^{(1/r)^{(1/\alpha)}}$ and α; we can't estimate s and r separately. Thus, we define $s' = s^{(1/r)^{(1/\alpha)}}$ and we use the following non-linear regression model to estimate the parameters by minimizing the sum of squared errors, where the error term $\epsilon_{i,t,time}$ is assumed to be independent and identically distributed with zero mean:[3]

$$CE_{i,t}/x_1 = e^{(-(-\ln(s_i')^t)^{\alpha_{i,time}}} + \epsilon_{i,t,time} \tag{3.11}$$

Under the model assumptions, $\alpha_{risk} = \alpha_{time}$ is supposed to hold, since in a unified model in equation (5) both risk from a gamble and risk from the uncertainty of the future are supposed to be distorted in the same way. We test this hypothesis and its robustness in section 5:

Hypothesis: $\alpha_{risk} = \alpha_{time}$

[3]Using the utility curvature from the risk preference tasks, we can also estimate s.

3.3 Experimental Design

The experiment took place as part of the DNB Household online survey (DHS) which is comparable to PSID in the USA. This subject pool, administered by CenterData (Tilburg University), consists of a representative sample of the Dutch population. We analyzed the answers of 361 subjects recruited as a random subsample of the DHS. The number of subjects were determined based on the available budget of €7500 for setting up the experiment plus the payment for the subjects. The experiment consisted of certainty equivalents elicitation for risky gambles and certainty equivalents elicitation for delayed payments. We used the same choice menu format with 16 list items for eliciting certainty equivalents for risk and time preferences to minimize the cognitive efforts to understand the tasks. The subjects were provided several examples and details about the tasks in the introductions to help them to get familiar with the questions (see the appendix for the general instructions). Each type of questions was randomized and each question within each type was also randomized to control for a potential ordering effect.

Each subject was paid based on his choice in a randomly selected question. Subjects received their payment immediately for risky gambles and all delayed payments were scheduled and paid by bank transfer from the account of CenterData. All subjects were invited via Internet and they could fill out the survey at their own pace. The median length of filling out the whole survey was 12 minutes 47 seconds and the average payment was €9.83. We didn't provide any "show-up" fee for the subjects. However, besides the payment of the experiment, the members of the subject pool are remunerated for the participation in the subject pool.

3.3.1 Elicitation of Certainty Equivalents for Risk Preference

Subjects were presented a 16 rows menu where each row presented a choice between the same binary gamble $L = (x_1, p; x_2)$ and a sure payment starting from the high payment $x_1 = €15$ to the low payment $x_2 = 0$ with €1 decrements. Subjects had to report in which row starting from the top (high payment) they preferred the gamble first. The certainty equivalent was calculated as the arithmetic mean of the two values around the respondent's indifference point. In each gamble the payoffs were the same (x_1=€15, x_2=€0) while p varies from 90% to 10% by 20% decrements. The order of the five questions were counterbalanced in the experiment.

3.3.2 Elicitation of Present Values for Time Preference

Subjects were presented the same 16 rows menu where each row presented a choice between the same future payment and an instant amount starting from the high payment (x_1=€15) to the low payment (x_2=€0) with €1 decrements (see the appendix for examples of the elicitation method). Subjects had to report again in which row starting from the top (high payment) they preferred the future payment first. The present value for the delayed payoff is the arithmetic mean of the two values around the subject's indifference point. There were only two tasks where the subjects had to report their indifference point for €15 with a delay of 6 and 12 months. In any experiment involving time preference and delayed payoffs, there could be a concern about the uncertainty of getting payment. However, CenterData has frequent interactions with their members in the subjects pool which mitigates the concern that any of the members would be doubtful about the reliability of what has been told to them. In general, there is another concern in time preference when there is a transaction cost for the future payment. To mitigate this concern, we applied scheduled bank transfers for both immediate payments and delayed payments.

3.4 Summary Statistics

One of the big advantages of the subject pool of DHS is the large variation and the detailed information about the subjects in the data. There are subjects from the age of 16 to the age of 88. There is also a great variation in the monthly net income of the subjects. Furthermore, there is a great variation in education.

Table 3.1: This table reports the averages, medians, standard deviations (Sd), minimums (Min), maximums (Max), and the available number of observations (N) of the demographic variables. The variable of Female is equal to 1 if the subject is female, the monthly net income is denoted in euros, and the variable of Higher education is equal to 1 if the subject holds a college or university degree.

	Average	*Median*	*Sd*	*Min*	*Max*	*N*
Age	57.22	59.5	16.31	16	88	361
Female	0.47	0	0.50	0	1	361
Monthly net income	1653	1700	998	0	6250	356
Higher education	0.36	0	0.48	0	1	360

Table 3.1 reports the summary statistics for various demographic variables. Subjects could refuse to answer any of these questions. Some data come from the experiment and some come from the surveys of DHS. Based on the subjects' ID, we can link their answers in the experiment to their answers in the regular surveys of DHS. All subjects reported their age in categories from the category of 15-24 to 65+ in the experiment. We also have the year of birth for most of the subjects in the DHS data. We use the year of birth when available (287 subjects out of

361) and we assign the arithmetic mean of the interval of the category for each subject otherwise. We assigned 73 to those subjects[4] who reported the category of 65+ without exact year of birth date. Subjects also reported their monthly net income which varied from 0 to €6250 (the average gross income was €2152 in the Netherlands in 2017 according to the Netherlands Bureau for Economic Policy Analysis[5]. However, five subjects refused to answer this question. The level of education from primary school to university was also reported by the subjects. In Table 3.1, we report the dummy variable of education whether the subject has a degree from higher education. 36% of the subjects have a diploma from higher education and one subject refused to answer this question.

This data was generated by sending 573 invitations to participate in the experiment and 361 subjects completed the experiment. To investigate how our sample resembles the parent sample, Table 3.2 reports the average values for our sample and the rest of the sample and it also reports the p values for their differences. Some of the variables and their number of observations are different from the rest of the study because some of the information is only available for those who participated in the experiment. Thus, we need to use those variables and observations that are available in the original representative sample. Specifically, we need to use the monthly household net income scaled from 1 to 6 instead of the logarithm of the net income because the accurate personal net income information is only available for those who participated in the experiment and some of the answers are not available for some of the subjects. According to Table 3.2, there is no difference between our sample and the rest of the sample for the monthly household income

[4] 73 is the average age for those who are older than 65 with available year of birth.
[5] https://www.cpb.nl/en

and the gender ratio at the conventional 5% level. However, our sample contains older and more educated subjects. To mitigate any concern that it might have an impact on our results, we also control for these demographic variables in our analyses.

Table 3.2: This table reports the averages, standard deviations (Sd) of the demographic variables, and the number of observations available for both our sample and for the rest of the original database of the representative sample of the Dutch population. It also reports the p value for the difference between the two samples based on the χ^2 tests for the dummy variables and based on the t-statistics of the non-dummy variables. The variable of Female is equal to 1 if the subject is female, the monthly household net income is scaled from 1 to 6, and the variable of Higher education is equal to 1 if the subject holds a college or university degree.

	Our Sample			Rest of the Sample			
	Average	*Sd*	*N*	*Average*	*Sd*	*N*	p
Age	57.36	0.87	352	51.11	0.29	3790	0.00
Female	0.46	0.03	353	0.51	0.01	4780	0.09
Monthly net income	4.04	0.07	308	3.96	0.02	2092	0.17
Higher education	0.36	0.03	352	0.26	0.01	4750	0.00

Subjects could also report how difficult or interesting they found the survey. Table 3.3 reports the answers of 334 out of the 361 subjects who gave their answers for these questions. Although 23% of the subjects answered that it was very difficult to answer the questions there were less than 10% of the subjects who didn't find the questions clear at all. In most of the cases, the subjects find the tasks interesting and enjoyable.

3.5 Results

In this section, we test our main hypothesis that estimating the model based on risky choices and estimating the model based on intertemporal choices provide the

Table 3.3: This table reports the summary statistics of the reflections on the experiment. These questions shows how difficult, clear, and interesting the experiment was for the subjects.

	1 Not at all	2	3	4	5 Very much	Avg
Did you find it difficult to answer?	19%	17%	21%	18%	25%	3.12
Did you find the questions clear?	10%	15%	26%	26%	21%	3.31
Did it make you think a lot?	20%	16%	30%	20%	14%	2.93
Did you find the topic interesting?	13%	9%	26%	31%	22%	3.40
Did you find it enjoyable?	9%	6%	31%	29%	25%	3.57

same α parameter according to the model of Epper and Fehr-Duda (2015). We use several approaches to test our main hypothesis.

We estimate the parameters of the model for each individual and we test our hypothesis that $\alpha_{time} = \alpha_{risk}$ across individuals. In this case, we need to exclude few subjects from these analyses. For instance, there is no estimate for α_{time} if a subject asked for no compensation for the delays. We perform several additional tests to investigate whether excluding these subjects yields a significantly different sample. We find that the characteristics of the subjects do not differ between the excluded subjects and the rest of the sample which indicates that the remaining sample can also be considered as a representative sample of the Dutch population. To test that $\alpha_{time} = \alpha_{risk}$, we perform both OLS and IV regressions including controls for several subjects' characteristics. We perform IV regressions to control for the potential bias arising from the problem that both α_{time} and α_{risk} are not observed but estimated. To mitigate any concern that the excluded observations can have an effect on our results or that few subject's answers can drive our results, we also estimate the parameters of the model assuming that the parameters of the model is the same for each individual. In this case, we do not exclude any subject and our estimates for α_{time} and α_{risk} depend less on an extreme answer of a subject.

Using both non-linear least squares method and GMM to estimate the parameters, assuming that the parameters of the model is the same for each individual, also support our hypothesis.

3.5.1 Descriptive Analysis

In this section, we estimate the parameters of the model for each individual using equation (3.7) and (3.11). There are two special cases using this approach. The first case is when the estimated $s' = 1$. In this case, the α_{time} parameter is not uniquely identified in the model. We find 79 out 361 subjects with estimates $s' = 1$ and we exclude them. Second, we exclude subjects with estimates $r = 0$ from our sample (16 out of 361 subjects). The estimate of r converges to zero only if subjects provided a certainty equivalent of 15 for each task in the risk preferences. We also exclude subjects without information on their income (5 out of 361) or on their educational level (1 out of 361).

First, we investigate the possible characteristics of the subjects which could predict whether he or she is excluded because of an estimated parameter of $s' = 1$ or $r = 0$. Second, we present summary statistics of the subjects after exclusion. Third, we present the results of our main question on the relationship between the estimated α parameters.

Table 3.4 reports the results of the logistic regression to predict whether a subject is more or less likely to have $s' = 1$, $r = 0$, or any of them based on age, gender, income, and level of education. Using the sample of the subjects whose estimated parameters are $s' < 1$ and $r > 0$ might lead to a sub-sample which is not a random sample from the representative sample of the Dutch population anymore.

However, according to Table 3.4, none of the demographic variables is a significant predictor of the exclusion of the subjects. It suggests that the excluded subjects are a random sub-sample of the subjects and the sample of the remaining subjects is still a random sample of the representative sample of the Dutch population.

Table 3.4: This table reports the results of the logistic regressions of a dummy variable of $s' = 1$ or $r = 0$, and a dummy variable of $s' = 1$ or $r = 0$ on several demographic variables, standard errors are in parentheses. *** p<0.01, ** p<0.05

	$s' = 1$	$r = 0$	$s' = 1$ or $r = 0$
Age	1.031	0.962	1.045
	(0.059)	(0.092)	(0.059)
Age^2	1.000	1.000	1.000
	(0.001)	(0.001)	(0.001)
$Female$	0.819	0.459	0.781
	(0.232)	(0.284)	(0.219)
$Log-Income$	1.361	0.840	1.286
	(0.457)	(0.566)	(0.416)
$Log-Income^2$	0.976	1.013	0.979
	(0.040)	(0.089)	(0.039)
$Higher-Education$	1.258	0.392	1.188
	(0.358)	(0.268)	(0.335)
$Constant$	0.055	0.237	0.058
	(0.087)	(0.568)	(0.089)
$Observations$	356	356	356
$Parameters$	7	7	7
$Prob > \chi^2$	0.47	0.49	0.62

Table 3.5 presents the summary statistics for the estimated parameters. There are several striking patterns in the distribution of the parameters. First, the parameter of α_{risk} is zero for a large portion of the subjects. It suggests that there were a large portion of subjects who did not understand the questions correctly or they apply extreme probability weighting. Second, there are large standard deviations for α_{risk} and α_{time}. There are also large differences between the mean

and the median suggesting that the distributions of these variables are positively skewed with possibly some outliers. An extremely high α_{risk} parameter indicates that the subject considers the higher probabilities almost constantly close to 1, while the subject considers the small probabilities almost constantly close to zero. The average α_{risk} is 0.68 which is close to what the literature documents (0.435 Donkers, Melenberg, and Van Soest, 2001; 0.48 Wu and Gonzalez, 1996; 0.589 Bleichrodt and Pinto, 2000; 0.505 Epper, Fehr-Duda, and Bruhin, 2011; 0.63 Abdellaoui, Diecidue, and Öncüler, 2011; 0.879 Jullien and Salanie, 2000), however the standard deviation is much larger for the α_{risk} estimates in our sample. This might be the consequence of the few questions that we use for estimation or of the large variety of the subjects which might increase the noise in the data. Third, the distribution of s' is quite extreme with fat tails. A large number of observations of s' is close[6] to one indicating that most of the subjects expect to receive the promised amount of money. However, more than 5% of the estimates of s' are close to zero. Fourth, the average utility curvature parameter is larger than one which is hard to interpret in the presence of probability weighting. Other scholars find similar utility curvature parameter in the presence of probability weighting (e.g., Abdellaoui, Diecidue, and Öncüler, 2011). Finally, Figure 3.2 displays the histogram of the difference of α_{risk} and α_{time} within subjects. Most of the subjects have a small difference between the two estimates; however, there are several subjects who have very different values for these parameters. In addition to our descriptive statistics, we find a positive and significant correlation for both Pearson (0.26) and Spearman (0.14) correlation between the estimated α_{risk} and α_{time}

[6]We present 1.00 (0.00) when it was rounded to 1 (0) and we display 1 (0) when the value was exactly 1 (0).

parameters.

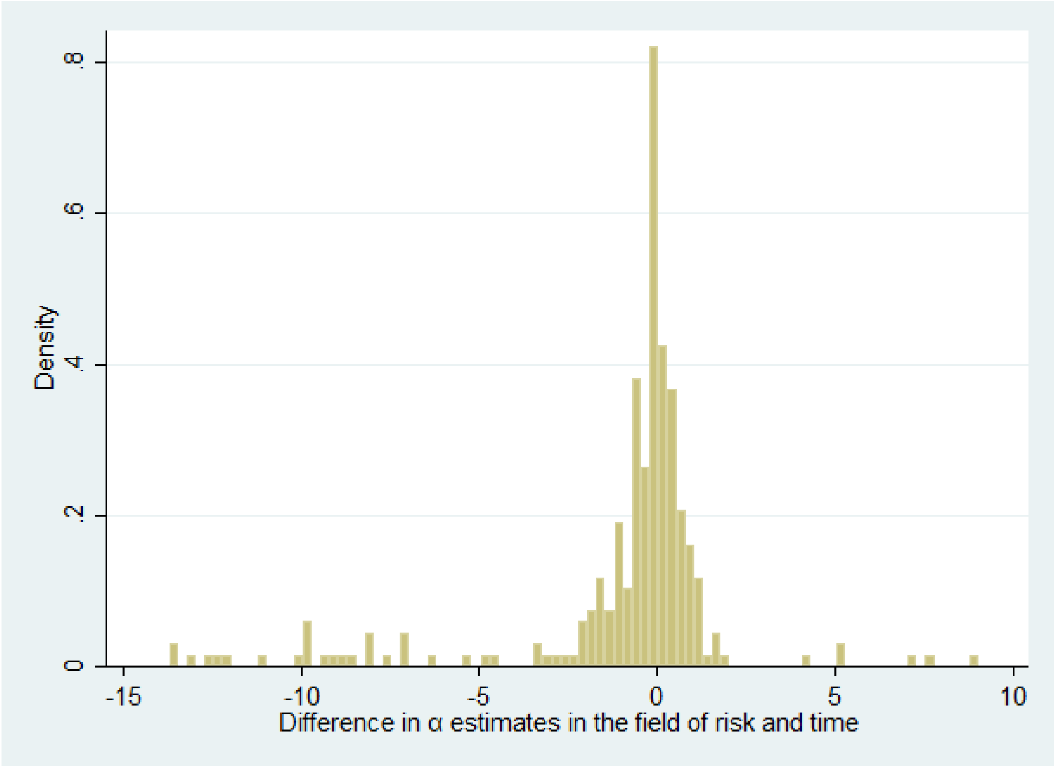
Table 3.5: This table reports the 5th, 25th, 50th, 75th, 95th percentiles and the mean, the standard deviation, the maximum, the minimum, and the number of observations of the estimated parameters of α_{risk}, α_{time}, $1/r$, and s'.

	α_{risk}	$1/r$	s'	α_{time}
5%	0	0.16	0.00	0.04
25%	0	0.36	0.63	0.13
50%	0.31	0.55	0.88	0.37
75%	0.78	0.79	1.00	1.40
95%	1.74	1.82	1.00	10.58
Mean	0.67	0.71	0.75	1.63
Sd	1.61	0.66	0.33	3.16
Max	20.85	3.41	1.00	14.51
Min	0	0.00	0.00	0
N	273	273	273	273

3.5.2 Relationship between Risk and Time Preferences

To address the main research question of the paper, we investigate the link between α_{time} and α_{risk} using instrumental variable (IV) and OLS regressions. Table 3.6 reports the regression of α_{time} on α_{risk} and a set of control variables such as gender, age, logarithm of the net monthly income, and the dummy of higher education. Table 3.7 reports the regression of α_{risk} on α_{time} and a set of several control variables. We use instrumental variable regression to control for the possible bias that might occur because our α_{risk} and α_{time} parameters are not observed but estimated. We use the answer for the gamble in which the better outcome happens with probability of 70% as an instrumental variable for α_{risk} (the correlation of the answer for that and estimated α_{risk} is 0.31) when α_{risk} is one of the independent variables. We use the present value answer of delayed payoff with 6 months as

Figure 3.2: Distribution of the difference of α_{risk} and α_{time} (i.e. $\alpha_{risk} - \alpha_{time}$)



an instrumental variable for α_{time} (correlation is 0.33) when α_{time} is one of the independent variables.

According to the first column in Table 3.6, there is a significant positive relationship between α_{risk} and α_{time} and the coefficient of α_{risk} is close to 1 as the theory predicts ($\alpha_{risk} = 1, \chi^2 = 0.11$, $p = 0.74$).

One might argue that these results are driven by those subjects who didn't understand or didn't enjoy the tasks. To mitigate this concern, we include the answers for the five questions about the clarity of the tasks as dummy variables presented in column 2 in Table 3.6. These dummy variables capture the degree to which subjects perceived these tasks difficult, unclear, and boring. The coefficient of α_{risk} remains significant and close to 1 (the coefficient of α_{risk} is not different

Table 3.6: This table reports estimation results for the IV and OLS regressions of α_{time} on α_{risk} and several control variables. It presents the link between α_{time} and α_{risk} even after controlling for a set of control variables. IV regressions account for the fact that α_{risk} is an estimated observation. Standard errors are in parentheses. *** p<0.01, ** p<0.05

	IV			OLS		
	α_{time}	α_{time}	α_{time}	α_{time}	α_{time}	α_{time}
α_{risk}	1.13***	1.20**	1.26**	0.54***	0.58***	0.55**
	(0.39)	(0.51)	(0.54)	(0.12)	(0.21)	(0.21)
$Female$	-0.69	-0.65	-0.52	-0.62	-0.77	-0.71
	(0.40)	(0.42)	(0.46)	(0.38)	(0.42)	(0.45)
Age	0.01	0.01	-0.04	0.01	0.01	0.01
	(0.01)	(0.01)	(0.09)	(0.01)	(0.01)	(0.08)
Age^2	-	-	0.00	-	-	-0.00
	-	-	(0.00)	-	-	(0.00)
$Log-Income$	-0.05	-0.05	-0.46	-0.05	-0.03	-0.32
	(0.09)	(0.09)	(0.49)	(0.09)	(0.09)	(0.51)
$Log-Income^2$	-	-	0.05	-	-	0.04
	-	-	(0.06)	-	-	(0.07)
$Higher-Education$	-0.82	-0.85*	-	-0.58	-0.70	-
	(0.45)	(0.44)	-	(0.41)	(0.44)	-
$Constant$	1.10	0.34	1.53	1.24	0.98	1.26
	(0.90)	(0.24)	(0.66)	(0.86)	(1.40)	(2.40)
$Clarity$	No	Yes	Yes	No	Yes	Yes
$Education-Levels$	No	No	Yes	No	No	Yes
$Observations$	273	249	249	273	249	249
$Parameters$	6	26	32	6	26	32
R^2	0.01	0.12	0.13	0.09	0.16	0.17

from one: $\chi^2 = 0.16$, $p = 0.69$). This relationship remains similar even if we extend the control variables beyond the questions about the clarity of the tasks with a more detailed control for education (including dummy variable for primary, two different types of secondary school, college, and university level) and the squared value of age and the logarithm of the net income. In column 3 in Table 3.6, we present the regression where all control variables are included. The coefficient of α_{risk} is still significant, positive, and close to 1 (the coefficient of α_{risk} is not different from one: $\chi^2 = 0.24$, $p = 0.62$). Table 3.6 also reports the coefficients of the OLS regressions to compare the results with instrumental variable coefficients. There is also a positive and significant coefficient on α_{risk} as in the instrumental variable case. However, it can be rejected at the 5% level that it is equal to 1. We also document a much lower standard error for the α_{risk} coefficient in each specification for the OLS regressions. These differences between the standard errors of the IV and OLS regressions suggest that it is important to control for the potential bias when we use α_{risk} as an independent variable.

We also perform IV and OLS regressions of α_{risk} on α_{time} including several control variables to investigate the robustness of our previous results. We use the answer for the gamble which has 70% probability for the better outcome for α_{risk} as an instrumental variable in Table 5 and the present value for the 6 months delayed payoff for α_{time} as an instrumental variable in Table 6. We report the results in Table 3.7. There is a positive and significant relationship between α_{risk} and α_{time} at a 5% level in each case. However, we can reject the hypothesis that the coefficient is equal to 1 in each specification. In this case, the IV and OLS regressions provide similar α_{risk} coefficients with similar standard errors. α_{time} is a noisier estimate [7] probably because it is also based on less observations than α_{risk}. This might be the reason why the coefficients of α_{time} in Table 3.7 are smaller compared to the coefficients of α_{risk} in Table 3.6 and not close to one. Another interesting difference between the results of Table 3.6 and Table 3.7 is that education and age become significant predictors of α_{risk} in Table 3.7, while none of the demographic variables could predict α_{time} in Table 3.6. It suggests that α_{risk} can capture most of the variation in α_{time} which makes all the other variable insignificant, while α_{time} can not capture most of the variation of α_{risk}

[7] $\sigma^2_{\alpha_{time}} = 9.98$ and $\sigma^2_{\alpha_{risk}} = 2.59$, we can reject that $\sigma^2_{\alpha_{risk}} = \sigma^2_{\alpha_{time}}$, $f = 0.259$, $p = 0.000$.

which helps other variables to predict partly the variation of α_{risk}. This might again come from that α_{time} variable is a noisier estimate than α_{risk}. All these results suggest that IV regressions in Table 3.6 provide the best specification to test our main hypothesis.[8]

These results suggest that assuming a survival probability and probability weighting can provide a direct link between risk taking and time discounting. First of all, these results provide additional novel evidence on the existence of a link between risk taking and time discounting. Second, it also provides a mechanism for such a link. Thus, it also suggests that models that assume independence between risk taking and time discounting have to be reconsidered.

3.5.3 Systematic Deviation from the Model

In this section, we investigate whether any characteristic of the subjects can explain the difference between the two alphas in Table 3.8. Regressing the difference of α_{risk} and α_{time} on several characteristics of the subjects, we find that there is no systematic predictor for the difference. We also regress the absolute value of the difference of α_{risk} and α_{time} on several characteristics of the subjects to investigate whether some of the characteristics predict the deviation from the model. One could argue that our results are driven by certain type of subjects. For instance, less educated people provide noisier answers which could make α_{time} and α_{risk} more

[8]There is a lot of noise in both the answers of the experiment and the parameter estimates according to the summary statistics. It raises the concern that our main result might have been influenced by the noise. To explore this concern, we run a placebo test. Specifically, we generate random answers for the time questions for each subject and we run the same IV regression as in the first column of Table 6. We repeat this exercise 1000 times and we find that a positive relationship between α_{risk} and α_{time} in 5.1% of the cases for the 5% significance level and in 1.9% of the cases for the 2.5% significance level. It suggests that noise does not help to get significant results in these tests.

Table 3.7: This table reports estimation results for the IV and OLS regressions of α_{risk} on α_{time} and several control variables. It presents the link between α_{time} and α_{risk} even after controlling for a set of control variables. IV regressions account for the fact that α_{time} is an estimated observation. Standard errors are in parentheses. *** p<0.01, ** p<0.05

	IV			OLS		
	α_{risk}	α_{risk}	α_{risk}	α_{risk}	α_{risk}	α_{risk}
α_{time}	0.19***	0.13**	0.13***	0.14***	0.06***	0.05***
	(0.07)	(0.05)	(0.05)	(0.03)	(0.02)	(0.02)
$Female$	0.22	-0.08	-0.16	0.19	-0.13	-0.23
	(0.20)	(0.14)	(0.14)	(0.19)	(0.14)	(0.14)
Age	-0.00	-0.01	0.06**	0.00	-0.01	0.07***
	(-0.01)	(0.00)	(0.02)	(0.01)	(0.00)	(0.03)
Age^2	-	-		-	-	-0.00***
	-	-	(0.00)	-	-	(0.00)
$Log-Income$	0.02	0.03	0.22	0.02	0.03	0.21
	(0.04)	(0.03)	(0.15)	(0.04)	(0.03)	(0.16)
$Log-Income^2$	-	-	-0.03	-	-	-0.02
	-	-	(0.02)	-	-	(0.02)
$Higher-Education$	0.49**	0.31**	-	0.47**	0.27	-
	(0.21)	(0.14)	-	(0.21)	(0.14)	-
$Constant$	-0.03	0.82	-0.51	0.04	0.92**	-0.44
	(0.45)	(0.43)	(0.73)	(0.44)	(0.44)	(0.75)
$Clarity$	No	Yes	Yes	No	Yes	Yes
$Education-Levels$	No	No	Yes	No	No	Yes
$Observations$	273	249	249	273	249	249
$Parameters$	6	26	32	6	26	32
R^2	0.08	0.10	0.13	0.09	0.14	0.18

similar or less similar because of random answers. We find no evidence that any of these characteristics would predict the deviation. Similarly, we find no evidence that any of these characteristics would predict the estimated survival probability (s') or the risk aversion parameter.

Surprisingly, as Table 3.9 shows, there is no significant Spearman correlation between any of the questions about the clarity of the tasks and the difference between α_{risk} and α_{time} or the absolute value of the difference of α_{risk} and α_{time} which suggests that our results are not affected by the level of clarity of the tasks

Table 3.8: This table reports the OLS estimation results for the regressions of the difference, the absolute value of the difference of α_{risk} and α_{time}, s', and $1/r$ on a set of demographic characteristics. It presents that there is no relation between these estimated parameters and the demographic characteristics of the subjects. Standard errors are in parentheses. *** p<0.01, ** p<0.05

	α_{risk}-α_{time}	$\lvert\alpha_{risk}$-$\alpha_{time}\rvert$	s'	$1/r$
Gender	0.67	-0.52	-0.07	0.06
	(0.39)	(0.36)	(0.04)	(0.08)
Age	-0.01	0.01	0.00	-0.00
	(0.01)	(0.01)	(0.00)	(0.00)
$Log - Income$	0.05	-0.04	-0.00	-0.00
	(0.09)	(0.08)	(0.01)	(0.02)
$Higher - Education$	0.77	-0.45	-0.01	0.04
	(0.41)	(0.38)	(0.04)	(0.09)
Constant	-1.12	1.45	0.80***	0.86***
	(0.88)	(0.81)	(0.09)	(0.19)
Observations	273	273	273	273
Parameters	5	5	5	5
R^2	0.03	0.02	0.01	0.01

for a subject.

3.5.4 Robustness

In this section, we test the hypothesis $\alpha_{risk} = \alpha_{time}$ assuming that there is one value for each parameter that fits all individuals' preferences and only noise in the model generates differences across the individuals' responses. We estimate this model both using non-linear least squares and Generalized Method of Moments (GMM). We do not exclude any observation in this specification since this method can also handle special cases such as $s' = 1$ (excluding these observations leads to the same implications). In the case of non-linear least squares, we estimate the following equation $\frac{CE_{i,j,t}}{x_1} = e^{(-(-\ln(p_j(s_i')^t))^{\alpha_{risk}+\alpha_{change}D}} + \epsilon_{i,j,t}$, where D is equal to

Table 3.9: This table reports the Spearman correlations between the question about the tasks and the difference and the absolute value of the difference of α_{risk} and α_{time}. It presents that there is no relationship between those have large difference between α_{risk} and α_{time} and those who did not understand the tasks or did not like these type of tasks. *** p<0.01, ** p<0.05

	α_{risk}-α_{time}	$\lvert\alpha_{risk}$-$\alpha_{time}\rvert$
Did you find it difficult to answer?	-0.02	0.04
Did you find the questions clear?	-0.00	-0.02
Did it make you think a lot?	0.05	0.01
Did you find the topic interesting?	-0.03	0.05
Did you find it enjoyable?	0.01	0.08

1 in the case of an answer for an intertemporal choice and zero otherwise, and $\epsilon_{i,j,t}$ is the error term which is assumed to be independent and identically distributed with zero mean, variances of σ^2.

Table 3.10: This table reports the parameter estimates assuming that each parameter has the same value for each individual using non-linear least square method based on the following equation $\frac{CE_{i,j,t}}{x_1} = e^{(-(-\ln(p_j(s_i')^t))^{\alpha_{risk}+\alpha_{change}D}} + \epsilon_{i,j,t}$, where D is equal to 1 in the case of intertemporal choice and zero otherwise.

	Coefficient	Standard errors
α_{risk}	0.26	0.02
α_{change}	-0.07	0.13
s'	0.96	0.08
$1/r$	0.52	0.01

Table 3.10 reports the estimation results for the joint estimates for α_{risk} and α_{time} (α_{time} is the sum of α_{risk} and α_{change}). First of all, α_{risk} and α_{time} indicate strong probability weighting. Second, α_{risk} and α_{time} are close to each other since the deviation is not significant ($p = 0.61$). We can't reject the hypothesis that they are the same at any conventional level. Thus, this approach also supports our main hypothesis. The value of 0.52 for $1/r$ is similar to the average value of the

individual estimates. Finally, the estimated survival probability after adjusting for the utility curvature and the probability distortion $s = 0.975$ which is higher than the median or average individual estimates.

To explore the parameter estimates, we also estimate α assuming that all individuals using the same parameters and the same $\alpha = \alpha_{risk} = \alpha_{time}$ in both risk and time domain, where $\epsilon_{i,j,t}$ is the error term which is assumed to be independent, identical, and normally distributed with zero mean and σ^2 variance:

$$\frac{CE_{i,j,t}}{x_1} = e^{-(1/r_i)(-\ln(p_j \times s^t))^\alpha} + \epsilon_{i,j,t} \tag{3.12}$$

Table 3.11 reports the estimation results of equation (3.12). The joint estimate for the probability distortion α is between the estimate for the probability distortion risk and time. The utility curvature is also almost the same in the joint estimates as in the previous one, however, the survival probability is much lower.

Table 3.11: This table reports the parameter estimates assuming that each parameter has the same value for each individual and that one α can describe both fields of risk and time using non-linear least square methods based on the following equation: $\frac{CE_{i,j,t}}{x_1} = e^{-(1/r_i)(-\ln(p_j \times s^t))^\alpha} + \epsilon_{i,j,t}$

	coefficient	standard errors
α	0.25	0.02
s	0.9167	0.02
$1/r$	0.52	0.01

In the next two tables, we report similar estimations to the non-linear least squares method, but using GMM. In this case, we use seven moment conditions, where each moment condition is based on a certainty equivalent using the risk or time preference questions. Moment condition j corresponds to the j^{th} certainty equivalent: $(E(\frac{CE_{i,j}}{x_1} - e^{-(1/r_i)(-\ln(p_j))^{\alpha_{risk}}}) = 0$ for $j = 1 \ldots 5$ and $E(\frac{CE_{i,t,j}}{x_1} - e^{(-(-\ln((s_i')^t))^{\alpha_{time}}}) = 0)$ for $j = 6, 7$.

Table 3.12 reports the estimation results without imposing $\alpha_{risk} = \alpha_{time}$. First of all, α_{risk} and α_{time} are small and similar to the estimates in the non-linear least squares method. Second, α_{risk} and α_{time} are close to each other in this case as well and we can not reject the hypothesis that they are the same ($p = 0.64$). The utility curvature and the survival probability estimates are not significantly different from the estimates in the non-linear least squares method.

Table 3.12: This table reports the parameter estimates assuming that each parameter has the same value for each individual using the general method of moments with the following two moment conditions: $E(\frac{CE_{i,j}}{x_1} - e^{-(1/r_i)(-\ln(p_j))^{\alpha_{risk}}}) = 0$ and $E(\frac{CE_{i,t}}{x_1} - e^{(-(-\ln((s_i')^t))^{\alpha_{time}}}) = 0$. Hansen J test: 24.09 ($p = 0.00$)

	coefficient	standard errors
α_{risk}	0.22	0.02
α_{time}	0.19	0.07
s'	0.9988	0.00
$1/r$	0.51	0.02

Table 3.12 reports the results with GMM imposing $\alpha_{risk} = \alpha_{time} = \alpha$. The joint estimates for the probability distortion α is between the estimates for the probability distortion risk and time. Thus, the estimates of the GMM provide the same implications as the non-linear least squares method.

Overall, we conclude that estimating the parameters assuming that there is one value for each parameter that fits all individuals' preferences yields the same conclusions as in our main results. Although the standard errors of the parameter estimates are lower in this approach the estimated probability weighting parameter based on time preferences is equal to the estimated probability weighting parameter

Table 3.13: This table reports the parameter estimates assuming that each parameter has the same value for each individual and that one α can describe both field using the general method of moments with the following moment condition: $E(\frac{CE_{i,j,t}}{x_1} - e^{-(1/r_i)(-\ln(p_j \times s^t))^\alpha}) = 0$. Hansen J test: 24.25 ($p = 0.00$)

	coefficient	standard errors
α	0.22	0.02
s	0.9969	0.00
$1/r$	0.51	0.02

in risk preferences as the theory predicts.

3.6 Conclusion

We find significant relationships among the behavior in time and risk preference tasks as the theory of Epper and Fehr-Duda (2015) predicts. It provides an experimental evidence for the descriptive validity of their model even after controlling for several different variables such as gender, age, education, income, clarity of the tasks in a representative sample of the Dutch population. This suggests that the model of Epper and Fehr-Duda provides not only an explanation for several known anomalies but it also captures their driving force.

First of all, we find that risk and probability weighting have an impact on time discounting in line withe the model of Epper and Fehr-Duda (2015).

Second, according to these results, economic models should consider the effect of the interaction between risk and time when both are present in a model. In other words, modeling risk also depends on the time dimension and they are not independent. The model of Epper and Fehr-Duda provides explanation for several puzzles in the experimental economics literature; however, it might also help to resolve other puzzles in the literature by providing a parsimonious model for their interaction. For instance, it can resolve why people exhibit strong risk-aversion in some of their actions while seeking out risk in others.

Third, these results suggest a new way of looking at time discounting yielding several new testable hypotheses. For instance, uncertainty plays an important role in time discounting. Higher uncertainty leads to stronger hyperbolic discounting. Another consequence of the results is that the perceived risk depends on the timing of the outcome. This could be important in long term economic decisions such as environmental challenges or long-term household decisions related to, for instance, mortgages or pensions.

3.7 Appendix

3.7.1 General Instructions

In this experiment, you are asked to make 8 choices. The 8 choices are divided into three parts. In the end, one of the questions will be randomly picked and you are going to be paid by bank transfer based on your answer in that question.

We show you an example of the format of "choice list" in which most of the questions will be presented. Please, read carefully the instructions.

In this format, there are two options, labeled LEFT and RIGHT. The options will be grouped together in a list with 16 rows. An example list is given below. This example is not a list that you will actually encounter during the experiment, but merely illustrates the format.

As you can see, in the example list, LEFT is the same gamble in each row.

Option LEFT: Gamble	You choose LEFT	You choose RIGHT	Option RIGHT: Guaranteed Payment Today	Rows
If the dice shows 1-12: the gamble pays **€15 today.** **If the dice shows 13-20:** the gamble pays **€0.**			€15, today	15
			€14, today	14
			€13, today	13
			€12, today	12
			€11, today	11
			€10, today	10
			€9, today	9
			€8, today	8
			€7, today	7
			€6, today	6
			€5, today	5
			€4, today	4
			€3, today	3
			€2, today	2
			€1, today	1
			€0, today	0

RIGHT yields different amounts of euros. In particular, as you move down the list, the amount of euros offered by RIGHT decreases, starting at €15 and decreasing in steps of €1 to €0.

Starting from the top row (row 15), you can decide in each row whether you prefer LEFT (the gamble) or RIGHT (a given amount of sure money today). We are interested in the first row when you prefer LEFT (the gamble) to RIGHT.

Let's assume that you have the following logic, in the top row (row 15) you prefer RIGHT (sure €15) to LEFT (the gamble). In the next row (row 14), you still prefer RIGHT (sure €14) to LEFT (the gamble). Then again in row 13, you prefer RIGHT (€13) to LEFT (the gamble). But in row 12, you think that your prefer LEFT (playing the gamble) to RIGHT (€12). In this case, you are supposed to type 12 as the first row where you prefer LEFT to RIGHT. We assume that once you prefer LEFT to RIGHT you will always prefer LEFT to RIGHT for the rest of the rows.

If this question was randomly selected then one of the rows will be randomly picked and your payment will be based on your choice in that row. For example, if this example choice is selected to be paid (according to the example you typed 12) and row 13 is randomly picked, you will get the option RIGHT, resulting in €13 for sure. On the other hand if this example choice is selected to be paid and row 4 is randomly picked, you will get LEFT, resulting in the gamble that pays you €15 if the dice shows a number from 1 to 12 and €0 when the dice shows a number from 13 to 20.

In this format, we ask you to report the first row, starting from the top row, in which you prefer LEFT to RIGHT by typing in the number that corresponds to your choice.

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