**Erasmus University Rotterdam**

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**Master Thesis, Behavioural Economics**

The Equity Premium Puzzle and Behavioural Stocks' Evaluation

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**Abstract**

The study investigates the phenomena of the equity premium puzzle from a behavioural prospective. In particular it is hypothesized that the puzzle could be explained by modelling investors propensity towards risk with a model of prospect theory & ambiguity aversion instead of the classic expected utility framework. The research constructs such behavioural model and derives the 5 population parameters needed to implement it. The results show that the behavioural model, under various specifications, predicts equity premiums that are consistently higher than the one predicted by expected utility and that better fit the historical data4. Moreover the study also investigates the equity premium puzzle from an inter-temporal prospective and finds support for the myopic loss aversion.

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## 1. Introduction

Mehra and Prescott (1985) confronted the academic community with some baffling evidence regarding the aggregate stock market behavior. In particular, they were able to show that the equity premium, which is the difference in returns between stocks and bonds (the reward for carrying risk), was too high to be explainable within a standard consumption-based expected utility framework with a reasonable[1] level of risk aversion. This phenomenon came to be known has the "equity premium puzzle", EPP, and it is still to date an open question in the financial literacy. Even if the puzzle has been named after the oddly high spread between equity and bonds' returns in its core it really is a consumption enigma rather than a retunes one. What standard theory fails to explain is why investors appear to be so unwilling to hold stocks even though the latest should be extremely attractive assets due to their high average returns and low covariance with consumption growth (Mehra and Prescott, 1985). Eventually investors' unwillingness to hold equity causes it to earn a substantial price premium needed to place in balance market supply and demand, hence the high equity premium. Of course one could think that there is no puzzle at all and that the general public simply has a high level of risk aversion that previous literature failed to capture. However, this argument falls short as it does not solve the puzzle but rather shifts it from the equity side to the bonds' one. In fact, it has been shown that the level of risk aversion that would be needed to justify the large equity premium should also imply unnaturally high bonds' prices, not coherent with the one observed in the market; a phenomenon known as the risk-free puzzle (Weil, 1989). At the end, under standard theory, whatever is the chosen level of risk aversion, we are left with one of the following questions: why is the equity premium so large? Or, why is anyone willing to hold bonds? (Barberis and Thaler; 2003). In the course of the years various possible explanations for the puzzle within the ream of traditional finance have been advanced (see Mehra, 2008 for an extended overview). The most popular ones rotate around liquidity limitations (Bansal and Coleman, 1996; Holmström, 1998), idiosyncratic income shocks (Constantinides and Duffie, 1996; Krebs, 2000) and tax reasons (McGrattan and Prescott, 2003; McGrattan and Prescott, 2005). Nevertheless, none of these arguments manages to fully accommodate every aspect of the EPP, underlining a deeper and more structural problem in our understanding of market dynamics.

Ultimately there exist only three possible explanations that can reconcile all the just presented evidence: either equity is overpriced, bonds are underpriced or both of them are rightfully priced but our current risk-based decision making models are inaccurate and therefore lead to the inconsistencies observed by Mehra and Prescott. The present study relates to recent literature, which suggests that the latest might be the case. Consequentially I will expand the common expected utility framework to accommodate for two behavioral findings that have found strong empirical and theoretical support in explaining the EPP: prospect theory preferences (in particular loss aversion) and ambiguity attitudes. For now all that is needed to be known about these two phenomena is that they impact decision-making

[1]What is meant by "reasonable" is the amount that is usually found in laboratory experiments and it is strongly robust across them: lower than one.

[2]We only exclude loss aversion and not prospect theory preferences as a hole since previous research has indicated at this as the most

process at the level of preferences making investors more risk adverse than what would be predicted by EU. Therefore in prospect theory or ambiguity models there is no puzzle when it comes to investors' unwillingness to hold equity, because under such models stocks are simply not as attractive as under expected utility. A great deal of research has investigated these behavioral effects, however none of them is universally accepted as a formal solution to the puzzle, yet. The reason being is that both of these lines of research are at preliminary stages and at least for the case of ambiguity most of existing models (Chateauneuf, 1991; Cozman, 2012; Gilboa and Schmeidler, 1989; Wald, 1950; Bossaerts, Ghirardato, Guarnaschelli, and Zame, 2010; Anderson, Ghysels and Juergens, 2009; Ju and Miao, 2012; Collard, Mukerji, Sheppard and Tallon, 2018) are too complex to be empirically tractable. Moreover, at the best of our knowledge, there is no empirical study that has never tried to compare these two phenomena nor that has tried to unify them in one comprehensive model with the aim of resolving the EPP. The current research will try to fill these holes in the previous literature by first implementing a tractable model that can accommodate for both prospect theory preferences and ambiguity attitudes. This model will then be used to estimate equity premiums and verify whether they are indeed higher than under standard expected utility. In the last step of the analysis I will re-run the equity premium estimations by excluding in turns the loss aversion[2] and the ambiguity components. Finally, these estimations will be compared to the previous ones (the full model) and to historical equity premiums in order to establish which one between loss aversion and ambiguity attitudes has the greatest explanatory power when it comes to the EPP. In addition to this, the model built in the paper will also be used to analyze a special case of prospect theory preferences: myopic loss aversion. This is a combination of loss aversion and narrow framing, which will be explained later in more details, that causes inter-temporal preferences between stocks and bonds to highly diverge (Benartzi and Thaler, 1995).

The rest of the paper will first give an in-depth overview of prospect theory preferences, myopic loss aversion and ambiguity aversion with the aim of explaining on which theoretical ground they can claim to accommodate for the equity premium puzzle. Following this a model that integrates all these behavioral findings will be constructed. After the model description the used data will be outlined, both behavioral and financial, and it will be showed how to elicit the needed parameters for the model from the (behavioral) data. Subsequently I will explain how the analysis of the equity premium was carried out and present the results. Finally the obtained results will be discussed together with a general discussion over study limitations and other secondary matters. The paper will be ended by a brief conclusion with the aim of summarizing and linking the findings presented during the course of the study.

[2]We only exclude loss aversion and not prospect theory preferences as a hole since previous research has indicated at this as the most influential component of prospect theory when it comes to the equity premium (Benartzi and Thaler, 1995).

## 2. Prospect Theory Preferences

A crucial component of any theory that aims to understand trading behavior or assets pricing (or the EPP) is an assumption about investors' preferences over risky prospects (gambles). To this end, most of past mainstream financial literature has used expected utility, EU, to model investors preferences regarding gambles. The theoretical foundation of EU dates back to von Neumann and Morgenstern (1947), who showed how, under a number of plausible axioms[3], preferences can be represented by expected utility. This framework usually assumes a power utility function characterized by one parameter and dependent on levels of total wealth. However, there exist a fruitful line of experimental work that has shown how people systematically violate EU predictions and its axioms (see Barberis and Thaler; 2003 for an overview of such violations in financial markets). Of course this experimental evidence should cast serious doubts on all financial models that assume expected utility's preferences since they will inevitably inherit EU's flaws and limitations.

Following these findings, during the past decades, numerous non-EU models have been proposed (Chew and MacCrimmon, 1979; Kahneman and Tversky, 1979; Gul, 1991; Bell, 1982; Quiggin, 1982; Yaari, 1987; Tversky and Kahneman, 1992). Among all of these prospect theory, PT, is the one that has received the greatest empirical support and has shown the most promising potential when it comes to financial applications. The superiority of PT over other non-EU models and EU itself comes from the fact that it is the only theory of decision-making that can claim to be fully descriptive. Prospect theory does not need to make any a prior assumption over the shape of the utility function, but rather leaves the data speak for themselves. Unlike EU, which is fully normative, and most of other non-EU models, which are considered quasi-normative in the meaning that they simply relax one or more of the EU axioms to fit experimental evidence. At first the PT approach might sound "ad hoc" and disorganized but it reveals to fit experimental data remarkably well, which is partially expected due to its descriptive nature. Even more impressive is that the shape of the prospect theory function seems to be robust across various laboratory experiments hinting to common systematic behaviours that were not captured by other models. Finally PT is the most general and inclusive framework to study decisions under risk because EU and most of other non-EU models can be interpreted as special cases of it.

Prospect theory was first proposed by Kahneman and Tversky (1979), however in its original design the PT formula did not respected the monotonicity assumption[4]. This problem was resolved when the authors proposed a second formulation of the theory (Tversky and Kahneman, 1992) that overcame the issue by integrating the findings of Quiggin (1982) over rank-dependent utility and cumulative distribution functions. This second formulation is known as cumulative prospect theory and it is the one that will be adopted throughout the present study. For the rest of the paper every time I referee to prospect theory or PT I really am referring to its cumulative relative. The prospect theory

[3]The axioms are: completeness, transitivity, continuity and independence. See the original von Neumann and Morgenstern, (1947) paper for a detailed description of the singular axioms.

[4]The monotonicity assumption states that, given a certain good (usually money) people prefer more to less. This is a logical and plausible assumption that is usually made both in mainstream and behavioural economics.

formula will be presented next starting from its two fundamental components: the utility function and the probability weighting function. We can intuitively think about them as “how much we like an outcome” (utility function) and “how much weight is given to the outcome” (probability weighting function). In prospect theory these two metrics alone shape investors preferences towards risky prospects and therefore their decision making process as a whole.

## 2.1. The Utility Function

The prospect theory utility function remained unchanged between its first and second formulation. Its functional form is as follow:

$$(1) \qquad U(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\beta} & \text{if } x < 0 \end{cases}$$

From the above formula it is possible to observe three clear and distinct points of departure from the usual EU utility function. First, utility is defined in terms of gains and losses rather than total wealth level, an idea advanced by Markowitz (1952). For this reason prospect theory is defined as a reference dependent theory in the meaning that the reference point used to conduct the prospect evaluation matters and it can be different form the total level of wealth. This reference dependency turns out to be a helpful feature in explaining the equity premium puzzle. Constantinides (1990) propose a model of habit formation depended to past levels of consumption as a solution to the EPP. The intuition behind his model was that investors seem to have preferences over retunes per se, rather than the consumption levels that said returns help achieving. Therefore they make decisions inconsistent with EU that eventually lead to higher premiums. I believe this intuition is more than plausible even though Constantinides failed to correctly model it in his habit formation theory[5]. On the other hand, because of its reference dependency, prospect theory is naturally defined over returns (gain and losses) rather than consumption (total wealth), it therefore perfectly fits within Constantinides intuition of investor behavior.

The second point of divergence between PT and EU is in the shapes of the utility functions. In particular, the EU function is usually concave in its entire interval while PT exposes concavity for gains and convexity for losses a phenomenon known as the reflection effect. The prospect theory functional shapes translate into risk aversion for gains and risk seeking for losses, which is a commonly observed behavior in various laboratory experiments (Kahneman and Tversky, 1979).

The final piece of the PT utility function is loss aversion; this is λ in equation *(1).* The original Kahneman and Tversky study (1979) estimated it to be 2.25, yet more recent researches have usually found values lower than that, but always well above 1 (Fox and Poldrack, 2009). The idea behind loss

[5]He models this as a difference between the current and the previous level of consumption, in this way we departure from total wealth dependency, but we are still defining preferences over consumptions levels.

aversion is that people have an aversion for losses themselves despite their particular amount. This behavior has been further confirmed by subsequent literature, which named it endowment effect (Kahneman, Knetsch and Thaler, 1990, 1991). Therefore, the endowment effect is modeled within the PT framework becoming an essential component of this decision theory. In the first PT formulation loss aversion was formally defined as the tendency for the decrease in utility caused by a loss to be larger than the utility increase caused by a corresponding gain (i.e. $-U(-x) > U(x)$ for all $x > 0$). Following this the loss aversion coefficient in equation *(1)* can be defined as the mean or median value of $-U(-x)/U(x)$ over a particular range of x (Kahneman and Tversky, 1979). However, past literature has not universally agreed on the precise parameterization of loss aversion and different formulations exist[6] (Tversky and Kahneman, 1992; Wakker and Tversky, 1993). Nonetheless all of these definitions are closely related; in fact they would all coincide if one assumes a simpler utility function (Abdellaoui, Bleichrodt and Paraschiv, 2007). For this reason I will not bother the reader with unnecessary details, but I do report that the present study uses the broadest definition, that is the one given by Kahneman and Tversky (1979).

Loss aversion surly is a key feature when it comes to explaining the EPP and intuitively it is easy to see why. According to the classic mean-variance framework, bonds are considered low mean - low variance assets. Thus, their returns are still risky in the meaning that the exact outcome when purchasing a bond it is not a guarantee, but they are sure in the meaning that it is unlikely to incur in a loss. As it will be revealed later in section 5 during the time spam considered by the present research, 1999 to 2019, there have been zero cases of negative bonds returns both in monthly and yearly frequencies[7]. As a result of this, bonds will be perceived equally attractive by both a model of loss aversion, PT, and one that does not account for it, EU (because bonds rarely cause losses). On the other hand stocks are high mean – high variance assets, therefore it is not uncommon to sometimes incur in losses even of large natures. Consequentially, stocks, which do present losses in their returns distribution, will be perceived far less attractive under PT rather than EU. On this theoretical ground, prospect theory's preferences and in particular loss aversion can claim to be a plausible solution for the EPP.

## 2.2 The Probability Weighting Function

The second component of prospect theory's utility function is a non-linear transformation of probabilities named the probability weighting function, PWF. The PWF is usually inverse-s shaped, as shown in fig *(1).* The PWF used in Tversky and Kahneman (1992) is slightly different than the one in the original study (Kahneman and Tversky, 1979) in the respect that the PWF is defined over the cumulative distribution rather than the simple probability distribution. Only the latest form (the cumulative) will be reported here since this is the one that will be used in the present research.

[6]See Fox and Poldrack, 2009 page 155 for an in-depth overview.

[7]We are claiming no negative returns only for the bond type considered by the present research, that is: 10years USA government bonds with indexed returns, USGG10YR:IND

$$w^{+}(P) = P^{\gamma} / (P^{\gamma} + (1- P^{\gamma}))^{1/\gamma} \quad \text{if reference outcome} \geq 0$$

*(2)*

$$w^{-}(P) = P^{c} / (P^{c} + (1- P^{c}))^{1/c} \quad \text{if reference outcome} < 0$$

As it can be seen in equation *(2)* the PWF, w(P), is split in two separate non-linear one-parameter equations, one for gains, $w^{+}(P)$, and one for losses, $w^{-}(P)$. This dual nature is not of interest for the current study and will be ignored in the following description of the PWF. It is important to remember that, since we are using cumulative probabilities instead of simple one, in order to use the results given by the PWF we first need to calculate decision weights, π, as showed in equation *(3).*

$$(3) \qquad \pi_i = w(P_i) - w(P_i^*)$$

Here, $w(P_i) - w(P_i^*)$ is the probability that the prospect will lead to an outcome at least as good as (strictly better than) $x_i$ (Tversky and Kahneman, 1992). Therefore, in the domain of gains, the decision weight $\pi_i$ will be equal to the probability weight of the probability of obtaining at least that outcome ($w(P_i)$), minus the probability weight of the probability of getting more than that outcome ($w(P_i^*)$). While in the case of losses the decision weight is calculated the other way around, as the probability weight of the probability of obtaining at most the evaluated outcome ($w(P_i)$), minus the probability weight of the probability of getting less than that outcome ($w(P_i^*)$). In order to better understand the implication of the PWF it is helpful to look at its graph, figure *(1).*

Prospect Theory's Probability Weighting Function

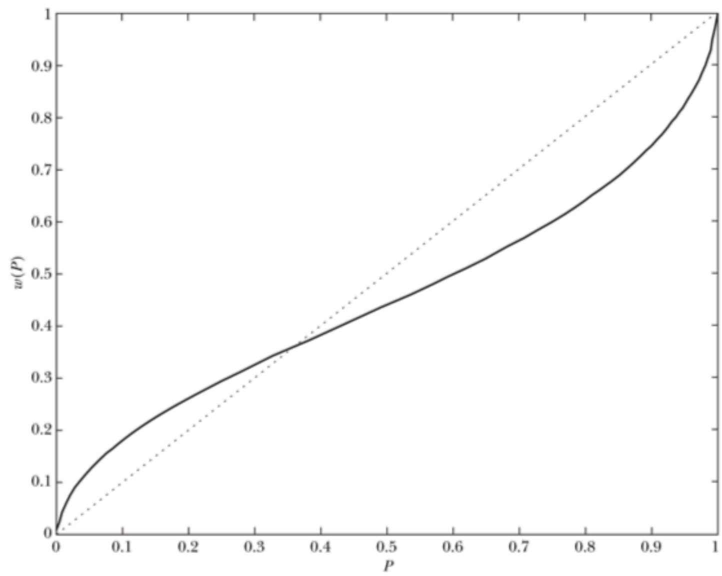


**Fig 1**: The graph shows the prospect theory's probability weighting function as it was found in Tversky and Kahneman, 1992.

The full line in figure *(1)* represents the prospect theory's PWF while the dashed line shows the real probabilities. Therefore the latest can be considered as the "PWF" of a model that treats probability linearly like EU. The shape of the PT's PWF implies a couple of interesting features worth mentioning. First of all we can observed how in the proximity of the lower extreme the full line is well above the dashed one, this translate in the overweight of small probabilities. On the other hand, when getting closer to the higher extreme we have the reversed situation, hence the underweight of high probabilities. Both of these behaviors are commonly observed in laboratory experiments (Kahneman and Tversky, 1979; Gonzalez and Wu, 1999) and their combination reveals to be an incredibly useful tool to reconcile people's interest for both lottery tickets and insurances[8]. In addition to this, the overweight of small probabilities can also be helpful in explaining the EPP. As mentioned earlier we can think of stocks as high mean – high variance assets in the meaning that they offer high average returns but with occasional losses. Because of the overweight of small probabilities this occasional losses will seem more likely than what they really are causing investors to become more risk adverse towards stocks than otherwise suggested by their utility function alone. Moreover, if we combine the overweight of small probabilities with loss aversion we arrive to a situation in which "stocks' occasional losses" seem more likely (overweight of small probabilities) and feel more painful (loss aversion) than in the classic EU framework. It should start becoming clear how the link of the various PT components offers a solid theoretical ground on which the theory can claim to offer a solution to the EPP, however this can only be confirmed by the empirical analysis that will follow later.

A second interesting characteristic of the PWF is its steepness, which is higher than the one of the dashed line near the extremes but lower than it in the middle section of the function. As a result of this. people with prospect theory's probabilities weighting function will be more sensitive to changes in high or low probability levels rather then in the intermediate ones. For this individuals a jump in probability form 0.75 to 0.95 or from 0.1 to 0.3 will feel as more striking than the same 20 percentage points jump happening in middle probabilities, say from 0.3 to 0.5. The extreme consequence of this is the certainty effect, which is an innate preference for certain outcomes over those that are merely probable. The certainty effect can also help shrinking the theoretical gap in our understanding of the EPP. It is straight forward how, because of the certainty effect, bonds, which offer extremely certain returns, will seem more attractive than what they really are when compared with stocks and their "risky" returns. Once again PT reveals to have numerous build in features that have a natural explanatory power when it comes to the EPP.

## 2.3. Myopic Loss Aversion

Because of the vast experimental support that PT received, and because of its applicability to the EPP, there has been a promising but yet short line of literature that tried to create a direct link between the two. The first, and most accomplished, attempt to do this was made by Benartzi and Thaler (1995) who

[8] The need of reconcile people interest in both lottery tickets and insurances comes from the fact that under EU models we usually arrive to a paradoxical situation in which the risk-seekingness that would be needed to justify the inters for lottery tickets should also imply the complete disinterest for insurances' policies and vice versa. However since the focus of the paper it is not the "lottery-insurance puzzle" we refer readers interested in the topic to Friedman and Savage (1948) who show an interesting occurrence of this problem in portfolio theory.

proposed a model of myopic loss aversion, which relied on two fundamental components. The first component is loss aversion, which has already been discussed in the previous section together with the mechanism through which it can justify higher equity premium than EU models. The second component is called narrow framing, a psychological bias that in financial markets concretizes in the tendency to evaluate returns in isolation. This is true both for returns on different investments within the same portfolio, but also (and more shockingly) for returns on the same investment in different moments in time (Thaler et al., 1997). It is interesting to notice that narrow framing perfectly capture Constantinides (1990) intuition that investors have preferences over returns rather than consumption profiles. Moreover, narrow framing brings this to its extreme by not only making people's preferences dependent on returns but also on the frequency with which such returns are evaluated. Narrow framing begins to show some explanatory power in the EPP context once we realise that stocks' return distributions are not time invariant. This means that the monthly return distribution for a given stock will likely look quite different from its yearly one and completely different form its 30years distribution. In particular the lower the time frequency considered the more likely it is to observe losses. This is the case because the stock market returns are usually found to be positively skewed, which means that they present a mean far greater that their median. Therefore, tying up everything together, because of myopic loss aversion, investors that evaluate their portfolios more frequently will be more likely to observe losses, which will be given an higher weight in their utility function making them more risk averse than what they would be if they were to evaluate their portfolio less frequently.

Given this Benartzi and Thaler investigate how often investors should evaluate their portfolio to justify the observed equity premium. They found the answer to be 1 year. They argue that it is a natural reference point for investors since the most comprehensive mutual founds and companies' reports are usually distributed on a yearly base (Benartzi and Thaler, 1995). Eventually, Benartzi and Thaler show that, under the assumption of a yearly evaluation period, investors that are affected by myopic loss aversion would require equity premiums of the same magnitude of the one empirically observed. However, Benartzi and Thaler paper can only be suggestive of a solution to the EPP. As emphasized before the EPP really is a consumption puzzle rather than a return one and because the just presented model do not account for inter-temporal consumption choices it cannot address the problem directly.

Following this line of work, Barberis, Huang and Santos (2001) included myopic loss aversion in a dynamic equilibrium model of stock returns. Their findings agree with the evidence earlier presented by Benartzi and Thaler. In particular they find that myopic loss aversion can indeed offer an explanation for the high sharp ratio[9] of the aggregate stock market. However the offered explanation is only partial since how much of the sharp ratio can be explained heavily depends on the secondary utility sources considered in the model (e.g. employment income). This issue was further confirmed by Epstein and Zin (1991) that showed how time-series models researching in this topic are particularly sensitive to the choices of consumption measures and instrumental variables. To the best of our knowledge these two

[9]This simply is a common measure of performance in financial markets that is here used as a proxy for the equity premium. The sharp ratio formally captures the risk-adjusted performance of a risky asset, compared to a risk-free one.

might be the only studies that tried to directly link prospect theory preferences with the EPP. In the course of the present research I will focus on Benartzi and Thaler results due to the more tractable form of their research. In particular I will use the model that will be later constructed to verify and expand their findings over myopic loss aversion.

## 3. Ambiguity Attitudes

The notion of ambiguity has also been proposed by the behavioral literature as a possible solution for the EPP. The idea of ambiguity as something other than risk was first advanced by Keynes (1921) and Knight (1921) who noticed that in real life contexts we rarely have knowledge of the exact probabilities associated with every possible outcome caused by our choices. This is particular applicable to financial markets. Starting from this idea, Savage (1954) expands the EU framework from risky to ambiguous situations; by demonstrating that, under a number of axioms, preferences can be represented with a EU function weighted by individuals' subjective estimates of the real probabilities. Of course what is left unsaid here is that we need to assume that people can indeed form consistent assessments of probabilities in ambiguous situations, as it will be shown shortly this is rarely the case. Ambiguity has been proven a useful tool in explaining various households' portfolio puzzles (see Dimmock, Kouwenberg, Mitchell and Peijnenburg, 2016 for a comprehensive overview), and it is usually connected to the EPP through the concept of ambiguity aversion. Ambiguity aversion is defined as the aversion to lotteries in which the probabilities associated with the outcomes involved are not specified; hence it can be defined as a preference for known risks over unknown ones. Following this intuition the ambiguity explanation for the EPP is fairly simple: people not only require a risk premium but also an ambiguity premium. Standard expected utility models cannot distinguish between the two and therefore lead to the puzzling results.

As a consequence a great deal of empirical research has worked tireless on the topic and found a strong statistical connection between ambiguity and equity premiums, but without being able to precisely quantify it (Erbas and Mirakhor, 2007; Rieger and Wang, 2012). This line of literature usually performs cross-sectional analysis of equity premiums levels across different countries using some proxy of ambiguity (e.g. ambiguity aversion indexes or World Bank institutional quality indexes). However, in order to prove more than a statistical relationship, a model, which can capture ambiguity aversion and make predictions based on it, is needed. Unfortunately, as already discussed in the introductory section the academic community has yet not agreed on a universal model of ambiguity attitudes. The precise parameterization used in the current study relies on Abdellaoui, Baillon, Placido and Wakker (2011) and Chew and Sagi, (2008) source function. The model will be presented later in section 4; for now it is only important to understand the mechanisms through which ambiguity can accommodate for large equity premiums. Such mechanisms will be explained in the following sub-sections starting from what recent literature has found to be the two major components in shaping people's ambiguity attitudes: ambiguity aversion and likelihood insensitivity. The importance of including both these elements was statistically confirmed by Dimmock, Kouwenberg and Wakker (2016), through a principal component analysis ran within a large dataset representative of the Dutch population.

## 3.1. Ambiguity Aversion

Ellsberg (1961) reports the first experimental evidence in support of ambiguity aversion. During the course of his experiment participants were presented two urns both of them containing 100 balls either blue or red. Participants were then told that the first urn, U1, contained 50 red balls and 50 blue ones, the distribution of the second urn, U2, was left unrevealed. Therefore U1 can be seen as a risky prospect (known probabilities) while U2 as an ambiguous one (unknown probabilities). Subjects were then asked to state their preferences over two pairs of gambles, each of which involves a possible payment of $100 depending on the colour of a ball drawn at random from one of the two urns.

$a_1$: A ball is drawn from U1, $100 if red, $0 otherwise.
$a_2$: A ball is drawn from U2, $100 if red, $0 otherwise.

$b_1$: A ball is drawn from U1, $100 if blue, $0 otherwise.
$b_2$: A ball is drawn from U2, $100 if blue, $0 otherwise.

What is commonly observed in the laboratory is that people usually prefer $a_1$ to $a_2$, while they prefer $b_1$ to $b_2$. These preferences are inconsistent with SEU since the choice of $a_1$ implies a subjective probability associated with drawing a red ball from U2 lower than 50%; therefore an individual that prefers $a_1$ to $a_2$ should also prefer $b_2$ to $b_1$ as he believes that in U2 there are fewer than 50 red balls, hence there must be more than 50 blue ones. All in all Ellsberg's experiment demonstrated that people dislike ambiguous situations per se, ambiguity aversion. The participants in the experiment had a fixed preference for U1 not because of their beliefs over U2's probability distribution, but rather because they disliked the ambiguity associated to it.

However, it has to be pointed out that the situation modelled by Ellsberg is not often observed in real life contexts. First, the ambiguity in Ellsberg's paradoxes is generated by deliberately hiding information form subjects, which is not representative for uncertainty in real life. Second, during the experiment subjects made choices between a risky and an ambiguous prospect. Yet, as above argued, most everyday choices are of an ambiguous nature only, therefore a trade off between two ambiguous prospects would have been more representative (Wakker, 2020, natural sources of ambiguity). Nevertheless, Ellsberg findings seem to be partially applicable to the EPP. Bonds surly aren't unambiguous investments, however they are less ambiguous than stocks at least to the extent that the range of possible outcomes that they can lead to is less spread. The hypothesis that ambiguity aversion also applies between two ambiguous prospects when one is of a more ambiguous nature than the other was experimentally tested, and confirmed, by Fox and Tversky (1995). The general idea behind these findings is that ambiguity attitudes are source dependent[10], so that we can think of bonds and stocks as two different sources of ambiguity. Because stocks are more ambiguous than bonds investors will require high premiums to hold equity in their portfolio, hence the EPP. This theoretical prediction was later tested by Maenhout (2004) who showed that large equity premium could be coherent with a dynamic equilibrium model in which investors are concerned with a misspecification in their return predictor models[11]. Yet, as pointed out by the author himself, his model does not offer a definitive solution to the puzzle since it can only partially explain the large price spread between bonds and equity. However, the limited explanatory power of Maenhout's model might depend on his definition of ambiguity, as investors being concerned with models' misspecification. This can only be considered as a proxy, hence its limited explanatory power. The current study will overcome such flaw by retrieving ambiguity attitudes directly from experimental data.

### 3.2. Likelihood Insensitivity

Besides the well-known ambiguity aversion, recent literature finds a second structural component of ambiguity attitudes: likelihood insensitivity or a-insensitivity. This translates in people not discriminating enough among levels of ambiguity and therefore assessing subjective probabilities biased towards 50-50. From a functional point of view likelihood insensitivity can be represented by an inverse s-shaped curve a lot similar to the prospect theory's PWF in figure *(1)*. This hints to strong similarities between ambiguity and risk attitudes. In fact previous literature argues that the former usually exhibits characteristics analogous to the latest, but to a stronger extent (Maafi 2011; Wakker 2010, §10.4; Dimmock, Kouwenberg and Wakker, 2016). In order to fully understand all the implication of likelihood insensitivity we refer to figure *(1)* with the only difference that now the full line represents the ambiguity function while the dashed one is the reference probability distribution. In practical terms we can think of the full line as the subjective probability distribution of U2 in the Ellsberg's paradox while the dashed one would be the probability distribution of U1. The later is called ambiguity-neutral, or a-neutral, probability distribution because it offers to subjects a natural (ambiguity neutral) reference point to asses U2 ambiguous probabilities with. As previously noticed in the case of risk the full line is above the dashed one in the proximities of the lower extreme while the opposite is true for the other side of the function. In the context of ambiguity this reflects ambiguity seeking behaviours for small reference ambiguity-neutral probabilities and ambiguity aversion for large ones (Ellsberg, 2001).

It can be seen how likelihood insensitivity helps accommodating for large equity premiums if one assumes that investors use bonds' probability distribution as a reference point to determine or at

[10]We will see in the model description section how this source dependency will reveal to be a fundamental feature to arrive to a one simple and tractable parameterization of ambiguity attitudes.
[11]The idea to model ambiguity as investors being concerned about a possible misspecification in their returns predictor models was first introduced by Anderson, Hansen and Sargent (1998) in the ream of portfolio theory.

lest judge subjective probabilities associated with stocks' returns. Following this, since bonds offer large probabilities of gains, likelihood insensitivity will fortify the sentiment of ambiguity aversion associated with stocks causing in turns the large premium. The above made assumption might sound unrealistic; yet there exist a large body of financial literature that deeply connects bonds and stocks returns. For example, according to the Capital Assets Pricing Model, CAPM, which remains one of the most empirically used assets pricing theories by practitioners, stocks returns can be broken down in two components the risk-free rate and the reward for carrying risks (Sharpe, 1964: Lintner, 1965). The risk free-rate is nothing but the bonds' return that here become a natural benchmark to evaluate equity with.

Of course there is more than bonds to determine stocks' subjective probabilities distributions; for example it is logical to think that one's level of information and knowledge of financial markets must play an important role as well. Indeed in real life context, likelihood insensitivity and ambiguity attitudes in general are found to have a lot to do with personal experience something known as the competence hypothesis (Heath and Tversky, 1991; Grieco and Hogarth, 2004; Klein, Cerully, Monin and Moore, 2010). This is a logical hypothesis to make because , after all, the more knowledgeable one becomes about a certain topic the less ambiguous that topic will seem to him. According to this view likelihood insensitivity is more of a reflection of a general ignorance in conceptualizing and dealing with probabilities rather than a behavioral tendency. Because of the high cognitive effort that the task would require people prefer to apply easy heuristics to obtain what they believe being satisfactory estimates. The application of heuristics to this type of calculations is usually found to bias the results in the direction of even splits or 50-50 distributions, which in turn create likelihood insensitivity as for the case of the "1/n heuristic" (Benartzi and Thaler, 2001). All in all the two above-presented components of ambiguity attitudes can be thought of as how much one dislike ambiguity (ambiguity aversion) and one's belief about the degree of ambiguity relative to a reference probability distribution (likelihood insensitivity). With regard of ambiguity aversion stocks seem less attractive because they carry a higher degree of ambiguity, this aversion towards equity is reinforced by likelihood insensitivity since bonds, which are assumed to be the reference probability distribution, offer large probabilities of gains. This is the mechanism trough, which ambiguity attitudes can theoretically accommodate for large equity premiums.

## 4. Model Description

This section presents a model of decision making comprising prospect theory preferences and ambiguity attitudes. The model will be construct in blocks. It will first present a model of generalized prospect theory, and then ambiguity attitudes will be directly integrated within it.

## 4.1 Generalized Prospect Theory

In the past decades there have been proposed numerous formulations of PT, all closely related but with minor differences dependent on the particular field in which they have been applied to. For the scope of this research I adopt a simpler formulation of the integral definition of PT suggested in the appendix of Starmer and Sugden (1989), which is a special case of the more general formulation presented by Wakker (2010, §9.7). The parameterization used in the present study differs from the original one because it approximates the integration with the summation of areas underlining the curve. This is done for the sake of simplicity since the format of the data used fits particularly well with this procedure. The PT formula follows:

$$(4) \qquad PT(x) = \sum^{+} \pi_i(p_i)\, U(x_i) - \sum^{-} \pi(p_i)\, U(x_i)$$

Where:

$$(5) \qquad \pi_i = w(p_i) - w(p_i^*)$$

$$(6) \qquad w(P) = P^{\Upsilon} / (P^{\Upsilon} + (1 - P^{\Upsilon}))^{1/\Upsilon}$$

$$(7) \qquad U(x) = \begin{cases} x^{\alpha} & \text{if } x \geq 0 \\ -\lambda(-x)^{\alpha} & \text{if } x < 0 \end{cases}$$

Equation *(4)* represents the PT model while equations *(5)* – *(7)* are the various specifications of its components. As showed in equation *(4)* we will treat the gain and loss domain separately. This entitles us to set all negative outcomes in the gain side of the equation equal zero and the same applies to positive outcomes in the loss side. Equation *(5)* and *(6)* are analogous to equations *(1)* and *(3)* presented in section 2.2. with the only difference that ϒ and c in equation *(2)* are here set to be equal, so that $w^+ = w^-$ = equation *(6).* This is done both to keep the model more tractable but also because the distinction between $w^+$ and $w^-$ seems to have little explanatory power when it comes to the EPP and can therefore be ignored[12]. I remind the reader that $w(P_i) - w(P_i^*)$, in equation *(5),* is the probability that the prospect will lead to an outcome at least as good as (strictly better than) $x_i$. Therefore, in the domain of gains, the decision weight $\pi_i$ is equal to the probability weight of the probability of obtaining at least that outcome ($w(P_i)$), minus the probability weight of the probability of getting more than that outcome ($w(P_i^*)$). While in the case of losses the decision weight is calculated the other way around, as the probability weight of the probability of obtaining at most that outcome ($w(P_i)$), minus the probability weight of the probability of getting less than that outcome ($w(P_i^*)$). Finally, equation *(7)* resembles equation *(1)* with

[12]This is a stylized empirical finding. Based on the literature discussed in section 2, it is clear that the components of PT that play key roles in explaining the EPP are others.

the difference that α and β are now set to be equal. This is again done for the sake of tractability and because, when elicited, these two parameters often are the same (Tversky and Kahneman, 1992; Wu and Gonzalez, 1996).

In order to give to the reader a broad and complete understanding of how prospects can be evaluated using equation *(4)* I propose next a 11 steps evaluation procedure similar to the one reported by Wakker (2010, §9.3).

Step 1: Rank outcomes from worst to best.

Step 2: Determine which outcomes are positive and which negative.

These first two-steps are needed to determine the sign ranking. We next look at the probabilities regarding the gain domain.

Step 3: For each positive outcome calculate the cumulative probability p associated with it.

Step 4: Transform all the obtained cumulative probabilities through the PWF, equation *(6).*

Step 5: Using the resulting w(p) calculate the decision weights π associated with each outcome, equation *(5)*[13]

The probabilities regarding the loss domain are treated symmetrically.

Step 6: For each negative outcome calculate the cumulative probability p associated with it.

Step 7: Transform all the obtained cumulative probabilities through the PWF, equation *(6).*

Step 8: Using the resulting w(p) calculate the decision weights π associated with each outcome, equation *(5)*[13]

We next look at the utility functions.

Step 9: Determine the utility of each outcome using equation, equation *(7) (which incorporates loss aversion).*

Step 10: Multiply the utility of each outcome of step 9 by its decision weight before determined.

Step 11: Sum together the results of the last step.

## 4.2. Ambiguity Source Function

Following the Ellsberg's paradox and the realization that ambiguity attitudes cannot be properly represented by the SEU, a flourishing line of literature tried to develop more accurate ambiguity models. Contributions to the field worth mentioning are the Choquet expected utility (Gilboa 1987; Schmeidler 1989), maxmin expected utility (Chateauneuf 1991; Cozman 2012; Gilboa and Schmeidler 1989; Wald 1950), maxmax expected utility (Drèze 1961), the α-maxmin model (Ghirardato et al. 2004; Bossaerts, Ghirardato, Guarnaschelli, and Zame, 2010) and more complex ones (Anderson, Ghysels and

[13] Note that despite the text of step 8 being written in the same lexical form of step 5 in practical terms the two materialize in different procedures. As explained above $\pi_i$ is the probability that the prospect will lead to an outcome strictly better than $x_i$. Therefore in the gain domain this means the probability of getting at least that outcome minus the probability of getting a bigger outcome, while in the loss domain it means the probability of getting at least that outcome minus the probability of getting a smaller outcome. This is the case since in the loss domain the smallest the outcome (which is a loss) the better the final result.

Juergens, 2009; Ju and Miao, 2012; Collard, Mukerji, Sheppard and Tallon, 2018). However, all the aforementioned share a couple of similar flaws, namely: they are not easily tractable and/or normative in nature. In section 2 the reders have already been warned about normative and quasi-normative models. The main issue here is that they usually capture only a few of the many experimental deviations from EU and/or SEU and therefore fail to precisely describe behaviour in its generality. As it turns out prospect theory, which is usually wrongfully interpreted as a theory of decision under risk only, can be easily extended to the case of ambiguity as well. The superiority of PT to other ambiguity theories has been experimentally proven by Kothiyal, Spinu and Wakker (2014) who compared the fit of the theoretical predictions made by all the mentioned ambiguity models in a bingo blower design. They concluded that PT predictions offered a far superior fit to their data than any other model analysed. This is in turns profs that PT is the best available theory to capture and model ambiguity attitudes.

Ambiguity attitudes can be incorporated into the PT formula using the source method developed by Abdellaoui, Baillon, Placido and Wakker (2011). This procedure is based on the source dependency of ambiguity, which was before introduced in section 3.1. The idea here is that investors hold subjective probabilities P over an ambiguous event E and they also hold a certain degree of trust in their subjective assessment of the probabilities. This level of trust is dependent on many factors[14] that eventually determine how ambiguous event E is perceived to be. We can now construct a function s that transforms the subjective probabilities P according to level of trust in the subjective distribution, which is in turn dependent on the source of event E. Function s exists between 0 and 1 and it is strictly increasing and continuous, with s(0) = 0 and s(1) = 1 (Abdellaoui, Baillon, Placido and Wakker, 2011). Therefore the ambiguity attitudes towards event E can be represented as: s(P(E)). In this definition it is important to notice that s by itself fully capture ambiguity attitudes, E is the objective event that we are analyzing (e.g. stocks/bonds) while P are subjective probabilities derived from behavior that may not even be known to subjects at any conscious level (Kothiyal, Spinu and Wakker, 2014). Additionally it is also interesting to see how, by allowing s to be different for different sources of ambiguity, the source method actively generalizes Machina and Schmeidler (1992) findings over probabilistic sophistication.

To model the source function s it is adopted a two-parameter function by the Prelec's (1998) family, which is a popular choice in the ambiguity literature (Abdellaoui, Baillon, Placido and Wakker, 2011; Kothiyal, Spinu and Wakker, 2014).

$$\textit{(8)} \qquad s(p) = (\exp(-(-\ln(p))^{z}))^{\delta}$$

Each parameter in equation *(8)* captures one of the two components of ambiguity attitudes before described in section 3. Parameter z determines the degree of flatness that the source function curve will have in the interior of its domain, thus, it reflects a-insensitivity. Parameter δ is a measure of the average heights of the curve therefore reflecting ambiguity aversion. Values of z and δ between 0 and 1

[14]E.g. personal knowledge, private information, confidence etc.

excluded lead to the typical inverse-s shape curve usually found in the literature. It is here important to remember that function s is dependent from the source of ambiguity (the event E that we are evaluating), therefore estimating s for different sources should lead to different estimates of z and δ. For the present study this means that we should estimate at least two separate source functions one for stocks and one for bonds. Unfortunately given the nature of the data used it was not possible to make this distinction and we therefore had to settle for using the same source function s for both equity and bonds. However, this flaw, even though unfortunate, shouldn't be seen as a fundamental threat to the validity of the study.

## 4.3. Full Model & Alternative Specifications

Combining together the generalized prospect theory in section 4.1 with the source function just presented leads to our complete model, equation *(9)*. We are going to call this APT to indicate that it unifies Ambiguity attitudes and Prospect Theory.

$$(9) \qquad APT(x) = \sum^{+} s(\pi(p))\, U(x) - \sum^{-} s(\pi(p))\, U(x)$$

The source function s in equation *(9)* is defined as in equation *(8)*, the decision weights function π is defined in equation *(5)* and *(6)* while the utility function U is defined as in equation *(7)*. The model in equation *(9)* is characterized by 5 parameters in total: two parameters for ambiguity attitudes, z (a-insensitivity) and δ (ambiguity aversion), one parameter for the PWF (ϒ) and two parameters for the utility function, α and λ (loss aversion). The estimation of these five parameters will be the focus of section 6. Finally equation *(9)* requires two inputs, namely: the possible outcomes that compose the prospect we wish to evaluate, x, and the subjective probabilities associated with each outcome, p. Given that the specific aim of the paper is to apply equation *(9)* to the EPP and use it to evaluate stocks and bonds, x will be the returns offered by these two assets and p the probabilities associated with said returns. Of course it is impossible to obtain exact values of x and p, which is why we repute stocks and bonds to be ambiguous rather than risky, however we will show in section 7 how to obtain satisfactory estimates of this values starting from bonds and equity's historical prices. To conclude in order to evaluate a prospect though equation *(9)* one can follow the 11 steps offered in section 4.1 with the addition of two extra steps insert after step 4 and 7 of the original ranking. In these two supplementary phases we will apply the source function s to the cumulative probability already transformed by the PWF. This is going to reflect that stocks and bonds are indeed ambiguous, but since we are using one source function for both we will not be able to discriminate across levels of ambiguity.

Additionally to the full model just presented we will use two variants of it. The need of these further specifications comes from our objective of comparing loss aversion and ambiguity attitudes. Therefore we will construct two version of the just presented model, one that excludes ambiguity attitudes and the other excluding loss aversion. The final objective is to compare the estimates made by these two. Once we eliminate the source function component the model reduces to the generalized prospect theory formula already presented in section 4.1, in particular equation *(4).* Therefore we will refer to this specification as PT. On the other hand the second specification will be equivalent to equation *(9)* with the only difference that the utility function U will be simply defined as:

$$(10) \qquad U(x) = x^{\alpha}$$

Equation *(10)* could also be seen as the utility function of a standard EU model. Therefore this second specification differs from EU at the level of probability sophistication only. We will call this last specification AEU, ambiguity expected utility model.

## 5. Data Description

In the course of the present research will use two categories of data: the behavioural data and the financial data. The former will be used for the estimations of the five parameters required by APT, while the latest will provide the inputs for the models.

The behavioural dataset was collected by Dimmock, Kouwenberg, Mitchell and Peijnenburg (2016) through a survey implemented in the RAND American Life Panel, the dataset is publically available on the ALP website. The ALP consists of thousands of households that agreed to regularly answer online surveys. Households lacking Internet connection or a laptop to access the surveys were provided with both; this is done to reduce possible selection bias. Moreover the ALP publishes survey weights that we use in all analysis and summary statistics to ensure that the sample is representative of the USA population. The survey took place between mid-March 2012 to mid-April of the same year. Furthermore subjects participating in the experiment could win real rewards dependent on their choices. This is important since prior studies show that the use of incentives produces more reliable estimates (Smith and Walker, 1993). In total $16,020.00 were paid to 2,703.00 subjects. The dataset contains 3258 observations. Given the regular involvement of subjects with ALP all possible concerns relative to incentives credibility are here minimized.

The financial data were collected through Thomson Eikon, the study uses data over the monthly and yearly returns of US 10years government bonds and the first 81 stocks[15] of the S&P500 ranked by market capital. The use of American bonds and equity follows naturally as the ALP sample is representative of the US population. The time horizon analysed goes from 1999 to 2019. In the case of equity returns are calculated using the total returns index, RI. This shows the theoretical growth in value of a share holding over the considered period, assuming that dividends are re-invested to purchase additional units of said equity at the closing price applicable on the ex-dividend date. The RI is

[15] The number 81 for the sample size was chosen through power calculations performed on G-Power (http://www.psycho.uni-duesseldorf.de/abteilungen/aap/gpower3/download-and-register), which showed that 81 was the minimum sample needed to obtain a reliable 95% confidence level.

constructed using the annualized dividend yield. This method adds increments of 1/260th part of the dividend yield to the price each weekday. There are assumed to be 260 weekdays in a year, ignoring market's holidays. Given that most of the companies' stocks considered have high dividends yielded, it is fundamental to use the RI to calculate returns instead of nominal changes in prices only. To compute bonds returns the study uses the US Generic Government (bonds) 10 years Index, USGG10YR:IND, this tracks bonds performances in a way similar to the one used by the RI to calculate equity returns. Therefore the index shows bonds growth in value over the considered period assuming that coupons payments are reinvested at the market risk-free rate. Coupons payments are annualized in the same way of dividends payments; adding increments of 1/260th part of the coupon yield to the price each weekday, assuming a total of 260 weekdays in a year.

I do not present descriptive statistics of the financial data within the main text because that would be a lengthy exercise of little interest to the reader, however these statistics are reported in the appendix. The only detail considered worth mentioning here is that in the time spam considered bonds returns both in yearly and monthly frequency have always been positive. This fortifies what was earlier said in section 2.1 about bonds returns being "sure".

## 6. Parameters Elicitation

### 6.1. Measuring Prospect Theory's Utility

#### 6.1.1. Elicitation Procedure

To elicit the PT utility function the survey used adopts a modified version of the method showed by Tanaka, Camerer and Nguyen (2010). This is a two-step elicitation procedure in which we first find parametric values for the gain domain and we then use these to determine loss aversion. Unfortunately this is not a very popular elicitation procedure, however given the nature of the survey data we cannot follow any other path. This procedure requires subject to answer to three series of chained questions, the first two regard a trade off between a sure prospect and a risky one within the gain domain. In the last series of questions subjects will be asked to state their preferences over two risky mixed prospects in the meaning that they can lead to both losses and gains. For each series participants will be asked to answer to four rounds of questions dependent on their previous answer in order to reach a more precise indifference point.

In the first series of questions subjects are presented with 2 boxes both containing 100 balls, either purple, yellow or orange. Subjects are then told that box S (sure prospect) contains only orange balls while box R (risky prospect) contains 10 purple balls and 90 yellow ones. Participants are then asked to choose one of the two boxes and told that from the chosen box a ball will be drawn at random; if the drawn ball is purple they win \$82, if orange they win \$10 while if it is yellow they only win \$3. Therefore Box S leads to a sure profit of \$10 while box R offers either \$82 with a 10% chance ore \$3 with a 90% chance with an expected value, EV, of \$10.9. Participants can also sate to be indifferent between the two boxes. Subjects were not given the opportunity to select the colors to bet on since prior studies have largely demonstrated that participants are indifferent over the balls colours (Abdellaoui, Baillon, Placido and Wakker, 2011; Fox and Tversky, 1998). A participant that prefers box S to box K reveals risk aversion; because he is ready to settle for a certain equivalent, CE, lower than the EV of the bet. Risk seeking behaviors would result in the opposite situation a CE higher than the expected value. Where certain equivalent means the amount of money that makes the subject indifferent between taking the bet or the sure payment. It is important to understand the relationship between CE and EV; The expected value is the average payoff that a risky prospect offers, however this average payoff is only theatrical, in practical terms if one takes the bet offered by box R only once than he will either win \$82 or \$3. The CE on the other hand is a sure amount of real money it is therefore risk free, it follows that a CE lower than the EV implies that the subject is willing to give up a bit of potential profit to eliminate the risk associated with the bet, hence risk aversion. The difference between the EV and the CE is called risk premium that is the extra compensation needed for carrying risks. If the opposite scenario presents itself (CE > EV) then the subject would want to be remunerated extra for not taking the bet, hence risk seeking. Risk neutrality implies CE = EV.

Following the first choice subjects will then be asked to state their preferences over the two boxes again just that now whatever box was preferred in the first stage is made relatively less attractive. Therefore if box R was chosen in round one its EV will be decreased to \$6.7 in round two. This is done by decreasing the winning associate with drawing a purple ball from \$82 to \$40. On the other hand if in the first round the subject selected box S, then expected value of box R is increased to \$24.7. This is done by increasing the winning associate with drawing a purple ball from \$82 to \$220. This procedure is repeated up to four times after which the certain equivalent for the risk box R can be precisely approximated. To be precise, the procedure does not find a subjective CE for the given box R, but rather finds the subjective box R that would correspond with the given CE of \$10. As previously explained it is the value of box R to vary while box S remains constant. In case, during any step of the elicitation procedure, a subject should chose to be indifferent between the two boxes than the exercise stops and the sure amount offered by box S is taken as certain equivalent of box R. The second series of questions is also regarding the gain domain and its design is analogous to the one just described with the only difference that the various outcomes associated with each colour are chanced. In round one of series two drawing a purple ball now worth \$85, a yellow ball \$5 and an orange one \$50. A part form this the procedure continues as before explained with the rewards associated with purple varying depending on the previous answers.

From these first two series of questions we can derive the parameter α of the utility function and parameter ϒ of the PWF. This is done by fitting the chosen parametric forms to the data and minimizing the Euclidean distance, sum of squared residuals, between the observed values, CE(x), and the one predicted by the model, CE(y), as showed in equation *(11)* (Gourieroux and Monfort, 1995).

$$(11) \qquad \sqrt{\textstyle\sum (CE(x)-CE(y))^2/n}$$

Given that these two series of questions were only about the gain domain the utility function indicated in equation *(7)* boils down to the form proposed in equation *(10)*. Therefore we are left with a system of two equations in two unknown, which can be easily solved. Moreover we here report that during the data fitting procedure we prefer to work with monetary unites rather than utility unites as showed in appendix A of Wakker (2010). This is the case because monetary unites are naturally defined on a ratio scale, meaning that they have a clear ranking and an unequivocal origin, therefore, it is not necessary to scale utility in any way, which would be otherwise needed. It is beneficial to not have to deal with utility scaling since it can lead to unwanted drawbacks, like measurement errors or incongruent estimates if the right scaling isn't adopted. Therefore we first calculate the utility associated with the risky prospects, we then take the inverse of such utility, which is the implied monetary CE by the theory, and finally we minimize the Euclidean distance between the observed CE, \$10, and the one just found. We will eventually choose the values of α and ϒ that best fit the data (minimize the difference).

From the third series of question we can derive the loss aversion parameter, λ. This third series is designed similarly to the two above. Only, now the choice is between two risky, mixed prospects; box 1 and box 2. In the first round box 1 offers 50% chance of winning \$2 and 50% chance of losing \$8, while box 2 offers 50% chance of winning \$60 and 50% chance of losing \$32. Following the first round whatever box was chosen is made relatively less attractive Just as before. The procedure continues for four rounds or until the subjects indicates to be indifferent between the two prospects. The need of comparing mixed prospects comes from the fact that only in this cases loss aversion plays a role and thus can be captured. I remind the reader that in section 2.1 loss aversion was defined as the mean or median value of –U(-x)/U(x) over a particular range of x (Kahneman and Tversky, 1979). Therefore, the loss aversion impacts us only when evaluating gains and losses jointly. Once again to obtain a value for λ we fit the model to the data and minimize the Euclidean distance. In this case the model that we are fitting is the one represented in equation (4) with all its various specifications. Of course we cannot derive the loss aversion parameter from the third series alone, because that would mean solving a single equation in three unknown (λ, α and ϒ), which is not mathematically possible. However we can go around this problem by assuming for α and ϒ the values previously found and therefore reducing the calculation in one equation in one unknown. The validity of this short cut was elegantly demonstrated by Abdellaoui, Bleichrodt and l'Haridon (2008).

Finally it is important to underline that throughout all elicitation procedures we will use a representative agent framework, so we will treat all the different choices made by the subjects as if they were all made by one representative subject. This procedure is usually adopted in behavioural sciences and finance to allow us to measure average parameters rather than subjects' specific ones and in turns making more precise estimates and more general conclusions (Geweke, 1985; Kydland and Prescott, 1991).

### 6.1.2. Summary Statistics

In this section reports some basic descriptive statistics over the risk attitudes of the survey population. For this aim we construct an index of risk aversion, RAI, starting from the connection between the CE and EV before explained in section 6.1.1. Given that risk adverse subjects will accept CE lower than the bet EV, while the opposite is true for risk seeking subject, to construct RAI we simply subtract the CE form the EV. The index will assume positive values in case of risk aversion and negative ones for risk seeking. The index will be equal to zero in the case of risk neutrality. Table 1 summaries the findings, in panel A there are reported some basic statistic for the index while panel B shows the proportions of the survey population being risk averse, neutral or seeking. Panel B confirms that risk aversion is the most commonly found behavior, with an overwhelming 75.78%.

Unfortunately, given the nature of the dataset this is the most I can show in terms of summary statistics. For example, I cannot show the fourfold pattern of risk attitudes that is usually found from similar studies (Tversky and Kahneman, 1992; Wu, Zhang and Gonzalez, 2004). However the weakness of the dataset over the risk domain is compensated by its richness in the ambiguity domain. Thanks to this in section 6.2.2 I will be able to show some more informative statistics over ambiguity attitudes.

**Table 1: Summary Statistics Risk Aversion**

| **Panel A**: Summary statistic risk aversion index | | | | | |
|---|---|---|---|---|---|
| | Mean | Std. dev | Min | Median | Max |
| RAI | 41.2453 | 38.0466 | -8.75 | 41.5 | 118.75 |
| **Panel B**: Risk attitudes (proportion of respondents for each type) | | | | | |
| Risk averse | | | 75,78 | | |
| Risk neutral | | | 3.53 | | |
| Risk seeking | | | 20.69 | | |

**Note:** The table shows summary statistics of the USA risk attitudes. Panel A describes the RA index, this is an index of risk aversion obtained by subtracting the CE to the EV. Panel B summaries the percentage of the total population being either risk averse, neutral or seeking. The statistics given in the table have been derived from non-mixed prospects only.

### 6.1.3. Elicitation Results

The elicitation results are displayed in table 2, In panel A it is reported the first elicitation step, which accounts for the gain domain only. Here we find values of α and ϒ respectively equal to 0,419 and 0,737. These translate in a concave utility function for gains (convex for losses) and in an inverse-s shaped PWF. Panel A also report the dollar fit of our model to the data, this is the residual Euclidean distance between the observed data and the one predicted by our model after the minimization exercise took place. The dollar-fit is an important indication of the goodness of fit with low values indicating a superior match. The dollar fit of our model is $0.001 this means that the predicted values of the model, CE(y) in equation *(11),* are on average only $0.001 off from the observed ones, CE(x) in equation *(11).* This is an extremely good result because it implies that the model predictions are accurate to the cent.

The outcomes of the second elicitation step are reported in table 2, panel B. the values for α and ϒ are the same as in Panel A since we assume them to be so in order to derive the loss aversion coefficient. We find for λ a value equal to 1.648, which is considerably smaller than the original estimate found by Tversky and Kahneman (1992), 2.25, but still implies a strong aversion towards losses. In practical terms this means that for an average USA citizen a loss will feel 1.6 times more painful than how pleasing a corresponding gain would feel. Even though our estimate of λ is lower than in the original study, more recent literature agrees with our finding, as a matter of fact it seems that todays general population is somewhat less loss averse than what estimated by Tversky and Kahneman (1979-1992). For a comprehensive over view over historical estimations of loss aversion and prospect theory parameters I refer the reader to Fox and Poldrack, (2009). Finally the dollar fit of our full model, panel B, is \$0.012. This is considerably higher than the one offered by the gain domain only, however this is expected due to the extra complexity caused by adding the loss domain to the evaluation process. Anyhow a fit of \$0.012 still implies a one-cent accuracy an it is should be considered a positive result.

**Table 2: Elicitation Results of Prospect Theory Risk Attitudes**

| | |
|---|---|
| **Panel A:** Prospect theory elicitation (gain side) | |
| α | 0.419 |
| ϒ | 0.737 |
| Dollar fit | 0.001 |
| **Panel B:** Prospect theory elicitation (gain and loss side) | |
| α | 0.419 |
| ϒ | 0.737 |
| λ | 1.648 |
| Dollar fit | 0.012 |

**Note:** the table reports the elicitation of the prospect theory parameters following the two step procedure of Tanaka, Camerer and Nguyen (2010). Panel A reports the first step, this is the gain domain only. While panel B shows the results of the second step, which includes both gains and losses. The parameters are chosen in order to minimize the Euclidean distance between the CE(x) and CE(y). The dollar fit is the residual "distance" left between the two after the minimization procedure has completed.

## 6.2. Measuring Ambiguity Source Function

### 6.2.1. Elicitation Procedure

To elicit ambiguity attitudes the survey model undertook for this study adopts the matching probability method, which has been widely used in previous literature (Baillon and Bleichrodt, 2015; Baillon, Cabantous, and Wakker; 2012; Dimmock, Kouwenberg, and Wakker, 2016). The method aims to elicit indifferences between a risky and an ambiguous prospect in an Ellsberg's paradox kind of design. To this aim subjects are taken through a series of choices (four rounds in total) dependent on their prior answers and aiming to converge towards a clear point of indifference. This procedure has many similarities to the one above described for risk. Participants in the first round are asked to choose between two prospects; an ambiguous one, box U (unknown) and a risky one, box K (known). As showed in fig(2) panel A, both of the boxes contain 100 balls of two possible colours (yellow or purple), however, while in box K the distribution of colours is known (50-50), box U does not give any hint over its colours distribution. As in the original Ellsberg's experiment subjects are told to choose a box and that following their choice a ball will be drawn at random form the chosen box, if the drawn ball is purple the participant wins $15 and otherwise nothing[16]. Participants also have the option to state their indifferences between the two options. A preference for box K reveals ambiguity aversion while a preference for box U ambiguity seeking. Subjects that indicate to be indifferent are defined as ambiguity neutral; these last treat the ambiguous probability of winning associated with Box U as if it was equal to the one of the known Box K (50%). For this reason, we refer to 50% as Box U's ambiguity-neutral probability of winning. This can also be interpreted as the reference probability of box U in the sense that it offers subjects a natural reference point to evaluate the ambiguous prospect with. Following this first choice the subject will then be asked to state his preferences over the two boxes again just that now whatever box was preferred in the first stage is made relatively less attractive. Therefore if box K was chosen in round one its known probability of winning will be decreased to 25% in round two. On the other hand if in the first round the subject selected box U, then the known probability of box K would have been raised to 75% in the second round making box U relatively less attractive. This procedure is repeated up to four times after which the probability that would make the participant indifferent between the two boxes can be precisely approximated. In case, during any step of the elicitation procedure, a subject should chose to be indifferent between the two boxes than the exercise stops and the probability of K is taken as indifference point. We refer to the probability of winning in box K that makes subjects indifferent between the two boxes as the matching probability. The just described procedure is then repeated other two times with the only difference that the initial reference probability (ambiguity neutral probability) is varied. In one case the probability will be brought down to only 10% this materializes in box K containing 100 balls of 10 different colours, 10 balls per colour, the participant wins only if a purple ball is extracted as shown in figure (2) panel B. we refer to this a the low-reference probability case. In the second case we have the opposite scenario, the reference probability is increased to 90%, in this case we have the same scenario of figure (2) panel B, but participants will win the $15 if any colour but purple is extracted. We call this the high-reference probability case. In the end of the experiment we obtain matching probabilities over this three scenarios for each subject.

[16]Once again subjects were not given the opportunity to choose the colour to bet on for the same reasons stated in section 6.1.1.

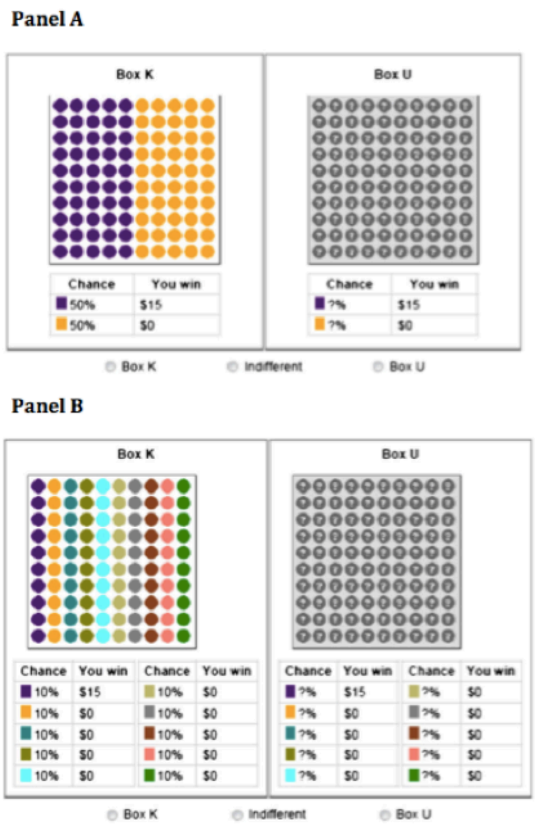


**Fig 2:** The figure shows screenshots of the first round of choice questions for the 50% (panel A) and 10% (panel B) reference probabilities (Dimmock, Kouwenberg, Mitchell and Peijnenburg, 2015).

Matching probabilities give important indications of subjects' ambiguity attitudes. Matching probabilities lower than the initial reference probability assigned to box K (either 10%, 50% or 90%) will indicate ambiguity aversion while matching probabilities higher than that reflects ambiguity seeking. Starting from here we can derive Jaffray (1989), Kahn and Sarin's (1988) AA-indexes, which represent the various level of local ambiguity aversion.

$$\begin{aligned} & AA^{0.1} = 0.5 - m(0.1) \\ (11) \qquad & AA^{0.5} = 0.5 - m(0.5) \\ & AA^{0.9} = 0.5 - m(0.9) \end{aligned}$$

The indexes' superscripts indicate what is the reference probability that we are considering. The value of the index simply equals the reference probability minus the matching one. As said before in case of ambiguity aversion the matching probability will be lower than the reference one causing the index to assume positive values. The opposite is true for ambiguity seeking behaviours. A major advantage of using matching probabilities comes from the fact that they measure ambiguity relative to risk because the alternative choice to the ambiguous prospect is a risky one. As a result all other feature of utility such as risk or loss aversion and the PWF are eliminated from the comparison (Dimmock, Kouwenberg, Mitchell and Peijnenburg, 2016). This is vitally important for the present research since we aim to use these data to understand the impact of ambiguity on the stock market as something other than risk.

Furthermore, given the richness of the ambiguity dataset, it is also possible to derive the two ambiguity indexes proposed by Abdellaoui, Baillon, Placido and Wakker's (2011), these are non-parametric indexes based on neoadditive weighting functions of the Chateauneuf, Eichberger and Grant (2007) type. These indexes can also be interpreted as more compact and easily tractable version of those earlier offered by Tversky and Fox (1995); Kilka and Weber (2001). The major benefit that these indexes offer lies in their non-parametric nature, which do not force data in pre-made functional forms but rather leaves them speak for themselves. Therefore in constructing the indexes we chose the neoadditive weighting function that best fits the data. This in turns will allow us to get a clearer and more realistic representation of ambiguity attitudes.

The first index is related to the elevation of the weighting function, it therefore captures pessimism in ambiguous situations with optimism as its counterpart. This index does not formally capture ambiguity aversion (seeking) per se since that would be the difference in the degree of pessimism (optimism) between a risky and ambiguous situation. On the other hand the second index captures the degree of curvature of the function and it can therefore be considered as an index of a-insensitivity. Both of the indexes can be easily retrieved, through linear regression, starting from the matching probabilities, m(p), obtained in section 6.2. As showed by Abdellaoui, Baillon, Placido and Wakker's (2011), we first measure the best fitting line between m(p) and the ambiguity neutral probabilities p in the open interval (0,1).

$$(14) \qquad y = c + sp$$

Where c is the intercept with the y-axis while s is the slope of the line. The two ambiguity indexes are then defined as follow:

$$(15) \qquad a = 1 - s$$

$$(16) \qquad b = 1 - s - 2C$$

The first index, a, captures a-insensitivity while the second one, b, is the index of pessimism. Index b can be rewritten as $b = d - c$ with d being the distance between the regression line and 1 at $p = 1$, this is $d = 1 - c - s$.

Finally, starting from the observed matching probabilities and the reference one we can derive the parameters need for equation *(8).* This is done by fitting the source function to the data by minimizing the sum of squared residuals, just as in section 6.1.1. Therefore the input of the source function will be the reference probabilities of box K (10%, 50%, 90%) and the parameters will be chosen in order to minimize the geometric difference (the sum of squared residuals) between the probabilities transformed by the source function and the observed matching probabilities. As in the case of risk the one representative agent framework will be used.

### 6.2.2. Summary Statistics

Before showing the results for the elicitation procedure, it is interesting and informative to look at some summary statistics. First we have constructed the AA-indexes mentioned in the section before, summary statistics of the indexes' together with the matching probabilities that generated them are offered in table 3, panel B. As it can be seen from table 3 the matching probability of the low-reference probability case, $m^{10}$, is well above its reference (0.227 > 0.1). This reflects ambiguity seeking, which causes the corresponding AA-index, $AA^{0.1}$, to be negative. For the medium and high-reference probability cases we have the opposite scenario (0.476 < 0.5 and 0.714 < 0.9) with positive values for the corresponding indexes. This reflects ambiguity aversion. The shift from ambiguity seeking for low-reference probabilities to ambiguity aversion for medium and high-reference probabilities is due to a-insensitivity. As previously explained in section 2 this is caused by subjects having a tendency to estimate ambiguous distributions biased towards 50-50. Therefore in the case of the low-reference probability, only 10% chances of winning, the ambiguous prospect seems to be preferable while the opposite is true for the other two cases.

**Table 3: Summary Statistics Ambiguity Aversion**

**Panel A**: Ambiguity attitudes (proportion of respondents for each level of likelihood)

| **Ambiguity attitudes** | Gain 10% | Gain 50% | Gain90% |
|---|---|---|---|
| Ambiguity averse | 19.16 | 52.22 | 55.98 |
| Ambiguity neutrality | 24.09 | 11.91 | 16.06 |
| Ambiguity seeking | 56.75 | 35.87 | 27.96 |

**Panel B**: Summary statistics of matching probabilities and ambiguity aversion

| **Matching probabilities** | Mean | Std. dev | Min | Median | Max |
|---|---|---|---|---|---|
| $m^{10}$ | 0.227 | 0.200 | 0.015 | 0.175 | 0.850 |
| $m^{50}$ | 0.476 | 0.211 | 0.030 | 0.470 | 0.940 |
| $m^{90}$ | 0.714 | 0.259 | 0.550 | 0.770 | 0.990 |
| **Ambiguity aversion** | | | | | |
| $AA^{10}$ | -0.013 | 0.200 | 0.750 | -0.075 | 0.085 |
| $AA^{50}$ | 0.024 | 0.211 | -0.440 | 0.030 | 0.470 |
| $AA^{90}$ | 0.019 | 0.259 | -0.090 | 0.130 | 0.845 |

**Panel C**: A-Insensitivity

| | Percentages of respondents |
|---|---|
| A-Insensitivity ($AA^{90}$-$AA^{10}$ > 0) | 77.89 |
| A-neutral ($AA^{90}$-$AA^{10}$ = 0) | 10.16 |
| A-Oversensitivity ($AA^{90}$-$AA^{10}$ < 0) | 11.95 |

**Panel D**: Correlations

| **Ambiguity aversion** | $AA^{10}$ | $AA^{50}$ | $AA^{90}$ |
|---|---|---|---|
| $AA^{10}$ | 1 | | |
| $AA^{50}$ | 0.406 | 1 | |
| $AA^{90}$ | 0.190 | 0.321 | 1 |

**Note:** This table shows ambiguity attitudes in the U.S. population measured in the freely available online ALP module from Dimmock et. Al 2015. The table offers a break down of the summery statistic similar to the one proposed by Kothiyal, Spinu and Wakker, (2014). Participants are asked three ambiguity questions regarding gains with ambiguity-neutral probabilities of 10%, 50%, and 90% for Box U, where subjects could win $15. Panel A displays the percentages of respondents that are ambiguity averse, ambiguity seeking, or ambiguity neutral, based on their choice between Box K and Box U for the three ambiguity questions. Panel B shows summary statistics for the matching probabilities and ambiguity aversion measures. Panel C summarizes a-insensitivity. Panel D presents correlations of the three ambiguity aversion indexes. The sample consists of 3291 participants

This shift from ambiguity seeking to ambiguity aversion with the increase of the reference probability is clearly showed in panel A of table 3. It can be here observed the proportion of subjects being ambiguity seeking/ neutral/ averse at the various reference probabilities. As it can be seen the percentage of risk aversion increases from only 19.6% for the low-reference probability to 55.98% for the high- reference probability case. Moreover in table 3 panel C we calculate the percentages of subjects exposing a-insensitivity, a-neutrality or a-oversensitivity (which is the opposite case to a-insensitivity). This can be done starting from the $AA^{0.9}$ and $AA^{0.1}$ indexes. By subtracting $AA^{0.1}$ from $AA^{0.9}$ we obtain an index of a-insensitivity. The index assumes positive values if the subject is a-insensitive (since $AA^{0.1}$ will be negative while $AA^{0.9}$ positive) and negative values if he is a-oversensitive (for the opposite reason). The index will equal zero in the case of a-neutrality. As it can be seen from panel C the overwhelming majority of our subjects is a-insensitive (77.89%) confirming it to be the most common behavioral pattern. Finally panel D shows correlations among the various indexes, it can be seen that the correlations are small and always lower than 0.5 which reflects that the indexes are capturing different behaviors.

Lastly, the results for the best-fitting line obtained through OLS regression and the estimates of the two non-parametric indexes are presented in table 4, panel A and B respectively. The obtained results are in line with previous literature Abdellaoui, Baillon, Placido and Wakker (2011); Dimmock, Kouwenberg and Wakker (2016) and with the parametric estimates obtained in section 6.2.3. The a index assumes a value of 0.392, which is coherent with a-insensitivity, ambiguity-neutrality would imply a value of the index equal to zero while a-oversensitivity would be represented by negative values. Index b reflects pessimism with a value of 0.05; also in this case neutrality would imply a value of the index equal to zero while optimism would be represented by negative values. Taken together the two indexes suggest that the ambiguity source function are best captured by two separate parameters and can be represented by an inverse-s shaped function like the one found in figure 3. All in all, the non-parametric estimations give a strong theoretical and empirical ground in justifying the use of the two parameters Prelec's function adopted by the present study.

**Table 4: Regression and Estimates Results Ambiguity Attitudes Indexes**

| **Panel A: OLS Regression Results** | |
|---|---|
| Constant C | $0.168^{***}$ (0.007) |
| Slope s | $0.608^{***}$ (0.004) |
| $R^2$ | 0.438 |
| **Panel B: Estimates Ambiguity Indexes** | |
| a $(1 - s)$ | 0.392 |
| b $(1 - s - 2c)$ | 0.05 |

**Note:** This table shows the regression results of the best-fitting line between m(p) and p in terms of quadratic distance. The results are then used to estimate the ambiguity indexes from Abdellaoui et al. 2011. . The superscripts indicate the confidence levels with one star being 10% and three stars 1%

### 6.2.3. Elicitation Results

The elicitation results are displayed in table 4. We obtain values for our a-insensitivity, z, and ambiguity aversion, δ, parameters equal to 0.485 and 0.947 respectively. These values translate into the inverse-s shaped curve reported in fig 3. All the obtained results are in line with previous literature and with the original study from which the dataset was generated (Abdellaoui, Baillon, Placido and Wakker, 2011; Stott, 2006; Dimmock, Kouwenberg, Mitchell and Peijnenburg, 2015). Moreover the obtained values imply both ambiguity aversion and a-insensitivity, on average, at a global level, therefore confirming the theoretical predictions and the general tendency highlighted in the summary statistics.

**Table 5: Estimates Results Source Function**

| | |
|---|---|
| Z | 0.485 |
| δ | 0.947 |

**Note:** The table reports the parameters obtained by fitting the Prelec's two-parameters function at the data by minimizing the Euclidean distance.

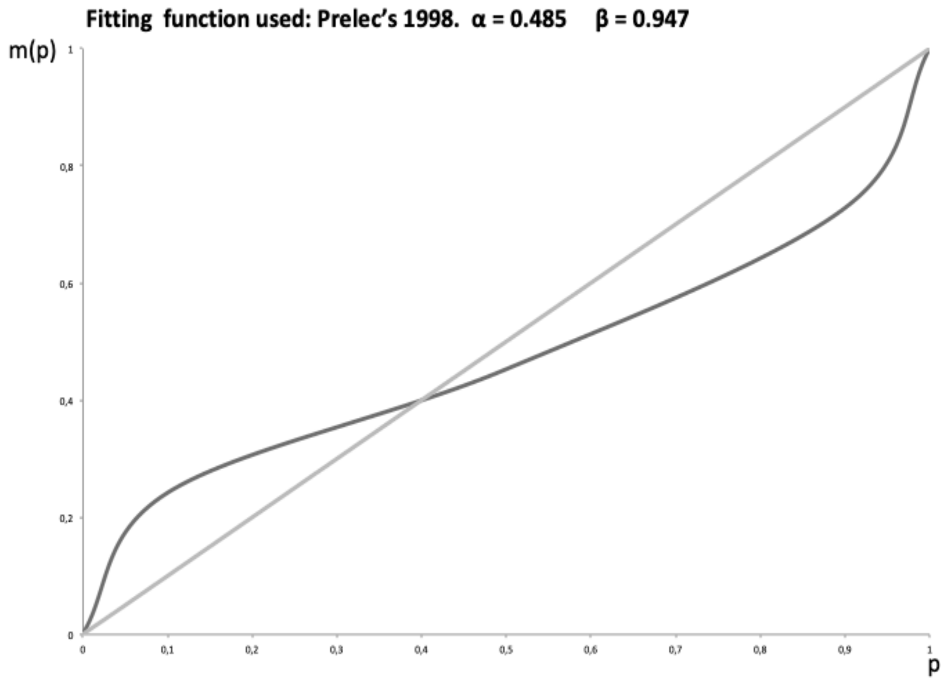


**Fig 3**: the figure displays the source function estimated with a two parameters Prelec's family function, equation *(8).* On the x-axes the reference probability

## 7. Analysis

### 7.1. Subjective Returns Distributions

While the previous section focused on estimating the model's parameters, this section aims to retrieve the model's inputs. That is the stocks and bonds subjective returns and associated probabilities. It is here important to put an extra emphasis on the word *subjective*. It has already been repeated multiple times in the course of the paper that it is not possible to obtain accurate prospects of all possible outcomes following the purchase of a bonds and/or stocks, which is why we consider them ambiguous rather than risky. However, as explained in section 4.2, given the impossibility of obtaining objective prospects (the real return distributions) people will create subjective ones on which they base their decisions. These subjective returns distributions might not be known at any conscious level, yet I argue that they can be retrieve starting from historical returns. This is the case because after all historical returns are the results of investors' interactions and past choices; they therefore contain intrinsic information over people preferences.

In fact, previous literature shows that subjective returns distributions can be obtained following a bootstrap procedure (Benartzi and Thaler, 1995; Gurevich, Kliger and Levy, 2009; Kliger and Levy, 2009), which is also often used by practitioners to obtain forecasts of the possible future outcomes of their investments[17]. The bootstrap is essentially a Montecarlo simulation with replacement and it is often used in statistics as a resample technique. In statistics we usually work with sub-samples of a wider population that is often unobservable. These sub-samples differ from the true population sample however, if they are big enough, their means should converge to the one of the true population. Following these, the main idea underlining the bootstrap is that if we construct many sub-samples (in the present case 10'000.00) by drawing random values with replacement from a starting sample that is big enough, we can then take all the means of these sub-samples and construct a sample distribution of means. The latest will not be exactly like the true population sample, but it can be mathematically showed that it closely resembles it especially in terms of mean (Efron, 1992). Additionally we can increase the accuracy of the procedure by eliminating the 2.5% extreme values from both tails of the sample distribution of means, therefore ensuring a result within the 95% confidence interval.

In practice we take the monthly return distribution of a stock within the time interval considered (1999-2019), this offers 251 observations. We then create 10'000.00 samples of 251 observations by randomly drawing with replacement values from our initial sample. The mean of the simulated samples are then used to construct the sample distribution of means within the 95% confidence interval. The obtained sample distribution of means are then used as the subjective returns distribution considered by investors. This procedure is repeated both for the monthly and yearly return distributions for bonds and each one of the 81 stocks considered in the study. Finally the sample

[17]Practitioners usually use the bootstrap only to obtain predictions over the "best and worst case scenarios" within a certain confidence interval. However this analysis can be easily expanded to the full range of possible outcomes implied by the historical return distribution.

distributions of means are divided into range of outcomes to which probabilities are assigned, we use the middle point of each range when evaluating the prospects. In total we created 20 intervals in accordance with Benartzi and Thaler (1995), who showed that using more than 20 intervals is redundant because it does not considerably improve the accuracy of the evaluation.

## 7.2. Cross-Sectional Analysis

Once obtained all the needed parameters and inputs for the models we can start evaluating equity and bonds, the evaluation process is going to produce utility amounts for bonds and stocks. These utility amounts give useful information over investors' preferences: the higher the utility produced the more interesting the stock/bond will seem. All things equal a prospect that offers higher utility should always be preferred to one that offers less. Moreover starting from these utility values we can also calculate the implied average equity risk premiums between stocks and bonds, this can be done in the following manner. First we calculate the CE and EV of each prospect. The latest simply is the average of all possible outcomes weighted for their probabilities, while the former is the inverse of the total utility produced by the stock (note that in case of negative utility λ also plays a role), equation *(12).*

$$(12) \qquad CE = \begin{cases} U^{(1/\alpha)}(x) & \text{if } U(x) > 0 \\ (U^{(1/\alpha)}(x)) \,/\, \lambda & \text{if } U(x) < 0 \end{cases}$$

Now we can subtract the CE from the EV, which gives us the risk premiums associate with each stock and bonds. It is here important to notice that these risk premiums are something other than the equity risk premium, the latest is the reward for carrying equity instead of bonds while the former are the minimum theoretical price premiums that must be associate with each stock and bond for investors to be willing to hold them instead of the CE. However it is relatively easy to obtain equity risk premiums starting from the calculated risk premiums, this can be done by simply subtracting the risk premium of bonds from those of the various stocks. In this way we obtain the equity price premium on top of the one offered by bonds, hence the equity premium.

Following this procedure we calculate the equity premiums associate to each stock according to all the presented models in section 4: EU, AEU, PT and APT. From these data we can verify which model would predict the highest premiums and even more interestingly we can look at which predictions best correlate with the average equity premiums implied by the bootstrap results, that is the mean of the stock sample distribution of means (its average return) minus the average bonds' return calculated in the same way. This is done for both monthly and yearly time frames. The final metric that will be considered is an additional measure of fit between the models' predictions and the average equity premiums implied by the bootstrap. This measure will look at the square root of the sum of squared differences between the models predictions and the bootstrap ones. It therefore resembles the dollar fit presented in section 6.1.3.

## 7.3. Inter-temporal Analysis

Given the utility data derived in the previous section 7.2 we can also construct a simple test for the myopic loss aversion discussed in section 2.3. To this aim only the utility predictions made by our full model, APT, will be used, because the focus of the inter-temporal analysis should not be the comparisons between different model specifications but rather to research the phenomena of myopic loss aversion itself. Myopic loss aversion was before defined as a combination of narrow framing and loss aversion that causes investors, who evaluate their portfolio more frequently, to become more risk adverse than they would if they were to evaluate their portfolios less frequently. This is due to the fact that stock market returns are positively skewed it is therefore more likely to observe losses in lower time frames, these losses will be over-weighted by loss aversion causing investors to become more risk adverse. Consequentially, the myopic loss aversion theory would predict a shift in preferences from bonds towards stock as we increase the considered time frame.

To test this prediction we construct an index of preferences, PI, by subtracting the bonds utility value from each stock both in the monthly and yearly time frame. In case the utility generated by bonds is superior to the one associated with the equity, hence bonds are preferred, the index will assume negative values. The opposite is true if equity was to be preferred. A Logit model is then used to test whether it is more likely to observe negative values of the index (preference for bonds) in monthly time frames rather than yearly ones. Many control variables like the company's industry, PE and CAPM betas are gradually added to test the robustness of the result.

$$\text{(13)} \qquad Pr(y=1 / x_1\, x_2) = \exp\,(\beta_0 + \beta_1\, x_1 + \beta_2\, x_2) / 1 + \exp\,(\beta_0 + \beta_1\, x_1 + \beta_2\, x_2)$$

Equation *(13)* describes the used Logit model. Y is a dummy variable equal to 1 in case the preference index is negative and 0 otherwise. The probability of y being 1 is dependent on $x_1$ and $x_2$, which are respectively a dummy that indicates the frequency with which reruns are evaluated, 1 if evaluated monthly 0 otherwise, and a variable to symbolize all the various controls. Finally starting from the Logit results we will calculate marginal effect and odd ratios relative to the main independent variable, $x_1$.

# 8. Results

## 8.1. Cross-Sectional analysis results

Table 6 reports the summary statistics for the equity premiums estimated by the various models following the procedure outlined in section 7.2. Panel A presents the results for the monthly time frame while the yearly ones are presented in panel B. The two panel agrees that EU offers on average equity premiums lower than any other model considered, giving a first confirmation of the predictions made by the theory. Moreover the ambiguity model seems to generate estimates on average higher than PT and more in line with the results of the full model, APT. This in turn could indicate a higher impact from ambiguity in determining the equity premium sizes.

**Table 6: Summary Statistics Estimated Equity Premiums**

| **Panel A**: Summary Statistics Monthly Estimated Equity Premiums | | | | |
|---|---|---|---|---|
| **Models** | **Mean** | **Std. dev.** | **Min.** | **Max.** |
| EU | 1.70 | 1.54 | 0.27 | 8.06 |
| PT | 2.35 | 3.63 | 0.56 | 20 |
| AEU | 3.96 | 4.77 | -0.15 | 20.14 |
| APT | 8.52 | 5.65 | 0.63 | 29.02 |

| **Panel B**: Summary Statistics Yearly Estimated Equity Premiums | | | | |
|---|---|---|---|---|
| **Models** | **Mean** | **Std. dev.** | **Min.** | **Max.** |
| EU | 0.1375 | 0.1022593 | 0.03 | 0.42 |
| PT | 0.448625 | 0.5187564 | - 0.01 | 3.02 |
| AEU | 0.650625 | 0.3805504 | - 0.15 | 2.01 |
| APT | 0.68625 | 0.486622 | - 1.17 | 2.36 |

**Note:** The table offers descriptive statistics over the estimated equity premiums. Panel A reports the monthly results while Panel B the yearly ones. The reported premiums are obtained following the procedure in section 7.2.

Table 7 reports the estimates of the OLS model used to compare the sizes of the various predicted equity premiums. The superscripts indicate the confidence levels with one star being 10% and three stars 1%, the standard errors are reported in brackets. EU was used as a reference category and it was left out from the model, therefore the results offered in the table should be interpreted in comparison to EU. For example the coefficient of APT for the yearly estimates should be interpreted as the equity premiums generated by the APT model are on average 6.8 times larger than the one generated by EU, cp. All the findings are significant within the 1% confidence level and their effect is in the hypostatised direction.

**Table 7: Regression and Fit Results Cross-Sectional Analysis**

| **Panel A:** OLS regressions | | |
|---|---|---|
| **Models** | **Monthly** | **Yearly** |
| PT | 0.311*** (0.59) | 2.257*** (0.44) |
| AEU | 0.513*** (0.44) | 5.459*** (0.653) |
| APT | 0.548*** (0.54) | 6.822*** (0.65) |

| **Panel B:** Fit measures | | |
|---|---|---|
| **Models** | **Monthly** | **Yearly** |
| EU | 1.257 | 13.325 |
| PT | 1.076 | 11.366 |
| AEU | 0.833 | 9.041 |
| APT | 0.832 | 8.380 |

**Note:** Panel A reports the OLS regression results for the various models, EU is left out since it was taken as reference category so that all results should be interpreted in comparison with it. Panel B shows the Euclidean distance between the historical observed equity premiums and the predictions made by the models, this is here used as a fit measure.

Panel B of table 7 reports the results for the first of the two fit measures considered. The metric proposed in panel B can be thought as the average Euclidean distance between the equity premium predicted by the model and the historical one, therefore the lower is the distance the better the fit. It can be though as an ex-ante non-parametric measure of fit. Finally figure 4 reports the correlations between the estimated equity premiums and the historical ones derived from the bootstrap, this is an indication of which models' predictions best approximates the data. The results of the correlations agree with the one of the previous fit measure and will be discussed in the coming section.

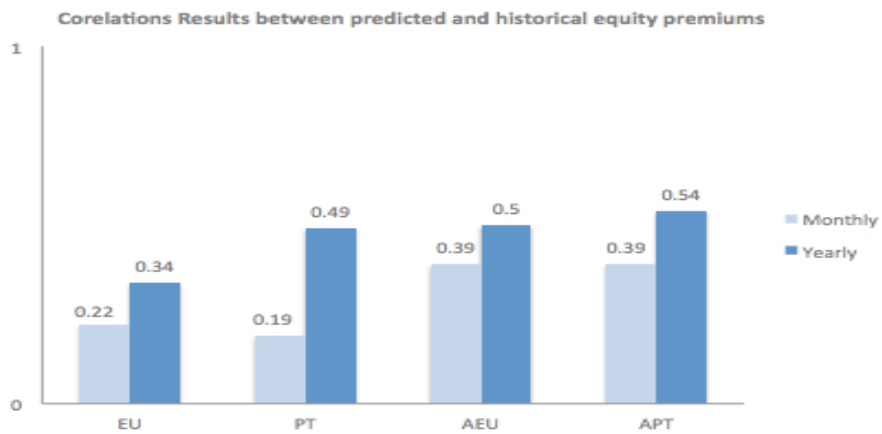


**Fig 4**: The figure reports the correlation results between the equity premiums predicted by each model and the historical once obtained through the bootstrap. The historical premiums are obtained by subtracting the average bond return from the average stock return as calculated by the bootstrap The light blue bar is the monthly correlations while the dark blue one is the yearly ones.

## 8.2. Discussion of Cross-Sectional analysis results

The results of the cross-sectional analysis clearly support all the predictions before made by the theory. All the analysed models offer average equity premiums higher than the one predicted by EU, this could be considered as evidence that the historical equity premium, which are too high to be explainable within an EU framework might be well explainable using more sophisticated models. Of course this is only a speculation since the only thing that the results in table 7 panel A can prove with certainty is that the premiums generated by PT, AEU and APT are on average larger than the one of EU both in monthly and yearly timeframes. Moreover it is interesting here to notice how the predictions of AEU are on average higher than the one of PT, this is evidence that ambiguity might have a more important role than loss aversion in explaining the EPP.

However producing higher equity premiums does not ensure to give the more accurate predictions. In order to test which model can more closely resemble the historically observed equity premiums we look at two measures of fit: the Euclidean distance and the correlation between the analysed models and the historical data. The Euclidean distance is reported in table 7 panel B, lower value indicate a better fit. Given the results it seems like independently from the time frame used APT offers the highest fit closely followed by AEU and then PT and EU. These results are confirmed by the correlations displayed in figure 4, once again APT offers the highest correlation, hence fit with the historical premiums. Also in the case of these two fit measures AEU and APT give results that closely resemble each other while PT follows from the close distance. This increases the number of evidence in favour of ambiguity being the major driver of the equity premiums sizes.

Finally it is important to notice that we never obtain correlations of 1, the best we get is 0.54. This indicates that we only manage to explain around half of the size of the historically observed premiums meaning that there might be something other than risk and ambiguity attitudes as we modelled them to determine equity premiums. However we still considered the 50% correlation as a huge success especially given the simplicity and limitations of the analysis used. To conclude we have to point out that Thaler remark that the EPP is really a consumption puzzle and therefore only explainable with an inter-temporal consumption based model also applies to the present case. The models used in this research are not consumption based nor dynamic equilibrium models but rather decision-making models on which returns are dependent on, for this reason they cannot claim to offer a formal solution to the puzzle, however the evidence just presented is at least highly suggestive of a deep connection between risk, ambiguity attitudes and the equity premium size.

## 8.3. Inter-Temporal analysis results

Panel A of table 8 reports summary statistics for the dependent and all independent variables that will be used in the study. The dependent variable, PI, is the index of bonds' preference derived in section 7.3. Panel A breaks the index into monthly and yearly in order to transmit more informative statistics, yet within the Logit regression we will use one full PI that includes both monthly and yearly data. From the break down offered in panel A it is possible to see that the yearly PI mean (1.369) is well above the monthly one (0.135), which hints to a preference shift towards stocks in yearly evaluations. This is further confirmed by the findings presented in panel C; it is here possible to observe the percentages of bonds preference for both monthly and yearly frequencies. While bonds are preferred in roughly 30% of the cases under a monthly horizon, they are preferred in only 12.50% of the cases in a yearly timeframe.

The main dependent variable for the model is *Freq,* short for frequency; this is a dummy variable that is equal to 1 if the corresponding PI value was obtained following a monthly evaluation and 0 in the case of a yearly one. In order to test the robustness of our results we gradually add various controls starting with the market betas, for then follow with the P/Es and Market-to-book values. Finally we will also add controls for the industry, to achieve this we construct a categorical variable that assumes values of 2 if the company works in the tech industry, 3 in case of healthcare, 4 for finance, 5 for consumers good and 1 for other minority sectors (energy, warehousing and industrial). The variable is than broken into dummy, which are included into the regression, category 1, other, is left out as a reference point. To conclude panel B offers the distribution of stocks across industries, the five sectors are all fairly represented with consumers good being a minority at 13.92%.

**Table 8: Summary Statistics Logit variables**

| **Panel A:** Summary statistics dependent & independent variables | | | | | |
|---|---|---|---|---|---|
| **Variables** | **Mean** | **Std. dev.** | **Min.** | **Max.** | |
| PI_ Yearly | 1.369 | 1.281 | -4.13 | 3.638 | |
| PI_ Monthly | 0.135 | 0.531 | -1.569 | 1.2 | |
| | | | | | |
| Beta | 3.6061 | 5.465 | 0.234 | 25 | |
| P/E | 31.593 | 24.957 | 5.74 | 139.52 | |
| Market-to-book | 16.816 | 63.099 | 0.62 | 547.73 | |
| | | | | | |
| Freq. | Freq. is a dummy variable = 1 for monthly time-frames = 0 for yearly time-frames | | | | |
| **Panel B:** Decomposition of stocks per industry | | | | | |
| | **Other (1)** | **Tech (2)** | **Healthcare (3)** | **Finance (4)** | **Consumer goods (5)** |
| Industry | 24.05 | 24.05 | 21.52 | 16.46 | 13.92 |
| **Panel C:** Percentage of Bonds Preferred to stocks | | | | | |
| | | | **Percentage of bonds preference** | | |
| Monthly | | | 30.01 | | |
| Yearly | | | 12.50 | | |

**Note:** The Table reports summary statistics for all variable used in the Logit regressions. The independent variable is PI which is here broke down in its two major components; yearly and monthly evaluations. The main independent variable is *Freq* this is a dummy variable that is equal to 1 if the corresponding PI value was obtained following a monthly evaluation and 0 in the case of a yearly one. *Beta, P/E, M/B and industry* are all used as controls, panel B shows a break down of stock by industries. In panel C are displayed the percentage of bonds preference for monthly and yearly horizon, that is when the PI is negative.

Panel A of table 9 reports the results for all the Logit specifications. The numbers reported in the table are the marginal effects and not the Logit's coefficients. The superscripts indicate the confidence levels with one star being 10% and three stars 1%, the standard errors are reported in brackets. The first thing that should be noticed is that the results for the study's dependent variable of interest, *Freq*, are always significant within the 1% confidence level and in the predicted direction. For example the value of 0.175 in specification *(1)* should be interpreted as the likelihood of bonds being preferred to stocks in monthly frequencies is 17.5 percentage points higher than in yearly frequencies, cp. Moreover the magnitude of the effect of *Freq* remains fairly constant and robust across the four specifications.

**Table 9: Regression Results Inter-temporal Analysis**

| **Panel A:** Margins estimations for the different Logit specifications | | | | |
|---|---|---|---|---|
| | **Different Logit specifications, independent variable PI_tot** | | | |
| **Variables** | *(1)* | *(2)* | *(3)* | *(4)* |
| Freq. | $0.175^{***}$ (0.063) | $0.175^{***}$ (0.061) | $0.185^{***}$ (0.061) | $0.211^{***}$ (0.062) |
| Beta | | $-0.016^{*}$ (0.008) | $-0.017^{**}$ (0.058) | $-0.019^{**}$ (0.009) |
| P/E | | | $-0.003^{*}$ (0.011) | $-0.002^{*}$ (0.002) |
| Market-to-book | | | -0.001 (0.012) | 0.001 (0.033) |
| **Industry** | | | | |
| Tech (2) | | | | $0.252^{***}$ (0.096) |
| Healthcare (3) | | | | -0.033 (0.844) |
| Finance (4) | | | | 0.043 (0.101) |
| Consumer goods (5) | | | | - |
| **Panel B: Odd ratios** | | | | |
| | | *(1)* | | |
| Freq. | | 3.00 | | |

**Note:** Panel A reports the results for the Logit regressions, we use 4 different specifications in which we gradually increase the number of controls in order to test the robustness of our independent variable of interest, *Freq*. The dependent variable used in each model is the PI including both monthly and yearly results. The estimations for category 5 of the industry variables was not possible since category 5 was found to be associated with zero variation of the PI. Panel B reports the odds ratio of *Freq* that is the ratio between probability of bonds being preferred in monthly evaluations divided the between probability of bonds not being preferred in monthly evaluations and the probability of bonds being preferred in yearly evaluations divided the between probability of bonds not being preferred in yearly evaluations.

Some of the controls variables are also found to have a significant effect even within the 1% confidence interval as in the case of being a member of tech industry. This result in particular was quite unexpected especially given its huge magnitude; being part of the tech industry compared to *other* increases the probability of bonds being preferred to equity by 25.2 percentage points. Apart for the special case of the tech industry none of the other industry variables is found to be significant, and estimates for category 5 are not possible because this variable capture zero variation of the PI index[18]. Market to book value is also insignificant while P/E is significant within a 10% confidence level but its magnitude is extremely small causing a negative variation of only 0.s percentage points (specification (4)), we therefore treat it as an insignificant results not of interest for the present research. Finally *Beta* is found to be significant within the 5% confidence level and its marginal effects seem to be robust across three specifications. In particular under specification 4, on average, having a 1point higher beta decreases the likelihood of bonds being preferred to stocks by 1.9 percentage points, cp. Finally panel B reports the odd ratio of *Freq* that is the ratio of the odds of bonds being preferred to stocks in monthly over yearly frequencies. The results indicates that the odds of bonds being preferred to equity in monthly time frames are three times as likely as in yearly one.

## 8.4. Discussion of Inter-Temporal analysis results

The results of the inter-temporal analysis confirm the theoretical predictions made by myopic loss aversion. In particular in panel A of table 9 the marginal effects associated to the variable *Freq* are always significant within the 1% confidence level and positive. This profs that bonds are more likely to be preferred under a monthly evaluation period rather than a yearly one, in the extreme case of specification (4) bonds are 21.1 percentage points more likely to be preferred in monthly horizons rather than yearly ones. This result is further confirmed by the odd ratio presented in panel B table 9, which indicates that the odds of bonds being preferred to equity in monthly time frames are three times as likely as in yearly one. Moreover it is important to notice that the coefficient of *Freq* remains fairly constant across various specifications, which indicates the robustness and structural importance of the result. Even though the results are in the same direction of what the theory would predict, our findings are considerably different from the one of Benartzi and Thaler (1995). In their research one year is found to be the evaluation frequency that makes investors indifferent between bonds and stocks while under a monthly evaluation bonds are always found to be preferred to equity. None of this is directly applicable to the present research, bonds are found to be more often preferred to equity in monthly time frames however, even in this short horizon, they are preferred to stock only the 30% of the times. Similarly the one year horizon it is not a point of indifference in our study as most stocks, 87.5%, are preferred to bonds in this evaluation period. This might be explainable by taking a deeper look into bonds returns, which have been steadily decreasing since the time of Benartzi and Thaler study. In the time frame considered in their dataset the 10years interest rates (an indication of bonds return) fluctuated between 10% and 5%, while in the present study it moves in the range of 4% to lower than 1%. This element plays in favour of equity in two different ways. First, all things equal, the lower returns make bond seem less attract. Secondly, and most importantly, when valuing equity following standard DCF analysis it is possible to obtain extremely high valuations if cash flows are being discounted at low rates. This in turns makes equity seems so much more attractive.

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[18]The stocks within the consumer goods industry are found to always be preferred to the bonds, hence causing zero variation and the impossibility of estimate a precise coefficient.

Following our main independent variable also the market betas are found to be significant within the 5% confidence level. This is somewhat expected because the betas are risk indicators and the riskiness of the stock logically plays a major role in determining preferences. In particular *beta* is associated with a negative effect on the dependent variable indicating that the higher the beta the less likely it is for bonds to be preferred to stocks. In order to properly interpret this result we need to remember that our independent variable, PI, contains both monthly and yearly estimates therefore the coefficient of beta should not be interpreted as time dependent but as an absolute value. Therefore having a higher beta will be associated with stocks being preferred to bonds regardless the time horizon. This finding might sounds puzzling at first since higher betas should also mean higher risks, which in turns should make bonds more preferable. A possible explanation for this negative statistical relationship might lay in the fact that beta does not represents risks in general but rather the priced in risk or better said the risk that gets priced in according to the CAPM. Therefore higher betas are also associated with higher rewards for carrying risks that in turn cause the equity to be more preferable than bonds.

Finally being part of the Tech industry is also found to have a significant result within the 1% confidence level. This finding was unexpected, as I did not have any a-prior expectations for any industry variable. In order to offer a correct interpretation I remind the reader that PI does not have an inter-temporal meaning in itself and that the results associated with tech should be compared to the left out reference category, in this case *Other*. Therefore the result can be interpreted as being part of the tech industry compared to *other* increases the probability of bonds being preferred to equity by 25.2 percentage points despite the time frame, cp. A possible explanation for this finding can be found in the particular structure of tech industry returns; companies within the tech industry are usually characterized by very positively skewed returns, which is a consequence of their R&D dependency (Scherer and Harhoff, 2000; Coad and Rao, 2008). Usually tech companies operate in losses or near losses spending massive amount of money in R&D until they manage to discover their "golden goose". This positive skewedness of the return distribution connects with myopic loss aversion and in particular narrow framing, in section 2.3 was explained how positively skewed return distributions will give investors the impression that stocks are more risky than what they really are when analysed in lower time frames. Once again from the PI index alone it is not possible to make any inter-temporal claim therefore we break down the index in its monthly and yearly component and we look within the two separate time frames how often are bonds preferred to equity in the various industry considered. These results are displayed in table 10, which confirms our intuition about the skewedness of tech returns playing an important role in the findings of table 9.

**Table 10: Break Down of Bonds Preferences by Industry and Evaluation Frequency**

| | Percentage of bonds preference | |
|---|---|---|
| **Industry** | Monthly | Yearly |
| Tech Industry | 62.50 | 25.00 |
| All Other Industries | 19.67 | 9.92 |

**Note:** The table reports a break down of percentage of bonds preference for industry and time frame. The numbers in the table are the percentage of times in which bonds are found to be preferable than stocks that is when the PI is negative. Note that "all other industries" does not refer to the variable "*Other*" but to all industries that are not the tech one.

In particular it can here be seen how the shift in preferences between the monthly and yearly horizon is for the biggest part caused by tech companies' stocks, their attractiveness seems to decrease of more than 50% when shifting from one time horizon to the other causing bonds to be preferred the 60% of the times in monthly timeframes but only 25% of the times in yearly one. This shift in preference can also be observed in all the other industries however it is stronger and more evident for tech companies. These findings seem to confirm our hypothesis over the positively skewedness of the tech industry being the cause of the significant marginal effect associated with this industry in table 9. Eventually we could think about being part of the tech industry as a weak proxy for narrow framing, which is here confirmed to have an high impact on the likelihood of preferring bonds to equity.

## 9. Conclusions

This paper proposes and tests a behavioural explanation for the equity premium puzzle, based on prospect theory for ambiguity. To do this I first develop a comprehensive and empirically tractable decision making model that I then apply to the case of interest. The obtained model needs five parameters and one input. The parameters are: two parameters for ambiguity attitudes, z (a-insensitivity) and δ (ambiguity aversion), one parameter for the PWF, ϒ (pessimism and insensitivity) and two parameters for the utility function, α (concavity) and λ (loss aversion). The input needed concerns the returns' historical distributions. The construction of the model is based on previous literature, however I do not assume any of the parameters used, but rather I derive them starting from behavioural data representative of the USA population. The model's inputs are bootstrapped from the historical returns' distributions.

The cross sectional results, concerning (predicted) equity premiums, prove that our model, under any specification used, predicts equity premiums well exceeding the one that would be otherwise obtained by a standard EU framework. Furthermore the premiums predicted by our model offer a superior correlation and fit with average historical premiums, underlining a greater explanatory power. These results hold for both yearly and monthly horizons. Moreover the paper also looks into myopic loss aversion for monthly and yearly evaluations, thus giving an inter-temporal application of prospect theory. The inter-temporal analysis indeed confirms the presence and effect of myopic loss aversion. In particular, It is showed that bonds are roughly 20 percentage points more likely to be preferred to equity in monthly horizon compared to yearly ones, with an odd ratio equal to 3. These findings are very robust to a series of controls. Additionally some of the controls used are also found to have an effect on the likelihood of preferring bonds to equity. This is the case for the market betas and operating in the tech industry. this finding are justifies by showing how these two variables can be considered as proxy for priced-in risk and skewedness of the return distribution.

All in all the paper's findings suggest that the equity premium puzzle may be no puzzle at all if one were to model preferences using non-EU models and, in particular, the APT model. The reason is that, compared to the EU-framework, under APT equity appears to be far less attractive, while bonds' allure remains constant, therefore creating a high spread between the price premiums associated to the two and, hence, the equity premium puzzle. In conclusion it seems clear that future financial models may highly benefit from leaving the EU assumptions behind and modelling investors' preferences and decision-making process in a more descriptive and accurate manner.

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**Appendix A: Equity Summary Statistics, Yearly Data**

| Stocks | mean | sd | min | max | Var | skewness | kurtosis |
|---|---|---|---|---|---|---|---|
| microsoft | 12.95 | 31.84 | -62.79 | 60.50 | 1,014 | -0.611 | 3.164 |
| apple | 42.76 | 68.52 | -73.42 | 196.2 | 4,695 | 0.481 | 2.824 |
| amazon | 35.78 | 69.77 | -82.59 | 178.6 | 4,868 | 0.554 | 2.579 |
| berkshirehathawaya | 10.84 | 16.46 | -31.78 | 32.70 | 270.9 | -0.789 | 3.268 |
| johnsonjohnson | 9.231 | 11.59 | -7.879 | 34.62 | 134.2 | 0.258 | 2.416 |
| walmart | 6.107 | 16.95 | -26.64 | 46.54 | 287.5 | 0.234 | 3.305 |
| proctergamble | 8.038 | 13.76 | -25.48 | 39.70 | 189.4 | -0.337 | 4.143 |
| unitedhealthgroup | 26.39 | 33.64 | -54.26 | 128.5 | 1,131 | 0.692 | 6.676 |
| intel | 9.555 | 36.04 | -50.31 | 106.6 | 1,299 | 0.612 | 3.896 |
| homedepot | 12.49 | 28.43 | -52.62 | 50.34 | 808.5 | -0.677 | 2.627 |
| verizoncommunications | 6.465 | 15.83 | -22.15 | 34.61 | 250.5 | -0.246 | 2.109 |
| nvidia | 53.19 | 93.84 | -82.80 | 308.3 | 8,806 | 1.065 | 4.242 |
| att | 6.077 | 21.26 | -28.30 | 53.17 | 451.8 | 0.390 | 3.091 |
| pfizer | 20.17 | 36.20 | -33.22 | 90.67 | 1,311 | 0.360 | 2.362 |
| bankofamerica | 11.77 | 37.62 | -63.14 | 109.8 | 1,415 | 0.193 | 4.321 |
| cocacola | 7.378 | 15.47 | -24.11 | 30.44 | 239.3 | -0.545 | 2.622 |
| ciscosystems | 5.904 | 34.01 | -52.65 | 84.96 | 1,157 | 0.460 | 2.923 |
| exxonmobil | 6.898 | 15.93 | -15.10 | 39.07 | 253.8 | 0.126 | 1.908 |
| adobenas | 22.87 | 37.95 | -50.18 | 77.61 | 1,44 | -0.357 | 2.234 |
| pepsico | 10.29 | 14.07 | -25.97 | 36.33 | 197.9 | -0.676 | 3.788 |
| comcasta | 10.22 | 28.91 | -35.29 | 63.31 | 835.8 | 0.246 | 2.147 |
| chevron | 10.69 | 18.09 | -23.12 | 36.64 | 327.3 | -0.358 | 2.139 |
| oracle | 6.882 | 24.84 | -52.48 | 40.38 | 617.3 | -0.574 | 2.649 |
| abbottlaboratories | 13.23 | 19.26 | -26.71 | 52.00 | 371.0 | -0.197 | 2.722 |
| nikeb | 18.74 | 21.98 | -20.11 | 55.65 | 483.2 | -0.319 | 2.437 |
| elililly | 8.643 | 20.34 | -21.23 | 43.95 | 413.8 | 0.200 | 1.953 |
| bristolmyerssquibb | 7.220 | 25.69 | -52.36 | 69.95 | 659.9 | 0.0914 | 3.977 |
| mcdonalds | 13.63 | 23.69 | -38.42 | 56.77 | 561.1 | -0.275 | 2.646 |
| thermofisherscientific | 21.98 | 32.57 | -40.93 | 98.33 | 1,061 | 0.362 | 3.231 |
| costcowholesale | 13.56 | 19.77 | -36.77 | 45.70 | 390.7 | -0.973 | 3.722 |
| amgen | 9.867 | 20.14 | -32.02 | 42.32 | 405.7 | -0.210 | 2.152 |
| medtronic | 10.35 | 24.85 | -36.33 | 75.67 | 617.5 | 0.722 | 3.838 |
| nexteraenergy | 18.91 | 22.05 | -23.47 | 81.46 | 486.3 | 0.650 | 4.946 |
| unionpacific | 19.40 | 21.10 | -32.85 | 49.19 | 445.1 | -0.936 | 3.489 |
| danaher | 17.59 | 20.39 | -35.37 | 49.55 | 415.6 | -0.651 | 3.578 |
| americantower | 24.53 | 55.80 | -75.00 | 206.5 | 3,114 | 1.336 | 7.239 |
| internationalbusmchs | 5.466 | 24.36 | -35.47 | 58.61 | 593.4 | 0.274 | 2.485 |
| texasinstruments | 13.19 | 38.61 | -52.74 | 96.58 | 1,491 | 0.166 | 2.623 |
| lockheedmartin | 21.43 | 25.71 | -18.58 | 70.69 | 661.0 | 0.265 | 2.385 |
| linde | 15.38 | 20.51 | -31.76 | 52.05 | 420.6 | -0.476 | 2.973 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| wellsfargoco | 9.640 | 18.37 | -21.82 | 45.42 | 337.4 | 0.0198 | 2.318 |
| honeywellintl | 11.93 | 26.14 | -45.33 | 47.03 | 683.3 | -0.556 | 2.454 |
| lowescompanies | 16.27 | 31.22 | -26.75 | 109.1 | 974.5 | 1.216 | 4.907 |
| gileadsciences | 25.00 | 34.94 | -27.61 | 104.5 | 1,221 | 0.607 | 2.624 |
| citigroup | 2.982 | 37.66 | -75.98 | 57.78 | 1,418 | -0.444 | 2.253 |
| starbucks | 27.21 | 45.35 | -53.79 | 143.8 | 2,056 | 0.555 | 3.623 |
| qualcomm | 6.358 | 30.97 | -54.17 | 60.67 | 959.1 | 0.00886 | 2.479 |
| 3M | 11.51 | 21.91 | -29.80 | 54.46 | 480.2 | 0.321 | 2.482 |
| unitedparcelserb | 6.635 | 17.06 | -19.79 | 46.53 | 290.9 | 0.472 | 2.708 |
| cvshealth | 12.06 | 27.10 | -50.35 | 59.40 | 734.6 | -0.376 | 2.884 |
| blackrock | 26.62 | 41.56 | -36.98 | 152.6 | 1,728 | 1.220 | 5.344 |
| boeing | 18.79 | 35.41 | -50.03 | 94.77 | 1,254 | 0.300 | 3.285 |
| intuit | 14.17 | 22.26 | -34.54 | 62.15 | 495.4 | -0.336 | 3.416 |
| vertexpharms | 31.67 | 80.77 | -65.61 | 280.7 | 6,524 | 1.652 | 5.776 |
| americanexpress | 12.83 | 38.07 | -63.72 | 126.1 | 1,449 | 0.942 | 5.592 |
| altriagroup | 20.73 | 27.43 | -31.31 | 102.1 | 752.3 | 0.748 | 5.626 |
| cigna | 20.35 | 41.89 | -68.61 | 109.9 | 1,755 | -0.217 | 3.206 |
| fiserv | 17.68 | 21.32 | -34.46 | 57.34 | 454.5 | -0.552 | 3.570 |
| bectondickinson | 15.38 | 16.80 | -16.92 | 44.27 | 282.2 | -0.135 | 2.214 |
| dominionenergy | 13.92 | 21.82 | -21.56 | 85.56 | 476.3 | 1.527 | 7.048 |
| stryker | 16.67 | 21.38 | -45.99 | 48.21 | 457.2 | -1.196 | 4.737 |
| bookingholdings | 49.54 | 98.98 | -97.44 | 343.7 | 9,798 | 1.342 | 5.139 |
| crowncastleintl | 23.33 | 59.26 | -64.89 | 194.1 | 3,512 | 1.112 | 4.927 |
| tjx | 20.96 | 24.64 | -27.42 | 80.51 | 607.0 | 0.445 | 3.189 |
| prologisreit | 15.44 | 23.45 | -57.96 | 55.85 | 549.7 | -1.378 | 6.023 |
| advancedmicrodevices | 39.47 | 114.7 | -71.20 | 348.1 | 13,146 | 1.518 | 4.523 |
| esteelaudercosa | 16.64 | 32.17 | -27.59 | 68.69 | 1,035 | 0.247 | 1.838 |
| regeneronpharms | 31.39 | 66.65 | -38.55 | 208.6 | 4,442 | 1.465 | 4.650 |
| morganstanley | 9.109 | 39.20 | -68.75 | 87.93 | 1,537 | 0.00703 | 2.481 |
| goldmansachsgp | 13.13 | 38.45 | -60.41 | 102.5 | 1,479 | 0.110 | 3.075 |
| dukeenergy | 11.69 | 24.98 | -48.20 | 82.81 | 624.2 | 0.377 | 5.735 |
| caterpillar | 16.41 | 32.10 | -36.81 | 86.11 | 1,03 | 0.693 | 2.942 |
| colgatepalm | 7.062 | 13.36 | -19.18 | 27.60 | 178.4 | -0.210 | 1.914 |
| target | 11.71 | 28.93 | -29.99 | 100.2 | 837.1 | 1.279 | 5.446 |
| ecolab | 14.88 | 16.08 | -30.51 | 46.60 | 258.4 | -0.796 | 4.712 |
| automaticdataproc | 10.90 | 16.22 | -32.67 | 45.58 | 263.0 | -0.503 | 4.482 |
| southern | 14.27 | 16.88 | -4.882 | 53.68 | 284.9 | 1.048 | 3.397 |
| activisionblizzard | 30.84 | 51.33 | -43.91 | 158.0 | 2,635 | 0.610 | 3.000 |
| generalelectric | 0.818 | 30.06 | -55.39 | 53.98 | 903.5 | -0.418 | 2.495 |

## Appendix B: Equity Summary Statistics, Monthly Data

| VARIABLES | mean | sd | min | max | Var | skewness | kurtosis |
|---|---|---|---|---|---|---|---|
| microsoft | 0.922 | 8.395 | -23.40 | 43.80 | 70.48 | 0.587 | 5.872 |
| apple | 2.580 | 11.75 | -61.77 | 42.02 | 138.0 | -0.687 | 7.063 |
| amazon | 2.230 | 14.23 | -36.80 | 85.61 | 202.4 | 0.822 | 8.554 |
| berkshirehathawaya | 0.883 | 5.087 | -16.60 | 19.46 | 25.87 | 0.0236 | 4.889 |
| johnsonjohnson | 0.788 | 4.819 | -16.24 | 15.25 | 23.22 | -0.315 | 4.275 |
| walmart | 0.542 | 5.454 | -16.93 | 22.14 | 29.75 | -0.0936 | 4.185 |
| proctergamble | 0.707 | 5.048 | -32.58 | 12.73 | 25.48 | -1.447 | 10.36 |
| unitedhealthgroup | 1.949 | 7.749 | -40.03 | 32.21 | 60.05 | -0.754 | 7.275 |
| intel | 0.820 | 9.914 | -45.73 | 29.64 | 98.30 | -0.538 | 5.458 |
| homedepot | 0.945 | 7.440 | -19.77 | 21.89 | 55.35 | -0.0780 | 3.245 |
| verizoncommunications | 0.608 | 6.149 | -17.17 | 32.01 | 37.81 | 0.571 | 5.502 |
| nvidia | 3.249 | 18.09 | -45.59 | 85.04 | 327.4 | 0.819 | 5.850 |
| att | 0.505 | 6.211 | -17.92 | 32.61 | 38.57 | 0.317 | 5.598 |
| pfizer | 1.571 | 9.314 | -19.37 | 59.47 | 86.75 | 1.391 | 8.943 |
| bankofamerica | 1.157 | 12.63 | -57.39 | 94.76 | 159.5 | 1.018 | 17.88 |
| cocacola | 0.623 | 5.056 | -16.08 | 15.42 | 25.56 | -0.166 | 3.859 |
| ciscosystems | 0.549 | 10.11 | -38.52 | 48.40 | 102.3 | -0.0841 | 6.082 |
| exxonmobil | 0.606 | 5.366 | -17.22 | 17.14 | 28.79 | -0.205 | 3.813 |
| adobenas | 1.911 | 11.85 | -38.24 | 79.64 | 140.5 | 0.816 | 10.90 |
| pepsico | 0.861 | 4.781 | -19.78 | 17.51 | 22.86 | -0.263 | 5.051 |
| comcasta | 0.773 | 7.096 | -17.47 | 23.67 | 50.35 | -0.146 | 3.095 |
| chevron | 0.917 | 6.216 | -20.37 | 22.67 | 38.64 | 0.0636 | 4.162 |
| oracle | 0.739 | 9.041 | -33.35 | 32.41 | 81.75 | -0.262 | 5.009 |
| abbottlaboratories | 1.067 | 5.573 | -17.88 | 15.25 | 31.06 | -0.478 | 3.646 |
| nikeb | 1.577 | 7.827 | -39.76 | 42.70 | 61.26 | -0.195 | 9.478 |
| elililly | 0.765 | 7.214 | -31.82 | 29.40 | 52.05 | 0.0904 | 6.757 |
| bristolmyerssquibb | 0.568 | 7.492 | -25.99 | 25.59 | 56.12 | -0.281 | 4.580 |
| mcdonalds | 1.050 | 5.897 | -23.06 | 23.20 | 34.78 | -0.138 | 5.057 |
| thermofisherscientific | 1.616 | 7.155 | -23.53 | 22.84 | 51.20 | -0.239 | 4.254 |
| costcowholesale | 1.188 | 6.923 | -44.60 | 22.41 | 47.93 | -1.262 | 10.36 |
| amgen | 0.906 | 7.466 | -19.74 | 34.13 | 55.74 | 0.388 | 4.828 |
| medtronic | 0.840 | 6.633 | -29.54 | 34.57 | 44.00 | -0.0988 | 7.131 |
| nexteraenergy | 1.450 | 5.446 | -20.01 | 25.95 | 29.66 | -0.0248 | 5.538 |
| unionpacific | 1.568 | 6.947 | -26.53 | 22.68 | 48.25 | -0.161 | 4.165 |
| danaher | 1.404 | 6.364 | -18.58 | 25.63 | 40.50 | 0.0857 | 4.894 |
| americantower | 1.782 | 15.41 | -46.15 | 171.5 | 237.3 | 5.535 | 64.00 |
| internationalbusmchs | 0.497 | 7.460 | -23.64 | 34.18 | 55.65 | 0.603 | 6.174 |
| texasinstruments | 0.968 | 9.907 | -25.91 | 45.30 | 98.15 | 0.392 | 5.365 |
| lockheedmartin | 1.677 | 6.798 | -23.65 | 32.11 | 46.21 | 0.0555 | 5.503 |
| linde | 1.231 | 6.242 | -21.42 | 28.81 | 38.97 | 0.131 | 6.331 |
| wellsfargoco | 1.039 | 8.617 | -42.53 | 35.43 | 74.26 | -0.180 | 9.049 |
| honeywellintl | 1.065 | 8.610 | -39.23 | 48.61 | 74.12 | -0.169 | 9.557 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| lowescompanies | 1.345 | 8.463 | -20.15 | 29.70 | 71.62 | 0.207 | 3.447 |
| gileadsciences | 2.049 | 10.29 | -24.89 | 73.14 | 105.8 | 2.233 | 16.64 |
| citigroup | 0.465 | 13.94 | -67.12 | 123.3 | 194.4 | 2.015 | 30.44 |
| starbucks | 1.837 | 8.617 | -36.55 | 31.05 | 74.25 | -0.180 | 5.320 |
| qualcomm | 0.681 | 10.69 | -37.13 | 49.40 | 114.4 | 0.131 | 5.060 |
| 3M | 0.916 | 5.954 | -14.45 | 20.95 | 35.45 | 0.0315 | 3.574 |
| unitedparcelserb | 0.619 | 5.905 | -23.10 | 28.65 | 34.87 | -0.203 | 6.028 |
| cvshealth | 0.984 | 7.607 | -31.17 | 25.76 | 57.87 | -0.418 | 4.542 |
| blackrock | 1.966 | 8.922 | -23.65 | 42.77 | 79.61 | 0.363 | 4.995 |
| boeing | 1.466 | 8.479 | -36.72 | 21.03 | 71.89 | -0.579 | 4.608 |
| intuit | 1.420 | 9.867 | -43.79 | 68.39 | 97.36 | 0.646 | 13.36 |
| vertexpharms | 2.335 | 16.81 | -53.78 | 108.5 | 282.6 | 1.370 | 10.38 |
| americanexpress | 0.889 | 8.925 | -34.86 | 68.21 | 79.66 | 1.320 | 17.43 |
| altriagroup | 1.621 | 6.994 | -26.62 | 38.33 | 48.91 | 0.0722 | 7.195 |
| cigna | 1.443 | 10.18 | -47.75 | 50.98 | 103.7 | -0.547 | 9.116 |
| fiserv | 1.470 | 7.159 | -26.33 | 37.73 | 51.25 | 0.142 | 6.489 |
| bectondickinson | 1.259 | 5.780 | -13.68 | 24.00 | 33.41 | 0.0301 | 3.770 |
| dominionenergy | 1.085 | 5.053 | -19.78 | 15.07 | 25.53 | -0.712 | 4.981 |
| stryker | 1.364 | 7.091 | -31.87 | 27.27 | 50.28 | -0.247 | 5.619 |
| bookingholdings | 2.679 | 20.26 | -60.65 | 116.8 | 410.6 | 1.490 | 12.08 |
| crowncastleintl | 1.666 | 13.68 | -46.71 | 80.35 | 187.1 | 0.998 | 11.45 |
| tjx | 1.688 | 7.271 | -21.64 | 44.32 | 52.87 | 0.593 | 8.034 |
| prologisreit | 1.446 | 9.664 | -45.53 | 78.11 | 93.39 | 1.039 | 23.99 |
| advancedmicrodevices | 2.282 | 19.85 | -44.60 | 86.14 | 394.0 | 0.514 | 3.985 |
| esteelaudercosa | 1.282 | 7.981 | -30.56 | 25.60 | 63.69 | -0.216 | 4.873 |
| regeneronpharms | 3.590 | 27.31 | -61.18 | 323.3 | 746.1 | 7.216 | 82.03 |
| morganstanley | 0.710 | 11.02 | -40.19 | 41.32 | 121.5 | -0.0558 | 5.030 |
| goldmansachsgp | 0.920 | 9.489 | -33.55 | 30.41 | 90.03 | 0.0977 | 4.536 |
| dukeenergy | 0.886 | 6.165 | -25.53 | 22.46 | 38.00 | -0.434 | 5.845 |
| caterpillar | 1.434 | 9.690 | -31.47 | 37.62 | 93.90 | 0.173 | 4.751 |
| colgatepalm | 0.627 | 5.033 | -17.04 | 21.47 | 25.33 | -0.00118 | 4.809 |
| target | 0.988 | 8.024 | -24.47 | 30.56 | 64.38 | 0.415 | 4.272 |
| ecolab | 1.214 | 5.571 | -23.70 | 29.24 | 31.03 | 0.0166 | 6.666 |
| automaticdataproc | 0.941 | 5.896 | -21.03 | 19.43 | 34.77 | -0.165 | 4.000 |
| southern | 1.132 | 4.611 | -13.50 | 20.97 | 21.26 | -0.0786 | 4.864 |
| activisionblizzard | 2.252 | 11.53 | -43.82 | 57.45 | 133.0 | 0.370 | 7.385 |
| generalelectric | 0.0105 | 8.674 | -32.58 | 34.61 | 75.24 | 0.221 | 5.639 |