# Pricing Indefinitely Lived Assets: Experimental Evidence

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**Abstract**

We study indefinitely-lived assets in experimental markets and find that the traded prices of these assets are on average about 40% of the risk neutral fundamental value. Neither uncertainty about the value of total dividend payments nor horizon uncertainty about the duration of trade can account for this low traded price, while the temporal resolution of payoff uncertainty plays a crucial role. We show that an Epstein and Zin (1989) recursive preference specification together with probability weighting can rationalize the low traded prices observed in our indefinite-horizon asset markets, while risk attitudes do not play such an important role.

**Keywords**: asset pricing, behavioral finance, experiments, indefinite horizon, random termination, risk and uncertainty, Epstein-Zin recursive preferences, probability weighting.

**JEL Codes**: C91, C92, D81, G12.

# 1 Introduction

Many economic models employ an infinite horizon with discounting in order to examine agents' behavior under the shadow of future. Such environments are quite natural for studying the pricing of assets because many assets, e.g., equities, are long-lived and have no definite maturity date. Nevertheless, experimental economists have typically studied asset pricing and trading behavior in finite-horizon settings with no discounting. In these settings, the standard *fundamental value* (FV) of the asset at any moment in time is taken to be the expected sum of the asset's remaining dividend payments, that is, the standard fundamental value is the risk neutral present value of the asset. Since the horizon is finite, the FV of the asset decreases over time, as in the canonical experimental design of Smith et al. (1988).

In this paper, we study the trade of assets in an experimental market with *indefinite* horizons, consisting of an unknown number of periods. The first period begins with trade in the asset. Following trade, each unit of the asset pays its holder a fixed dividend. Thereafter, with a constant probability $\delta$, traders' holdings of the asset carry over to the next period, and in each new period, trade in the asset takes place and asset holders earn dividends per unit held. With probability $1 - \delta$, the asset ceases to exist; the asset market shuts down and the asset has a zero continuation value. This indefinite-horizon or random-termination design, initially proposed by Roth and Murnighan (1978), is the most commonly used approach to implementing infinite horizons with discounting in the laboratory.

Unlike most finite horizon asset markets where the FV of the asset is decreasing over time, the stationarity associated with indefinite horizons implies that the FV of the indefinitely-lived asset is constant over time.[1] The stationarity associated with indefinite horizons may be a more natural setting for understanding asset pricing decisions.[2]

In our **baseline** treatment, subjects trade in indefinite-horizon asset markets implemented by random termination (more precisely, a modified version of the block random termination scheme of Frechette and Yuksel (2017)). In each period the market is open, subjects first

[1]While it is possible to generate constant values for the FV in finite-horizon settings, this is typically done by having some known constant terminal period payoff value for the asset as in Smith et al. (2000), possibly also accompanied by a dividend process where the expected dividend payment is 0 as in Noussair et al. (2001). In the indefinite-horizon design, the value of the asset is constant over time with positive dividend payments and zero terminal value.

[2]Kirchler et al. (2012) have shown that the trend of the FV process (i.e., whether it is constant, increasing, or decreasing over time) has a large impact on the formation of non-rational asset price "bubbles" (which we define as sustained departures from the FV). Giusti et al. (2016) show that in addition to the trend of the FV process, the sign of the expected dividend payment (positive, zero, or negative) also affects traded prices. Our experimental setting, which features a constant FV and a positive dividend payment in each period, serves as a more natural setting for understanding asset pricing.

trade, then receive dividend payments for each asset share they hold, and finally a random number determines whether the asset market will continue to a new period. In each session, subjects participate in three indefinite horizon markets (with different pre-drawn market lengths) to reveal the effect of experience as in Smith et al. (1988). We find that traded prices are *quite low*, averaging around 40% of the standard FV, and they remain low even as traders gain experience. This result is rather surprising given that the vast majority of experimental asset market studies, following the Smith et al. (1988) design find asset price *bubbles*, or prices greatly *in excess* of the standard FV, in the first market played, with approximate convergence to the standard FV within three market repetitions.

To better understand the low traded prices of our indefinitely lived asset (relative to the standard FV), we design two auxiliary treatments, noting that indefinite-horizon asset markets involve two types of intertwined risks: payoff uncertainty and trading horizon uncertainty. Payoff uncertainty refers to the uncertain sequence of dividend realizations an investor earns from adopting a buy and hold strategy. In terms of the sum of dividend payments, the asset can be viewed as a lottery, as described in Table 1, involving an infinite number of states, $t = 1, 2, ..., \infty$. State $t$ is the event that the asset lasts until period $t$ yielding a payoff of $td$, which occurs with probability $\delta^{t-1}(1-\delta)$. By contrast, trading horizon uncertainty refers to uncertainty about the length of time over which agents can expect to buy or sell the asset, or the asset's liquidity. While payoff uncertainty affects the holding value of the asset, trading horizon uncertainty may affect a traders' strategy, especially for speculators. If the horizon over which the asset has value is perfectly known, then speculators might time their asset purchases and sales with this information in mind as in the asset pricing literature using the Smith et al. (1988) design. In that design, speculators buy early and sell when they sense the bubble to be peaking. By contrast, in an indefinite horizon, such speculative timing is more difficult. Thus, there is reason to believe that an indefinite horizon for asset markets might *depress* prices and trade volume relative to asset markets with known, finite horizons.

Table 1: Total Dividend Payments of an Asset with an Indefinite Horizon

| Market Duration | 1 | 2 | 3 | ... | $t$ | ... |
|---|---|---|---|---|---|---|
| Probability | $1-\delta$ | $\delta(1-\delta)$ | $\delta^2(1-\delta)$ | ... | $\delta^{t-1}(1-\delta)$ | ... |
| Total dividend payments | $d$ | $2d$ | $3d$ | ... | $td$ | ... |

Our **second** experimental treatment aims to single out the effect of trading horizon uncertainty from payoff uncertainty by separating the asset market into two separate stages. Stage one consists of a *fixed* number of trading periods and subjects do not observe nor receive dividend payments in this stage. Stage two reveals dividend realizations and subjects receive the realized dividend payments for each share held at the end of the trading stage. The dividend realization process in stage two mimics the distribution of the sum of remaining dividend payments as in the baseline treatment (characterized by Table 1). We find that the traded price in the second treatment is fairly close to the standard FV.

The notable difference in traded prices between these two treatments might be attributed to trading horizon uncertainty. However, given the robust finding from the experimental asset pricing literature that traded prices tend to converge to the FV after three market repetitions, we suspect that the difference we find in traded prices in later markets may not be fully attributable to trading horizon uncertainty. The two-stage design of our second treatment allows us to fix the trading horizon and control for the distribution of the sum of dividend payoffs, but it also induces a difference in the *timing* of those dividend realizations. In the baseline treatment, dividend payments for each trading period are revealed and paid out at the end of the period. In the second treatment, all dividend payments are revealed and paid altogether at once, only after all trading activities have ended. In other words, the payoff uncertainty involved in an asset market with an indefinite horizon has two dimensions: (1) uncertainty in the sum of dividend payments and (2) the temporal resolution of that uncertainty. The second treatment coincides with the baseline treatment along the first dimension (uncertainty in the sum of dividend payments) but differs from the baseline treatment along the second dimension (the temporal resolution of uncertainty). To separate the effects of trading horizon uncertainty and the timing of dividend realizations, we conducted a **third** treatment. This treatment involves two separate stages as in the second treatment, but keeps the uncertain trading horizon of the baseline treatment. Thus, our third treatment serves as a bridge between the first two treatments. The difference between the second and third treatments reveals the effect of trading horizon uncertainty. The difference between the first and third treatments reveals the effect of the timing of dividend realizations. We find that the traded price in the third treatment is also fairly close to the standard FV and not significantly different from the second treatment.

Considering the evidence from all three treatments, we come to the conclusion that our results are *not* due to uncertainty about the value of total dividend payments nor horizon uncertainty as we initially suspected. Instead, what matters more is the *timing* of dividend realizations, or the temporal resolution of payoff uncertainty. Our remaining task is to explain these experimental results. In particular, we investigate whether the significantly lower traded price in the baseline treatment relative to the other two treatments can be rationalized as a lower FV due to considerations of the temporal resolution of payoff uncertainty.

One way to capture the difference in the temporal resolution of payoff uncertainty in treatment A relative to the other two treatments is to represent the asset as a dynamic lottery where payoff uncertainty is realized over time instead of the static lottery shown in Table 1. In particular, the asset in treatment A can be viewed as the combination of the fixed dividend payment in the current period with a binary lottery in the next period that yields a zero payoff with probability $1 - \delta$ and a replica of the asset with probability $\delta$. By contrast, in treatments B and C where payoff uncertainty is resolved completely only after the trading stage, it is more reasonable to represent the asset using the static lottery shown in Table 1.

We first note that under the assumption of risk neutrality, the holding value of the dynamic lottery and the static lottery is the same. A natural next step is to investigate whether incorporating subjects' (heterogeneous) risk attitudes into the dynamic and static lotteries can explain the low traded prices in treatment A versus treatments B and C. For this purpose, we develop a new methodology for calculating the FV of the asset that incorporates the market participants' risk attitudes toward payoff uncertainty. Specifically, we infer subjects' risk parameter using the individual choice task of Holt and Laury (2002) by assuming relative risk aversion (CRRA) preference. We then derive each individual's demand curve for asset as the solution to a portfolio choice problem, combining individual's asset and cash profile and the estimated risk parameter. Finally, we estimate the risk-adjusted FV of the asset as the market price that clears the market. The computed dynamic risk-adjusted market FV (following the Epstein and Zin (1989) recursive preference specification to aggregate payoffs across periods) is about two thirds of the standard FV, and the static risk-adjusted market FV is about 90% of the standard FV. For treatment A, the computed dynamic risk-adjusted FV can therefore partially account for the low traded prices. For treatments B and C, the static risk-adjusted FV tends to underestimate the traded price.

Given the limited success of risk attitudes in explaining the traded price in the three treatments, we continue to explore other factors. The second factor we examine is probability weighting, an important factor in several non-expected utility theories. In our baseline treatment, the market ends and the asset becomes worthless with a small probability (0.1), and it seems likely that probability weighting could potentially affect traded prices. Similar to our analysis involving risk attitudes, it is important to distinguish whether subjects view the asset as a static or dynamic lottery even under the assumption of risk neutrality. Applying probability weighting to the dynamic lottery implies a market FV that is about 46% of the standard FV. Applying probability weighting to the static lottery raises the FV slightly above the standard FV. The probability-weighted dynamic FV is very close to the traded market price in treatment A both quantitatively and statistically. At the same time, the static probability-weighted FV is also reasonably close to the traded price in treatments B and C, both quantitatively and statistically. We therefore conclude that the recursive preference specification together with probability weighting can rationalize the low traded prices that we find in our main treatment A, while risk attitudes do not play such an important role.

There is a large literature involving experimental asset markets with known, finite horizons following Smith et al. (1988). Surveys can be found in Palan (2009, 2013) and Noussair and Tucker (2013). In this set-up, the asset traded yields dividends up to some known terminal date, beyond which the asset pays no further dividends (it either ceases to have value or pays some final buyout value). By comparison, there are relatively fewer experimental studies of asset markets with indefinite horizons. The studies we are aware of include Camerer and Weigelt (1993), Ball and Holt (1998), Hens and Steude (2009), Kose (2015), Fenig et al.(2018), Asparouhova et al. (2016), Crockett et al. (2019), Halim et al. (2020), Weber et al. (2018) and Kopányi-Peuker and Weber (2021). Camerer and Weigelt (1993), Ball and Holt (1998), Kose (2015) and Kopányi-Peuker and Weber (2021) study environments where subjects only engage in asset-trading activities. Hens and Steude (2009), Fenig et al. (2018), Asparouhova et al. (2016), Weber et al. (2018), Crockett et al. (2019) and Halim et al. (2020) consider experimental economies where subjects also participate in other activities such as consumption, employment, production decisions, or IPOs of new assets.

Relative to the above papers on experimental asset markets with indefinite horizons, our study makes three contributions. First, we quantitatively evaluate the effects of payoff uncertainty and horizon uncertainty that are embedded in indefinite-horizon markets. Second, our study suggests that the temporal resolution of payoff uncertainty plays an important role in the determination of asset prices in indefinite-horizon asset markets, a new finding that has not been discussed in previous studies. Third, our paper makes a methodological contribution in the development of a new procedure to determine the market FV for an asset that incorporates traders' heterogeneity, here with respect to risk attitudes as we collected data on such attitudes from our subjects. Still, our methodology could also be used to incorporate other attributes about market participants, for instance heterogeneity in agents' time preferences or the parameter that governs probability weighting, etc.[3]

[3] Related to our work, some recent papers methodologically examine the effect of random termination procedures in the context of the repeated Prisoner's Dilemma game (Frechette and Yuksel, 2017) and the effects of different payment schemes in indefinite-horizon experimental games (Sherstyuk et al. 2013). Experimental asset markets have several distinct features as compared to repeated games. First, in most repeated games, subjects make discrete choices and risk considerations may or may not result in a change/switch in choices. In asset market experiments, traded price and quantity are continuous variables, and risk considerations can be captured incrementally. Second, in repeated games, discount factors mainly matter for whether or

The remainder of the paper is organized as follows. Section 2 presents the experimental design and procedures. Sections 3 to 5 report on the experimental results across treatments and estimate the market FV. Section 6 concludes.

# 2 Experimental Design

In this section, we describe the main characteristics of our baseline treatment with an indefinite horizon. We then describe two auxiliary treatments designed to understand traded prices in our baseline treatment. Finally, we describe the experimental procedures that we follow in running all three treatments.

## 2.1 Baseline Treatment

The baseline treatment (treatment A) implements asset markets with an indefinite horizon. Each experimental session consists of two parts. In the first part, subjects complete a Holt and Laury (2002) risk preference elicitation task that involves choosing between 10 pairs of lotteries with different expected payoffs. This task allows us to obtain a measure of each subject's risk attitude, which we later use to investigate whether subjects' risk attitudes can help to explain the traded price of the asset. In the second part, subjects trade assets in three consecutive and ex-ante identical asset markets. The repetition of three markets allows for subject learning and to examine the possibility of price convergence in indefinite-horizon markets. Repetition is motivated by the observation in Smith et al. (1988) and follow-up studies that when the same group of traders interact in consecutive fixed-horizon asset markets, prices converge toward the standard FV by the third market having an identical market structure.

Each asset market lasts for an indefinite number of periods. The indefinite horizon is implemented through a modified version of the *block random termination* scheme of Frechette and Yuksel (2017); therefore we also label this treatment BRT.[4]

not they support the play of certain strategies. By contrast, in asset pricing experiments, discount factors figure directly into the determination of the market price of the asset. Third, in repeated games, subjects typically have *no choice* but to participate in the game. Differently, in many asset market experiments, subjects can *choose* whether to participate in the asset market or not (An exception is the literature on "learning-to-forecast" asset pricing experiments, where subjects are typically required to participate in every period via the elicitation of their forecast for future asset prices. See, e.g., Hommes et al. (2005, 2008)).

[4]Camerer and Weigelt (1993) and treatment T2 in Kose (2015) generate indefinite-horizon markets using the original random termination method.

At the beginning of each of the three asset markets, subjects are endowed with shares and cash (in units of experimental money or EM). They then trade shares for an indefinite number of periods. In each period, subjects first trade shares through a double-auction trading interface subject to budget and asset supply constraints (subjects cannot borrow cash or shares). Following the completion of asset trading, subjects receive a dividend of $d = 5$ EM for each share of the asset that they hold post trading. The dividend payments are placed in a separate account and cannot be used to purchase shares in the future.[5] Finally, a randomly drawn number determines whether or not the market will continue with another period. If the market continues, then each trader's asset position carries over to the next period; if it does not continue, then the asset shares have a zero value and the market is declared over. The probability of continuation is $\delta = 0.9$, and so the probability that a market ends is $(1 - \delta) = 0.1$. In practice, a random number between 1 and 100 is drawn and if the random number is less than or equal to 90, the market continues with another period; if it is greater than 90, the market ends and the asset ceases to have value. Subjects' earnings in EM from the asset market consists of their cash balance at the end of the market and all dividends earned over the course of that market; this amount was converted into dollars at a fixed and known exchange rate.

Unlike the standard random termination scheme, where subjects are informed about the random draw realization at the end of each period, with our BRT implementation scheme, in the first "block" of 10 periods, subjects receive no feedback on the random draws and participate in the market anyway. At the end of period 10, subjects are told whether or not the market has actually ended and, if so, in which period this occurred within that block of 10 periods. If the market did not end within the 10-period block, then subjects will continue to participate in the market as in regular indefinite-horizon markets with random termination, that is, at the end of each period the realization of the random draw will be revealed. If the market ends within the first 10 periods, then all trading activities and dividend payments in the subsequent periods after the market has actually ended are void. Subjects are made well aware of this block random termination procedure before they participate in the asset market. The BRT allows us to obtain, at a minimum, a 10-period data series to analyze asset (mis-)pricing; without it, we may have sessions where markets are too short to have any meaningful discussion of whether assets are correctly priced in an indefinite-horizon setting.

[5] Caginalp et al. (1998, 2001), Haruvy and Noussair (2006) and Kirchler et al. (2012) report that high initial or increasing cash-to-asset (C/A) ratios can drive bubble formation in experimental asset markets. In our experiment, the supply of assets is held constant and dividend payments are placed in a separate account so that the subject cannot use dividend income for asset purchases in later periods of the market. This restriction prevents the dividend payments from increasing the C/A ratio and affecting market outcomes.

In Frechette and Yuksel (2017), subjects play the game in fixed-length blocks and a full-length new block is played if the game has not ended in the previous block. We modify their design in that beyond the first block, the market continues with the regular random termination design, so that from period 11 on, subjects receive live information about whether the current period has ended or not. The main purpose of this modification is to save on time and guarantee that we run three markets of at least 10 periods to examine the possibility of price convergence in indefinite-horizon markets. Repeating 10-period blocks would make each market longer and it would be difficult to complete three markets in one session.

The expected horizon of each asset market is $T = 1/(1-\delta) = 10$ periods from the start of the market or from any period reached. The standard FV of the asset, which measures the expected value of total dividend payments, is constant in all periods at

$$U_0 = d\sum_{\tau=t}^{\infty}\delta^{\tau-t} = \frac{d}{1-\delta} = 50.$$

The realized life span of the asset, however, can be any number of periods, $t = 1, 2, 3, \cdots$. Since random termination can result in a large variance in the lengths of asset markets and we are restricted in the length of time that we can keep subjects in the laboratory, we pre-drew a set of three sequences of random numbers and used the same set of draws to control the lengths of the three asset markets in all experimental sessions to reduce uncertainty and facilitate a comparison across different sessions.[6] These sequences of random numbers imply market lengths of 6, 20, and 9 periods, respectively (for an average of 11.67 periods per market). Note that under the BRT scheme, in asset markets 1 and 3, subjects are prompted to trade for 10 periods, but their actions and dividend payments after period 6 (9) are void. In market 2, all 20 periods count.

Previous studies on definite-horizon experimental asset markets suggest that traded prices converge to the standard FV, the expected value of total dividend payments, after subjects repeat the same trading market three times. We will check whether that convergence result also holds in our asset markets with indefinite horizons, i.e., whether the traded price in market 3 converges to the standard FV of 50 EM.

[6]The first two sequences of random numbers were obtained from a pilot session that consisted of just two asset markets and the last sequence of random numbers was produced using a random number generator.

## 2.2 Auxiliary Treatments

To our surprise, the mean traded price of the asset in market 3 of the baseline treatment is about 40% of the standard FV. In order to understand this surprising result, we design two auxiliary treatments, where the asset market part differs from the baseline treatment (while the first, risk elicitation part remains the same).

While designing the second treatment (treatment B), we note that the asset market in the baseline treatment involves two types of intertwined risks: (1) *payoff uncertainty*, and (2) *trading horizon uncertainty*. Payoff uncertainty refers to uncertainty about the asset's dividend payments. Note that if a trader buys a share of the asset in any period and holds it until the end of the market, in terms of total dividend payments, it is similar to buying a lottery as in Table 1. Trading horizon uncertainty refers to the length of time that agents can expect to trade the asset, which affects the asset's *liquidity*. While payoff uncertainty affects the holding value of the asset, trading horizon uncertainty may affect traders' strategy, especially for speculators. If the horizon over which the asset has value is perfectly known, then speculators might time their asset purchases and sales with this information in mind. By contrast, in an indefinite horizon, timing such speculation is more difficult. Thus, an indefinite horizon for asset markets might depress prices and the volume of trade relative to a known, finite horizon markets.

**Treatment B (D-2)** is designed to disentangle the effect of trading-horizon uncertainty and payoff uncertainty. It replicates treatment BRT regarding payoff uncertainty by having the same distribution of total dividend payments, while fixing the trading horizon and therefore eliminating the trading horizon uncertainty. To achieve this, we divide the asset market into two phases: the trading phase and the dividend realization phase. In the first phase, subjects trade assets for a definite duration of $T = 10$ periods (as in much of the experimental asset pricing literature beginning with Smith et al. (1988)). We chose $T = 10$, as that is the expected number of periods from the beginning of an indefinitely repeated asset market with a continuation probability of $\delta = 0.9$, i.e., $T = 1/(1 - \delta) = 10$. During these $T$ trading periods, there are no dividend realizations. In each trading period, subjects can choose to buy or sell assets as they wish, subject only to budget and (asset) supply constraints.

Following the final trading period $T$, all asset positions are considered final and subjects move on to the second phase of the market where they experience/observe a random sequence of dividend payments. Specifically, each share of the asset that a subject holds at the *end* of the trading phase yields at least one dividend payment of $d = 5EM$. Following each dividend payment, a random number between 1 and 100 is drawn to determine whether or not there will be further dividend payments. If the random number is greater than 90, then there will be no further dividend payments. Otherwise, each share yields another dividend payment, $d$, followed by another independent random draw to determine further dividend payments. Using this procedure, the asset in treatment B not only has the same standard FV of 50, but the same distribution of total dividend payments as in treatment A (represented by the lottery in Table 1). In fact, we use the same three sequences of random numbers used to determine market durations in treatment A to determine the realized number of dividend payments in the second stage of treatment D-2; i.e., for each share held at the end of the trading stage, subjects receive 6 dividend payments in market 1, 20 dividend payments in market 2, and 9 dividend payments in market 3. We label this treatment "D-2," with "D" standing for definite horizon, and "2" for two phases.

We find that the mean traded price of the asset is close to the standard FV in treatment B. At first sight, the low traded price in treatment A relative to treatment B could be attributed to trading horizon uncertainty. However, given the finding in the literature that traded prices tend to converge to the FV after three market repetitions, it is possible that the persistent difference in traded prices that we observe between treatments A and B in the later markets cannot be fully attributable to trading horizon uncertainty. The two-stage design of our second treatment allows us to fix the trading horizon while controlling for the distribution of total dividend payoffs, but it also induces an unavoidable difference in the *timing* of dividend realizations. In treatment A, dividend payments are revealed and paid period-by-period as subjects trade. In treatment B, all dividend payments are revealed and paid altogether, after trading activities have ended. To separate the effects of the trading horizon and the timing of dividend realizations, we conducted a third treatment.

**Treatment C (BRT-2)** combines the uncertain trading horizon of the baseline treatment with the two-stage design of treatment D-2, while keeping the distribution of total dividend payments identical to the first two treatments. We label this treatment "BRT-2" to reflect the block random termination of the trading horizon and the two-stage design. Similar to treatment D-2, no dividends are realized during the trading phase and there is no trading during the dividend realization phase. This new treatment serves as a bridge between the first two treatments. The difference between treatments B and C serves as a clearer indicator of whether trading horizon uncertainty matters than does the difference between treatments A and B. The effect of the timing of dividend realizations, or the temporal resolution of payoff uncertainty, is also more cleanly captured by comparing treatments A and C.

The number of dividend realizations remains 6, 20 and 9 for the three markets of treatment C. We independently draw another three sequences of random numbers with the same continuation probability $\delta = 0.9$ to determine the actual lengths of the trading phases of the three markets of treatment C. These turned out to be 11, 5 and 16 periods, respectively.[7] As in Treatment A, subjects did not know the number of trading periods for each market and as in Treatments B and C, they did not know the number of dividend realizations for each market.

Table 2 summarizes the differences in the design of the three treatments.[8] Table 3 provides a summary of the number of trading periods and dividend realizations in the three markets of our three treatments.

Table 2: Treatments

| Treatment | Trading Horizon | Uncertain $FV_t$? | Dividends Realized after Trading Phase? |
|---|---|---|---|
| A (BRT) | Random | Yes | No |
| B (D-2) | Definite | Yes | Yes |
| C (BRT-2) | Random | Yes | Yes |

Table 3: Number of Trading Periods and Dividend Payments

| | No. Trading Periods | | | No. Dividend Payments | | |
|---|---|---|---|---|---|---|
| Treatment | Mkt 1 | Mkt 2 | Mkt 3 | Mkt 1 | Mkt 2 | Mkt 3 |
| A (BRT) | 6 | 20 | 9 | 6 | 20 | 9 |
| B (D-2) | 10 | 10 | 10 | 6 | 20 | 9 |
| C (BRT-2) | 11 | 5 | 16 | 6 | 20 | 9 |

## 2.3 Experimental Procedures

The experiment was conducted at a North American University using university student subjects. We conducted five sessions each of our three treatments. Each session had 10 participants (except for two sessions where nine and eight subjects showed up, respectively) with no prior experience in any treatment of our experiment. Each subject participated in one session of one treatment only.

[7] The realizations of the random variable that determine trading duration and dividend realizations are independently drawn to ensure that the distribution of total dividend payments remains the same across time. If we used the same realizations for the two stages, then the distribution would have a lower bound of $d$ multiplied by the current trading period, and the holding value of the asset would increase across time.

[8] Another difference between treatment A and treatments B and C is that in treatment A the dividend payment depends on the quantity of shares held at the end of each trading period, while in treatments B and C it depends on each trader's final share position at the end of the entire trading phase. However, given that all three treatments have the same, stationary dividend generating process, the standard FV remains the same at 50 EM, and the distribution of the value of total dividend payments is identical across periods and treatments.

Table 4: Session Characteristics

| Session | Duration | No. of Subjects | Avg. Payment |
|---|---|---|---|
| A1 | 2.5 hr | 10 | $34.98 |
| A2 | 2.5 hr | 10 | $35.87 |
| A3 | 2.5 hr | 10 | $35.34 |
| A4 | 2.5 hr | 9 | $34.17 |
| A5 | 2.5 hr | 10 | $34.45 |
| B1 | 2 hr | 10 | $42.29 |
| B2 | 2 hr | 10 | $35.26 |
| B3 | 2 hr | 10 | $36.00 |
| B4 | 2 hr | 10 | $35.64 |
| B5 | 2 hr | 10 | $34.58 |
| C1 | 2.5 hr | 10 | $41.99 |
| C2 | 2.5 hr | 8 | $35.83 |
| C3 | 2.5 hr | 10 | $35.86 |
| C4 | 2.5 hr | 10 | $36.61 |
| C5 | 2.5 hr | 10 | $35.12 |

Each session had two parts. In the first part, subjects completed a Holt and Laury (2002) risk preference elicitation task - details are provided in Appendix D. For this individual choice task, subjects were instructed to make 10 choices between pairs of lotteries and were paid based on their choice from one randomly chosen lottery out of the 10 pairs.[9] This part of the experiment took about 10 minutes.

The second part of a session consisted of the three asset markets. Following the risk elicitation procedure, subjects were given written instructions for the asset market corresponding to either Treatment A, B or C. The experimenter read aloud these instructions (in an effort to make them common knowledge) and subjects were asked to answer a set of quiz questions. After reviewing the answers to these questions with the experimenter, subjects practiced using the computerized trading interface before the formal asset market was officially opened. The trading interface uses a double auction mechanism programmed in $z$-Tree (Fischbacher, 2007).[10] It took about 45 minutes to go through the instructions and practice periods using the trading interface. Subjects then participated in the three consecutive asset markets.[11] Each asset market took between 20-40 minutes to complete, depending on the treatment and the realized market length. At the beginning of asset market, one-half of participants were

[9]Payments from this task were made only at the *end* of the experiment and the average earning from this part is $4.

[10]The $z$-Tree program we used was modified from a program published by Kirchler et al. (2012).

[11]In the instructions, subjects were told that after one asset market, depending on the time remaining, another market might open, so they did not know in advance that there would be only 3 asset markets.

endowed with 20 shares of the asset and 3,000 EM units, while the other half were endowed with 60 shares of the asset and 1,000 EM units; at the standard FV of 50 EM, the values of these endowments are identical.[12] In each trading period of the asset market, the trading interface is open for two minutes. Subjects' earnings from all three markets consisted of their end of market cash balance and all dividends earned over the course of each market. This amount, denominated in EM, was converted into Canadian dollars at a fixed and known exchange rate of 500 EM = 1 Canadian dollar at the end of the experiment.[13] Given that there are 6, 20, and 9 dividend payments in markets one, two, and three, respectively, the average earnings from the asset markets was $26.

The sessions of treatments A and C last for two and a half hours, while the sessions of treatment B last for two hours. The average total payment per subject is about $35 ($26 from the asset markets, plus $4 from the Holt-Laury risk elicitation task, plus a $5 show-up fee). Participants were paid in cash and in private at the end of each session. Table 4 summarizes the characteristics of the 15 experimental sessions.

# 3 Experimental Results: Comparison across Treatments

We analyze the experimental data from two perspectives. In this section, we compare market outcomes among the three treatments and infer the effect of horizon uncertainty and the different timing of dividend payments. In the next section, we will focus on whether we can explain traded prices in the final market 3 with a market FV that incorporates risk aversion and the effects of the different timing of dividend realizations.

Figure 1 shows the average prices of the asset over time in each treatment. The three vertical bars in this figure indicate the first period of each new market. The average price in the first market starts at about 50 (the standard FV) in treatments A and C and at about 60 in treatment B; as we will see later, the average prices in the first market are not significantly different from one another. However, the average price in treatment A in the second and third markets steadily declines, falling to around 20 by the end of market 2 and remaining there in market 3, while the average price in treatments B and C remains at or above 50

[12] In session A4, we had nine subjects. Since odd-numbered subjects have endowment profile 1, the value of cash relative to shares is slightly higher in this session. This does not seem to significantly affect the market outcome (see Table 5). In addition, the cash and asset supplies are incorporated into the calculation of FV in Table C.2.

[13] In sessions B1 and C1 only, the exchange rate was 400 EM=$1, which results in a higher payment in the asset markets as shown later in Table 4. All other sessions had an exchange rate of 500 EM=$1.

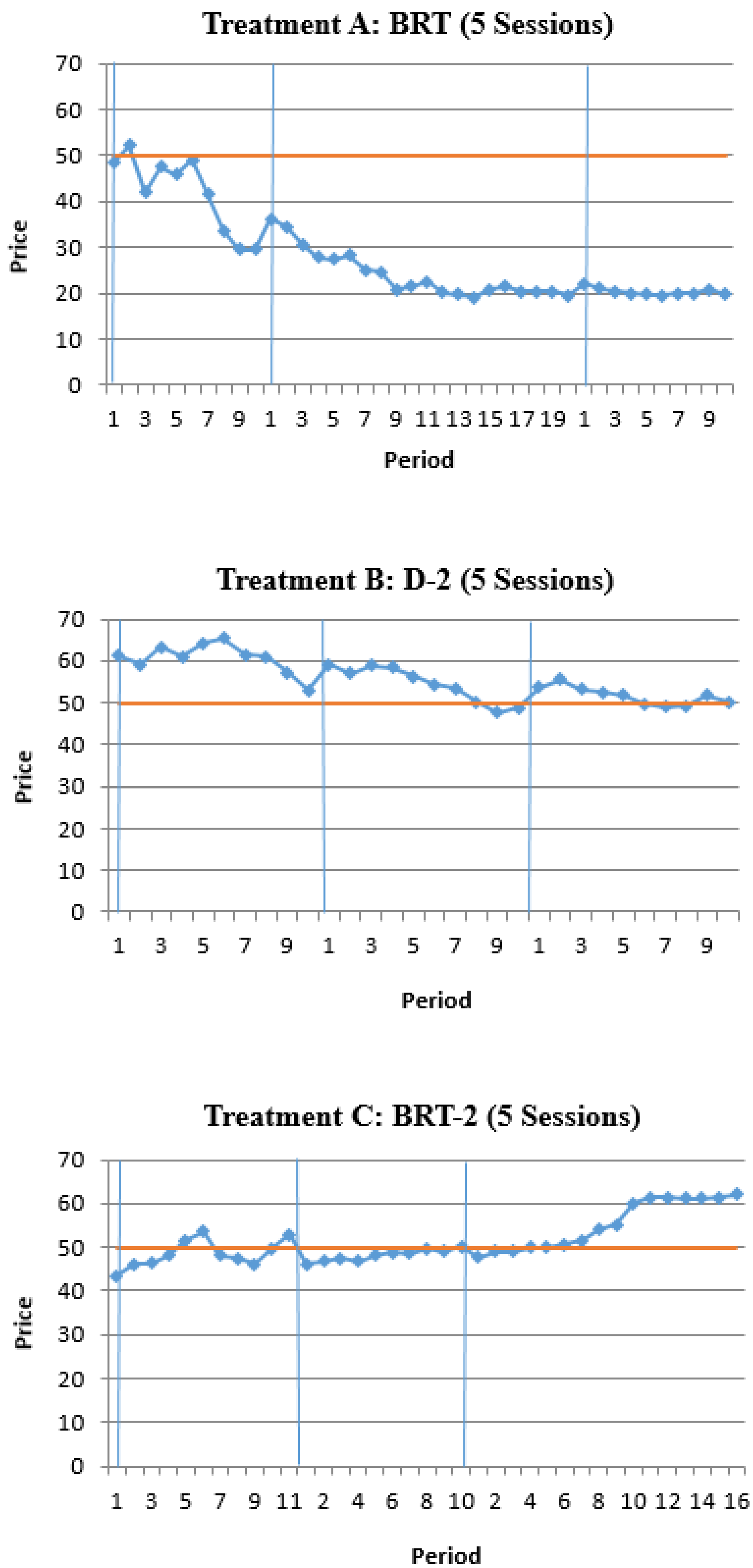


Figure 1: Average Traded Prices Over Time for Each Treatment.
*Note*: The red horizontal line is the standard FV, which is equal to 50.

Table 5: Average traded Price and Volume by Session and Market

| Session | Average Price | | | Average Volume | | |
|---|---|---|---|---|---|---|
| | Mkt1 | Mkt2 | Mkt3 | Mkt1 | Mkt2 | Mkt3 |
| A1 | 30.9 | 18.9 | 17.9 | 60.7 | 45.2 | 67.3 |
| A2 | 34.3 | 24.0 | 11.5 | 54.3 | 64.7 | 62.6 |
| A3 | 84.9 | 40.9 | 33.3 | 58.7 | 58.5 | 64.3 |
| A4 | 18.3 | 15.7 | 16.5 | 52.5 | 72.7 | 101.0 |
| A5 | 41.3 | 20.6 | 22.1 | 122.8 | 146.9 | 221.6 |
| **Treatment A** | **41.9** | **24.0** | **20.3** | **69.8** | **77.6** | **103.4** |
| B1 | 77.9 | 52.8 | 45.0 | 32.0 | 22.7 | 10.8 |
| B2 | 73.6 | 70.9 | 67.7 | 71.1 | 85.3 | 67.9 |
| B3 | 39.5 | 48.8 | 49.5 | 65.2 | 64.6 | 66.4 |
| B4 | 52.7 | 50.3 | 50.2 | 57.4 | 48.9 | 48.5 |
| B5 | 59.8 | 49.0 | 45.3 | 125.3 | 90.2 | 65.8 |
| **Treatment B** | **60.7** | **54.3** | **51.5** | **70.2** | **62.3** | **51.9** |
| C1 | 49.1 | 45.6 | 47.7 | 37.2 | 40.7 | 24.6 |
| C2 | 42.6 | 46.5 | 46.8 | 54.8 | 52.5 | 75.5 |
| C3 | 58.6 | 60.6 | 62.1 | 32.5 | 43.6 | 29.6 |
| C4 | 55.6 | 48.4 | 49.5 | 55.9 | 54.1 | 22.9 |
| C5 | 36.6 | 40.0 | 70.6 | 84.4 | 88.3 | 60.4 |
| **Treatment C** | **48.5** | **48.2** | **55.3** | **52.9** | **55.8** | **42.6** |

*Notes*: Average Price is the mean of the period price over all trading periods in a market. For treatments A and C, it includes 10 periods if the market ends within the block. The period price is the volume-weighted average traded price in the period. Average volume is the mean of trading volume (number of assets traded) over all trading periods in a market.

Table 6: $p$-values from Mann-Whitney Tests of Treatment Differences in Average Market Price and Trading Volume

| Treatment Comparison | Average Price | | | Trading Volume | | |
|---|---|---|---|---|---|---|
| | Mkt1 | Mkt2 | Mkt3 | Mkt1 | Mkt2 | Mkt3 |
| A vs. B | 0.175 | 0.009 | 0.009 | 0.602 | 0.754 | 0.251 |
| A vs. C | 0.175 | 0.016 | 0.009 | 0.347 | 0.175 | 0.047 |
| B vs. C | 0.175 | 0.076 | 0.465 | 0.347 | 0.602 | 0.602 |
| No. of Obs. | 10 | 10 | 10 | 10 | 10 | 10 |

in the last two markets. Importantly, the pattern holds at the *disaggregated* session level as well, which is shown in Figure A.1 in Appendix A.[14]

Table 5 shows the average price and the trading volume in each market of each session. We

[14]Given that the price pattern across our three different treatments is quite clear, we choose not to report the bubble (mis-pricing) measures (as deviations from the standard FV) as in most of the experimental papers on asset markets. The statistical tests on bubbles measures, RAD and RD, developed in Stockl et al (2010), are consistent with the test results we do report for price differences from the standard FV.

conduct two-tailed Mann-Whitney tests on session-level average prices and trading volume to assess whether there are any treatment differences in these market measures. There are 9 tests (3 markets x 3 treatments) each for traded price and for volume. We present the $p$-values from the Mann-Whitney tests in Table 6. The results reported in that table provide support for the following three findings.

**Finding 1** *There is no systematic significant difference in the average trading volume across the three treatments.*

The experimental data suggest that the treatment variables, horizon uncertainty and the timing of dividend payments, have no significant effect on average trading volume. Among eight out of the nine pairwise tests, we cannot reject the hypothesis that it is equally likely that the observation is drawn from the two alternative treatments. The $p$-value is $< 0.05$ only for market 3 between treatments A and C (where trading volume is higher in treatment A).

**Finding 2** *In market 1 the average traded price is not significantly different between any two treatments.*

Again, support for this finding comes from Table 6. Note that while prices are not significantly different in market 1, they are on average higher in treatment B, where the horizon is known to be finite. As we noted earlier, definite horizon asset markets have been shown to be prone to speculative trading behavior.

**Finding 3** *In markets 2 and 3, the average market price is significantly lower in treatment A (BRT) than for the other two treatments in markets 2 and 3. Relative to treatment C, the average market price in treatment B is marginally higher in market 2, and not significantly different in market 3.*

In treatment A, the average traded price in markets 2 and 3 are 24.0 and 20.3, respectively. By contrast, in treatment B, the prices in markets 2 and 3 are 54.3 and 51.5, respectively and in treatment C, they are 48.2 and 55.3, respectively. The average traded price in markets 2 and 3 is therefore significantly *lower* in treatment A than in the other two treatments. The $p$-value is $< 0.01$ for a Mann-Whitney test between treatments A and B, and $< 0.02$ for the comparison between treatments A and C. Comparing treatments B and C, the average price is marginally lower in market 2 of treatment C ($p$-value$< 0.1$ and the magnitude of the difference is 6.1), but this difference disappears when subjects gain further experience in market 3 ($p$-value$> 0.4$ and the magnitude of the difference is 3.8).

Based on these statistical results, we conclude that market outcomes in treatment A, specifically prices, are significantly different from the other two treatments. The insignificant difference in traded price between treatments B and C in the final market 3 indicates that the uncertain trading horizon itself does not significantly affect the market price. In addition, given that all three treatments share the same distribution of the value of total dividend payments, the experimental results suggest that the uncertainty in the value of total dividend payments cannot account for the low trading price in treatment A relative to the other two treatments. Instead, it appears that the *timing* of the dividend realizations is what matters for the significant difference we observe in traded prices.

Next, we try to rationalize the differences in traded prices observed in the third market of our three treatments. The approach we take is to calculate the market FV based on the actual risk preferences of the market participants, and test whether it is significantly different from the traded price in market 3. The rationale is that since the same subjects repeat the same market game three times, the market price in the third market can be reasonably expected to approximate what we refer to as the *market* FV of the asset.[15]

One way to capture the consideration of the temporal resolution of payoff uncertainty in treatment A is to represent the asset as a dynamic lottery where the payoff uncertainty is realized across time instead of a static lottery as shown in table 1. In particular, the asset in treatment A can be viewed as the combination of the fixed dividend payment in the current period with a binary lottery in the next period that entails zero payoff with probability $1-\delta$ and the replica of the asset with probability $\delta$. By contrast, in treatments B and C, because the payoff uncertainty is resolved completely after the trading stage, it is more reasonable to represent the asset in these two treatments as the static lottery in table 1.

We first note that under the assumption of risk neutrality, the holding value of both the dynamic lottery and the static lottery coincide with the standard FV (denoted by $V_0$, which is equal to $U_0 = 50$ for all three treatments). The standard FV cannot capture the low traded price of the asset in treatment A: the average traded price in market 3 is 20.3, which is about 40% of the standard FV. Statistically, this result is also confirmed by a two-tailed, Wilcoxon signed rank test that compares this traded price with the standard FV of 50: the $p$-value is 0.043. By contract, the traded price in market 3 of the other two treatments is close to the standard FV of 50 ($p$-value=0.5).

[15]As shown in Tables 5 and 6, the traded price changes little from market 2 to market 3, so it seems that convergence is achieved in market 2 and strengthened in market 3. We focus on the comparison between the traded price in market 3 and the FV to save on unnecessary repetition.

# 4 Risk Attitudes and Market FVs

Noting that the risk-neutral, standard FV cannot explain the low traded price in treatment A, a natural next step is to investigate whether incorporating subjects' (heterogeneous) risk attitudes into the static and dynamic lotteries can explain the low traded prices in treatment A versus treatments B and C. For this purpose, we construct a three-step procedure to compute the market FV that accounts for subjects' risk attitudes. In Step 1, we estimate each individual's risk parameter by using individual data from the Holt-Laury risk preference elicitation task. In step 2, we derive each individual's net demand curve for asset as a function of the share price. We derive the demand curve as the solution to a portfolio choice problem, combining each individual's asset and cash profile assigned in the experiment and their risk parameter estimated in the first step. In step 3, we aggregate the individual demand curve for each session and calculate the market equilibrium price, where net demand equals zero, which we refer to as the market FV of the asset.

As we will show below, the imputed risk-adjusted market FV depends on subjects' perceptions about the underlying asset, i.e., whether they view the asset as a static lottery in table 1, or as a dynamic lottery where payoff uncertainty is revealed across time. Since the asset in treatment A shares the same distribution of the sum of total dividend payments as the other two treatments, it is unlikely that the static risk-adjusted FV could account for the low traded price in treatment A, while the dynamic risk-adjusted FV is more promising. Nonetheless we will calculate the static risk-adjusted FV for treatment A as well. We will then calculate the dynamic risk-adjusted FV for treatment A and discuss its marginal contribution in explaining the traded FV relative to the static FV.

## 4.1 Risk Parameter

We first estimate the risk parameter for each subject from their Holt-Laury tasks. This is step 1 of the three-step procedure to calculate risk-adjusted market FV, and it is the same for computing static and dynamic market FVs. We assume that subjects' utility functions take the form $u(x, \alpha) = x^{\alpha}/\alpha$, where $\alpha$ is a risk preference parameter, with $\alpha = 1$, $\alpha < 1$ and $\alpha > 1$ corresponding to risk neutrality, risk aversion and risk loving behavior, respectively. Using this functional form, we first calculate the value of $\alpha$ such that an individual with risk parameter $\alpha$ is exactly indifferent between Option A, the safe choice, and Option B, the risky choice, for each of the 10 paired lottery choices in the Holt-Laury procedure. The 10 choices can be found in Appendix D (experimental instructions). For example, in choice

$i$, the payoff from Option A is $\bar{x}_A = \$4.0$ with probability $p_i = i/10$ and $\underline{x}_A = \$3.2$ with probability $1 - p_i$, while Option B offers $\bar{x}_B = \$7.5$ with probability $p_i$ and $\underline{x}_B = \$0.2$ with probability $1 - p_i$.[16] An agent who is indifferent between the two options in choice $i$ has preferences $u(x, \hat{\alpha}_i)$, with $\hat{\alpha}_i$ solving $Eu_A(x, \hat{\alpha}_i) = Eu_B(x, \hat{\alpha}_i)$ or

$$p_i \bar{x}_A^{\hat{\alpha}_i} + (1 - p_i)\underline{x}_A^{\hat{\alpha}_i} = p_i \bar{x}_B^{\hat{\alpha}_i} + (1 - p_i)\underline{x}_B^{\hat{\alpha}_i}.$$

In the Holt-Laury data elicited from the experiment, we observe the number of safe (A) choices that each subject made (denoted by $n_A$). We now describe how we estimate $\alpha(n_A)$, the risk parameter as a function of the number of safe choices.

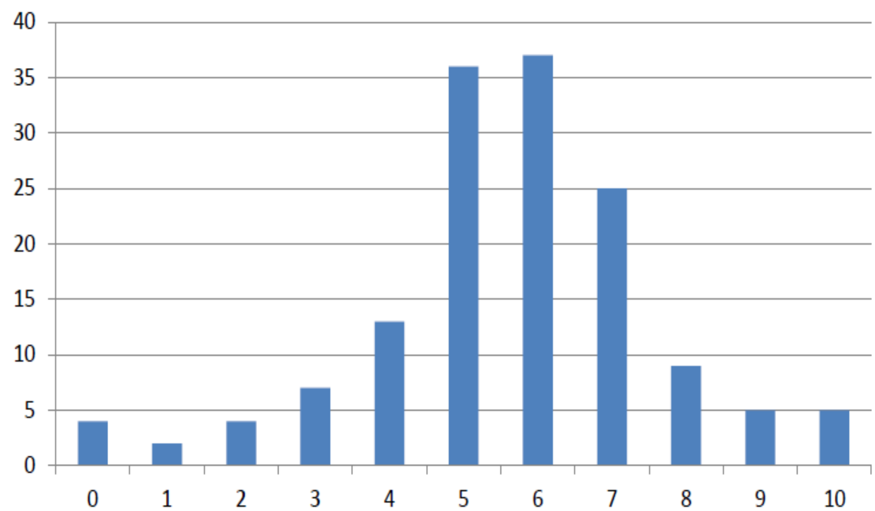


Figure 2: Distribution of the Number of Safe Choices (Lottery A) in Holt-Laury Task

If we observe that a subject switched from the safe Option A to the risky Option B at the $i$th choice (or equivalently, with $n_A = i$), then we infer that the subject is indifferent between option A and option B at a choice with a $p$ value lying between $p_i$ and $p_{i+1}$, and his/her risk parameter lies on the interval $[\hat{\alpha}_{i+1}, \hat{\alpha}_i]$. We estimate the subject's risk parameter as the midpoint of this interval.[17] For instance, if a subject chooses Option $A$ for the first four choices ($n_A = 4$) and switches to option $B$ beginning with choice 5, that implies the subject is indifferent between Option $A$ and Option $B$ when $p$ takes a value between 0.4 and 0.5. Therefore, the risk parameter of this subject lies between $\hat{\alpha}_5$ and $\hat{\alpha}_4$, i.e., in the interval

[16] The payoffs we used in the lottery are twice the payoffs used in the low stakes treatment of Holt and Laury (2002). Given the CRRA assumption, the two sets of payoffs should lead to the same estimation of $\alpha$ given the same switch point.

[17] Our robustness checks show that the estimation of the market FV does not change significantly when the estimated risk parameter takes on values other than the midpoint of the interval (e.g., either endpoint).

Table 7: Estimation of the CRRA Parameter from the Holt-Laury Task

| Choice $i$ | $n_A$ | $p_i$ | $\hat{\alpha}_i$ | $\alpha(n_A)$ |
|---|---|---|---|---|
| | 0 | | | 2.7128 |
| 1 | 1 | 0.1 | 2.7128 | 2.3298 |
| 2 | 2 | 0.2 | 1.9468 | 1.7167 |
| 3 | 3 | 0.3 | 1.4866 | 1.3146 |
| 4 | 4 | 0.4 | 1.1426 | 0.9981 |
| 5 | 5 | 0.5 | 0.8536 | 0.7211 |
| 6 | 6 | 0.6 | 0.5885 | 0.4562 |
| 7 | 7 | 0.7 | 0.3288 | 0.1766 |
| 8 | 8 | 0.8 | 0.0294 | −0.1695 |
| 9 | 9 | 0.9 | −0.3684 | −0.3684 |
| 10 | 10 | 1 | $-\infty$ | −0.3684 |

*Notes.* We assume subjects have CRRA utility functions, $u(x) = x^\alpha/\alpha$.

$(0.8536, 1.1426)$. We estimate this subject's risk parameter as 0.9981, the midpoint between $\hat{\alpha}_4$ and $\hat{\alpha}_5$.

If a subject always chose the risky option $B$, then the interval for the estimate of his/her risk parameter is open and we use the lower bound of 2.7128. If the subject chooses the safe option $A$ nine or ten times, then the interval for the estimate of his/her risk parameter is again open, and we use the upper bound of −0.3684.

Table 7 provides a summary of $\alpha(n_A)$, the estimated value of the risk parameter as a function of the number of safe choices, $n_A$, made by individual subjects. Table 7 suggests that risk neutral subjects (those whose true $\alpha = 1$) would switch from option A to option B after the fourth choice ($n_A = 4$), and risk averse (loving) agents would switch later (earlier). Out of the 147 participants, 13, or 9% (who chose 4 safe choices), can be classified as risk-neutral, 117 or 80% (who chose more than 4 safe choices) are classified as risk-averse and 17 or 11% (who chose 0-3 safe choices) are classified as risk-loving. Figure 2 shows a histogram of the number of safe choices across all sessions. The results are consistent with previous findings in the literature.[18]

[18] Also consistent with previous findings in the literature, around 27% of subjects had multiple switch points in the Holt-Laury task. For those cases, we count the number of times that each individual chose option A and we use that as an approximation for $n_A$, as if the subject had chosen Option $A$ for the first $n_A$ choices and Option $B$ for the remaining choices.

## 4.2 Static Risk-adjusted FV

In this subsection, we use the estimated risk parameter to calculate the static risk-adjusted market FV (steps 2 and 3 of the three-step procedure), and we examine whether it can capture the traded price in our experiment.

First, we derive each subject's demand for assets. Let $m_0$ and $s_0$ be the subject's endowment of money and shares, $p$ be the market price, and $s$ be the holding of shares after trading. An individual with risk parameter $\alpha$ solves the following portfolio choice problem

$$\max_s \Sigma_{t=1}^{\infty}(1-\delta)\delta^{t-1}[tds + m_0 + (s_0 - s)p]^{\alpha}/\alpha \quad (1)$$
$$\text{subject to: } s \geq 0; m_0 + (s_0 - s)p \geq 0$$

where the two constraints imply there are no short sales of shares and subjects cannot borrow money to buy shares. Let $s(p)$ be the solution to (1), then the subject's individual net demand for shares is $q(p) = s(p) - s_0$. We then construct the aggregate demand $Q(p)$ as the sum of individual demands. The market FV, $V$, solves $Q(V) = 0$. In Table 8, we report the estimated static risk-adjusted market FV which we denote by $V_1$.[19]

Given that most (80%) of our subjects are risk averse, this risk-adjusted FV, $V_1$, is always found to be lower than the standard FV, $V_0 = 50$, but $V_1$ lies in a relatively small range between 40.2 and 47.2 across all treatments. Incorporating risk attitudes toward uncertainty in the value of total dividend payments brings the market FV closer to the traded prices in market 3 of treatment A, which are repeated in the second column of Table 8 for comparison purposes. However, for treatment A there is still a large gap between $V_1$ and the market 3 traded prices. As Table 8 reveals, $V_1$ averages 44.1 across all five sessions of Treatment A while the actual average market traded price for the five sessions of Treatment A is lower at 20.3.

Table 9 reports on signed rank tests of the null hypothesis that the market traded prices are equal to $V_1$ or $V_0 = 50$ in market 3 of our three treatments. There we see that for Treatment A, market 3 our method of adjusting the static FV for market risk aversion still leads us to reject the null of no difference in favor of the alternative that traded prices in market 3

[19] We find the market-clearing price numerically, following the steps below. (1) Set the interval for possible prices, for instance, from 1 to 100, with a fine grid, 0.1. Index these prices by $j$. (2) For each price $p_j$ in the interval, use subjects' individual risk parameter $\alpha$ measured in step 1 to solve the maximization problem (1) and find the individual's desired asset holding $s(p_j)$. The net demand for the individual is $s(p_j) - s_0$. (3) Sum up the net demands across all subjects to get the net total demand $Q(p_j)$. (4) The equilibrium price is the $p_j$ that minimizes $|Q|$.

Table 8: Estimated Fundamental Value by Treatment and Session

| Session | Avg Mkt3 Price | $V_0$ | $V_1$ | $V_2$ |
|---|---|---|---|---|
| A1 | 17.9 | 50 | 44.7 | 36.7 |
| A2 | 11.5 | 50 | 44.5 | 36.7 |
| A3 | 33.3 | 50 | 40.2 | 24.3 |
| A4 | 16.5 | 50 | 46.2 | 36.8 |
| A5 | 22.1 | 50 | 45.0 | 30.0 |
| **Treatment A** | **20.3** | **50** | **44.1** | **32.9** |
| B1 | 45.0 | 50 | 44.9 | |
| B2 | 67.7 | 50 | 40.7 | |
| B3 | 49.5 | 50 | 44.6 | |
| B4 | 50.2 | 50 | 44.3 | |
| B5 | 45.3 | 50 | 43.9 | |
| **Treatment B** | **51.5** | **50** | **43.7** | |
| C1 | 47.7 | 50 | 44.4 | |
| C2 | 46.8 | 50 | 44.5 | |
| C3 | 62.1 | 50 | 47.2 | |
| C4 | 49.5 | 50 | 44.3 | |
| C5 | 70.6 | 50 | 42.3 | |
| **Treatment C** | **55.3** | **50** | **44.5** | |

*Notes.* $V_0$ is the standard (risk-neutral) FV; $V_1$ is the static risk-adjusted FV; and $V_2$ is the dynamic risk-adjusted FV.

Table 9: $p$-values from Wilcoxon Signed Rank Tests: Average Market 3 Prices against Market FVs

| Treatment | $V_0$ | $V_1$ | $V_2$ |
|---|---|---|---|
| A | 0.043 | 0.043 | 0.138 |
| B | 0.686 | 0.043 | |
| C | 0.686 | 0.043 | |

Notes. $V_0$ is the standard (risk neutral) FV, $V_1$ is the static risk-adjusted FV, and $V_2$ is the dynamic risk-adjusted FV.

of treatment A are significantly lower than $V_1$ ($p = 0.043$). By contrast, for treatments B and C, we see in Table 8 that market 3 average traded prices are higher than $V_1$ ($p = 0.043$, although the difference is modest in terms of magnitude at about 15% for treatment B and 20% for treatment C).

We conclude that the static risk-adjusted FV, $V_1$, is unable to capture the actual mean traded price in our experiment, especially in treatment A. We next ask whether a dynamic risk-adjusted FV could account for the lower traded prices found in treatment A relative to the other two treatments.

## 4.3 Dynamic Risk-adjusted FV

In this subsection we calculate the dynamic risk-adjusted FV for treatment A (for the other two treatments, the static FV remains an appropriate benchmark). To incorporate the time dimension of the resolution of payoff uncertainty into the analysis of the FV for treatment A, we resort to a recursive preference specification due to Kreps and Porteus (1978) and Epstein and Zin (1989). This specification involves two components: a risk aggregator that aggregates risky payoffs within the same period, and a time aggregator that aggregates the certainty equivalence of risky payoffs across periods. We adopt the popular specification, due to Epstein and Zin (1989), that uses a constant elasticity of substitution (CES) time aggregator to combine the current payoff, in our case, the dividend $d$, with the certainty equivalence value of all future payoffs.[20] To calculate the FV of the asset in treatment A, we consider a special case of the CES time aggregator where subjects treat the payoff in the current trading period and the certainty equivalence of future payoffs as perfect substitutes. This is a reasonable assumption (and perhaps the only assumption that can be made) for time aggregation in the context of treatment A, because each trading period lasts for only two minutes and it is hard to imagine subjects would have any motive to smooth payoffs across different trading periods (or discount payoffs in later periods). For the risk aggregator, we continue using the CRRA specification to aggregate the risk associated with future payoffs. With these assumptions, each subject solves the following portfolio choice problem:

$$\begin{aligned} &\max_s ds + m_0 + p(s_0 - s) + \delta^{1/\alpha} ps \\ &\text{subject to: } s \geq 0; m_0 + (s_0 - s)p \geq 0 \end{aligned} \tag{2}$$

where the last term is the certainty equivalence of the lottery that pays $ps$ with prob $\delta$ and 0 with prob $1 - \delta$. Note it is assumed that the economy is in its stationary equilibrium where

[20] Epstein-Zin preferences are commonly used in the finance literature to rationalize the equity premium and risk-free rate puzzles (see, e.g., Campbell (2018)). These preferences relax the restriction that the elasticity of inter-temporal substitution equals the reciprocal of the coefficient of relative risk aversion by allowing different parameters for each, so that agents can treat current consumption values and the certainty equivalence of future values in a nonlinear way that violates the independence axiom of expected utility theory. Brown and Kim (2014) report experimental results from a choice menu elicitation (such as the Holt-Laury risk elicitation as well as time and uncertainty resolution preferences) which reveal that most subjects have an estimated coefficient of relative risk aversion that differs from their estimated inter-temporal elasticity of substitution, consistent with the Epstein-Zin specification. Meissner and Pfeiffer (2018) conduct an experiment that also uses the MPL method to test the recursive preference. Instead of monetary payments the lotteries in their paper are defined over real consumption, represented by a real effort task and YouTube watching time. They find that recursive utility has no predictive power in explaining preferences over the temporal resolution of consumption uncertainty. We show that this non-expected utility approach can help to account for differences that we observe in market traded prices when we change the timing of dividend realizations under random termination.

the price of the asset is constant across time. The solution to (2) gives the individual's demand for the asset:

$$q = \begin{cases} \frac{m_0}{p} \text{ if } p < \frac{d}{1-\delta^{\frac{1}{\alpha}}} \\ -s_0 \text{ otherwise} \end{cases},$$

We then construct the aggregate demand curves to calculate the dynamic market FV ($V_2$) following the same procedures as in the estimation of the static FV ($V_1$). The estimated $V_2$ for treatment A is shown in Table 8. The $p$-values from Wilcoxon signed rank tests comparing the market 2 and 3 traded prices with the estimated $V_2$ values are shown in Table 9.

For treatment A, Table 8 reveals that the static and dynamic FVs are very different from one another. The dynamic FV is always lower than the static FV, with the former being in a range between 24.3 and 36.8, with a treatment average of 32.9. Compared with the static FV, which averages 44.1, the dynamic FV is significantly closer to the average traded price in market 3 of Treatment A, 20.3. A signed rank test reported in Table 9 suggests that average traded prices in market 3 of treatment A are *not* significantly different from the estimated dynamic FV at the 10% significance level ($p$-value = 0.138).

As shown above, the dynamic risk-adjusted FV, $V_2$, greatly improves upon the static risk-adjusted FV, $V_1$, in terms of capturing the low traded price in the baseline indefinite-horizon asset market (treatment A). However, there is still a noticeable gap between the estimated market FV and the actual market price: the dynamic FV, $V_2$, remains higher than the average market 3 price by about 50% in treatment A (although not statically different from the market price), and $V_1$ is lower than the market price by about 15% in treatment B and 20% in treatment C (and statistically different from the market price). We summarize the result in the following finding.

**Finding 4** ***Market Price and Risk-adjusted FV.***

1. *For treatment A, the traded price in market 3 is significantly lower than the standard FV or the static risk-adjusted FV. The dynamic risk-adjusted FV overestimates the traded price by about 50%, but is not statistically significantly different (at the 10% significant level) from the traded price.*

2. *For treatments B and C, the traded price in market 3 is significantly higher than the static risk-adjusted FV predictions by about 15% and 20%, respectively, and are not significantly different from the standard FV prediction.*

# 5 Probability Weighting

Given the limited success of risk-adjusted FV in accounting for the experimental results, we continue to search for additional/alternative explanations for the final market 3 traded prices, especially for the low traded prices in treatment A. The second factor that we explore is the possibility from cumulative prospect theory (Tversky and Kahneman, 1992) that subjects employ probability weighting (PW) in evaluating the lotteries that characterize the asset.[21] In treatment A, the market ends and the asset becomes worthless with a small probability 0.1. It may be that subjects overweight this small probability, thereby lowering their valuation of the asset.[22]

In view of the limited success of risk attitude in explaining the traded price, in this section we will calculate the market FV assuming risk neutrality. For treatment A, similar to the consideration of risk attitudes, it is important to distinguish whether subjects perceive the asset as a static or dynamic lottery. For the other two treatments, it is more appropriate to consider the static FV.

Probability weighting works as follows. Suppose agents face a risky prospect with $n$ (ordered) outcomes $x_1 < x_2 < x_i < ... < x_n$, each with probability $p_1, p_2, ..., p_i, ..., p_n$. Probability weighting transforms each of the original probabilities, $p_i$, through two functions $\pi_i(\cdot)$ and $w(\cdot)$, with commonly used functional forms $\pi_i = w\left(\sum_{j=i}^{n} p_j\right) - w\left(\sum_{j=i+1}^{n} p_j\right)$ and $w(q) = \frac{q^\gamma}{[q^\gamma+(1-q)^\gamma]^{1/\gamma}}$. The effect is that small probabilities are over-weighted while large probabilities are under-weighted relative to their true values. We set $\gamma = 0.71$ following Wu and Gonzalez (1996).[23]

The estimation of risk-neutral FV under probability weighting follows a two-step procedure.

[21] Probability weighting, together with loss aversion and reference dependence, are fundamental principles of prospect theory, an alternative to expected utility theory. Given that it is not clear what the appropriate reference point is in the context of the market game that we study, we focus only on the probability weighting aspect of Prospect Theory.

[22] Ackert et al. (2009) report direct evidence of probability judgment errors on low-probability, high-payoff events in a SSW type of experimental asset market, and find the probability judgment error is correlated with the occurrence of asset price bubbles measured relative to the standard FV. Although our experimental design was not intended to directly measure the effect of biased probability judgments, we find that, consistent with Ackert et al. (2009), probability weighting helps to explain the traded price in our experimental asset markets. Different from Ackert et al. (2009), we also investigate the contribution of risk preferences and dynamic considerations, and formally model the three components in our calculation of the new market FV measure.

[23] As we did not elicit subjects' probability weighting parameters, we rely on values suggested in the literature. Other values of $\gamma$ suggested are 0.56 in Camerer and Ho (1994) and 0.61 in Tversky and Kahneman (1992). We use the highest value of $\gamma$ among the three, 0.71, as it involves the least distortion of the objective probabilities. We will also discuss the implications of different $\gamma$ values later.

The first step is to transform the probabilities of the lottery outcomes. In the second step, we use the transformed probabilities to calculate the expected value of the lottery. Note that under the assumption of risk neutrality, the expected value of the lottery is also the market FV.

In the case of the static lottery, the weighted probability of receiving $t$ dividends is given by the following equation (refer to Appendix B for more details):

$$\pi(td) = w(\delta^{t-1}) - w(\delta^t).$$

As a result, the extreme outcomes (i.e., receiving $t$ dividends when $t \geq 22$ or when $t \leq 2$) are overweighted and other outcomes are underweighted, given the functional form of $w()$, our choice of $\delta = 0.9$ and the value $\gamma = 0.71$. The risk-neutral, probability-weighted market FV is the expected value of dividend payments using the weighted probabilities, $\pi(td) = w(\delta^{t-1}) - w(\delta^t)$, in place of the original probabilities, $(1-\delta)\delta^{t-1}$:

$$V_1^{PW} = \sum_{t=1}^{\infty} [w(\delta^{t-1}) - w(\delta^t)](td) = 57.3.$$

To derive probability-weighted dynamic FV, we first transform the probabilities of the two-outcome lottery: the share maintains its value with probability $\pi_2 = w(0.9) - w(0) = w(0.9) < \delta = 0.9$ and loses all of its value with probability $\pi_1 = w(1) - w(0.9) = 1 - w(0.9) > 1 - \delta = 0.1$. As a result, the bad outcome is overweighted and the good outcome is underweighted. The risk-neutral probability-weighted dynamic FV is

$$V_2^{PW} = \frac{d}{1-\pi_2} = 23.6.$$

The (risk-neutral) probability-weighted FV seems to capture the traded price in all three treatments reasonably well. For treatment A, the dynamic probability-weighted FV is 23.6, which is only slightly above the average price in market three, 20.3. The signed rank test suggests that the average traded prices in market three of treatment A are not significantly different from the probability weighted dynamic FV. Table 10 lists the $p$-value of the signed rank tests. The $p$-value for the test between probability-weighted dynamic FV and average market 3 price in treatment A is 0.345. For treatments B and C, the $p$-value for the test between probability-weighted static FV and average market 3 price is 0.225 and 0.686, respectively. We summarize the analysis in this section as the finding below.

Table 10: $p$-values from Wilcoxon Signed Rank Tests: Average Market 3 Prices against Risk Neutral Probability-Weighted Market FVs

| Treatment | $V_1^{PW}$ | $V_2^{PW}$ |
|---|---|---|
| A | 0.043 | 0.345 |
| B | 0.225 | |
| C | 0.686 | |

Notes. $V_1^{PW}$ is the risk-neutral probability-weighted static FV, and $V_2^{PW}$ is the risk-neutral probability-weighted dynamic FV.

**Finding 5** ***Market Price and Risk-Neutral Probability-weighted FV.***

1. *For treatment A, the traded price in market 3 is not significantly different from the probability-weighted dynamic FV.*
2. *For treatments B and C, the traded prices in market 3 of treatment B and C are not significantly different from the standard FV or the static probability-weighted FV.*

Before concluding, we would like to make two remarks. First, we have also tried combining risk attitudes and probability weighting for the calculation of market FV (the detailed procedure can be found in Appendix D). Although risk adjustment is neither sufficient nor necessary to rationalize the traded prices in our data, the risk-adjusted probability-weighted FV is not significantly different from the traded prices in all three treatments (again we use the dynamic FV for treatment A and the static FV for treatments B and C). In addition, risk adjustment results in a wider range of values for $\gamma$ that can rationalize the prices we observe in treatment A and the other two treatments as well relative to the absence of risk adjustment (the risk neutral) case.[24] Therefore, although the effect of risk preferences is not crucial, we cannot exclude its potential marginal contribution to the experimental results either.

The second remark is that the probability-weighted dynamic FV is also consistent with the convergent traded prices in SSW-type markets. For example, in one configuration used in SSW the asset lasts for a finite number of periods, and in each period, the dividend follows an iid distribution with four possible outcomes $\{0\ 4\ 8\ 20\}$ with equal probabilities. The standard FV is $= 8\times$ the number of remaining periods. The weighted probabilities assuming $\gamma = 0.71$ as above are $\{0.3611, 0.1783, 0.1677, 0.2929\}$. The probability-weighted dynamic FV is $= 7.9122\times$ the number of remaining periods, which is very close to (98.9% of) the standard FV.

[24]For the risk-adjusted FV, the range of $\gamma$ that is consistent with the traded price in all three treatments (in the sense that a Wilcoxon signed rank test comparing the risk-adjusted FV with traded prices has a $p$-value higher than 0.1) is [0.54,0.85], while it shrinks to [0.65,0.76] for the risk neutral FV.

# 6 Conclusion

Most asset pricing models employ infinite horizons, as the duration of assets, such as equities, is typically unknown. By contrast, experimental asset markets typically have finite horizons making it difficult to test the predictions of infinite horizon models. While strictly speaking infinite horizons cannot be studied in the laboratory, one can mimic the environment with indefinite horizons, where in each period the asset continues to yield future dividend payments with a known probability. If agents are risk-neutral expected utility maximizers, then the probability that the asset continues to yield payoffs plays the role of the discount factor and the price predictions under the infinite horizon economy extend to the indefinitely repeated environment. In both environments, the fundamental price of the asset is constant over time and equal to the expected value of total dividend payments, a standard measure of FV found in asset pricing models.

In this paper, we study the empirical relevance of the indefinite horizon model for understanding the predictions of deterministic infinite horizon asset pricing models with discounting. In our baseline treatment A, which implements a random termination design, we find that experienced subjects consistently price the asset *below* the standard FV a finding that is new to the literature.

Compared with the infinite horizon model with discounting, the indefinite horizon model introduces two types of risks, risk in dividend payoffs (payoff uncertainty) and risk in the duration of trading (trading horizon uncertainty). In order to understand whether the low trading price can be attributed to these risks, we consider two additional treatments with a two-stage design. In the first stage, subjects trade assets without receiving or observing the dividend payments on those assets. In the second stage, they observe dividend realizations, and the total dividend payoff replicates the distribution in the baseline treatment. The two auxiliary treatments differ in that the number of trading periods is fixed in one, and uncertain in the other. In these two auxiliary treatments the asset is priced close to the standard FV and to each other.

As a result, we conclude that neither uncertainty about the trading horizon nor uncertainty regarding total dividend payoffs can account for the low traded prices observed in the baseline treatment A relative to the other two treatments. Instead, the experimental results suggest that the temporal resolution of payoffs plays a critical role in accounting for the low traded price in treatment A relative to the other two treatments. While this was initially a surprise to us, it is intuitively quite reasonable. As the baseline treatment features temporal resolution of payoff uncertainty, subjects in that treatment are more likely to view the asset as a dynamic lottery. In each period, the asset consists of two parts: certain dividend payments in the current period and an uncertain continuation value in the future. In the other two treatments, as dividend realizations are realized quickly together following the trading stage, subjects are more likely to view the asset as a static lottery and care about the total dividend payments.

Under the assumption of risk neutrality, the valuation of the dynamic lottery coincides with the valuation of the static lottery over the distribution of total dividend payments. However, once we deviate from risk neutrality, the valuation of the static and dynamic lotteries deviate from each other. To investigate whether risk attitudes together with dynamic considerations could account for the low traded prices in treatment A, we introduce a new procedure to adjust the estimated FV for observed heterogeneity in subjects' risk attitudes (and departures from risk neutrality). For moderately risk averse subjects (as we have in our experiment and which are typically found in asset pricing experiments), the risk-adjusted dynamic FV can account for a significant fraction of the low traded price that we observe in our baseline treatment A. However, it still overshoots the traded price in treatment A by a noticeable margin. In addition, the (static) risk-adjusted FV tends to undershoot the traded price in the other two treatments. Therefore, the risk-adjusted FV has only limited success in accounting for the experimental results.

Finally, we combined probability weighting (according to which subjects overreact to the small probability of market termination) with the recursive preference specification that accounts for the temporal resolution of payoff uncertainty. We find that with this approach we are able to fully rationalize the low traded prices observed in our baseline treatment. Incorporating probability weighting can also fully rationalize the observation that the traded price in these two treatments is close to the standard FV.

Our findings are of relevance to both finance and experimental researchers. For finance researchers, our results suggests that in the presence of risk non-neutrality or probability weighting, modelling the asset as a static lottery over total dividend payments could be misleading in calculations of the FV of the asset. We have also provided some empirical support for probability weighting in the context of asset markets where subjects both trade and receive dividends from their asset holdings.

An important take-away for experimental economists is that the mis-pricing behavior found in experimental asset markets may be quite different under random termination, as compared with the more typically studied finite horizon case which follows the lead of Smith et al. (1988). Rather than finding over-pricing relative to the standard FV ("bubbles") among inexperienced subjects and close tracking of the standard FV among experienced subjects as in the literature initiated by Smith et al. (1988), we find substantial under-pricing relative to the standard FV in our baseline random termination treatment with experienced subjects. We can rationalize this departure from the standard FV by incorporating probability weighting to the valuation of the asset as a dynamic lottery.

Finally, while our experiment was not designed to directly test whether subjects engage in probability weighting, we find that incorporating it helps to explain our experimental results, while risk aversion plays a less important role. In future research involving asset markets with indefinite horizons it would be of interest to directly elicit the parameter that biases the probabilities, in a manner similar to the way in which we elicited individual risk preferences. Note that the procedure that we developed to incorporate individual subjects' risk into the estimation of market FV is quite general and can easily incorporate this additional individual characteristic. We leave this exercise to future research.

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# Appendix A Average Traded Prices by Session (for Online Publication)

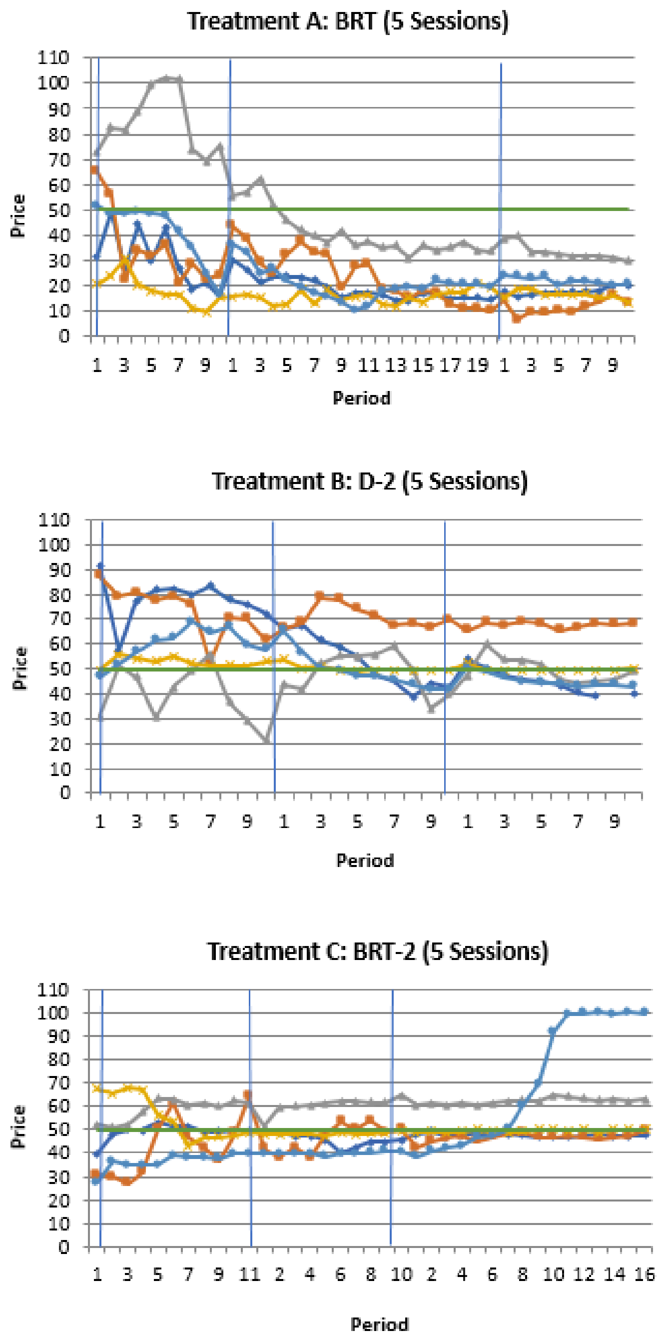


Figure A.1: Average Traded Prices Over Time for Each Session, Grouped by Treatment

*Notes*: The green horizontal line is the standard FV, which is euqal to 50.

# Appendix B Probability Weighting (for Online Publication)

In this appendix, we explain how probability weighting is conducted in our analysis. We first provide a short description about probability weighting. Suppose agents face a risky prospect with $n$ outcomes $x_1 < x_2 < x_i < ... < x_n$, with probability $p_1, p_2, ..., p_i, ..., p_n$. Probability weighting transforms the original probability $p_i$ to $w_i$ through

$$\pi_i = w\left(\sum_{j=i}^{n} p_j\right) - w\left(\sum_{j=i+1}^{n} p_j\right) = w(q_i) - w(q_{t+1}),$$

and one often-used functional form for $w(\cdot)$ is

$$w(q) = \frac{q^\gamma}{[q^\gamma + (1-q)^\gamma]^{1/\gamma}}.$$

Note the following:

1. The function $w(\cdot)$ is applied to the cumulative density function, where $q_i = \sum_{j=i}^{n} p_j$ is the cumulative probability of getting an outcome weakly better than $x_i$, i.e., $\Pr(x \geq x_i)$, and $q_{i+1} = \sum_{j=i+1}^{n} p_j$ is the the probability of outcomes strictly better than $x_i$. The transformed density probability $\pi_i$ is derived from the transformed cumulative probabilities.
2. The transformed probabilities $\pi_i$ satisfy $\sum_{i=1}^{n} \pi_i = 1$.
3. We say event $i$ is overweighted if $\pi_i > p_i$, and underweighted if $\pi_i < p_i$. Note that since

$$\frac{\pi_i}{p_i} = \frac{w(q_i) - w(q_{i+1})}{p_i},$$

whether event $i$ is over/under weighted depends on the slope of the line that connects the two points $(q_i, w(q_i))$ and $(q_{i+1}, w(q_{i+1}))$. If there are many events, then the slope of this line can be approximated by the slope of the function $w$ at point $q_i$. Note that $q_i$ is cumulative probability counting events better than event $i$ (not counting downward as in convention). Roughly speaking, event $i$ is overweighted if $w'(q_i) > 1$ and underweighted if $w'(q_i) < 1$.

Next we describe how to apply probability weighting to our experimental treatments. **In**

**treatment A,** at the end of each period after the dividend payment of 5 points, there is a random draw that determines whether the market will continue. With probability $\delta = 0.9$, the market continues, and with probability $1 - \delta = 0.1$, the market ends. So from a subject's point of view, there are two outcomes, the bad outcome has a small probability of 0.1.

| outcome $i$ | prob ($p_i$) |
|---|---|
| 1: market ends (bad) | $p_1 = 1 - \delta = 0.1$ |
| 2: market continues (good) | $p_2 = \delta = 0.9$ |

We can calculate transformed probabilities $\pi_i$ as follows:

$$\begin{aligned}\pi_1 &= w(1) - w(0.9) = 1 - w(0.9) > 0.1 \\ \pi_2 &= w(0.9) - w(0) = w(0.9) < 0.1\end{aligned}$$

so that the bad outcome is overweighted and the good outcome is underweighted.

**In treatments B and C**, subjects trade the asset first (for a fixed 10 periods in treatment B and a random number of periods in treatment C), and then learn about the dividend realizations of the underlying asset in a separate stage. In the dividend realization stage, subjects get one dividend for sure, after that, there is a random draw, with probability 0.1, dividend payment stops, and with probability 0.9, dividend payment continues. The asset can be viewed as the following lottery: outcome $i$ (i.e., $i$ dividends) with probability $p_i = \delta^{i-1}(1-\delta)$ for $i = 1, 2, ...\infty$.

| outcome $i$ | prob ($p_i$) |
|---|---|
| $d$ | $1 - \delta = 0.1$ |
| $2d$ | $\delta(1-\delta) = 0.09$ |
| ... | ... |
| $id$ | $\delta^{t-1}(1-\delta)$ |
| ... | ... |

Define $D$ as the random variable of accumulated dividends. According to the probability weighting function, the weighted probability of receiving $i$ dividends is

$$\begin{aligned}\pi_i &= \pi(id) \\ &= w(\Pr(D \geq id)) - w(\Pr(D > id)) \\ &= w(q_i) - w(q_{i+1}) \\ &= w(\delta^{i-1}) - w(\delta^i)\end{aligned}$$

For examples,

$$\begin{aligned}\pi_1 &= \pi(d) = w\,(1) - w\,(0.9) = 1 - w(0.9), \\ \pi_2 &= w(0.9) - w(0.81).\end{aligned}$$

Note that $\pi(d)$ for treatments B and C is the same as $\pi(bad)$ in treatment A.

As mentioned earlier, for a prospect involving many outcomes, whether an event $i$ is over/under weighted can be approximated by whether $w'(q_i) > 1$. In figure B.1, we draw the function $w(q)$ using $\gamma = 0.71$ and the $45^0$ line (which corresponds to $\gamma = 1$ and leads to the objective probabilities per se). We solve $w'(q) = 1$ which has two solutions $\underline{q}= 0.11$ and $\bar{q} = 0.835$. Roughly speaking, events with $q_i$ lying within the interval $[\underline{q},\bar{q}]$ are underweighted, while those with $q_i$ lying outside the interval are overweighted. In the case of treatments B and C, extremely good and bad outcomes are overweighted, while the outcomes in the middle are underweighted. With $\gamma = 0.71$, we know $d$ and $2d$ are overweighted, and events with more than 22 dividends are also overweighted. The rest are underweighted. The solution 22 is acquired from solving the equation $q_i = \delta^{i-1} = \underline{q}$ or $\bar{\imath} = \frac{\log \underline{q}}{\log \delta} + 1$.

Figure B.2 shows the effect of probability weighting using $\gamma = 0.71$, plotting the transformed probabilities $\pi$ against the original probabilities (the dotted line is the 45 degree line). For treatment A, after probability weighting, the bad outcome is overweighted, and the good outcome is underweighted. For treatments B and C, the worst two outcomes and very good outcomes are overweighted, and the rest outcomes are underweighted.

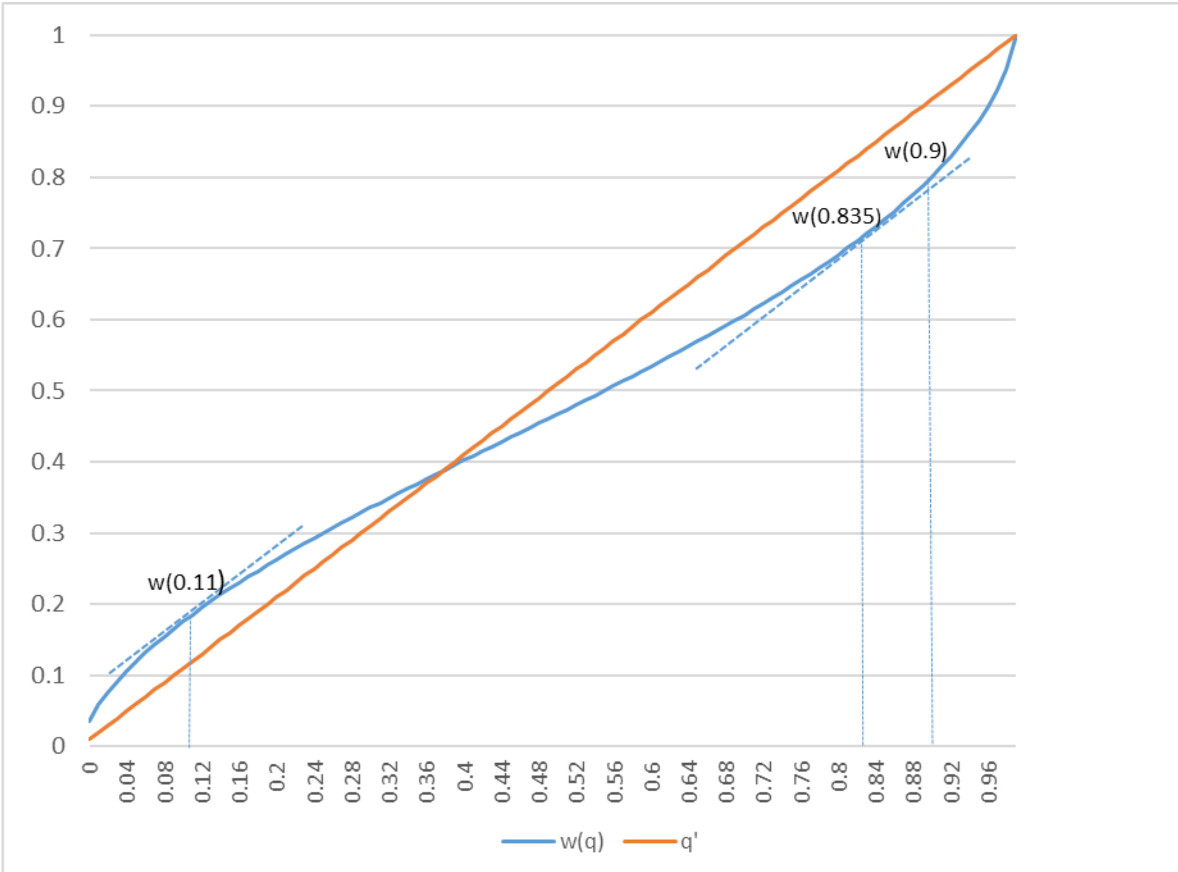


Figure B.1: Transformed Probabilities

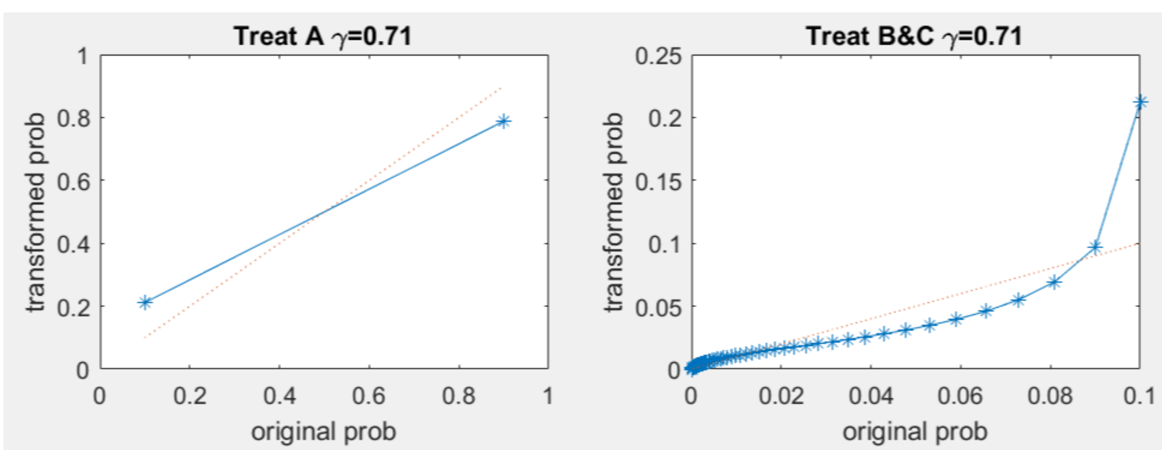


Figure B.2: Transformed Probabilities in Treatments

# Appendix C Risk-adjusted FV with Probability Weighting

In this appendix, we illustrate how to calculate the market FV incorporating both individual subjects' risk attitudes and probability weighting. We will follow the same three-step procedure to estimate the risk-adjusted FV without probability weighting as in section 4. The only difference is that we will use the transformed probabilities, $\pi_i$, in place of the original probabilities, $p_i$, in *both* the Holt-Laury task and in the lotteries characterizing the asset being traded (as in section 5).

In **step 1**, the estimation of the risk parameter, $\alpha(n_A)$, uses the transformed probabilities $\pi_i$ in place of the original probabilities $p_i$. We update Table C.1 to include the transformed probabilities and the estimated risk parameter with probability weighting, denoted by $\alpha^{PW}$. Probability weighting increases small probabilities (for $p_i < 0.4$) and decreases large probabilities (for $p_i > 0.4$). In both estimations with and without probability weighting, risk neutral agents would switch from option A to option B after the fourth choice. Probability weighting makes the estimated CRRA parameter as a function of the number of safe choices *pivot* at the risk neutral value for $n_A$, i.e., 4, and become flatter. The estimated $\alpha^{PW}(n_A)$ is smaller than $\alpha(n_A)$ for risk-seeking individuals and $\alpha^{PW}(n_A)$ is larger than $\alpha(n_A)$ for risk-averse individuals. The distribution of $\alpha^{PW}(n_A)$ is therefore more condensed in the direction of the risk-neutral case ($\alpha = 1$).

Table C.1: Calculation of the CRRA Parameter from the Holt-Laury Task

| | | w/o Prob. Weighting ($\gamma = 1$) | | | with Prob. Weighting ($\gamma = 0.71$) | | |
|---|---|---|---|---|---|---|---|
| Choice $i$ | $n_A$ | $p_i$ | $\hat{\alpha}_i$ | $\alpha(n_A)$ | $\pi_i$ | $\hat{\alpha}_i$ | $\alpha^{PW}(n_A)$ |
| | 0 | | | 2.7128 | | | 2.1566 |
| 1 | 1 | 0.1 | 2.7128 | 2.3298 | 0.17 | 2.1566 | 1.9151 |
| 2 | 2 | 0.2 | 1.9468 | 1.7167 | 0.25 | 1.6736 | 1.5272 |
| 3 | 3 | 0.3 | 1.4866 | 1.3146 | 0.33 | 1.3807 | 1.2688 |
| 4 | 4 | 0.4 | 1.1426 | 0.9981 | 0.40 | 1.1569 | 1.0601 |
| 5 | 5 | 0.5 | 0.8536 | 0.7211 | 0.46 | 0.9633 | 0.8716 |
| 6 | 6 | 0.6 | 0.5885 | 0.4562 | 0.53 | 0.7798 | 0.6851 |
| 7 | 7 | 0.7 | 0.3288 | 0.1766 | 0.60 | 0.5903 | 0.4812 |
| 8 | 8 | 0.8 | 0.0294 | $-0.1695$ | 0.68 | 0.3721 | 0.2198 |
| 9 | 9 | 0.9 | $-0.3684$ | $-0.3684$ | 0.79 | 0.0674 | 0.0674 |
| 10 | 10 | 1 | $-\infty$ | $-0.3684$ | 1 | $-\infty$ | 0.0674 |

*Notes.* We assume subjects have CRRA utility functions, $u(x) = x^\alpha/\alpha$.

In **step 2**, we derive the individual demand for the asset by solving (1), using the risk pa-

Table C.2: Estimated Fundamental Value by Treatment and Session

| | | w/o Prob. Weighting ($\gamma = 1$) | | | with Prob. Weighting ($\gamma = 0.71$) | | |
|---|---|---|---|---|---|---|---|
| Session | Avg Mkt3 Price | $V_0$ | $V_1$ | $V_2$ | $V_0$ | $V_1$ | $V_2$ |
| A1 | 17.9 | 50 | 44.7 | 36.7 | 57.3 | 51.9 | 21.0 |
| A2 | 11.5 | 50 | 44.5 | 36.7 | 57.3 | 52.2 | 21.0 |
| A3 | 33.3 | 50 | 40.0 | 24.3 | 57.3 | 45.7 | 17.1 |
| A4 | 16.5 | 50 | 46.2 | 36.8 | 57.3 | 52.7 | 24.8 |
| A5 | 22.1 | 50 | 45.0 | 30.0 | 57.3 | 51.8 | 21.0 |
| **Treatment A** | **20.3** | **50** | **44.1** | **32.9** | **57.3** | **50.9** | **21.0** |
| B1 | 45.0 | 50 | 44.9 | | 57.3 | 51.9 | |
| B2 | 67.7 | 50 | 40.7 | | 57.3 | 46.3 | |
| B3 | 49.5 | 50 | 44.6 | | 57.3 | 52.0 | |
| B4 | 50.2 | 50 | 44.3 | | 57.3 | 50.9 | |
| B5 | 45.3 | 50 | 43.9 | | 57.3 | 51.3 | |
| **Treatment B** | **51.5** | **50** | **43.7** | | **57.3** | **50.5** | |
| C1 | 47.7 | 50 | 44.4 | | 57.3 | 51.6 | |
| C2 | 46.8 | 50 | 44.5 | | 57.3 | 52.0 | |
| C3 | 62.1 | 50 | 47.2 | | 57.3 | 54.1 | |
| C4 | 49.5 | 50 | 44.3 | | 57.3 | 51.4 | |
| C5 | 70.6 | 50 | 42.3 | | 57.3 | 49.4 | |
| **Treatment C** | **55.3** | **50** | **44.5** | | **57.3** | **51.7** | |

*Notes.* $V_0$ is the standard (risk-neutral) FV; $V_1$ is the static risk-adjusted FV; and $V_2$ is the dynamic risk-adjusted FV.

rameter estimated in step 1, and the transformed probabilities for the lotteries characterizing the asset described in Appendix B. Step 3 remains the same as before, while we find the price that clears the market.

Table C.2 shows the estimated market FV with probability weighting (for comparison, the estimated market FV without probability weighting is also listed). As the rightmost columns of Table C.2 reveal, probability weighting increases the treatment average static FV, $V_1$, moderately, from 43.7 to 50.5 for treatment B, and from 44.5 to 51.7 for treatment C, bringing the static FV closer to the average market 3 traded prices in treatments B and C (51.5 in treatment B and 55.3 in treatment C). Further, we see that probability weighting reduces the treatment average dynamic FV, $V_2$ for treatment A from 32.9 to 21.0, which is very close to the average market 3 traded price of 20.3 in treatment A.

With probability weighting, using a Wilcoxon signed rank test (see table C.3), we cannot reject the null that the average price in the third market of treatment A differs from the dynamic FV, $V_2$, while it is significantly different from the standard FV, $V_0$, and the static

Table C.3: $p$-values from Wilcoxon Signed Rank Tests: Average Market 3 Prices against Risk-adjusted Probability-Weighted Market FVs

| Treatment | $V_1^{PW}$ | $V_2^{PW}$ |
|---|---|---|
| A | 0.043 | 0.686 |
| B | 0.500 | |
| C | 0.686 | |

Notes. $V_1^{PW}$ is the risk-neutral probability-weighted static FV, and $V_2^{PW}$ is the risk-neutral probability-weighted dynamic FV.

risk-adjusted FV, $V_1$. For the other two treatments, the traded price is not significantly different from all three FVs. These results suggest that the market FV under recursive utility with probability weighting *can* account for the traded price in *all three* treatments.

We have discussed how to estimate different market-based measures of the FV and evaluate their ability to account for the traded price in market 3. It is useful to summarize this discussion in the following findings.

**Finding C.1** ***Market Price and FV: Treatment A (BRT).***

1. *For treatment A, the traded price in market 3 is significantly lower than the standard FV or the static risk-adjusted FV, regardless of whether or not probability weighting is considered.*

2. *The average traded prices are not statistically significantly different (at the 10% significant level) from the dynamic risk-adjusted FV, regardless of whether or not probability weighting is considered. Probability weighting brings the dynamic FV closer (from 32.9 to 21.0) to the average traded price in the final market of Treatment A (20.3).*

3. *The average traded prices are not statistically significantly different (at the 10% significant level) from the dynamic FV with probability weighting, regardless of whether risk attitudes are considered.*

**Finding C.2** ***Market Price and FV: Treatments B (D-2) and C(BRT-2).***

1. *Without probability weighting, the traded prices in market 3 of treatments B and C are significantly higher than the static risk-adjusted FV predictions, and are not significantly different from the standard FV prediction.*

2. *With probability weighting, the traded prices in market 3 of treatment B and C are not significantly different from the standard FV or the static risk-adjusted FV.*