Experimental Asset Markets with An Indefinite Horizon*

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Abstract

We study the trade of indefinitely-lived assets in experimental markets. We find that the traded prices of these assets are on average more than 40% below the expected present value of their dividend payments, 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 can. We propose a procedure to calculate a new measure of the fundamental value considering individual traders' risk attitudes. We find that incorporating risk aversion into recursive preferences together with probability weighting can rationalize the low prices observed in our indefinite-horizon asset markets.

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

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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. As 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 amount of dividend. Thereafter, with a constant probability δ, 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, e.g. for repeated prisoner's dilemma experiments. An asset subject to such random termination and an asset that lives forever with discount factor of δ share the same standard FV if agents are risk neutral with regard to uncertain money earnings.[1]

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.[2] The stationarity associated with indefinite horizons may be a more natural setting for understanding asset pricing decisions.[3] In addition, the indefinite-

[1]Another method of implementing infinite horizons involves subjects playing a fixed number of periods with discounting on the instantaneous payoffs, followed by play of a game that captures the continuation payoff (Cooper and Kuhn, 2011).

[2]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.

[3]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. (2014) 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

horizon design is also useful for studying environments with bankruptcy or default risk where the value of the asset becomes zero with a certain probability.

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 proposed by Frechette and Yuksel (2017)). In each period the market is open, subjects first trade, then receive dividend payments for each unit of shares 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 on average more than 40% below the standard FV, and remain low as traders gain experience. The result is astounding given that vast majority of experimental asset market studies find asset price *bubbles*, or prices greatly in excess of the standard FV, in the first market with approximate convergence to the standard FV within three market repetitions.

In order to understand the low traded price 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. The lottery involves 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 asset markets with known, finite horizons.

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

period, serves as a more natural setting for understanding asset pricing.

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	...

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 are revealed and paid out at the end of each trading period. In the second treatment, all dividend payments are revealed and paid altogether at once, but 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 keeping the uncertain trading horizon of the baseline treatment. This new treatment serves as a bridge between the first two treatments. The difference between the second and third treatments serves as a better indicator of the effect of trading horizon uncertainty. The effect of the timing of dividend realizations is captured by comparing the first and third treatments. We find that the traded price in the third treatment is also fairly close the standard FV and not significantly different from the second treatment.

Combining evidence from all three treatments, we arrive at the somewhat surprising conclusion that neither the uncertainty in the value of total dividend payments nor horizon uncertainty has a significant effect on the traded price. What matters more is the timing of dividend realizations, or the temporal resolution of payoff uncertainty. Thus, 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.

The standard FV, calculated as the expected sum of remaining dividend payments, is the most often used benchmark for the analysis of finite-horizon experimental asset markets and from which various mis-pricing measures have been derived. But in the indefinite horizon setting, subjects face uncertainty about the horizon length and associated uncertainty about payoffs from buying or selling the asset. If they are not risk neutral, the uncertainty regarding their money earnings may affect the FV of the asset.

As a result, we incorporated a risk elicitation task due to Holt and Laury (2002) into all of our experimental treatments. We develop a new methodology for calculating the fundamental value of the asset that incorporates the market participant's own (heterogeneous) risk attitudes toward payoff uncertainty. Specifically, we assume that agents have constant relative risk aversion (CRRA) preferences and we infer their risk parameter using the Holt-Laury task. We then calculate the holding value of the asset for each individual subject using the inferred individual risk parameter, construct individual supply and demand curves and use the price that clears the market as a measure of the risk-adjusted FV of the asset. Our experimental results from the first two treatments suggest that incorporating risk attitudes toward the value of total dividend payments cannot rationalize the low traded prices that we observe in our baseline treatment. The third treatment that we added further rules out trading horizon uncertainty as the reason for the low traded prices the baseline treatment, and suggests the important role played by the timing of dividend realizations, or the temporal resolution of uncertainty. In order to capture the feature of gradual dividend realizations in our baseline treatment A, we resort to recursive preferences (Kreps and Porteus, 1979). Specifically, we combine an Epstein and Zin (1989) recursive preference specification with our new methodology for calculating the risk-adjusted fundamental market price of the asset. We find that the addition of recursive preferences to our approach can account for a significant part of the low traded prices observed in our baseline treatment. Meanwhile, the risk-adjusted FV calculated for our other two treatments, which we denote as the static risk-adjusted FV, are also consistent with the Epstein-Zin recursive preference as a special case.

Finally, since in our baseline treatment the market ends and the asset becomes worthless with a small probability, it seems likely that probability weighting could potentially affect traded prices as well. We find that a risk-adjusted FV under recursive preferences that also incorporates probability weighting can fully rationalize the low prices observed in our baseline treatment, and at the same time, the traded price in the two auxiliary treatments.

There is a large literature involving experimental asset markets with known, finite horizons beginning with Smith et al. (1988). Surveys of this literature are 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 (2018). Camerer and Weigelt (1993), Ball and Holt (1998), Kose (2015) and Kopányi-Peuker and Weber (2018) 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. Second, our study suggests that the timely resolution of payoff uncertainty plays an important role in determining the trading price 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 a risk-adjusted FV for an asset that incorporates the traders' own risk attitudes.

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). In this study, we examine the effect of random termination in experimental asset markets. Experimental asset markets have several distinct features as compared to repeated games. First, heterogeneous risk attitudes, combined with random termination, can create incentives for trade in such assets in settings where the dividend process is common knowledge such as in Smith et al. (1988). Second, 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. Third, in repeated games, discount factors mainly matter for whether or 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. Fourth, 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.[4] Specifically, in most asset pricing experiments, subjects can immediately (i.e., in the very first period) sell off *all* of their asset holdings and receive a certain monetary payoff rather than continue to participate in the lottery. Alternatively, subjects can buy all the assets they want in the first period and hold that asset position for the duration of the trading horizon. In the first case, subjects who sell off their assets immediately face neither payoff uncertainty nor horizon uncertainty; they sell their assets for a known amount and are not engaged in any further trading for the duration of the asset market. In the second case of the subject employing a buy-and-hold strategy, the subject continues to face payoff uncertainty, e.g., as to the sum of dividends each of his assets yields over the indefinite horizon, but because this subject ceases to engage in further trading after the first period, s/he no longer faces any trading horizon uncertainty. There is, of course, a third case where a subject trades in each period so that his asset position is constantly changing, in which case the subject faces both payoff and trading horizon uncertainty. As a result, the risk induced by random termination may play a larger role in influencing individuals' behavior in *asset market* experiments as compared with repeated game settings.

The remainder of the paper is organized as follows. Section 2 presents the experimental design and procedures. Sections 3 and 4 report on the experimental results across treatments and estimate the market FV. Section 5 concludes.

2 Experimental Design and Hypotheses

In this section, we describe our experimental design and hypotheses. We first describe the main characteristics of the treatments, followed by the experimental procedures. We then formulate our hypotheses before presenting our experimental results in the next section.

2.1 The Three Treatments

Our experimental design involves 3 treatments. The baseline treatment implements asset markets with an indefinite horizon. The two auxiliary treatments are intended to understand

[4] 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).

the traded prices observed in the baseline treatment. In all three treatments, 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 use later to construct a risk adjusted, market-based FV for 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 the identical market structure. The first part of the experiment (risk elicitation) remains the same across all three treatments, while the asset market part is different, which we describe in detail below.

Treatment A (BRT). In the baseline treatment, subjects trade in asset markets that last for an indefinite number of periods. The indefinite horizon is implemented through a modified version of the *block random termination* scheme proposed by Frechette and Yuksel (2017); therefore we label this treatment BRT.[5]

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.[6] 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'

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

[6]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.

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.

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 predraw a set of three sequences of random numbers and use the same set of draws to control the lengths of the three asset markets in all experimental sessions to reduce uncertainty and facilitate comparison across different sessions.[7] 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.

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. In order to disentangle the effect of trading-horizon uncertainty and payoff uncertainty, we design a second treatment.

Treatment B (D-2). Treatment B (D-2) aims to replicate 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

[7] 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.

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.

To preview our experimental results, we find that in our baseline treatment A, the mean traded price of the asset is more than 40% *below* the standard FV, while it is much closer to the standard FV in treatment B. We initially attributed this difference in the traded prices between treatments A and B to trading horizon uncertainty, which we saw as the main difference between the two treatments. However, given the finding in the literature that traded prices tend to converge to the FV after three market repetitions, we think the persistent difference in trading 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.[8]

Treatment C (BRT-2). 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

[8]The idea of exploring the effect of the timing of dividend realizations through a new treatment only dawned upon us after we pondered the experimental results of the first two treatments.

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.[9] 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.[10] 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

2.2 Experimental Procedures

The experiment was conducted at the Bell economics lab at CIRANO in Montreal. Subjects were recruited for the experiment using ORSEE (Greiner, 2004). Most subjects were students

[9]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.

[10]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.

from McGill and Concordia Universities in Montreal. 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.

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 C. 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.[11] 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).[12] 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.[13] 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 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.[14] 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.[15] 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.

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

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

[13]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.

[14]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 9.

[15]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.

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

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.

2.3 Hypotheses

In all three treatments, the asset traded has the same total dividend payments as represented by the lottery shown in Table 1. With this in mind, we formulate the following hypothesis:

Hypothesis 1: Market outcomes, i.e., prices and quantities, are not significantly different between treatments A, B, and C.

The comparison between treatments A and C identifies the effect of the timing of dividend payments or the temporal resolution of payoff uncertainty.[16] The comparison between treatments B and C captures the effect of uncertain trading horizons, which may affect subjects' ability to engage in speculative transactions.

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

[16]Similarly, but less cleanly, a comparison between treatments A and B also sheds light on differences in the temporal resolution of payoff uncertainty.

repeat the same trading market three times. We will check whether that convergence result also holds in our asset markets with indefinite horizons by comparing the traded prices in the final market with the standard FV, which is constant at 50 in all three treatments.

In addition, given the payoff uncertainty involved in our indefinite horizon setting, we also consider FVs that incorporate the risk preferences of traders. That is, after all, the purpose of our risk preference elicitation in the first part of each session. Using data from that risk elicitation, we propose a procedure to estimate the risk-adjusted FV for the asset, which will be elaborated upon later in section 4. The standard FV is derived under the assumption of risk neutrality. Based on previous experimental findings showing that most agents are risk averse (Holt and Laury, 2002), we propose the following hypothesis.

Hypothesis 2: The traded prices in the final, market 3 of all three treatments are significantly different from the standard FV, but not significantly different from the risk-adjusted FV.

3 Experimental Results: Comparison across Treatments

Following our hypotheses, 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 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.[17]

Table 5 shows the average price and the trading volume in each market of each session. To evaluate hypothesis 1, we conduct two-tailed Mann-Whitney tests on session-level average

[17] 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.

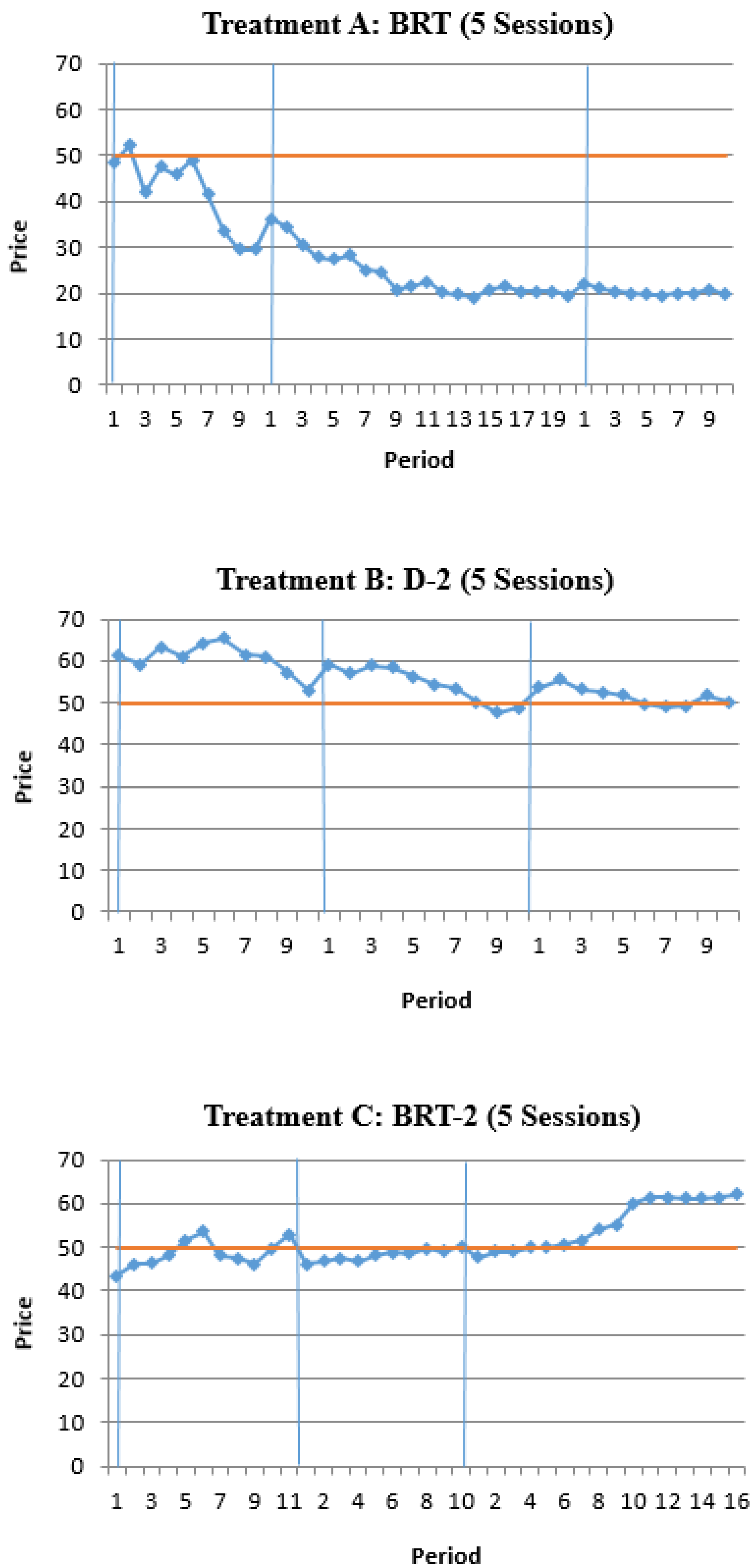

Figure 1: Average Traded Prices Over Time for Each Treatment. *Note*: The red horizontal line is the standard FV, which is equal to 50.

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

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 3 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 ($p < 0.1$ and the magnitude of the difference is 6.1), but this difference disappears when subjects gain further experience in market 3 ($p > 0.4$ and the magnitude of the difference is 3.8).

Based on these statistical results, we reject Hypothesis 1, as 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.

4 Experimental Results: Traded Prices and Market FVs

In this section, we try to rationalize the differences in traded prices observed in the third market of our three treatments. 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, or the FV based on the actual preferences of the market participants.[18] As we will show, the calculation of this market FV depends on whether the resolution of payoff uncertainty is static or dynamic (and a corresponding assumption about the utility function), as well as on whether risk preferences are incorporated, or risk neutrality is assumed.

We begin by noting that the standard FV (denoted by V_0, which is equal to $U_0 = 50$ for all three treatments)–the most often used benchmark for the analysis of finite-horizon experimental asset markets and from which various mis-pricing measures have been derived–cannot capture the low traded price of the asset in treatment A. The average traded price in market 3 is 20.3, which is just 41% of the standard FV. This result is 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. The traded price in market 3 of the other two treatments is close to the standard FV of 50 ($p = 0.5$). In the following subsections, we will explore whether risk preferences and/or utility specifications capturing timing differences in the resolution of payoff uncertainty, can help us rationalize the observed traded prices in all three treatments.

4.1 Static Risk-adjusted FV

A first natural alternative to the standard FV is the risk-adjusted FV that accounts for risk attitudes toward the uncertainty in the value of total dividend payments. Specifically, in this subsection we estimate traders' holding value for the asset under the assumption that they treat the asset value as a lottery of the type shown in Table 1, by taking into account each traders' attitude toward risk. Given the experimental results, we suspect that uncertainty in the value of total dividend payments is unlikely to account for the low trading price we observe in treatment A, while the timing of dividend realizations is the more promising avenue. Nonetheless, it is useful to know the contributions of these two dimensions of payoff uncertainty, the risk in total dividend payments and the timing in the resolution of uncertainty. In addition, the risk-adjusted market FV estimation procedure that we describe in this subsection can be easily adjusted to derive a FV that incorporates

[18] 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.

the timing of uncertainty resolution as well. We will label the FV in this subsection as the static, risk-adjusted FV (which considers only the uncertainty in total dividend payments), and the FV that considers the temporal resolution of payoff uncertainty, discussed in the next subsection, as the dynamic risk-adjusted FV.

The derivation of the static, risk-adjusted FV follows a three-step procedure. 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 estimate the certainty equivalence or "holding value" of the asset for each individual. In Step 3, we combine each individual's asset profile assigned in the experiment and the certainty equivalence or holding value of the asset estimated in Step 2. Using these, we construct aggregate demand and supply curves for each session and calculate the market equilibrium price, where demand equals supply, which we refer to as the market FV of the asset.

Step 1: Estimation of the Risk Parameter. In step 1, we assume that subjects' utility functions take the form $u(x, \alpha) = x^\alpha/\alpha$, where α 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 α such that an individual with risk parameter α 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 C (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 $1 - p_i$.[19] 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.

If we observe a subject switched from the safe Option A to the risky Option B at the ith choice (or equivalently, with $n_A = i$), then we can 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

[19]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 α given the same switch point.

the midpoint of this interval.[20] 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 $(0.8536, 1.1426)$. 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. For the moment, we consider the columns of this table under the heading without (w/o) probability weighting (we will consider probability weighting and its adjustment to our estimates of $\alpha(n_A)$ later on in section 4.3). These left columns of Table 7 suggest 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.[21]

Step 2: Estimation of Holding Value. After determining each subject's risk parameter as a function of his/her number of safe choices, $\alpha(n_A)$, we can estimate each subject's holding value of the asset, $U_1(n_A)$, as the certainty equivalence for the lottery presented in Table 1. The probability of receiving t dividends is $(1-\delta)\delta^{t-1}$, so we can define the risk-adjusted certainty equivalence, U_1, as the solution to the following equation (noting that α is a function of n_A),

$$\frac{U_1^{\alpha}}{\alpha} = \sum_{t=1}^{\infty}(1-\delta)\delta^{t-1}\frac{(td)^{\alpha}}{\alpha},$$

[20] 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).

[21] 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.

Table 7: 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	$\hat{\alpha}_i$	$\alpha(n_A)$	π_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, $u(x) = x^{\alpha}/\alpha$.

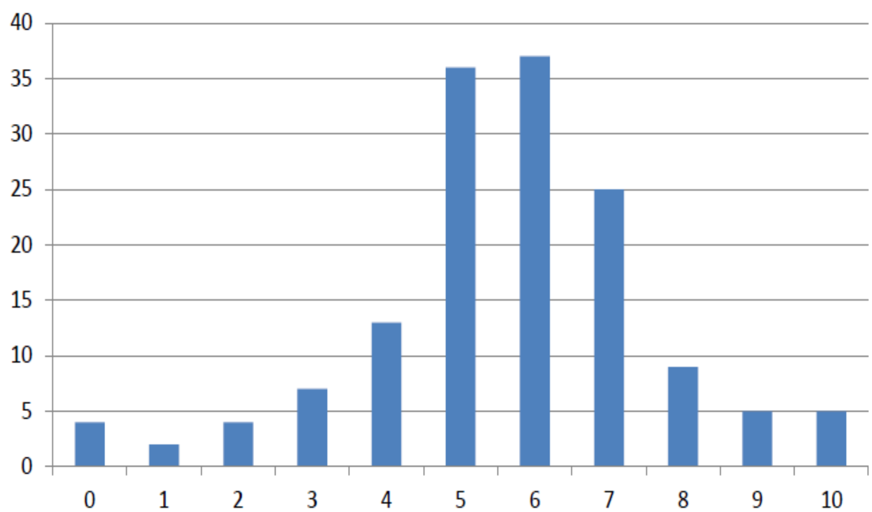

Figure 2: Distribution of the Number of Safe Choices (Lottery A) in Holt-Laury Task

or

$$U_1 = \left\{ \sum_{t=1}^{\infty} (1-\delta)\delta^{t-1}(td)^{\alpha} \right\}^{\frac{1}{\alpha}}.$$

The latter is the certain amount that a subject would accept in exchange for forgoing the expected utility from the lottery under CRRA preferences and the subject's estimated risk parameter, α. Table 8 (left columns w/o Prob. Weighting) reports on U_1 as a function of n_A. Figure A.2 in Appendix A (top panel A) graphs the estimated holding value U_1 as a function of the estimated risk parameter α (left panel), and the number of safe choices in the Holt-Laury task n_A (right panel).

Table 8: Estimated Holding Value as a Function of the Number of Safe Choices

	w/o Prob. Weighting ($\gamma = 1$)			with Prob. Weighting ($\gamma = 0.71$)		
n_A	U_0	U_1	U_2	U_0	U_1	U_2
0	50	82.4	131.3	57.3	94.1	47.8
1	50	75.2	113.1	57.3	86.7	42.8
2	50	63.6	84.0	57.3	74.4	34.6
3	50	55.9	64.9	57.3	66.0	29.2
4	50	50.0	49.9	57.3	59.2	24.9
5	50	44.8	36.8	57.3	53.1	20.9
6	50	40.0	24.2	57.3	47.2	17.0
7	50	35.2	11.1	57.3	41.0	12.8
8	50	29.6	-5.8	57.3	33.8	7.6
9	50	26.8	-15.1	57.3	30.0	5.2
10	50	26.8	-15.1	57.3	30.0	5.2

Notes. U_0 is the standard (static risk neutral) holding value; U_1 is the static risk-adjusted holding value; and U_2 is the dynamic risk-adjusted holding value.

Step 3: Estimation of the Market FV. After acquiring each individual's holding value (certainty equivalence), we can construct each individual's demand and supply for the asset. Let s and m be an individual's endowment of asset shares and cash (EM) respectively. The individual's demand for the asset is therefore given by:

$$q^d = \begin{cases} m/p \text{ if } p < U_i \\ 0 \text{ otherwise} \end{cases},$$

and the individual's supply of the asset is given by:

$$q^s = \begin{cases} s \text{ if } p > U_i \\ 0 \text{ otherwise} \end{cases}.$$

Finally, we construct the aggregate demand, $Q^d(p)$, and supply, $Q^s(p)$, as the sum of individual demands and supplies. The market FV, V, solves $Q^d(V) = Q^s(V)$. In Table 9 (under the heading w/o Prob Weighting) we report the estimated static risk-adjusted market FV which we denote by V_1.

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 35.2 and 44.9 across all treatments. Incorporating risk attitudes toward uncertainty in the value of total dividend payments brings the market FV closer to the final market 3 traded prices of treatment A, which are repeated in the second column of Table 9 for comparison purposes. However, for treatment A there is still a large gap between V_1 and the market 3 traded prices. As Table 9 reveals, V_1 averages 42.5 across all five sessions of Treatment A while the actual average market traded price for the 5 sessions of Treatment A is 20.3.

Table 10 reports on signed rank tests of the null hypothesis that the market traded prices are equal to V_1 or $V_0 = 50$ in markets 2 and 3 of our three treatments. There we see that for Treatment A, market 3 (w/o probability weighting) our method of adjusting the 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 of treatment A are significantly lower than V_1 ($p = .043$). By contrast, for treatments B and C, we see in Table 9 that market 3 average traded prices are higher than V_1 (although the difference is modest in terms of magnitude at around 20%). Still, as shown in Table 10, a Wilcoxon signed rank test of the null hypothesis that the mean traded price is equal to V_1 has a p-value of 0.043 for treatments B and C as well. The static risk-adjusted FV, V_1, is therefore unable to capture the actual mean traded price in our experiment, and as a result we were inclined to reject Hypothesis 2. However, as we discuss next, some greater support for Hypothesis 2 can be found if we also consider the temporal resolution of payoff uncertainty in the specification of subjects' preferences.

4.2 Dynamic Risk-adjusted FV

The experimental results suggest that differences in the timing of dividend realizations, i.e., differences in the temporal resolution of payoff uncertainty, significantly affect the traded price of the asset. In treatment A, payoff uncertainty is resolved gradually in each trading period, and the dividend payment subjects receive in each period is directly affected by their trading activities in that same period. In this treatment, dividends realized (and received) in different periods have different time stamps and subjects may distinguish the dividend payoffs received in different trading periods as separate payoffs. Thus, for treatment A it is reasonable to incorporate the time dimension of the resolution of payoff uncertainty. By contrast, in treatments B and C, payoff uncertainty is resolved all at once and after the trading stage based on the asset position in the last trading period.[22] In other words, all dividend payments in treatments B and C have the same time stamp, and the asset can be represented as the static lottery shown in Table 1. For these two treatments, the static risk-adjusted FVs estimated in the last subsection remain an appropriate benchmark (we will later consider further adjusting these FVs using probability weighting).

To incorporate the time dimension of the resolution of payoff uncertainty into the analysis of

[22]In stage two of treatments B and C, dividend realizations are revealed very fast in a matter of seconds because there is no trading.

Table 9: 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	44.8	36.7	57.3	50.0	21.0
A2	11.5	50	44.8	36.7	57.3	53.1	21.0
A3	33.3	50	40.0	24.3	57.3	47.2	17.1
A4	16.5	50	42.7	36.7	57.3	47.3	24.8
A5	22.1	50	40.1	30.0	57.3	47.3	21.0
Treatment A	20.3	50	42.5	32.9	57.3	49.0	21.0
B1	45.0	50	44.8		57.3	50.0	
B2	67.7	50	35.2		57.3	41.1	
B3	49.5	50	44.8		57.3	53.1	
B4	50.2	50	40.1		57.3	47.3	
B5	45.3	50	44.8		57.3	50.0	
Treatment B	51.5	50	41.9		57.3	48.3	
C1	47.7	50	44.8		57.3	50.0	
C2	46.8	50	44.8		57.3	53.1	
C3	62.1	50	44.9		57.3	53.1	
C4	49.5	50	40.1		57.3	47.3	
C5	70.6	50	40.1		57.3	47.3	
Treatment C	55.3	50	42.9		57.3	50.2	

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

Table 10: p-values from Wilcoxon Signed Rank Tests: Average Market Prices against different market FVs for the Asset

Treatment	Average Price in Market 2			Average Price in Market 3		
	V_0	V_1	V_2	V_0	V_1	V_2
	w/o Prob. Weighting					
A	0.043	0.079	0.225	0.043	0.043	0.138
B	0.500	0.043		0.686	0.043	
C	0.500	0.079		0.686	0.043	
	with Prob. Weighting ($\gamma = 0.71$)					
A	0.043	0.043	0.893	0.043	0.043	0.686
B	0.500	0.500		0.225	0.686	
C	0.080	0.686		0.686	0.500	
No. of Obs.	5	5	5	5	5	5

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

the FV for treatment A, we resort to a recursive preference specification (Kreps and Porteus, 1978; 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. A popular specification, due to Epstein and Zin (1989), 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:[23] 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, the holding value of the asset under recursive preferences in period t, $U_{2,t}$, can be expressed by

$$U_{2,t} \quad = \quad d + (E\tilde{U}_{2,t+1}^{\alpha})^{1/\alpha},$$

where the second term represents the risk-adjusted certainty equivalence value of future payoffs. Notice that the static risk-adjusted FV estimated in the last subsection will remain the same under the Epstein-Zin utility specification.

The derivation of the market FV with recursive preferences in treatment A follows the same three-step procedure as described in the previous subsection. Notice that step 1, or the estimation of the risk parameter, $\alpha(n_A)$, remains the same because the Holt-Laury task consists of static gambles. In step 2, the estimation of the dynamic holding value differs

[23]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.

from the static holding value, which indirectly affects the market FV of the asset in step 3.

Using the estimated risk parameter, the holding value of the asset in treatment A under recursive preferences can be expressed as

$$\begin{aligned} U_{2,t} &= d + (E\tilde{U}^{\alpha}_{2,t+1})^{1/\alpha} \\ &= d + [\delta U^{\alpha}_{2,t+1}]^{1/\alpha} \\ &= d + \delta^{1/\alpha} U_{2,t+1}, \end{aligned}$$

where $(E\tilde{U}^{\alpha}_{2,t+1})^{1/\alpha}$ is the certainty equivalence of the asset's continuation value (or future payoffs), $\tilde{U}_{2,t+1} = U^{\alpha}_{2,t+1} > 0$ with probability δ and $\tilde{U}_{2,t+1} = 0$ with probability $1 - \delta$. Imposing $U_{2,t} = U_{2,t+1}$, we can calculate the recursive holding value as

$$U_2 = \frac{d}{1 - \delta^{\frac{1}{\alpha}}}. \tag{1}$$

Note that if $\alpha = 1$, then $U_2 = U_1 = U_0$.

Table 8 presents U_2 as a function of n_A. In Figure A.2 (upper panel A), the estimated holding value under recursive preferences, U_2, is graphed together with U_0 (the standard holding value) and U_1 (the static risk-adjusted holding value). Note that for risk averse agents, for whom $\alpha < 1$, the holding value estimated under the recursive utility specification is lower than the static risk-adjusted holding value, and further lower than the static risk-neutral holding value, i.e., $U_2 < U_1 < U_0 = 50$. When $\alpha > 1$, this ordering reverses, with $U_2 > U_1 > U_0 = 50$. Finally, for risk neutral agents, the three holding values coincide with each other at 50.

After estimating the holding value, we can construct the individual and aggregate supply and 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 9 (under heading w/o probability weighting). 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 10 (under heading w/o probability weighting).

For treatment A, Table 9 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 42.5, 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 10 suggests that average traded prices in markets 2 or 3 of treatment A are *not* significantly different from the estimated dynamic FV at the 10% significance level ($p = .225$ for market 2 and $p = .138$

for market 3).

4.3 Probability Weighting

As shown in the previous subsection, 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 small 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 20% in treatments B and C (and statistically different from the market price). We therefore continue to search for additional/alternative explanations for the final market 3 traded prices, especially for the low traded prices in treatment A. For this purpose, we consider the possibility from cumulative prospect theory (Tversky and Kahneman, 1992) that subjects employ probability weighting (PW) in evaluating the lotteries that characterize the asset.[24] 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.[25] In the following, we will examine whether and how probability weighting affects the calculation of the three alternative FVs considered so far: the standard (static risk neutral) FV, V_0, the static risk-adjusted FV, V_1, and the dynamic risk-adjusted FV, V_2. We will then evaluate the contribution of probability weighting for capturing the traded price.

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

[24]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.

[25]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.

(1996).[26]

To derive the FV with probability weighting, we follow the same three-step procedure as before. The only difference is that we will use the transformed probabilities, π_i, in place of the original probabilities, p_i, in *both* the Holt-Laury task and in the lotteries characterizing the asset being traded.

In **step 1**, the estimation of the risk parameter, $\alpha(n_A)$, uses the transformed probabilities π_i in place of the original probabilities p_i. We update Table 7 to include the transformed probabilities and the estimated risk parameter with probability weighting, denoted by α^{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 ($\alpha = 1$).

In **step 2**, for the estimation of the static holding value, we use the risk parameter estimated in step 1, α^{PW}, and the transformed probabilities for the lotteries characterizing the asset. In the case of the static risk-adjusted holding value, the (weighted) probability of receiving t dividends is now 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 $\gamma = 0.71$. Correspondingly,

$$U_1^{PW} = \left\{ \sum_{t=1}^{\infty} [w(\delta^{t-1}) - w(\delta^t)](td)^{\alpha^{PW}} \right\}^{\frac{1}{\alpha^{PW}}}. \quad (2)$$

In the case of the dynamic holding value, the estimation is similar except that $\tilde{U}_{t+1} = U_{t+1}^{\alpha^{PW}} > 0$ with probability $\pi_2 = w(0.9) - w(0) = w(0.9) < \delta = 0.9$ and $\tilde{U}_{t+1} = 0$ with probability $\pi_1 = w(1) - w(0.9) = 1 - w(0.9) > 1 - \delta = 0.1$, so the bad outcome is overweighted and the

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

good outcome is underweighted. Correspondingly,

$$U_2^{PW} = \frac{d}{1 - \pi_2^{\frac{1}{\alpha^{PW}}}}. \tag{3}$$

Table 8 shows the estimated holding values *with* and *without* probability weighting. Relative to the no probability weighting case, probability weighting affects the estimated holding values as follows. The standard, static risk-neutral holding value, U_0, increases slightly from 50 to 57.3. The static risk-adjusted holding value, U_1, increases for each n_A, and the magnitude of increase is larger for more risk-loving individuals. The dynamic risk-adjusted holding value, U_2, decreases relative to the no probability weighting case for $n_A \leq 6$ and increases for $n_A \geq 7$.[27]

Step 3 remains the same as before (using the holding value derived from step 2). The effect of probability weighting on the market FV estimates is consistent with its effect on the holding value of the average subject (with $n_A = 5$ or 6). As the rightmost columns of Table 9 reveal, probability weighting increases the treatment average static FV, V_1, moderately, from 42.5 to 49.0 for treatment A, from 41.9 to 48.3 for treatment B, and from 42.9 to 50.2 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$_2 fortreatmentAfrom32.9to21.0, whichisveryclosetotheaveragemarket3tradedpriceof22.1intreatmentA$

With probability weighting, using a Wilcoxon signed rank test, 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 static 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, so that we would not reject hypothesis 2.

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 4 ***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*

[27]Note that probability weighting changes the estimation of α. The average α is about 0.6 without probability weighting, and 0.8 with probability weighting. So we compare the estimated values with and without probability weighting given the number of safe choices rather than the value of α.

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 (22.1).*

Finding 5 ***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.*

Note that to better account for the traded prices, especially in treatment A, we make three modifications to the standard FV, which views the asset as a static lottery and assumes risk neutrality: risk preferences, dynamic considerations (captured by recursive utilities) and probability weighting. Considering risk preferences is a very natural step given the risk associated with the asset's payoffs. Recursive preferences and probability weighting are less straightforward considerations, and we incorporated them to better explain the observed traded price. Among the three deviations, dynamic considerations are crucial, and the other two components are also useful in rationalizing the traded prices that we observe across all three of our treatments.

The dynamic consideration is critical in accounting for the low traded price in treatment A: the static FV adjusted for either risk preferences or probability weighting or both, is substantially higher than the traded price in treatment A. In the absence of probability weighting, the dynamic risk-adjusted FV can account for a significant amount of the low traded price in treatment A, and the static risk-adjusted FV modestly overestimates the traded price in treatments B and C. The value-added of probability weighting to our risk adjustment procedure is that it improves the ability of the risk-adjusted FV to capture the low traded price in treatment A, and simultaneously enables the static risk-adjusted FV to better match the traded price in the other two treatments as well.

During our analysis above, we note that at $\gamma = 0.71$, the dynamic risk-neutral FV with probability weighting is around 25 (see the row with $n_A = 4$ in Table 8), which is fairly close to the average traded price in market 3 of treatment A (at 20.3). In view of this, we carry out additional analyses to evaluate the contribution of adding risk preferences to probability weighting. It seems that when $\gamma = 0.71$, the additional contribution of considering risk preferences is modest.[28] However, we find that risk adjustment of the dynamic FV results in a *wider range* of values for γ 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.[29] At higher values of γ, the difference between the risk-adjusted and risk-neutral FVs is more substantial.[30] Given that we did not directly elicit subjects' probability weighting parameters (while the risk parameters are disciplined by subjects' choices in the Holt-Laury task), the ability of the risk-adjusted FV to account for the traded price in a larger range of γ is an advantage.

4.4 Individual Trading Behavior

Our analysis so far focuses on whether the FV can account for the aggregate (average) market traded price. In addition to rationalizing the aggregate results, we examine the trading behavior of *individual* subjects in the final market, or market 3. In particular, we ask how well do the different FV specifications – risk neutral (RN) or risk adjusted, static or dynamic, and without or with probability weighting – explain individual trading decisions. We characterize an individual as employing a fundamental trading strategy if the buying price is $\leq (1+\epsilon)$FV, or the selling price is $\geq (1-\epsilon)$FV, where we set $\epsilon = .10$, and FV the market FV estimated using our procedures. This 10% band around the market FV allows for a certain level of experimentations close to the FV. We then calculate the percentage of fundamental trading with reference to each of the FV that we have estimated for each subject.

Table 11 presents the percentage of fundamental trading averaged across all subjects in each treatment with reference to the standard FV, static risk-adjusted FV and dynamic risk-adjusted FV, with or without probability weighting, respectively. We see that for treatment A, the dynamic FV under the recursive utility specification captures the highest percentage of fundamental trading, regardless of whether probability weighting is considered. Probability weighting increases the percentage of fundamental trading for the dynamic risk-adjusted FV from 52.9% to 58.3%, slightly increases the percentage of fundamental trading for the static risk-adjusted FV from 47.5% to 50.2%, and marginally reduces the percentage of fundamental

[28]The Wilcoxon signed rank test between the traded price in treatment A and the dynamic risk-neutral FV with probability weighting with $\gamma = 0.71$ has a p-value of 0.345; in addition, the tests between the static risk neutral FV with probability weighting and the traded price in other two treatments have also high p values, at 0.225 and 0.686, respectively.

[29]For the risk-adjusted FV, the range of γ 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 [0.51,0.88], while it shrinks to [0.64,0.76] for the risk neutral FV.

[30]For example, for $\gamma = 0.88$, the dynamic risk-adjusted FV (27.6) is substantially lower than the risk-neutral FV (38.1).

Table 11: Average Percentage of Fundamental Trading

	Treatment A	Treatment B	Treatment C
	w/o Prob. Weighting		
V_0	47.4	77.5	83.0
V_1	47.5	63.4	68.4
V_2	52.9		
	with Prob. Weighting ($\gamma = 0.71$)		
V_0	47.2	58.8	63.7
V_1	50.2	67.6	75.5
V_2	58.3		
No. of Obs.	49	47	46

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

trading for the standard FV (from 47.4% to 47.2%). For treatments B and C, without probability weighting, the percentage of fundamental trading explained by the standard FV is higher than the static risk-adjusted FV and the opposite is true with probability weighting. Probability weighting improves the "fit" of the static risk-adjusted FV (from 63.4% to 67.6%), while it reduces the "fit" of the standard FV (from 77.5% to 58.8% for treatment B, and from 83.0% to 63.7% for treatment C).

Figures 3 and 4 report on the percentage of fundamental trading for the 49 subjects in treatment A under no probability weighting ($\gamma = 1$, upper panels) and under probability weighting ($\gamma = .71$, lower panels). The horizontal axis is the percentage of fundamental trading, which runs from 0 to 100 percent with 50 equal-sized bins. Figure 3 graphs the probability density of fundamental trading while Figure 4 shows the cumulative density. The two figures convey similar results, which together with the results of Table 11 can be summarized as follows.

Finding 6 ***Individual trading strategies.***

1. *In treatment A, (with or without probability weighting) the percentage of fundamental trading is highest according to the dynamic risk-adjusted FV, followed by the static risk-adjusted FV, and then by the standard FV.*
2. *In treatments B and C, without probability weighting, a higher percentage of fundamental trading is associated with the standard FV than with static risk-adjusted FV. With probability weighting the reverse is true.*

5 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, 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 used in the literature on experimental asset markets.

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. Compared with the infinite horizon model with discounting, the indefinite horizon 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 the assets without receiving or observing dividend payments. 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 trading price in the baseline treatment. Instead, the low trading price can be attributed to the temporal resolution of payoff uncertainty: dividends are realized gradually over time in the baseline treatment while all at once in the other two treatments.

In addition, we propose a procedure to calculate the market-based FV incorporating market participants own tolerance for risk (elicited using the Holt-Laury procedure) and we examine whether this new FV measure can account for the traded prices observed in our experimental asset markets. As the baseline treatment features gradual resolution of payoff uncertainty, subjects are more likely to view the asset as a dynamic lottery and view the (certainty equivalence of) dividend payments in different periods as separate payoffs. In each period, the asset consists of two parts: certain dividend payments in the current period and an uncertain continuation value in the future. For moderately risk averse subjects (as we have in our experiment and which are typically found in asset pricing experiments), the recursive preferences where the certainty equivalence of future dividend payoffs is viewed as a perfect substitute for current certain dividend payments can account for a significant fraction of the low traded price that we observe in our baseline treatment A.[31] Finally, combining the recursive utility with probability weighting (according to which subjects overreact to the small probability of market termination) we are able to fully rationalize the low traded prices observed in our baseline treatment.

In the other two treatments, as dividend realizations are realized quickly together after the trading stage, subjects are more likely to view the asset as a static lottery and care about the total dividend payments. The fundamental value in these two treatments is calculated as the certainty equivalence of the static lottery, which is slightly lower than the standard FV. Incorporating probability weighting can also fully rationalize the observation that the traded price in these two treatments is close to the standard FV.

An important take-away from our study 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 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 elicited risk attitudes of individual subjects combined with recursive preferences and probability weighting. An important take-away for finance researchers is that we have provided some empirical support for the widely used Epstein-Zin recursive preference specification and probability weighting in the context of asset markets where subjects both trade and receive dividends from their asset holdings.

Finally, while our experiment was not designed to test whether subjects have recursive preferences or engage in probability weighting, we find that incorporating both helps in explaining our experimental results. In future research involving asset markets with indefinite horizons it would be of interest to elicit directly the parameters used in these two frameworks: the parameter that governs the elasticity of inter-temporal substitution, and the parameter that biases the probabilities. Note that the procedure that we developed to incorporate

[31] The assumption that the certainty equivalences of payoffs in different periods are perfect substitutes is reasonable considering that each trading period lasts for only two minutes.

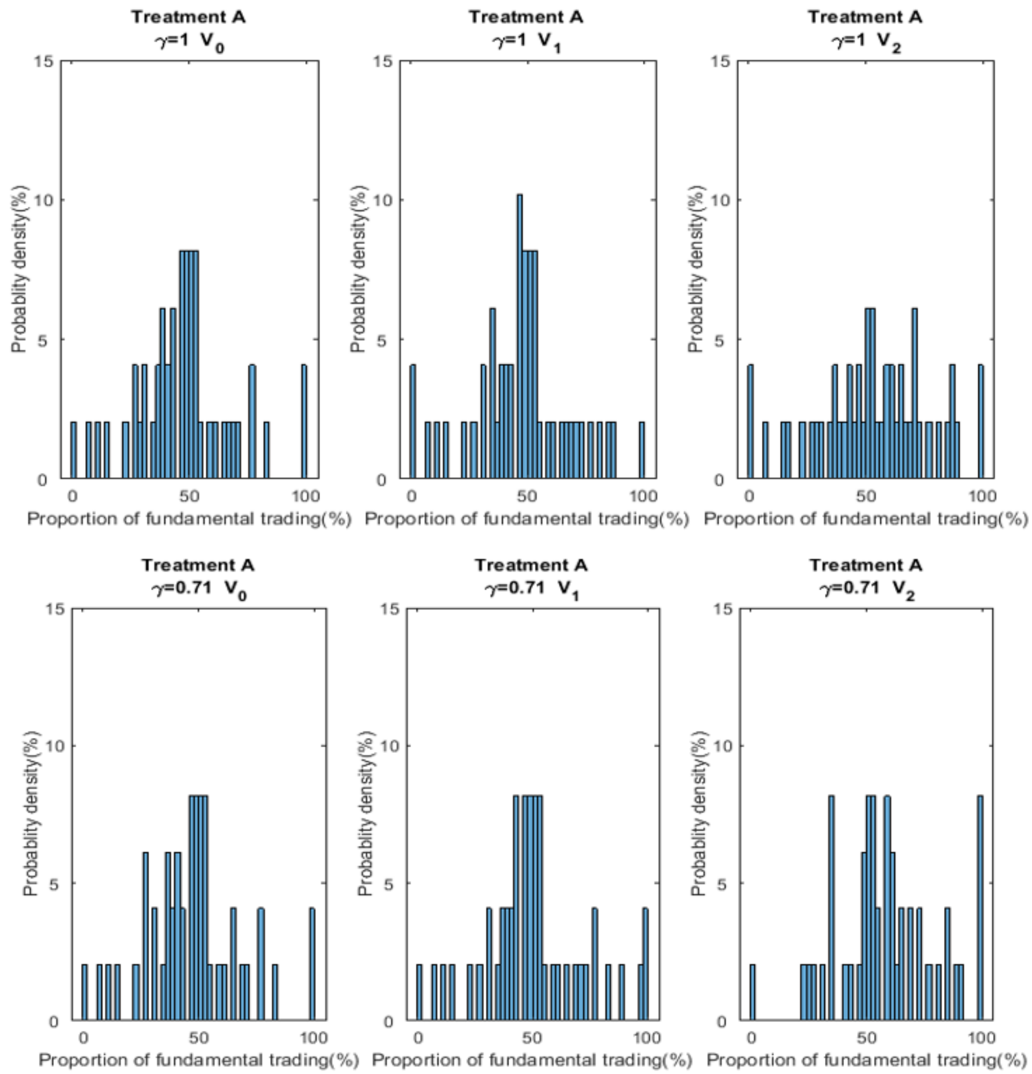

Figure 3: Histogram of the Percentage of Fundamental Trading in Treatment A—Probability Density

Notes: (1)V_0 is the standard (static risk neutral) FV, V_1 is the static risk-adjusted FV, and V_2 is the dynamic risk-adjusted FV. (2)We characterize an individual as employing a fundamental trading strategy if the buying price is $\leq$ (1 + 10%)FV, or the selling price is $\geq$ (1-10%)FV.

individual subjects' risk into the estimation of market FV is quite general and can easily incorporate these two additional individual characteristics. We leave this exercise to future research.

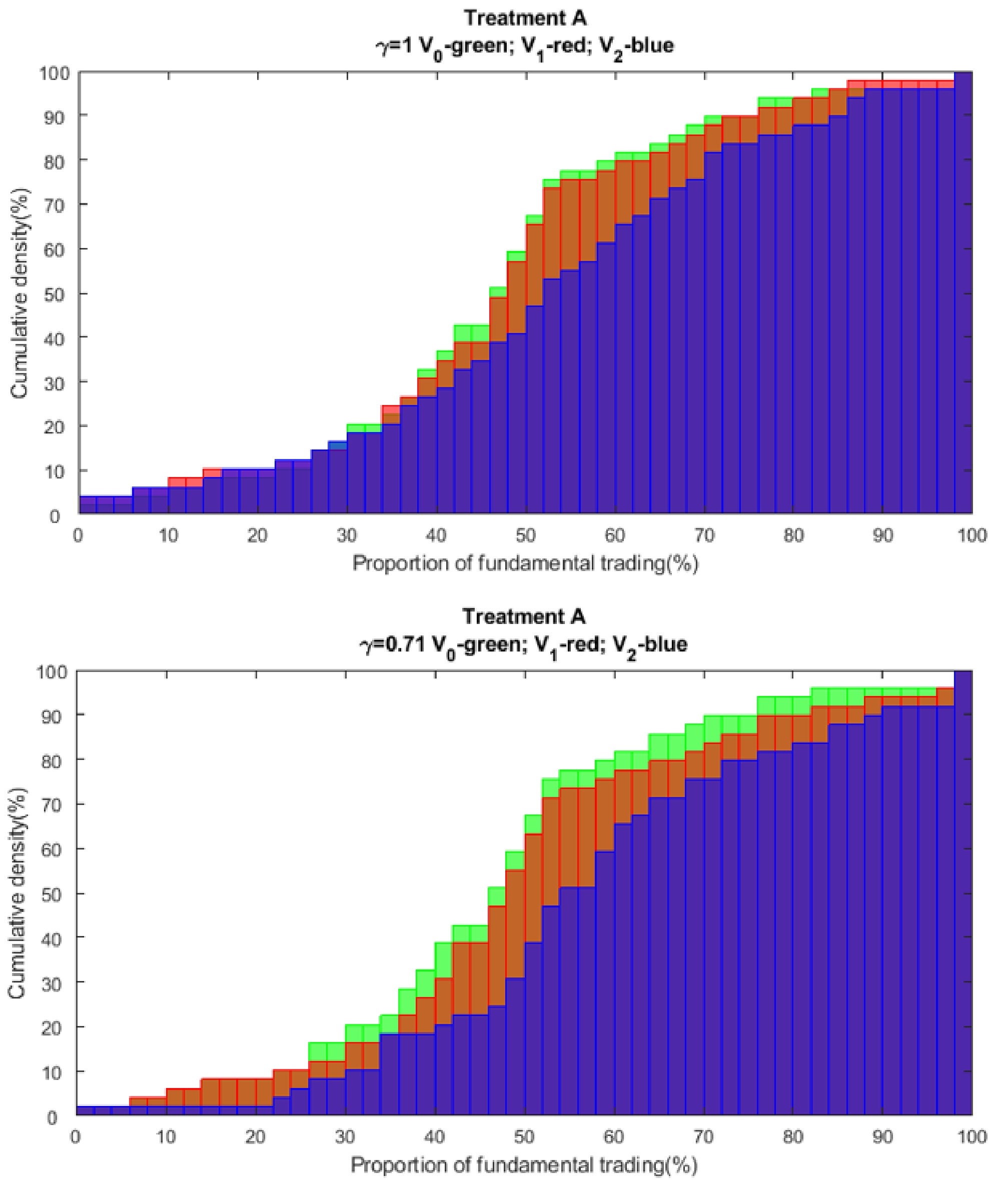

Figure 4: Histogram of the Percentage of Fundamental Trading in Treatment A—Cumulative Density

Notes: (1)V_0 is the standard (static risk neutral) FV, V_1 is the static risk-adjusted FV, and V_2 is the dynamic risk-adjusted FV. (2)We characterize an individual as employing a fundamental trading strategy if the buying price is $\leq$ (1 + 10%)FV, or the selling price is $\geq$ (1-10%)FV.

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

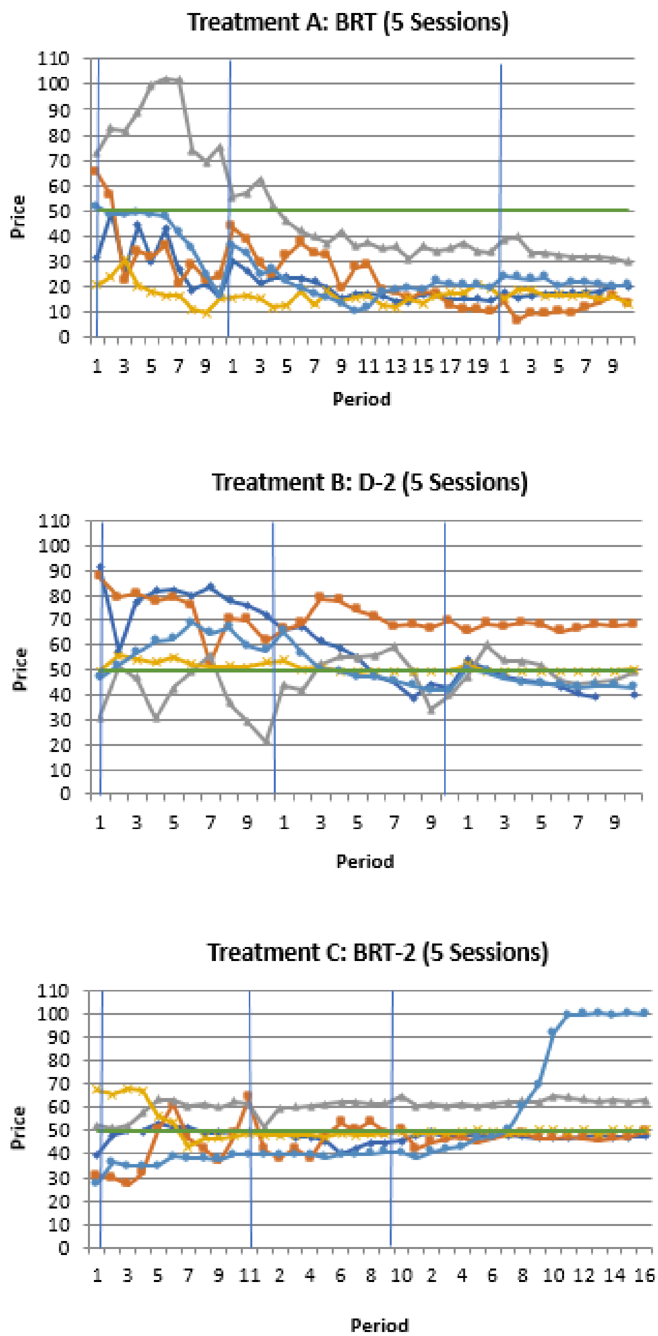

Figure A.1: Average Traded Prices Over Time for Each Session, Grouped by Treatment

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

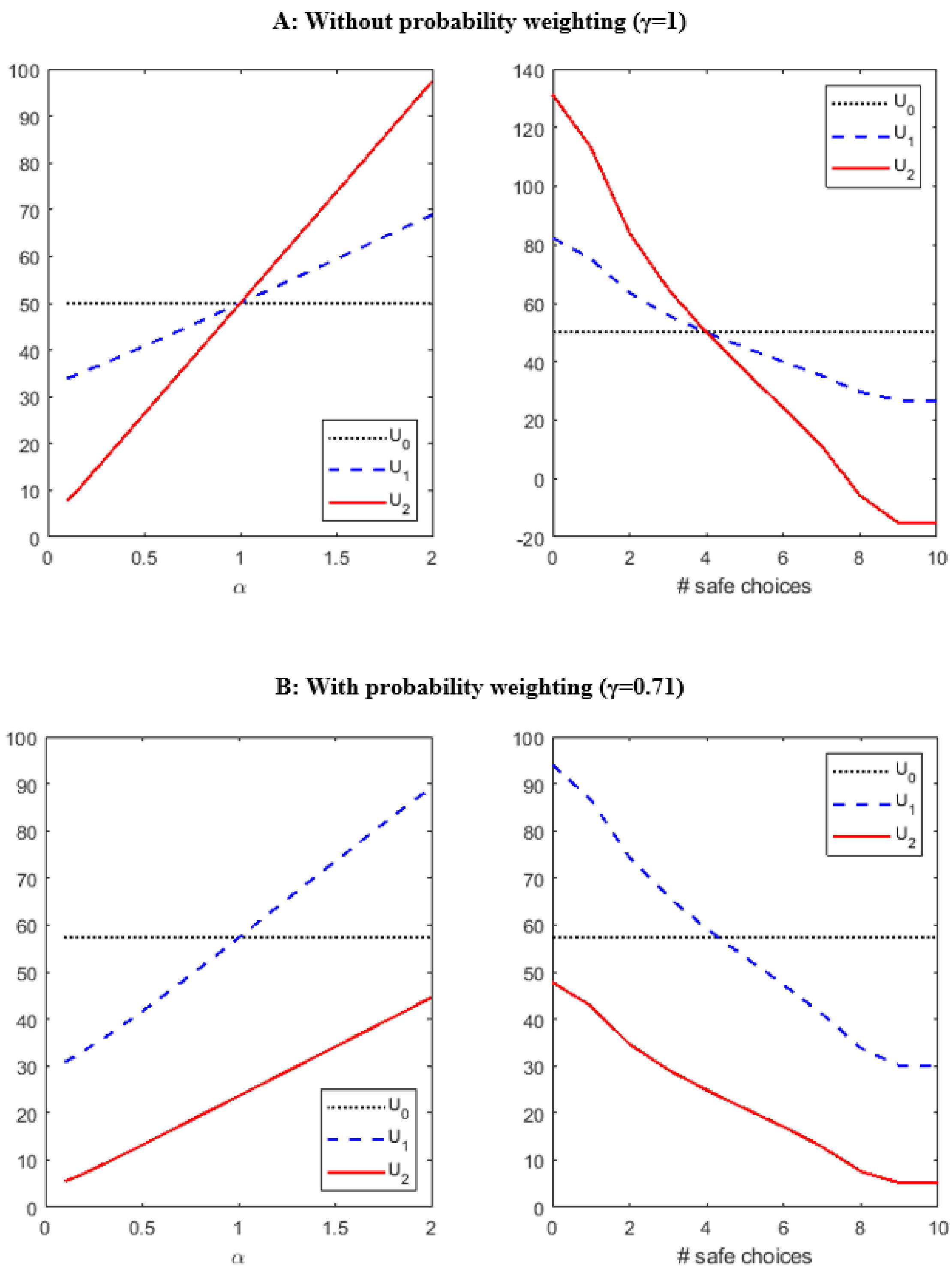

Figure A.2: Holding Value

Notes: U_0 is the standard (static risk neutral) holding value, U_1 is the static risk-adjusted holding value, and U_2 is the dynamic risk-adjusted holding value.

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

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

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

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

   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 π_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 $\bar{\imath} = \frac{\log \underline{q}}{\log \delta} + 1$.

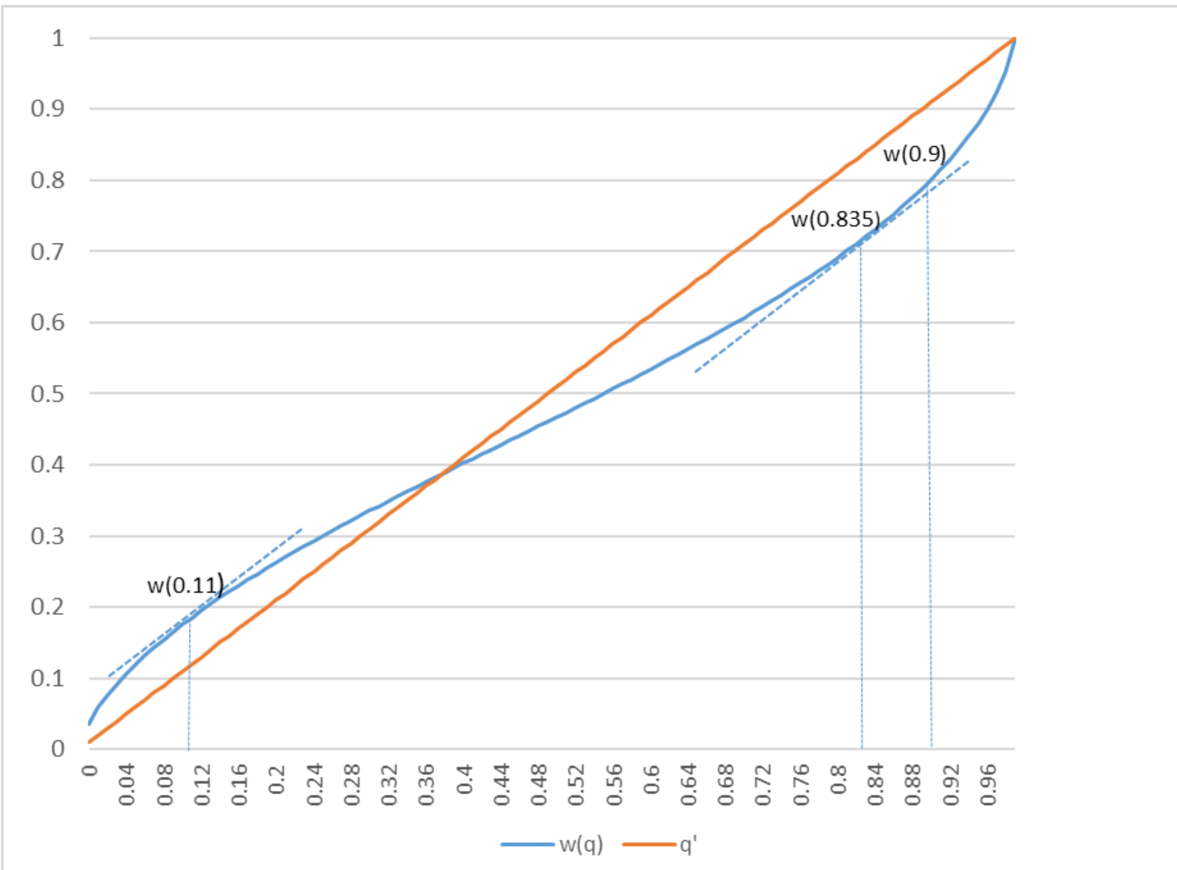

Figure B.1: Transformed Probabilities

Figure B.2 shows the effect of probability weighting using $\gamma = 0.71$, plotting the transformed probabilities π 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.

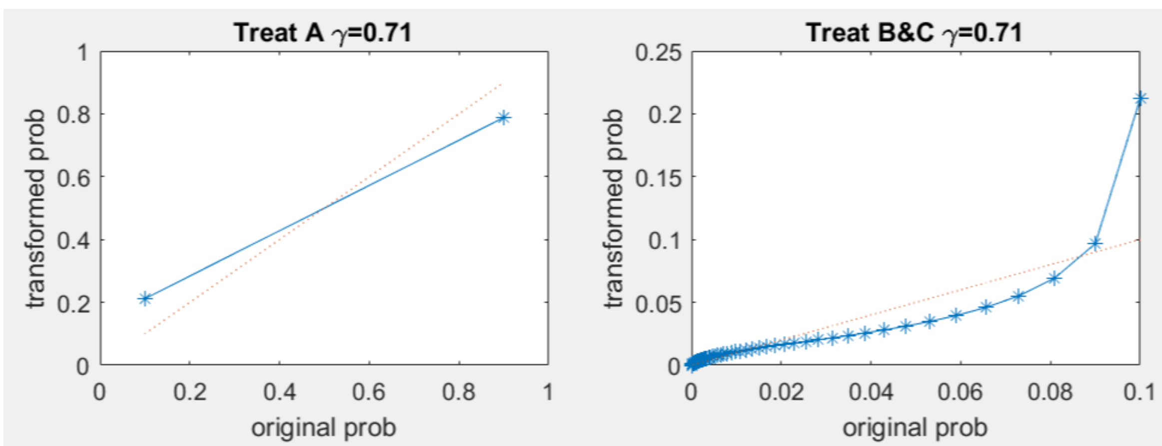

Figure B.2: Transformed Probabilities in Treatments

Appendix C: Experimental Instructions (for Online Publication)

Welcome

Welcome to this experiment on economic-decision making. You will receive $5 for showing up in the session. Your additional earnings will depend on your own decisions, other participants' decisions and some random events as explained below. Please read the instructions carefully as they explain how you earn money from the decisions that you make. Please do not talk with other participants and silence your mobile device during the experiment.

Part I Instructions (Same for all three treatments)

Your screen shows ten decision Tasks listed below. Each Task is a paired choice between "Option A" and "Option B." Each Option is a lottery of two possible realizations with different probabilities. For Option A, the two realizations are $4 and $3.2. For Option B, the two realizations are $7.7 and $0.2. For each Task, choose which lottery option, A or B, you would like to play. As you move down the table, the chances of the higher payoff for each option increase. In fact, for Task 10 in the bottom row, each option pays the higher payoff for sure, so your choice here is between $4 and $7.7.

Task	Option A Two possible realizations: $4.0 and $3.2	Option B Two possible realizations: $7.7 and $0.2
1	☐ **1/10** of $4.0. **9/10** of $3.2	☐ **1/10** of $7.7. **9/10** of $0.2
2	☐ **2/10** of $4.0. **8/10** of $3.2	☐ **2/10** of $7.7. **8/10** of $0.2
3	☐ **3/10** of $4.0. **7/10** of $3.2	☐ **3/10** of $7.7. **7/10** of $0.2
4	☐ **4/10** of $4.0. **6/10** of $3.2	☐ **4/10** of $7.7. **6/10** of $0.2
5	☐ **5/10** of $4.0. **5/10** of $3.2	☐ **5/10** of $7.7. **5/10** of $0.2
6	☐ **6/10** of $4.0. **4/10** of $3.2	☐ **6/10** of $7.7. **4/10** of $0.2
7	☐ **7/10** of $4.0. **3/10** of $3.2	☐ **7/10** of $7.7. **3/10** of $0.2
8	☐ **8/10** of $4.0. **2/10** of $3.2	☐ **8/10** of $7.7. **2/10** of $0.2
9	☐ **9/10** of $4.0. **1/10** of $3.2	☐ **9/10** of $7.7. **1/10** of $0.2
10	☐ **10/10** of $4.0. **0/10** of $3.2	☐ **10/10** of $7.7. **0/10** of $0.2

Although you make 10 decisions, only one of them will be used in the end to determine your earnings. However, you will not know in advance which decision will be used. Each decision has an equal chance of being used in the end.

After you have made all of your choices, the computer will draw two numbers randomly between 1 and 10. The **first draw** is used to select one of the ten decisions to be used. For example, if the first draw is 4, then Task 4 is selected to determine your earnings. The **second draw** determines what your payoff is for the option you chose, A or B, for the particular decision selected. Continue to suppose that Task 4 is selected, and you chose Option A for Task 4. Your earnings will be $4 if the second draw is between 1 and 4 and $3.2 if the second draw is between 5 and 10. Alternatively, if you chose Option B for Task 4, then your earnings will be $7.7 if the second draw is between 1 and 4 and $0.2 if the second draw is between 5 and 10.

To summarize, you will make ten choices: for each decision row you will have to choose between Option A and Option B. You may choose A for some decision rows and B for other rows, and you may change your decisions and make them in any order. When you are finished, the computer will draw two random numbers. The first random number determines which of the ten tasks will be used. The second number determines your money earnings for the option you chose for that task.

Part II Instructions (Treatment BRT)

General Information

This part of the experiment consists of several asset markets, in which 10 participants (including yourself) trade stocks of a fictitious company.

Market Description

At the beginning of each market, half of the participants are endowed with 20 shares and 3,000 units of cash measured in experimental money (EM), and the other half participants are endowed with 60 shares and 1,000 EM of cash.

Each market consists of an indefinite number of rounds, which will be explained later. Each round lasts for 2 minutes, during which you can sell and/or buy shares. At the end of each round, for each share you own, you receive a dividend of 5 EM. Dividends are collected in a separate account: they will count toward your earnings, but cannot be used to buy shares. If the market continues, then your shares and cash, as well as the dividend account balance, will be carried over to the next trading round.

Length of A market

Each market consists of an indefinite number of rounds. The length of the market is determined by the following rules. At the end of each round, the computer will draw a random number between 1 and 100 to determine whether the market will continue or not. Specifically, if the computer draws a random number between 1 and 90 (inclusively), the market will continue; otherwise, if the random number is between 91 and 100 (inclusively), then the market ends. Therefore, after each round, the market will continue with a chance of 90%, and end with a chance of 10%.

However, in the first 10 rounds, called a **block**, you will trade without being informed of the realization of the random draws, even if a random number greater than 90 has been drawn. At the end of round 10, you will be shown the realization of the random draws for all 10 rounds in the block and learn whether or not the market has actually ended within the block. If the market has ended within the block of the first 10 rounds, the **final round** of the market will be the first round in which the realization of the random draw exceeds 90, and your decisions after the final round will be ignored. If the market has not ended within the block, the market continues to round 11. From round 11 on, you will be informed of the realization of the random draw at the end of each round. The **final round** of the market is reached once the random draw exceeds 90.

Trading Interface

In each trading round, you will trade using an interface similar to figure 1 (you will have the opportunity to practice with the interface for 3 minutes before the formal experiment starts).

Trade is organized as a double auction: all traders can submit offers to buy and offers to sell, and accept others' offers.

Each offer has two parts, the price and quantity. The price quote can be any integer from 1 to a maximum of 500 EM. The quantity is the number of shares you intend to trade at this price. You must have enough cash to support your offer to buy and enough shares to support your offer to sell.

Otherwise, you will receive a reminder and your offer will not go through. All offers are listed in the order book. Your own offers are in blue, and other people's offers are in black. The offers are ordered according to prices, with the best offer at the top. For your convenience, the best offer posted by others is highlighted. The following rules will apply when you post or accept offers to buy and offers to sell.

- When you post an offer to buy, the price has to be lower than the lowest offer to sell in the order book. (Otherwise, you can simply accept the lowest offer to sell.)
- When you post an offer to sell, the price has to be higher than the highest offer to buy in the order book. (Otherwise, you can simply accept the highest offer to buy.)
- When you accept an offer by others, the offer has to be the best offer available. That is, when you accept an offer to buy, it has to be the highest offer to buy. When you accept an offer to sell, it has to be the lowest offer to sell.
- You cannot accept your own offers.

Trade is realized whenever an offer is accepted. If you would like to accept the highlighted offer, enter a number in the field "quantity" located at the bottom of the screen, then click on the "Sell" or "Buy" button.

Your share and cash inventories will be updated to reflect your trading activities. If you buy shares, your shares increase by the quantity traded, and your cash is diminished by the amount = price*quantity. The reverse happens if you sell shares.

Number of Markets

After a market ends, depending on the time remaining, the experimenter will inform you whether or not a new market will start. If yes, you repeat the same procedure: your endowment of shares and cash will be **reset**, and the market will last for an indefinite number of rounds as described above. If there is no new market open, you will be informed of your total earnings in this part of the experiment.

Calculate Your Earnings

Your earnings for a market is calculated as

Market earnings= cash at the end of the **final round**

+ balance in the dividend account at the end of the **final round**

Your total earnings in this part of the experiment are the summation of earnings from all markets, which are converted into Canadian dollars at a rate of 500 EM = $1.

Review of Important Information

- In any trading round, the current market may continue with probability 0.9 and ends with probability 0.1. Therefore, on average the length of a market is 10 rounds.
- If you decide to hold on to a share without ever selling it, on average, you will receive 10x5=50 EM in terms of dividend payment.
- Your earnings in a market will be determined by your cash holdings and dividends in the **final round** of the market; the final round could be within the block or outside of the block.
- Within the block of the first 10 periods of a market, you will not be informed of whether the market has ended or not.
- Each round in a market lasts for 2 minutes (120 seconds).

Quiz

After you have read the instructions, please answer the following quiz questions. The experimenter will check whether your answers are correct. If you answer any question incorrectly, the experimenter will discuss with you why your answer is wrong and explain what the correct answer is. The purpose of this quiz is to ensure that you fully understand the instructions prior to the start of the experiment.

1. Suppose in a market, after the block of 10 rounds finishes, the random draws are revealed as:

round	1	2	3	4	5	6	7	8	9	10
Random draw	52	3	86	74	21	8	93	5	24	12

The **final round** of the market is ______

2. Suppose in a market, the random draw sequence is

round	1	2	3	4	5	6	7	8	9	10	11	12
Random draw	41	9	88	41	31	29	33	5	24	2	14	96

The **final round** of the market is ______

3. Suppose a market has lasted for 15 rounds already. The chance that a market continues to new round is

   A. 90%

   B. Lower than 90%

   C. Higher than 9%

   D. None of the above

4. Suppose at the end of the final round of the market, you have 22 shares, 4,500 EM in cash, and 2,000 EM in the dividend account, your earnings in this market is ________ EM

5. If you hold on to a share from the beginning to the end of the market, on average, you earn ____ EM of dividends.

Part II Instructions (D-2)

General Information

This part of the experiment consists of several asset markets, in which 10 participants (including yourself) trade stocks of a fictitious company.

Market Description

At the beginning of each market, half of the participants are endowed with 20 shares and 3,000 units of cash measured in experimental money (EM), and the other half participants are endowed with 60 shares and 1,000 EM of cash.

Each market consists of two stages: a **trading stage** and a **dividend realization stage**.

The trading stage of each market consists of 10 trading rounds. Each round lasts for 2 minutes, during which you can sell and/or buy shares using an interface described later. At the end of each trading round and before the trading stage ends, your shares and cash will be carried over to the next trading round.

After the trading stage finishes, the dividend realization stage starts, where you collect dividends for the shares you own at the end of the trading stage. All shares receive an indefinite number of 5-EM dividend payments; the number of payments is determined as follows. You receive one dividend payment for sure. After each dividend payment, the computer will draw a random number between 1 and 100: if the number is greater than 90, then there will be no further dividend payments; otherwise, there will be a new dividend payment followed by another random draw. The number of dividend payments can potentially run from 1 to infinity. On average, you will receive 10 dividend payments, or 50 EM, for each share you own at the end of the trading stage. In the dividend payment stage, you no longer make decisions: the computer will decide how many dividends you receive, and you simply watch dividends accrue.

Trading Interface

In each trading round, you will trade using an interface similar to figure 1 (you will have the opportunity to practice with the interface for 3 minutes before the formal experiment starts).

Trade is organized as a double auction: all traders can submit offers to buy and offers to sell, and accept others' offers.

Each offer has two parts, the price and quantity. The price quote can be any integer from 1 to a maximum of 500 EM. The quantity is the number of shares you intend to trade at this price. You must have enough cash to support your offer to buy and enough shares to support your offer to sell. Otherwise, you will receive a reminder and your offer will not go through. All offers are listed in the order book. Your own offers are in blue, and other people's offers are in black. The offers are ordered according to prices, with the best offer at the top. For your convenience, the best offer posted by others is highlighted. The following rules will apply when you post or accept offers to buy and offers to sell.

- When you post an offer to buy, the price has to be lower than the lowest offer to sell in the order book. (Otherwise, you can simply accept the lowest offer to sell.)

- When you post an offer to sell, the price has to be higher than the highest offer to buy in the order book. (Otherwise, you can simply accept the highest offer to buy.)
- When you accept an offer by others, the offer has to be the best offer available. That is, when you accept an offer to buy, it has to be the highest offer to buy. When you accept an offer to sell, it has to be the lowest offer to sell.
- You cannot accept your own offers.

Trade is realized whenever an offer is accepted. If you would like to accept the highlighted offer, enter a number in the field “quantity” located at the bottom of the screen, then click on the “Sell” or “Buy” button.

Your share and cash inventories will be updated to reflect your trading activities. If you buy shares, your shares increase by the quantity traded, and your cash is diminished by the amount = price*quantity. The reverse happens if you sell shares.

Number of Markets

After a market ends, depending on the time remaining, the experimenter will inform you whether or not a new market will start. If yes, you repeat the same procedure: your endowment of shares and cash will be **reset**, and the market will consist of a trading stage and a dividend realization stage as described above. If there is no new market open, you will be informed of your total earnings in this part of the experiment.

Calculate Your Earnings

Your earnings (in EM) in each market are the sum of two parts:

(1) cash at the end of the trading stage
(2) the number of shares at the end of the trading stage *the number of dividend payments * 5

Your total earnings in this part of the experiment are the summation of earnings from all markets, which will be converted into Canadian dollars at a rate of 500 EM = $1.

Review of Important Information

- There will be several markets, each consisting of a trading stage and a dividend realization stage. You start with the same endowment of cash and shares in each new market.
- The trading stage consists of 10 trading rounds. Each trading round lasts for 2 minutes.
- In each market, during the trading stage, your share and cash holdings at the end of a trading round will be carried over to the next trading round.
- In the dividend realization stage, you collect dividends for the shares you own at the end of the trading stage for an indefinite number of times. After each dividend payment, there will be more dividends with a chance of 90%, and no further dividends with a chance of 10%. On average, you will receive 10 dividend payments, or 50 EM, for each share you own at the end of the trading stage.
- Your earnings in a market will be determined by your cash holdings at the end of the trading stage plus the total dividends received during the dividend realization stage.

Quiz

After you have read the instructions, please answer the following quiz questions. The experimenter will check whether your answers are correct. If you answer any question incorrectly, the experimenter will discuss with you why your answer is wrong and explain what the correct answer is. The purpose of this quiz is to ensure that you fully understand the instructions prior to the start of the experiment.

6. For each share you hold at the end of the trading stage, you receive
    a. nothing.
    b. on average 10 dividend payments.
    c. exactly 10 dividend payments.
    d. exactly 50 EM of dividend payments.
7. In each new market, you
    a. start with the same endowment of shares and cash.
    b. inherit cash and shares from the previous market.
8. Suppose we are in the trading stage, trading round 5 of market 1, you
    a. start with the same endowment of shares and cash as in round 1.
    b. inherit cash and shares from the previous trading round.
9. Suppose we are in the dividend realization stage of a market. There have been 15 dividend payments already. The chance that you receive more dividend payments is
    a. 90%.
    b. lower than 90%.
    c. higher than 90%.
    d. none of the above.
10. Suppose at the end of the trading stage of a market, you have 20 shares and 4,500 EM in cash. In the dividend realization stage, there are 6 dividend payments. Your earning from this market is ________ EM.

Part II Instructions (BRT-2)

General Information

This part of the experiment consists of several asset markets, in which 10 participants (including yourself) trade stocks of a fictitious company.

Market Description

At the beginning of each market, half of the participants are endowed with 20 shares and 3,000 units of cash measured in experimental money (EM), and the other half participants are endowed with 60 shares and 1,000 EM of cash.

Each **market** consists of two stages: a **trading stage** and a **dividend realization stage**.

Trading Stage

The trading stage consists of an indefinite number of rounds. Each round lasts for 2 minutes, during which you can sell and/or buy shares using an interface described later. At the end of each trading round and before the trading stage ends, your shares and cash will be carried over to the next trading round.

The length of the trading stage is determined by the following rules. At the end of each round, the computer will draw a random number between 1 and 100 to determine whether the trading stage will continue or not. Specifically, if the computer draws a random number between 1 and 90 (inclusively), the trading stage will continue; otherwise, if the random number is between 91 and 100 (inclusively), then the trading stage ends. Therefore, after each round, the trading stage will continue with a chance of 90% and end with a chance of 10%.

However, in the first 10 rounds, called a **block**, you will trade without being informed of the realization of the random draws, even if a random number greater than 90 has been drawn. At the end of round 10, you will be shown the realization of the random draws for all 10 rounds in the block and learn whether or not the trading stage has actually ended within the block. If the trading stage has ended within the block of the first 10 rounds, the **final round** of the trading stage will be the first round in which the realization of the random draw exceeds 90, and your decisions after the final round will be ignored. If the trading stage has not ended within the block, then it continues to round 11. From round 11 on, you will be informed of the realization of the random draw at the end of each round. The **final round** of the trading stage is reached once the random draw exceeds 90.

Dividend Realization Stage

After the trading stage finishes, the dividend realization stage starts, where you collect dividends for the shares you own at the end of the final round of the trading stage. All shares receive an indefinite number of 5-EM dividend payments; the number of payments is determined as follows. You receive one dividend payment for sure. After each dividend payment, the computer will draw a random number between 1 and 100: if the number is greater than 90, then there will be no further dividend payments; otherwise, there will be a new dividend payment followed by another random draw. The number of dividend payments can potentially run from 1 to infinity. On average, you will receive 10 dividend payments, or 50 EM, for each share you own at the end of the final round of the trading stage. In the dividend payment stage, you no longer make decisions: the computer will decide how many dividends you receive, and you simply watch dividends accrue.

Trading Interface

In each trading round, you will trade using an interface similar to figure 1 (you will have the opportunity to practice with the interface for 3 minutes before the formal experiment starts).

Trade is organized as a double auction: all traders can submit offers to buy and offers to sell, and accept others' offers.

Each offer has two parts, the price and quantity. The price quote can be any integer from 1 to a maximum of 500 EM. The quantity is the number of shares you intend to trade at this price. You must have enough cash to support your offer to buy and enough shares to support your offer to sell. Otherwise, you will receive a reminder and your offer will not go through. All offers are listed in the order book. Your own offers are in blue, and other people's offers are in black. The offers are ordered according to prices, with the best offer at the top. For your convenience, the best offer posted by others is highlighted. The following rules will apply when you post or accept offers to buy and offers to sell.

- When you post an offer to buy, the price has to be lower than the lowest offer to sell in the order book. (Otherwise, you can simply accept the lowest offer to sell.)
- When you post an offer to sell, the price has to be higher than the highest offer to buy in the order book. (Otherwise, you can simply accept the highest offer to buy.)
- When you accept an offer by others, the offer has to be the best offer available. That is, when you accept an offer to buy, it has to be the highest offer to buy. When you accept an offer to sell, it has to be the lowest offer to sell.
- You cannot accept your own offers.

Trade is realized whenever an offer is accepted. If you would like to accept the highlighted offer, enter a number in the field "quantity" located at the bottom of the screen, then click on the "Sell" or "Buy" button.

Your share and cash inventories will be updated to reflect your trading activities. If you buy shares, your shares increase by the quantity traded, and your cash is diminished by the amount = price*quantity. The reverse happens if you sell shares.

Number of Markets

After a market ends, depending on the time remaining, the experimenter will inform you whether or not a new market will start. If yes, you repeat the same procedure: your endowment of shares and cash will be **reset**, and the market will consist of a trading stage and a dividend realization stage as described above. If there is no new market open, you will be informed of your total earnings in this part of the experiment.

Calculate Your Earnings

Your earnings (in EM) in each market are the sum of two parts:

(3) cash at the end of the **final round** of the trading stage
(4) the number of shares at the end of the **final round** of the trading stage * the number of dividend payments in the dividend realization stage * 5

Your total earnings in this part of the experiment are the summation of earnings from all markets, which will be converted into Canadian dollars at a rate of 500 EM = $1.

Review of Important Information

- There will be several markets, each consisting of a trading stage and a dividend realization stage. You start with the same endowment of cash and shares in each new market.
- The trading stage consists of an indefinite number of trading rounds. In any trading round, the trading stage may continue with probability 0.9 and end with probability 0.1. Therefore, on average the length of the trading stage is 10 rounds.
- Within the block of the first 10 rounds of the trading stage of a market, you will not be informed of whether the trading stage has ended or not.
- Each trading round lasts for 2 minutes.
- In each market, during the trading stage, your share and cash holdings at the end of a trading round will be carried over to the next trading round.
- Your earnings in a market will be determined by your cash holdings at the end of the **final round** of the trading stage plus the total dividends received during the dividend realization stage; the final round could be within the block or outside of the block.
- In the dividend realization stage, you collect dividends for the shares you own at the end of the **final round** of the trading stage for an indefinite number of times. After each dividend payment, there will be more dividends with a chance of 90%, and no further dividends with a chance of 10%. On average, you will receive 10 dividend payments, or 50 EM, for each share you own at the end of the final round of the trading stage.

Quiz

After you have read the instructions, please answer the following quiz questions. The experimenter will check whether your answers are correct. If you answer any question incorrectly, the experimenter will discuss with you why your answer is wrong and explain what the correct answer is. The purpose of this quiz is to ensure that you fully understand the instructions prior to the start of the experiment.

11. Suppose in the trading stage of a market, after the block of 10 rounds finishes, the random draws are revealed as:

round	1	2	3	4	5	6	7	8	9	10
Random draw	52	3	86	74	21	8	93	5	24	12

The **final round** of the trading stage is ______

12. Suppose in the trading stage of a market, the random draw sequence is

round	1	2	3	4	5	6	7	8	9	10	11	12

Random draw	41	9	88	41	31	29	33	5	24	2	14	96

The **final round** of the market is ______

13. Suppose the trading stage of a market has lasted for 15 rounds already. The chance that the trading stage continues to a new round is
    E. 90%
    F. Lower than 90%
    G. Higher than 9%
    H. None of the above
14. For each share you hold at the end of the final round of the trading stage, you receive
    a. nothing.
    b. on average 10 dividend payments.
    c. exactly 10 dividend payments.
    d. exactly 50 EM of dividend payments.
15. In each new market, you
    a. start with the same endowment of shares and cash.
    b. inherit cash and shares from the previous market.
16. Suppose we are in the trading stage, trading round 5 of market 1, you
    a. start with the same endowment of shares and cash as in round 1.
    b. inherit cash and shares from the previous trading round.
17. Suppose we are in the dividend realization stage of a market. There have been 15 dividend payments already. The chance that you receive more dividend payments is
    a. 90%.
    b. lower than 90%.
    c. higher than 90%.
    d. none of the above.
18. Suppose at the end of the final round of the trading stage of a market, you have 20 shares and 4,500 EM in cash. In the dividend realization stage, there are 6 dividend payments. Your earning from this market is ________ EM.