BANK OF CANADA
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Staff Working Paper/Document de travail du personnel—2023-25

Last updated: April 24, 2023

Pricing Indefinitely Lived Assets: Experimental Evidence

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DOI: https://doi.org/10.34989/swp-2023-25 | **ISSN** 1701-9397

Acknowledgements

We thank audience members at many conferences and workshops as well as David Freeman, Jian Li, Bing Miao, Yohanes Eko Riyanto and Mike Shin for helpful comments and suggestions. We are grateful for staff support from the experimental economics laboratory at CIRANO where the experiments reported on in this paper were conducted. We gratefully acknowledge funding support from the Bank of Canada and Concordia University.

Abstract

We study indefinitely lived assets in experimental markets and find that the traded prices of these assets are, on average, about 40% of the risk-neutral fundamental value. Neither uncertainty about the value of total dividend payments nor horizon uncertainty about the duration of trade can account for this low traded price. An Epstein and Zin (1989) recursive preference specification that models the dynamic realization of dividend payments and incorporates risk preferences can rationalize the low traded price observed in our indefinitely lived asset market.

Topics: Asset pricing, Financial markets
JEL codes: C91, C92, D81, G12

Résumé

Nous étudions les actifs à durée indéterminée dans des marchés expérimentaux et constatons que les prix négociés de ces actifs s'établissent, en moyenne, à 40 % environ de la valeur fondamentale neutre face au risque. Ce faible prix négocié ne s'explique ni par l'incertitude quant à la valeur totale des versements de dividendes ni par l'incertitude entourant l'horizon de négociation. Une spécification de préférences récursives d'Epstein et Zin (1989), qui permet de modéliser la réalisation dynamique des versements de dividendes tout en intégrant les préférences à l'égard des risques, peut expliquer ce bas prix observé dans notre marché d'actifs à durée indéterminée.

Sujets : Évaluation des actifs, Marchés financiers
Codes JEL : C91, C92, D81, G12

1 Introduction

Many economic models employ an infinite horizon with discounting to examine agents' behavior under the shadow of the 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 risk-neutral present value of the asset. Since the horizon is finite, the FV of the asset decreases over time, as in the canonical experimental design of Smith et al. (1988).

In this paper, we study the trade of assets in an experimental market with *indefinite* horizons, consisting of an unknown number of periods. The first period begins with trade in the asset. Following trade, each unit of the asset pays its holder a fixed dividend. Thereafter, with a constant probability 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 no continuation value. This indefinite-horizon, or random-termination, design, initially proposed by Roth and Murnighan (1978), is the most commonly used approach in the laboratory to implementing infinite horizons with discounting.

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

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

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

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

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

To better understand the low traded prices of our indefinitely lived asset (relative to the standard FV), we design two auxiliary treatments, noting that indefinite-horizon asset markets involve two types of intertwined risks: payoff uncertainty and trading horizon uncertainty. Payoff uncertainty refers to the uncertain sequence of dividend realizations an investor earns from adopting a buy-and-hold strategy. In terms of the sum of dividend payments, the asset can be viewed as a lottery, as described in Table 1, involving an infinite number of states, $t = 1, 2, ..., \infty$. State t is the event that the asset lasts until period t, yielding a payoff of td, which occurs with probability $\delta^{t-1}(1-\delta)$. By contrast, trading horizon uncertainty refers to uncertainty about the length of time in 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 trader's 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, with an indefinite horizon, such speculative timing is made difficult. Thus, there is reason to believe that an indefinite horizon for asset markets might *depress* prices and trade volume relative to asset markets with known, finite horizons.

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

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

Our **second** experimental treatment (treatment B) aims to single out the effect of trading horizon uncertainty from payoff uncertainty by separating the asset market into two stages.

Stage one consists of a *fixed* number of trading periods, and subjects do not observe nor receive dividend payments in this stage. Stage two reveals dividend realizations, and subjects receive the realized dividend payments for each share held at the end of the trading stage. The dividend realization process in stage two mimics the distribution of the sum of remaining dividend payments as in the baseline treatment (characterized in Table 1). We find that traded prices in this second treatment are fairly close to the standard FV.

At first sight, the notable difference in traded prices between these two treatments might be attributed to trading horizon uncertainty. However, given that many studies in the experimental asset pricing literature report that traded prices tend to converge to the FV after three market repetitions, we suspect that the differences we find in traded prices in later markets may not be fully attributable to trading horizon uncertainty.[3] 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 realized dynamically across each trading period. In the second treatment, all dividend payments are revealed and paid altogether at once, only after all trading activities have ended.

To separate the effects of trading horizon uncertainty and the timing of dividend realizations, we conducted a **third** treatment (treatment C). This treatment involves two separate stages, as in the second treatment, but keeps the uncertain trading horizon of the baseline treatment. Thus, our third treatment serves as a stepping stone between the first two treatments. The difference between the second and third treatments reveals the effect of trading horizon uncertainty. The difference between the first and third treatments reveals the effect of the timing of dividend realizations. We find that the traded price in the third treatment is also fairly close to the standard FV and not significantly different from the second treatment.

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

[3] Recent studies by Kopányi-Peuker and Weber (2021, 2022) find that bubbles can persist even with three market repetitions. As shown in their first paper, this finding is mainly due to their use of a high cash-to-asset ratio; with a lower cash-to-asset ratio similar to the one that we use, they observe prices closer to FVs.

More specifically, in treatment A, dividends are realized dynamically in each trading period. The stationarity of our dynamic asset trading environment implies that the asset can be viewed as a combination of the fixed dividend payment in the current trading period with a binary lottery in the next trading period (or at the end of the current trading period) that yields a zero payoff with probability $1-\delta$ and a replica of the asset with probability δ. By contrast, in treatments B and C, there is no dividend realization in any trading period, and all dividend payments are realized after the entire trading phase. From the point of view of all trading periods, all the risks of dividend payments are resolved in a batch in one single instance and the FV of the asset is captured solely by the certainty equivalence of the static lottery shown in Table 1.

To conduct our analysis, we develop a new methodology for calculating the FV of the asset that incorporates the market participants' risk attitudes toward payoff uncertainty. Specifically, we infer subjects' risk parameters using the individual choice task of Holt and Laury (2002) by assuming constant relative risk-aversion (CRRA) preferences. We then derive each individual's demand curve for the asset as the solution to a portfolio choice problem, combining an individual's asset and cash profile and the estimated risk parameter. Finally, we estimate the risk-adjusted FV of the asset as the market price that clears the market.

Using this procedure we computed both the dynamic (following the Epstein and Zin (1989) recursive preference specification to aggregate payoffs across periods) and static risk-adjusted market FV (in which case the Epstein-Zin specification reduces to the expected utility specification).[4] The computed dynamic risk-adjusted market FV is about 70% of the standard FV, and the static risk-adjusted market FV is about 90% of the standard FV. The risk-adjusted FVs can reasonably account for the traded price in our experimental asset markets. For treatment A, the computed dynamic risk-adjusted FV is not statistically significantly different from the traded price according to signed-rank tests (although there remains a noticeable gap in the magnitude). For treatments B and C, the static risk-adjusted FV moderately underestimates the traded price (even if the difference is statistically significant according to signed-rank tests).

As an extension, we also examine the static and dynamic FVs under alternative assumptions; particularly, we compute both FVs by incorporating probability weighting instead of risk

[4]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.

attitudes in recursive preferences. We find the probability-weighted FVs are consistent with the traded prices in all three treatments, both quantitatively and statistically.

There is a large body of literature involving experimental asset markets with known, finite horizons following Smith et al. (1988). Surveys can be found in Palan (2009, 2013) and Noussair and Tucker (2013). In this set-up, the asset 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). This set-up reliably generates asset prices bubbles and crashes among inexperienced subjects. With experienced subjects, the price tends to approach the standard FV.

By comparison, there are relatively fewer experimental studies of asset markets with indefinite horizons. Table 2 provides a summary of the 11 studies involving the pricing of indefinitely lived assets that we are aware of, the continuation values they used, and what they found in terms of asset pricing behavior. As this table indicates, both overpricing and underpricing of assets has been found using indefinitely repeated asset pricing models. Although these papers adopt an experimental framework where the number of trading periods is uncertain, their main focus is often not on the *indefinitely lived* feature itself, and they often introduce other confounding design features. This makes it difficult to directly compare their results to ours and pinpoint the exact reasons behind the different results. In Appendix A, we provide further details on how these studies compare with our own and why the results with regard to prices may differ from ours.

Among these studies, our indefinite-horizon treatment is most similar to treatment 2 in Kose (2015), who uses the standard random termination instead of the block variation of our study. Like us, he also finds *under*pricing of the asset relative to the standard FV, but he does not offer a theory or deep explanation about this anomalous phenomenon. We confirm that this finding is robust and develop an in-depth analysis about *why*.[5] By designing the auxiliary treatments, we rule out trading horizon uncertainty as the driver of low traded prices and identify the importance of modeling the dynamic realization of dividend payments while calculating the FV. We question the applicability of expected utilities in this setting and

[5]The low traded price of an indefinitely lived asset relative to the standard FV is a robust finding, at least where the risk of termination without a buyout value is salient and there is careful control of other confounding factors (e.g., asset trading is the single main activity, the dividend payment scheme and termination probability are clearly defined and communicated, the C/A ratio is moderate and subjects have the opportunity to gain experience). Kose (2015) has the same finding with standard random termination. As part of revising the paper, we conducted five more sessions of indefinitely lived assets (three with block random termination and two with standard random termination) after the COVID pandemic, and all five sessions again exhibited a low traded price.

Table 2: Summary of Indefinitely Repeated Asset Pricing Experiments

Authors	Market Details	δ	Results
Camerer and Weigelt (1993)	Asset pays different dividends to different subject types	.85	Overpricing and underpricing
Ball and Holt (1998)	Random termination with a terminal value	.833	Overpricing, bubble crash
Hens and Steude (2009)	Dividend process is stochastic and unknown to subjects	.97	Overpricing and underpricing
Kose (2009)	Definite versus indefinitely repeated asset pricing models	.875	Underpricing of assets in indefinitely repeated model
Asparouhova et al. (2016)	Asset and bond pricing with consumption smoothing	.833	Prices close to fundamentals but excessively volatile
Fenig et al. (2018)	Asset market competes with production income	.865	Overpricing, bubble crash
Weber et al. (2018)	Pricing of risky bond subject to default risk	Endogenous*	Prices close to or greater than fundamental values
Crockett et al. (2019)	Consumption smoothing using Lucas assets	.833	Underpricing with a consumption smoothing objective
Kopányi-Peuker and Weber (2021)	Forecasting versus trading models of asset pricing	Unknown†	Recurrent bubbles and crashes unless the C/A ratio is low
Kopányi-Peuker and Weber (2022)	Definite versus indefinite and short versus long	0.9 after some periods	Recurrent bubbles with high C/A ratio
Halim et al. (2022)	Consumption smoothing using Lucas assets	.833	Overpricing even with a consumption smoothing objective

* The continuation probability, or discount factor, is determined as a function of an initial price offering.
† Subjects were not told the number of periods for each market, only that it would lie between 25 and 40 periods.

show that recursive utilities can explain the low traded price.

Moreover, we show the dynamic FV is also consistent with the finding in other experimental asset markets, such as the original design of Smith et al. (1988) with fixed, finite trading periods, or indefinite-horizon asset markets with a buyout value. In those settings, the dynamic FV is close to the standard FV and is, therefore, consistent with the experimental finding that the traded price is close to the standard FV with experienced subjects. Our study suggests that it is important to study experimental asset markets with a dynamic perspective: this is especially critical for indefinite-horizon markets. Finally, our paper makes a methodological contribution in the development of a new procedure to determine the market FV for an asset that incorporates traders' heterogeneity, here with respect to data we collected on our subjects' risk preferences. This methodology could also be used to incorporate other subject attributes as well as, for instance, heterogeneity in agents' time preferences.

Our work is also related to a growing experimental literature on preferences for the timing of uncertainty resolution (see Nielson (2020) for an excellent survey). Among them, Brown and Kim (2014) and Meissner and Pfeiffer (2022) are most closely related to this paper. Brown and Kim (2014) report that most subjects prefer early resolution of risk and provide supportive evidence for Epstein-Zin preferences. In particular, individuals predicted to prefer early resolution according to Epstein-Zin preferences choose early resolution with 20–50% higher probability. However, Meissner and Pfeiffer (2022) find a negative correlation between the (model-free) elicited-timing premia and the predicted-timing premia under Epstein-Zin preferences. Our paper shows that recursive utility specifications can help to account for the low traded price in indefinitely lived asset markets relative to the standard FV, as well as differences that we observe in market traded prices when we change the timing of dividend realizations. However, we did not design our experiment to test for Epstein-Zin preferences or preferences for the timing of risk resolution.[6]

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

In this section, we describe the main characteristics of our baseline treatment with an indefinitely lived asset market. We then describe two auxiliary treatments designed to understand

[6] It is still under debate how long the time delay should be between stages of uncertainty resolution when eliciting such preferences. Nielsen (2020) points out that if the time delay between two stages of uncertainty resolution is over days or weeks it may introduce instrumental information concerns, especially with monetary payments. Meissner and Pfeiffer (2022) argue that it requires a meaningful amount of time to test the recursive utility. Nielsen (2020) implements a non-instrumental framework, where the time delay between the two stages of resolution is 30 minutes during which subjects were occupied by other activities. The preference for early (late) resolution in her framework is represented by the choice of the multi-stage lottery or information structure in which the first-stage random draw or signal is more (less) informative on the final outcome. She finds framing matters: a preference for early resolution with a frame of information structures and late resolution with isomorphic multi-stage lotteries. Using Nielsen's (2020) information structure frame with non-instrumental information, Brown et al. (2022) elicit subjects' preferences on risk (objective uncertainty) and ambiguity (subjective uncertainty) resolution. They find that subjects most frequently exhibit a preference for early resolution of both risk and ambiguity and that the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) can explain their experimental findings.

traded prices in our baseline treatment. Finally, we describe the experimental procedures that we follow in running all three treatments.

2.1 Baseline Treatment

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

Each asset market lasts for an indefinite number of periods. The indefinite horizon is implemented through a modified version of the *block random termination* scheme of Frechette and Yuksel (2017); therefore, we also label this treatment BRT.[7]

At the beginning of each of the three asset markets, subjects are endowed with shares and cash (in units of experimental money (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, so the cash-to-asset ratio (C/A) is kept constant and equal to 1 given the traders' endowment profiles, as described below.[8] Finally, a randomly drawn number determines whether or not

[7]For a robustness check of the block implementation, we report two sessions of treatment A using standard random termination without blocks. The results, as reported in Appendix C, are similar to BRT. In addition, Kose (2015) runs three sessions of an indefinitely lived asset market implemented with standard random termination and has similar findings.

[8]Caginalp et al. (1998, 2001), Haruvy and Noussair (2006), Kirchler et al. (2012) and Kopányi-Peuker and Weber (2021, 2022) report that high initial or increasing 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

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. As noted, the probability of continuation is $\delta = 0.9$, and so the probability that a market ends is $(1 - \delta) = 0.1$. In practice, a random number between 1 and 100 is drawn and if the random number is less than or equal to 90, the market continues with another period; if it is greater than 90, the market ends and the asset ceases to have value. Subjects' earnings in EM from the asset market consists of their cash balance at the end of the market and all dividends earned over the course of that market; this amount is 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 does not end within the 10-period block, then subjects 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 is 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 pricing; without it, some markets would be too short for meaningful discussion.

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

and affecting market outcomes. As our focus is on the fundamental price, not price bubbles, we choose a moderate C/A ratio of 1, as in Kirchler et al. (2012). In addition, we keep the same C/A ratio across all treatments so that the differences in traded prices across the treatments cannot be attributed to the C/A ratio.

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

$$V_0 = d \sum_{\tau=t}^{\infty} \delta^{\tau-t} = \frac{d}{1-\delta} = 50.$$

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

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

2.2 Auxiliary Treatments

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

While designing the second treatment (treatment B), we note that the asset market in the baseline treatment involves two types of intertwined risks: (1) *payoff uncertainty* and (2) *trading horizon uncertainty*. Payoff uncertainty refers to uncertainty about the asset's dividend payments. Note that if a trader buys a share of the asset in any period and holds it until the end of the market, in terms of total dividend payments, it is similar to buying a lottery, as in Table 1. Trading horizon uncertainty refers to the length of time that agents

[9] 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.

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 known, finite horizon markets.

Treatment B (D-2) is designed to disentangle the effect of trading-horizon uncertainty and payoff uncertainty. It replicates BRT treatment 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 finite 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 $\delta = 0.9$, that is, $T = 1/(1 - \delta) = 10$. During these T trading periods, there are no dividend realizations. In each trading period, subjects can choose to buy or sell assets as they wish, subject only to budget and (asset) supply constraints.

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

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

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

The number of dividend realizations remains 6, 20 and 9 for the three markets of treatment C. We independently draw another three sequences of random numbers with the same continuation probability, $\delta = 0.9$, to determine the actual lengths of the trading phases of the three markets of treatment C. These turned out to be 11, 5 and 16 periods.[10] 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.

Another difference between treatment A and treatment B is that in treatment A the dividend payment depends on the quantity of shares held at the end of each trading period, while

[10]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.

in treatment B it depends on each trader's final share position at the end of the entire trading phase, i.e., trading period 10. Note that treatment C helps to bridge the other two treatments in this respect too. In treatment C, similar to treatment A, the asset position in *every* trading period counts as well because each trading period can be the last trading period.

Table 3 summarizes the main differences in the design of the three treatments. Table 4 provides a summary of the number of trading periods and dividend realizations in the three markets of our three treatments.

Table 3: 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 4: Number of Trading Periods and Dividend Payments

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

2.3 Experimental Procedures

The experiment was conducted at CIRANO economics lab using university student subjects. Subjects were recruited for the experiment using ORSEE (Greiner, 2004). We conducted eight sessions for each of our three treatments. Most sessions had 10 participants (five sessions had eight or nine subjects) 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 D). For this individual choice task, subjects were instructed to make 10 choices between pairs of lotteries and were paid based on their choice from one randomly chosen lottery out of the 10 pairs.[11] This part of the experiment took about 10 minutes.

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

Table 5: Session Characteristics

Session	Duration	No. of Subjects	Avg. Payment
A1	2.5 hr	10	$29.98
A2	2.5 hr	10	$30.87
A3	2.5 hr	10	$30.34
A4	2.5 hr	9	$29.17
A5	2.5 hr	10	$29.45
A6	2.5 hr	10	$30.41
A7	2.5 hr	10	$30.03
A8	2.5 hr	10	$32.43
B1	2 hr	10	$37.29
B2	2 hr	10	$30.26
B3	2 hr	10	$31.00
B4	2 hr	10	$30.64
B5	2 hr	10	$29.58
B6	2 hr	8	$29.20
B7	2 hr	10	$29.88
B8	2 hr	10	$27.86
C1	2.5 hr	10	$36.99
C2	2.5 hr	8	$30.83
C3	2.5 hr	10	$30.86
C4	2.5 hr	10	$31.61
C5	2.5 hr	10	$30.12
C6	2.5 hr	10	$30.57
C7	2.5 hr	9	$28.02
C8	2.5 hr	9	$30.84

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 20–40 minutes to complete, depending on the treatment and the realized market length. At the beginning of the asset market, half

[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.

of the participants were endowed with 20 shares of the asset and 3,000 EM units, while the other half was endowed with 60 shares of the asset and 1,000 EM units; at the standard FV of 50 EM, the values of these endowments were identical.[14] In each trading period of the asset market, the trading interface was 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 were 6, 20, and 9 dividend payments in markets one, two, and three, respectively, the average earning from the asset markets was $26.

The sessions of treatments A and C lasted two-and-a-half hours, while the sessions of treatment B lasted two hours. The average total payment per subject was about $30 ($26 from the asset markets, plus $4 from the Holt-Laury risk-elicitation task), excluding the show-up fee. Participants were paid in cash and in private at the end of each session. Table 5 summarizes the characteristics of the 24 experimental sessions.

3 Experimental Results: Comparison across Treatments

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

Figure 3 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 left (right) panel shows the mean (median) of session average prices across the 8 sessions in each treatment. For treatments A and B, the mean and median trajectories are very close. For treatment C, the mean trajectory is noticeably higher than the median. This was caused by session C7, which is an outlier with persistently high prices (see Figure B.1 in Appendix B, which shows

[14]In three sessions, we had nine subjects. Since odd-numbered subjects were given endowment profile 1, the value of cash relative to shares was slightly higher in this session. This did not seem to significantly affect the market outcome (see Table C.1). In addition, the cash and asset supplies are incorporated into the calculation of market FV in Table 9.

[15]In sessions B1 and C1 only, the exchange rate was 400 EM=$1, which resulted in a higher payment in the asset markets, as shown in Table 5. All other sessions had an exchange rate of 500 EM=$1. We tried a different exchange rate for the first sessions of treatments B and C considering they involved a two-stage procedure, and we wanted to pay the subjects a bit more to compensate for that. We then found from the first sessions that the second stage (the dividend realization stage) went very quickly. As a result, we scaled the exchange rate back to be the same as for treatment A.

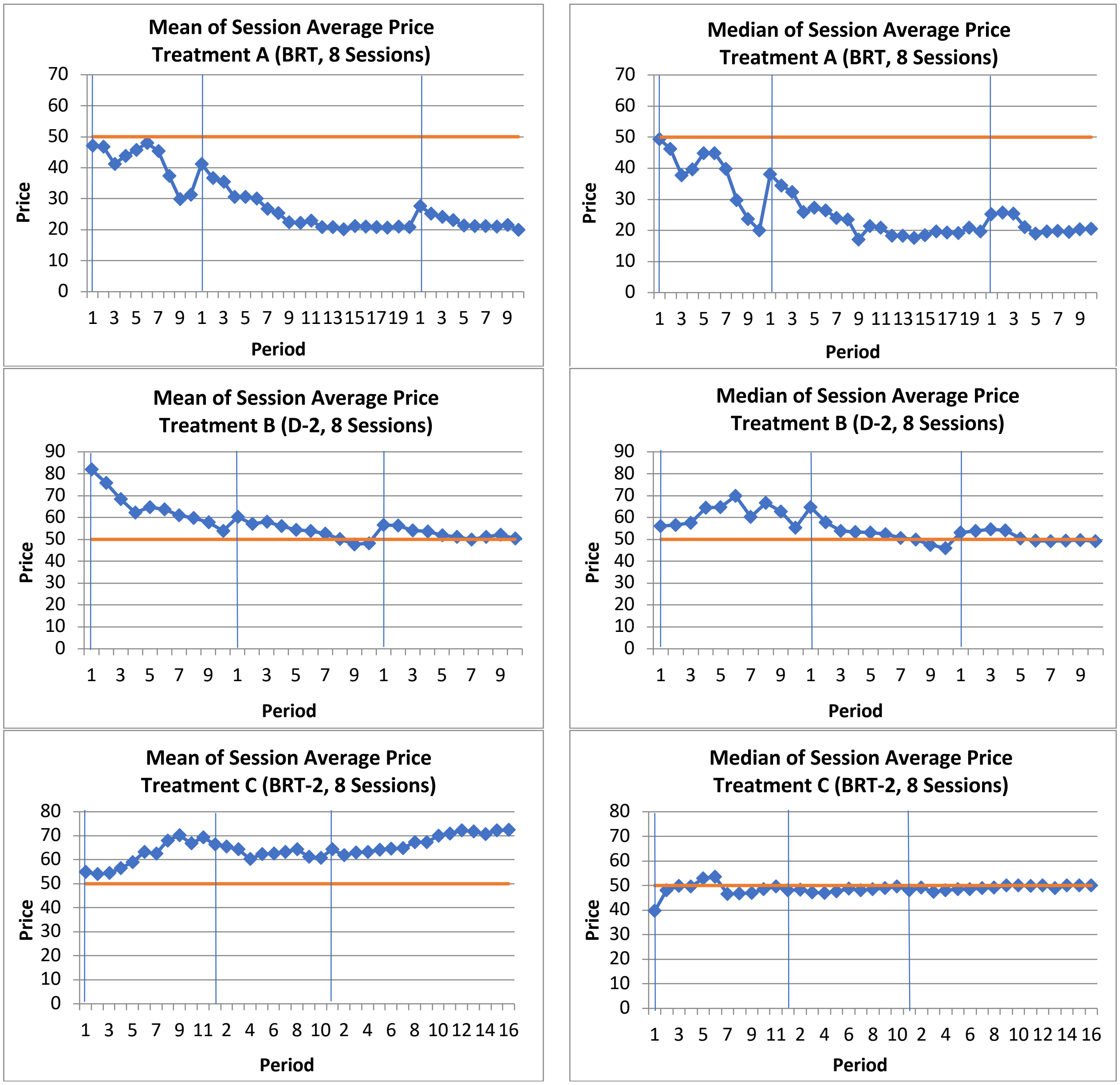

Figure 1: Mean and Median of Session-Level Average Traded Prices over Time, by Treatment

Notes: The red horizontal line is the standard FV, which is equal to 50. The left (right) panel is the mean (median) of the session-level average traded price across the 8 sessions in each treatment.

the average price trajectory for each session). Our discussion will focus on the median. In treatment A, the median of the session average price in the first market starts at around 50 (the standard FV), 55 in treatment B and 40 in treatment C; as we will see later, the session average prices in the first market are not significantly different across the three treatments.

However, the median of the session 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 it stays around 50 in the last two markets in treatments B and C.[16] The pattern tends to hold at the disaggregated session level as well. Further, the underpricing of the asset observed in treatment A is robust to replacing the block random termination design with standard random termination, as shown in Appendix C.[17]

Table 6 shows the average price and the trading volume in each market of each session. We also show in boldface the mean and median of session average prices. We conduct two-tailed Mann-Whitney tests on session average prices and trading volume to assess whether there are any treatment differences in these market measures. There are nine tests (3 markets x 3 treatments) each for traded price and volume. We present the p-values from the Mann-Whitney tests and the Bonferroni adjusted p-values for multiple hypothesis testing, in Table 7. The results reported in that table provide support for the following three findings.[18]

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 by the Bonferroni adjusted p-values 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.

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 7. Although the traded price tends to be lower in treatment A versus the other two treatments, the difference is not statistically significant by the Bonferroni adjusted p-values.

Finding 3 *In markets 2 and 3, the average market price is significantly lower in treatment*

[16]From Figures 3 and B.1, there is only a very mild restart effect. This is likely because the environment is stable across rounds and across markets.

[17]Given that the price pattern across our three different treatments is quite clear, we choose not to report the bubble (mispricing) 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 report for price differences from the standard FV.

[18]The results from the Kruskal-Wallis tests support similar findings. The average traded price across the three treatments is marginally significantly different in market 1 ($p < 0.05$), and very significantly different in markets 2 and 3 ($p < 0.001$). The average trading volume is not significantly different in markets 1 and 2 ($p > 0.1$) and marginally significantly different in market 3 ($p < 0.05$).

Table 6: 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
A6	37.1	13.4	17.5	60.1	57.45	22.6
A7	37.3	27.4	27.3	85.9	61.55	91.4
A8	49.3	43.8	34.9	72.3	63.45	89.9
Treatment A Mean	**41.7**	**25.6**	**22.6**	**70.9**	**71.3**	**90.1**
Treatment A Median	**37.2**	**22.3**	**20.0**	**60.4**	**62.5**	**78.6**
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
B6	39.6	49.2	55.7	15.3	17.3	16.4
B7	66.6	55.5	51.1	48.6	42.2	54.2
B8	109.9	54.3	56.8	23.3	57.5	62.8
Treatment B Mean	**64.9**	**53.8**	**52.6**	**54.8**	**53.6**	**49.3**
Treatment B Median	**63.2**	**51.5**	**50.6**	**53.0**	**53.2**	**58.5**
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
C6	56.7	44.6	47.2	27.8	32.4	18.3
C7	152.6	177.7	170.4	13.0	23.5	22.6
C8	41.9	41.8	46.0	73.0	57.5	35.3
Treatment C Mean	**61.7**	**63.1**	**67.5**	**47.3**	**49.1**	**36.2**
Treatment C Median	**52.4**	**46.0**	**48.6**	**46.0**	**48.1**	**27.1**

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 shares traded) over all trading periods in a market. The mean and median of both session average price and volume are in bold face.

A (BRT) than for the other two treatments in markets 2 and 3. The average market price in markets 2 and 3 is not significantly different between treatments B and C.

In treatment A, the median of session average traded prices in markets 2 and 3 are 22.3 and

Table 7: p-values from Mann-Whitney Tests of Treatment Differences in Average Market Price and Trading Volume

Treatment	Average Price			Trading Volume		
Comparison	Mkt1	Mkt2	Mkt3	Mkt1	Mkt2	Mkt3
A vs. B	0.028	0.000	0.000	0.234	0.328	0.065
	[0.253]	[0.002]	[0.002]	[1.000]	[1.000]	[0.585]
A vs. C	0.065	0.001	0.000	0.105	0.028	0.015
	[0.585]	[0.010]	[0.002]	[0.944]	[0.253]	[0.137]
B vs. C	0.382	0.083	0.900	0.879	0.742	0.442
	[1.000]	[0.747]	[1.000]	[1.000]	[1.000]	[1.000]
No. of Obs.	16	16	16	16	16	16

Notes: Bonferroni adjusted p-values are in square brackets to correct for multiple hypotheses testing (tests on average trading price and trading volume corrected separately for 9 hypotheses, 3 comparisons between treatments x 3 markets).

20.0, respectively. By contrast, in treatment B, the prices in markets 2 and 3 are 51.5 and 50.6, respectively, and in treatment C, they are 46.0 and 48.6, respectively. The average traded price in markets 2 and 3 is, therefore, significantly *lower* in treatment A than in the other two treatments. The Bonferroni adjusted p-value is ≤ 0.01 for the two-tailed Mann-Whitney tests between treatment A and either treatment B or C. Comparing treatments B and C, the average traded price is very close. The difference in the median of the session average traded price is 5.5 in market 2 and 2.0 in market 3. The difference in the session average traded prices is statistically insignificant (the Bonferroni adjusted p-value is > 0.5 for all three markets).

Based on these statistical results, we conclude that market outcomes in treatment A, specifically prices, are significantly different from the other two treatments. The insignificant difference in traded prices between treatments B and C indicates that the uncertain trading horizon itself does not significantly affect the market price with experienced subjects. 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 traded 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 Market FVs

Next, we try to rationalize the differences in traded prices observed in the third market of our three treatments. The approach we take is to calculate what we refer to as the *market*

FV of the asset based on the actual risk preferences of the market participants and test whether it is significantly different from the traded price in market 3. The rationale is that since the same subjects repeat the same market game three times, the market price in the third market can reasonably be expected to approximate the market FV of the asset.[19]

First, as shown in the second column of Table 10, the standard FV ($V_0 = 50$) cannot capture the low traded price of the asset in treatment A: the median of the session average traded price in market 3 is 20.0, which is 40% of the standard FV. Statistically, this result is also confirmed by a two-tailed, Wilcoxon signed rank test that compares this traded price with the standard FV of 50: the Bonferroni adjusted p-value is 0.024. By contrast, the traded price in market 3 of the other two treatments is close to the standard FV of 50 (the Bonferroni adjusted p-value is 0.766 for treatment B and 1 for treatment C).

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

As discussed in the experimental design section, treatment A differs from treatments B and C regarding the timing of dividend realization. In treatment A, dividends are dynamically realized in each trading period. In treatments B and C, trading and dividend realization take place in two separate stages, and all dividends are realized after trading ends. In these two treatments, in all trading periods, the asset can be viewed as a static lottery, as described in Table 1; we call the related market FV the *static risk-adjusted FV*. In treatment A, in principle, it is possible that subjects view the asset as the same as in the other two treatments if they care only about total dividend payments. However, given the significant difference in traded price between treatment A and the other two treatments, it is unlikely that subjects take this perspective. For treatment A, we also calculate what we call the

[19] As shown in Tables 6 and 7, 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.

dynamic risk-adjusted FV. The stationarity of the dynamic asset market in treatment A implies that the asset can be viewed as a combination of the fixed dividend payment in the current trading period with a binary lottery in the next trading period (or at the end of the current trading period) that yields a zero payoff with probability $1-\delta$ and a replica of the asset with probability δ. In the following steps, we will describe in more detail how to calculate the risk-adjusted FVs.

Step 1 of the three-step procedure, which is the same for computing static and dynamic market FVs, is to estimate the risk parameter for each subject from their Holt-Laury tasks. 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. Table D.1 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. More details about how we derive the numbers can be found in the online appendix D. Table 8 suggests that risk-neutral subjects would choose $n_A = 4$, and risk-averse (loving) agents would choose $n_A \geq 5$ ($n_A \leq 3$). Out of the 233 participants, 31, or 13%, (who chose 4 safe choices) can be classified as risk-neutral, 177, or 76%, (who chose more than 4 safe choices) are classified as risk-averse, and 25, or 11%, (who chose 0–3 safe choices) are classified as risk-loving. Figure D.1 shows a histogram of the number of safe choices across all sessions. The results are consistent with previous findings in the literature.

Table 8: Estimation of the CRRA Parameter from the Holt-Laury Task

n_A	$\alpha(n_A)$
0	2.7128
1	2.3298
2	1.7167
3	1.3146
4	0.9981
5	0.7211
6	0.4562
7	0.1766
8	−0.1695
9	−0.3684
10	−0.3684

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

4.1 Static Risk-Adjusted FV

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

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

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

where the two constraints imply there are no short sales of shares and subjects cannot borrow money to buy shares. Let $s(p)$ be the solution to equation(1), then the subject's individual net demand for shares is $q(p) = s(p) - s_0$. We then construct the aggregate demand $Q(p)$ as the sum of individual demands. The market FV, V, solves $Q(V) = 0$. In Table 9, we report the estimated static risk-adjusted market FV, which we denote by V_1.[20]

Given that most (76%) of our subjects are risk-averse, this risk-adjusted FV, V_1, is always found to be lower than the standard FV, $V_0 = 50$, but V_1 lies in a relatively small range between 40.2 and 49.9 across all treatments. Incorporating risk attitudes toward uncertainty in the value of total dividend payments brings the market FV closer to the traded prices in market 3 of treatment A, which are repeated in the second column of Table 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, the median of V_1 is 45.0 across the eight sessions of treatment A while the median of the actual average market traded price is much lower, at 20.0.

Column 3 in Table 10 reports on signed rank tests of the null hypothesis that the market traded prices are equal to V_1 in market 3 of our three treatments. There we see that for market 3 of treatment A, our method of adjusting the static-market FV by incorporating individual risk attitudes still leads us to reject the null hypothesis of no difference in favor of the alternative that traded prices in market 3 of treatment A are significantly lower than V_1 (Bonferroni adjusted $p = 0.024$). By contrast, for treatments B and C we see in Table 9 and 10 that although market 3 average traded prices are higher than V_1 statistically (Bonferroni adjusted $p < 0.05$), the difference is modest in terms of magnitude. The median of V_1

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

Table 9: Estimated Risk-Adjusted FV, by Treatment and Session

Session	Avg Mkt3 Price	V_0	V_1	V_2
A1	17.9	50	44.7	36.7
A2	11.5	50	44.5	36.7
A3	33.3	50	40.2	24.3
A4	16.5	50	46.2	36.8
A5	22.1	50	45.0	30.0
A6	17.5	50	49.9	49.9
A7	27.3	50	44.9	36.7
A8	34.9	50	45.7	36.7
Treatment A Mean	**22.6**	**50**	**45.1**	**36.0**
Treatment A Median	**20.0**	**50**	**45.0**	**36.7**
B1	45.0	50	44.9	
B2	67.7	50	40.7	
B3	49.5	50	44.6	
B4	50.2	50	44.3	
B5	45.3	50	43.9	
B6	55.7	50	42.6	
B7	51.1	50	48.0	
B8	56.8	50	47.3	
Treatment B Mean	**52.6**	**50**	**44.5**	
Treatment B Median	**50.6**	**50**	**44.5**	
C1	47.7	50	44.4	
C2	46.8	50	44.5	
C3	62.1	50	47.2	
C4	49.5	50	44.3	
C5	70.6	50	42.3	
C6	47.2	50	43.3	
C7	170.4	50	45.2	
C8	46.0	50	46.7	
Treatment C Mean	**67.5**	**50**	**44.7**	
Treatment C Median	**48.6**	**50**	**44.5**	

Notes. V_0 is the standard (risk-neutral) FV; V_1 is the static risk-adjusted FV; and V_2 is the dynamic risk-adjusted FV. The treatment mean and median are taken over the session values.

undershoots the median of the session average price by 12% for treatment B and by 8% for treatment C.

4.2 Dynamic Risk-Adjusted FV

In this subsection we calculate the dynamic risk-adjusted FV for treatment A (for the other two treatments, the static FV remains an appropriate benchmark). To incorporate the

Table 10: p-values from Wilcoxon Signed Rank Tests: Average Market 3 Prices against Market FVs

Treatment	V_0	V_1	V_2
A	0.008	0.008	0.039
	[0.024]	[0.024]	[0.117]
B	0.383	0.008	
	[0.766]	[0.016]	
C	0.742	0.016	
	[1.000]	[0.032]	
No. of Obs.	8	8	8

Notes: V_0 is the standard (risk-neutral) FV, V_1 is the static risk-adjusted FV, and V_2 is the dynamic risk-adjusted FV. Bonferroni adjusted p-values are in square brackets to correct for multiple hypothesis testing (tests for each treatment corrected separately).

dynamic realization of dividend payments into the analysis of the FV for treatment A, we employ a recursive preference specification as per Kreps and Porteus (1978) and Epstein and Zin (1989). This specification involves two components: a risk aggregator that aggregates risky payoffs within the same period and a time aggregator that aggregates the certainty equivalence of risky payoffs across periods. We adopt the popular specification, as per Epstein and Zin (1989), which 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. 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 (and the implied elasticity of inter-temporal substitution is infinity). 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 future payoffs. With these assumptions, each subject solves the following portfolio choice problem:

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

where the last term is the certainty equivalence of the lottery that pays ps with prob δ and 0 with prob $1 - \delta$. Note, it is assumed that the economy is in its stationary equilibrium where the price of the asset is constant across time. The solution to equation (2) gives the individual's demand for the asset:

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

We then construct the aggregate demand curves to calculate the dynamic-market FV (V_2) following the same procedures as in the estimation of the static FV (V_1). The estimated V_2 for treatment A is shown in the last column of Table 9. The p-values from Wilcoxon signed rank tests comparing the market 3 traded prices with the estimated V_2 values are shown in Table 10.

For treatment A, Table 9 reveals that the static and dynamic FVs are very different from one another.[21] The dynamic FV is noticeably lower than the static FV for seven out of the eight sessions.[22] Compared with the static FV, which has a median of 45.0, the dynamic FV has a median of 36.7 and is significantly closer to the median of the session average traded price in market 3 of treatment A, which is 20. A signed rank test reported in column 4 in Table 10 suggests that average traded prices in market 3 of treatment A are *not* significantly different from the estimated dynamic FV at the 10% significance level (the Bonferroni adjusted p-value is 0.117). We summarize the results regarding the standard FV and risk-adjusted FVs in the following finding.

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

1. *For treatment A, the traded price in market 3 is significantly lower than the standard FV or the static risk-adjusted FV. The dynamic risk-adjusted FV is not statistically significantly different (at the 10% significance level) from the traded price, although the magnitude of overshooting is still noticeable.*

2. *For treatments B and C, the traded price in market 3 is not significantly different from the standard FV prediction. The traded price is statistically significantly higher than the static risk-adjusted FV predictions, but the magnitude of overshooting is modest at about 12% and 8%, respectively.*

[21] To understand the difference, note that in the dynamic context, subjects view the asset as a current dividend payment plus certainty equivalence of the future value of the asset, which is zero if the market ends. If subjects view the asset as a static lottery, then they consider all possibilities of the total number of dividend payments, which ranges from 1 to infinity. With concave utilities, the prospect of a zero payment lowers the dynamic FV.

[22] The exception is session A6, where the Holt-Laury task suggests that 4 out of the 10 subjects are risk-neutral and the computed static and dynamic FVs are both close to the standard FV.

The dynamic risk-adjusted FV reasonably captures the low traded price in treatment A. One may wonder whether the result can be generalized to other experimental asset markets. In Appendix E, we apply the analysis to two other types of markets studied in the literature. The first is the widely studied market with a fixed, finite horizon, as in Smith et al. (1988). The second is the market with an indefinite horizon and a buyout/terminal value of the asset (this type of treatment is studied in Kose (2015)). We find that unlike in treatment A, where the dynamic FV is substantially lower than the standard FV, they are much closer in these two setups. In terms of experimental evidence of the traded price in these alternative experimental settings, the general finding is that the traded price is close to the standard FV, with experienced subjects. Given that the risk-adjusted dynamic FV is close to the standard FV, the traded price in those settings is also close to the risk-adjusted dynamic FV. The take-away is that the dynamic consideration and recursive preferences apply generally to our treatments as well as to other settings in the literature. In our treatment A with random termination and no buyout value, the dynamic FV is very different from the standard FV so it is critical to use the dynamic FV to explain the traded price with experienced subjects. In the settings with definite horizons and/or the existence of a buyout value for the asset, the dynamic FV is close to the standard FV, so the standard FV constitutes a good approximation.

Finally, given that there is still a noticeable gap between the dynamic risk-adjusted FV and the traded price in treatment A, we extend our analysis of static and dynamic FVs under alternative assumptions; particularly, we compute both FVs by incorporating probability weighting (following the cumulative prospect theory of Tversky and Kahneman (1992)) instead of risk attitudes in recursive preferences. In our baseline treatment, the market ends and the asset becomes worthless with a small probability (0.1), and it seems likely that probability weighting could affect traded prices.[23] The procedure and results are reported in Appendix F.[24] We find the probability-weighted FVs are consistent with the traded prices in all three treatments, both quantitatively and statistically. One point to emphasize is that, with probability weighting, it is still crucial to distinguish the dynamic and static realizations of dividend payments, which affects how small probabilities are over-weighted and is critical in accounting for the different traded prices in treatment A versus B and C.

[23] Ackert et al. (2009) report direct evidence of probability judgment errors on low-probability, high-payoff events in experimental asset markets, similar to Smith et al. (1988), and find the probability judgment error is correlated with the occurrence of asset price bubbles measured relative to the standard FV.

[24] As we did not elicit subjects' probability weighting parameters, we rely on parameter values suggested in the literature, such as Tversky and Kahneman (1992), Camerer and Ho (1994), and Wu and Gonzalez (1996). We use the value in Wu and Gonzalez (1996) as it involves the least distortion of the objective probabilities.

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, then the probability that the asset continues to yield payoffs plays the role of the discount factor and the price predictions under the infinite horizon economy extend to the indefinitely repeated environment. In both environments, the fundamental value of the asset is constant over time and equal to the expected value of total dividend payments, a standard measure of FV found in asset pricing models.

In this paper, we study the empirical relevance of the indefinite-horizon model for understanding the predictions of deterministic infinite-horizon asset pricing models with discounting. In our baseline treatment A, which implements a random termination design, we find that experienced subjects consistently price the asset *below* the standard FV, a surprising finding given the literature.[25]

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

As a result, we conclude that neither uncertainty about the trading horizon nor uncertainty regarding total dividend payoffs can account for the low traded prices observed in the baseline treatment A relative to the other two treatments. Instead, the experimental results suggest that the dynamic realization of dividend payments plays a critical role in accounting for the low traded price in treatment A relative to the other two treatments. In treatment A,

[25]Kose (2015) has a similar finding but does not offer a deep explanation about the phenomenon.

in each trading period, subjects receive dividend payments in the current period and face an uncertain continuation value in the future. In the other two treatments, as all dividend realizations are realized after the trading is completed, subjects are more likely to view the asset as a static lottery and care about the total dividend payments.

To investigate whether risk attitudes together with dynamic considerations could account for the low traded prices in treatment A, we introduce a new procedure to adjust the estimated FV for observed heterogeneity in subjects' risk attitudes (and departures from risk neutrality). We find that the risk-adjusted dynamic FV can account for a significant fraction of the low traded price that we observe in our baseline treatment A, and the two are not significantly different according to signed-rank tests. However, the risk-adjusted FV still overshoots the traded price in treatment A by a noticeable margin. At the same time, for the other two treatments, the static risk-adjusted FV tends to undershoot the traded price according to a signed-rank test, but the magnitude of undershooting is moderate.

We also extend the application of recursive preferences by incorporating probability weighting, according to which subjects overreact to the small probability of market termination, while assuming risk neutrality. The probability-weighted FVs can rationalize the low traded prices observed in our baseline treatment, as well as the observation that the traded prices in treatments B and C are close to the standard FV.

Our findings are of relevance to both finance and experimental researchers. For finance researchers, our results suggest that in the presence of risk non-neutrality (or probability weighting), modeling the asset as a static lottery over total dividend payments could be misleading in calculations of the FV of the asset. An important take-away for experimental economists is that the mis-pricing behavior found in experimental asset markets may be quite different under random termination, as compared with the more typically studied finite-horizon case that follows the lead of Smith et al. (1988). Rather than finding overpricing relative to the standard FV (bubbles) among inexperienced subjects and close tracking of the standard FV among experienced subjects, we find substantial underpricing 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 risk attitudes or probability weighting of the Epstein-Zin type of recursive preferences.

Finally, while our experiment was not designed to directly test the Epstein-Zin preferences or whether subjects engage in probability weighting, we find that incorporating these features helps to explain our experimental results. In future research involving asset markets with indefinite horizons, it would be of interest to directly elicit the parameters of the Epstein-Zin preferences and probability weighting, in a manner similar to the way in which we elicited individual risk preferences. Note that the procedure that we developed to incorporate individual subjects' risk into the estimation of market FV is quite general and additional individual characteristics can easily be incorporated. We leave this exercise to future research.

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Appendices for Online Publication Only

A Details of Related Experimental Literature with Indefinitely Lived Markets

In this appendix, we provide details on all known papers that use indefinite horizons to study asset pricing behavior, as reported in Table 2. We explain differences in the experimental designs of these papers relative to our own design and why these design differences may matter for differences between the results of those studies and our results.

1. Camerer and Weigelt (1993) study pricing of stochasticly lived assets using continuous double auctions and random termination with a continuation probability $\delta = 0.85$. Each period, assets paid one of three dividend levels rotated to different subject types (1/3 of each), so the dividend value of the asset was not common to all subjects as in our design. They find that prices converge to equilibrium values slowly and unreliably, with prices lying above or below the equilibrium price for long periods of time. Relative to our own study, they have an induced motivation for trade (and it is more difficult for subjects to find the equilibrium price due to heterogeneous valuation of the asset), whereas we rely on heterogeneity in risk attitudes. Still, their finding of underpricing of the asset in some sessions is consistent with our findings for treatment A.

2. Ball and Holt (1998) report on a classroom experiment involving 15 assets traded by 5 or more players using an oral double auction. Each asset survives from one period to the next with probability $\delta = 5/6$. The asset pays a constant and known dividend per period. Any asset that survives 10 periods receives a redemption value, so this is not a pure random termination design as in our approach. They report that in using this game, there are bubbles (overpricing) of the asset "in some classes but not in others." One design feature is that the survival risk is applied to each individual share, so as time goes by, the number of shares decreases, while cash increases with accrued dividends. Together, this induces a high cash-to-asset ratio, which could have contributed to the high trading price in their experiment.

3. Hens and Steude (2009) are interested in the correlation of lagged returns with future asset price volatility—the leverage effect says that volatility rises (falls) when lagged returns are negative (positive). They study an indefinitely lived asset using a continuous double auction market. The continuation probability is $\delta = .97$. The dividend process is stochastic but unlike in our study it is *unknown* to subjects. Further, the

dividend is probabilisticly biased to be upward sloping over time, which may bias prices upward. They find evidence for a leverage effect in their data. Prices seem to track the dividend process with a lag and are often above the fundamental value.

4. Kose (2015) compares both definite and indefinitely repeated asset pricing designs using a continuous double auction. Subjects are endowed with assets and trade over either a fixed horizon or an indefinite horizon with or without a final terminal redemption value. Here $\delta = .875$ and the dividend is a random draw from a known distribution. In his treatment 2, which is the most similar to our treatment A, Kose studies an indefinite horizon with a positive dividend and no terminal value and finds underpricing of the asset relative to the fundamental value just as we do. Where we differ is that we run auxiliary treatments to distinguish between uncertainty about dividend payoffs and uncertainty about the horizon length, and we develop an in-depth explanation about the low traded price.

5. Weber et al. (2018) study the pricing of risky bonds that are subject to default risk. The bonds are auctioned off in an IPO, and the IPO price affects the default rate or the probability with which bonds continue to exist and pay interest. Thus, unlike in our study, the continuation probability and thus the fundamental value of the asset is not exogenous. The market mechanism is a call market. Regarding prices, they are observed both at or above the fundamental value; positive bubbles disappear among experienced subjects.

6. Kopányi-Peuker and Weber (2021) compare asset pricing in a call market trading setup using a Smith et al. (1988) type asset with asset pricing in a learning-to-forecast design, where expectations of future prices matter for current price realizations. They study whether experience reduces the incidence of bubbles and crashes and adopt an indefinite horizon to make the two asset pricing approaches comparable. They are also interested in how the amount of information subjects have matters for the role of experience in reducing mispricing. They find that neither experience nor greater information reduces the frequency of the bubble crash phenomenon assets unless the cash-to-asset ratio is low as in our study.

7. Kopányi-Peuker and Weber (2022) study the role of a trading horizon in a Smith et al. (1988) type of asset market. They have a 2x2 design of the trading horizon: short or long x definite or indefinite. They find recurring bubbles and similar price dynamics in all treatments.

Two potential factors that have contributed to the high traded price in Kopányi-Peuker and Weber (2021, 2022): high cash-to-asset ratio and a buyout value, which tends to move the dynamic risk-adjusted FV closer to the standard risk-neutral FV.

8. Fenig et al. (2018) use random termination ($\delta = .965$) to implement an infinitely lived production economy where subjects play the role of households supplying labor to firms and use wage income to consume goods. The main focus is how asset trading affects the real economy and how different policies affect asset market activities. In some treatments, subjects are endowed with dividend paying assets and can use dividends and capital gains from asset market trades as an alternative to labor income. However, subjects are paid primarily on consumption and labor decisions, and a rational subject should have little incentive to participate in the asset market. Nonetheless, they find that when subjects actively participate in the asset market, asset bubbles emerge and persist but have no significant effect on real allocation. The introduction of leverage constraints and asset inflation targeting monetary policy have either no or a small effect on mis-pricing. In this experiment, overpricing may arise because subjects are not sufficiently experienced with the asset market, they must divert attention to production-consumption decisions, or they find asset trading easier to comprehend or more interesting than the production-consumption decision and therefore trade.

   Finally, there are three papers (Asparouhova et al. 2016, Crockett et al. 2019, and Halim et al. 2022) that study the consumption based, Lucas asset pricing model. All of them use random termination to implement an infinitely lived economy. Their results regarding the trading price relative to the risk-neutral fundamental value are mixed. It would be useful to unify the mixed results and see if the fundamental value is different in these three studies (the recursive preferences can potentially offer a new perspective), but we must leave this for a new paper. Because assets are used for intertemporally smoothing consumption, these papers are not directly comparable to ours and other experimental studies following the tradition of Smith et al. (1988), as listed above.

9. Asparouhova et al. (2016) study trade of two assets, one a consol bond paying a fixed dividend and the other an indefinitely lived Lucas asset paying a random dividend. Several indefinite markets are played with $\delta = 5/6$. Agents choose how much to consume and save, with savings in the form of long-lived consols or assets. Trade in assets is via a continuous double auction. Consumption smoothing is induced by paying consumption only in the last period of an indefinite replication (sequence). They

find that asset prices are quite volatile but do not depart too far from fundamentals. However, there is not much of an equity premium for the asset over the bond. Finally, agents use assets to smooth consumption.

10. In Crockett et al. (2019), the only method of intertemporally smoothing consumption is to buy/sell shares of a long-lived asset (trees) over an indefinite horizon ($\delta = 5/6$). Subjects are of two types in terms of the variability of income. Crockett et al. use a continuous double auction market mechanism. They find that agents use the asset to smooth consumption. Prices are observed to be above fundamental values when there is a linear utility (payoff) function, but prices are below fundamental value when there is a concave utility (payoff) function. As noted earlier, we are not studying the use of assets as a means of intertemporally smoothing consumption.

11. In Halim et al. (2022), $\delta = 5/6$, and the motivation to have a smooth consumption profile is induced by the same scheme as in Asparouva et al. (2016) (only cash holdings at the end of the terminal period count toward earnings). Players have different income profiles, some constant and so without a need to smooth consumption while others are variable and have consumption smoothing motivations. Halim et al. also add aggregate risk in terms of uncertain dividend payoffs. They do not find underpricing of the asset; generally prices trade at or above FVs regardless of the composition of traders in terms of having a consumption smoothing motivation and irrespective of whether there is aggregate risk. Despite this mispricing, agents use the asset to intertemporally smooth consumption.

B Average Traded Prices by Session

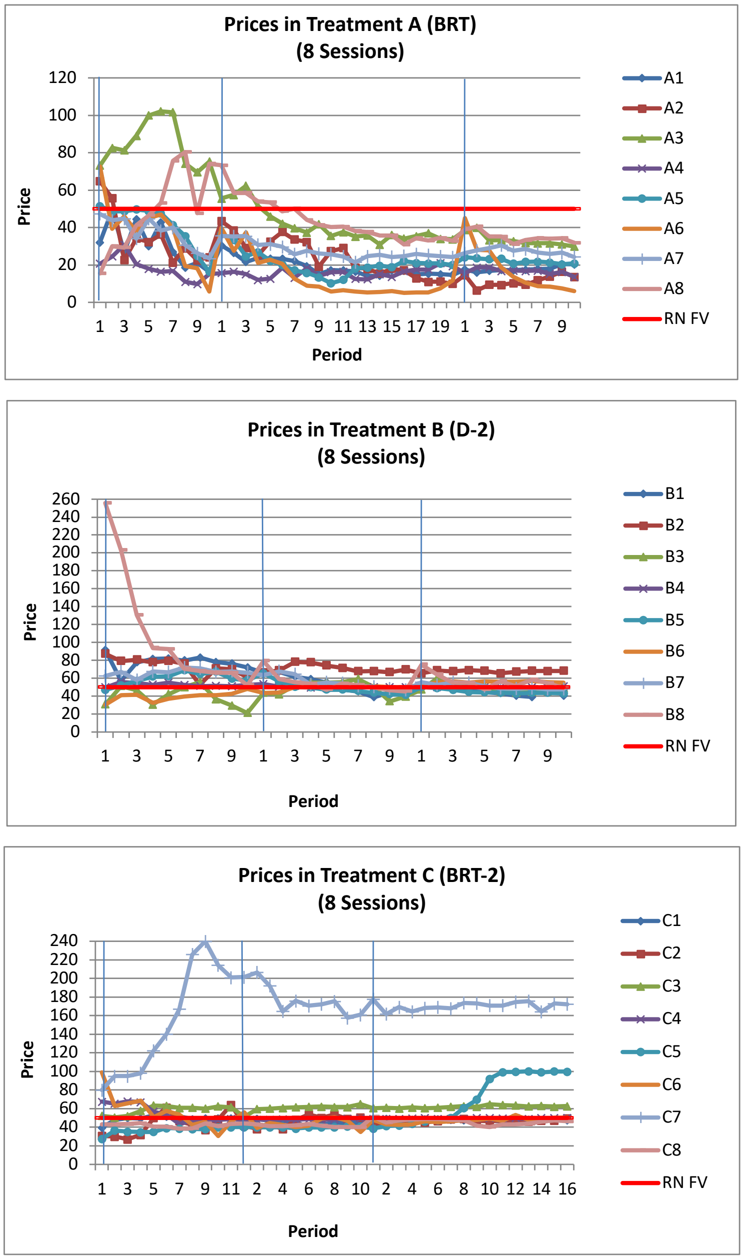

Figure B.1: Average Traded Prices over Time for Each Session, Grouped by Treatment

Notes: The red horizontal line is the standard FV, which is equal to 50.

C Treatment A with Standard Random Termination (SRT)

In this appendix, we report the results from two additional sessions of treatment A where the block is removed. As in treatment A, traders participated in 6, 20, and 9 trading periods in markets 1, 2, and 3, respectively.

Table C.1: Average Traded Price and Volume by Session and Market

Session	Average Price			Average Volume		
	Mkt1	Mkt2	Mkt3	Mkt1	Mkt2	Mkt3
SRT1	68.2	33.0	26.1	52.0	43.9	46.6
SRT2	40.6	40.8	38.1	107.5	106.0	65.0
SRT	54.4	36.9	32.1	79.8	74.9	55.8

Table C.2: Estimated Fundamental Value by Session (SRT)

Session	Avg Mkt3 Price	V_0	V_1	V_2
SRT1	26.1	50	44.0	24.3
SRT2	38.1	50	44.4	36.7
SRT	**32.1**	**50**	**44.2**	**30.5**

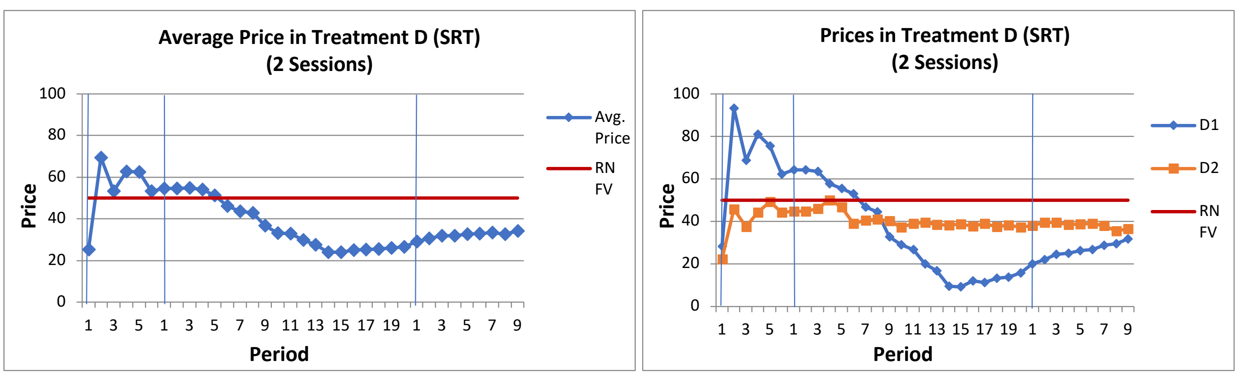

Figure C.1: Traded Prices over Time for the Standard Random Treatment (left panel average of 2 sessions; right panel individual session data)

Notes: The red horizontal line is the standard FV, which is equal to 50.

D Risk-Parameter Estimates

In this appendix, we explain how to estimate the risk parameter for each subject from their Holt-Laury tasks. This is step 1 of the three-step procedure to calculate risk-adjusted market FV, and it is the same for computing static and dynamic market FVs. We assume that subjects' utility functions take the form $u(x,\alpha) = x^\alpha/\alpha$, where 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 D (experimental instructions). For example, in choice i, the payoff from option A is $\bar{x}_A = \$4.0$ with probability $p_i = i/10$ and $\underline{x}_A = \$3.2$ with probability $1 - p_i$, while option B offers $\bar{x}_B = \$7.7$ with probability p_i and $\underline{x}_B = \$0.2$ with probability $1 - p_i$.[26] An agent who is indifferent between the two options in choice i has preferences $u(x, \hat{\alpha}_i)$, with $\hat{\alpha}_i$ solving $Eu_A(x, \hat{\alpha}_i) = Eu_B(x, \hat{\alpha}_i)$ or

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

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

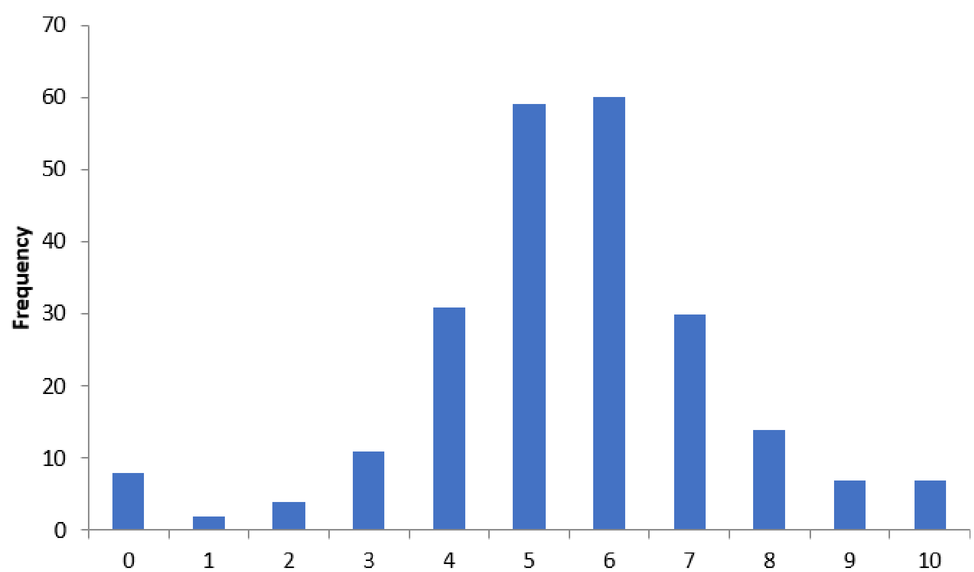

Figure D.1: Distribution of the Number of Safe Choices (Lottery A) in the Holt-Laury Task

If we observe that 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 infer that the subject is indifferent between

[26]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.

Table D.1: Estimation of the CRRA Parameter from the Holt-Laury Task

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

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

option A and option B at a choice with a p value lying between p_i and p_{i+1}, and his/her risk parameter lies on the interval $[\hat{\alpha}_{i+1}, \hat{\alpha}_i]$. We estimate the subject's risk parameter as the midpoint of this interval.[27] 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 D.1 provides a summary of $\alpha(n_A)$, the estimated value of the risk parameter as a function of the number of safe choices, n_A, made by individual subjects. Table D.1 suggests that risk-neutral subjects (those whose true $\alpha = 1$) would switch from option A to option B after the fourth choice ($n_A = 4$), and risk-averse (loving) agents would switch later (earlier). Out of the 233 participants, 31, or 13%, (who chose 4 safe choices) can be classified as risk-neutral, 177, or 76%, (who chose more than 4 safe choices) are classified as risk-averse, and 25, or 11%, (who chose 0–3 safe choices) are classified as risk-loving. [28]

[27] 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).

[28] 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

E Dynamic Risk-Adjusted FV for Finitely Lived Assets and Indefinitely Lived Assets with Buyout

In the main text, we calculate the dynamic risk-adjusted FV for our treatment A, which is indefinitely lived without a buyout value. In this appendix, we illustrate how to calculate the risk-adjusted dynamic FV for two other types of markets. The first is the widely studied market with a fixed, finite horizon, as in Smith et al. (1988). The second is the market with an indefinite horizon with buyout/terminal value (Kose (2015) has this type of treatment).[29]

Finitely lived asset, as in Smith et al. (1988)

To be more concrete, we look at the following configuration in Smith et al. (1988). The asset lasts for 10 periods, and in each period, the dividend follows an iid distribution with four possible realizations, $x_i \in \{0, 4, 8, 20\}$, with equal probabilities. The expected dividend is 8 and, thus, the standard FV of the asset equals $8\times$ the number of remaining periods.

Given this setup, we compare the standard (risk-neutral) FV with the dynamic risk-adjusted FV. The latter is computed as follows. First, in the last period, T, the FV is the certainty equivalence (CE) of the lottery associated with one round of dividend payments:

$$V_T = \left\{ (1/4) \sum_{i=1}^{4} x_i^\alpha \right\}^{1/\alpha}.$$

We can then calculate recursively the FV in the second last period, $T-1$, V_{T-1}, where we assume the payments in different periods are perfect substitutes, as in our paper:

$$V_{T-1} = \left\{ (1/4) \sum_{i=1}^{4} (x_i + V_T)^\alpha \right\}^{1/\alpha}.$$

The dynamic risk-adjusted FV in other periods can be calculated similarly. In table E.1, we list the imputed risk-adjusted dynamic FV for $T = 10$ and $\alpha = 0.63$, the mean of the estimated risk parameters of subjects who participated in our experiment.

From this example, we can see that for a finitely lived asset, the dynamic risk-adjusted FV is very close to the standard FV, especially when multiple rounds of trading still remain. By contrast, in our setting with random termination and no buyout value, subjects always view the asset as today's dividend payment plus an uncertain future where the asset may become

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.

[29] There are also settings where the horizon is finite and the asset has a buyout value (e.g., Kirchler et al. (2012); Kose (2015)); the application is a straightforward combination of our analysis here.

Table E.1: Dynamic FV of Finitely Lived Assets, as in Smith et al. (1988)

t	1	2	3	4	5	6	7	8	9	10
V_2	75.6	67.8	59.9	52.1	44.3	36.5	28.8	21.1	13.6	6.3
V_0	80	72	64	56	48	40	32	24	16	8
V_2/V_0	0.95	0.94	0.94	0.93	0.93	0.91	0.90	0.88	0.85	0.78

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

totally worthless and the risk-adjusted FV can be substantially lower than the standard FV, as shown in Table 9.

Indefinitely lived assets with a terminal value

Now we calculate the dynamic risk-adjusted FV for an indefinitely lived asset with a terminal value, which is studied by Kose (2015). Let B be the buyout value. The holding value of the asset can be calculated from the following equation:

$$V = d + \{\delta V^{\alpha} + (1-\delta)B^{\alpha}\}^{1/\alpha}.$$

To see how the dynamic risk-adjusted FV is affected by the buyout value, we change B and d simultaneously such that the standard FV is constant. As a concrete example, we set $\delta = 0.9$ and aim at RN-FV=50, as in our treatment A. As in the previous exercise, we use $\alpha = 0.63$. Figure E.1 below shows the dynamic risk-adjusted FV as B increases from 0 to 50 (and as d decreases from 5 to 0 to keep RN-FV the same). The dashed line is the standard FV, and the solid line is the dynamic risk-adjusted FV. Our treatment A corresponds to $B = 0$, and Kose's (2015) treatment 1 corresponds to $B = 50$. As shown in Figure E.1, as the buyout value increases, the dynamic risk-adjusted FV (V_2) gets closer and closer to the standard FV (V_0). Kose (2015) shows that in his treatment 1, the traded price is very close to the standard FV, which coincides with the dynamic risk-adjusted FV.

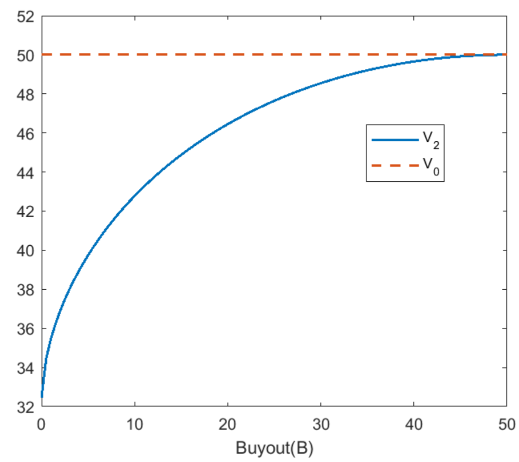

Figure E.1: Dynamic Risk-Adjusted FV with Buyout Value

F Probability Weighting

The analysis in Section 4 suggests that the dynamic risk-adjusted FV, V_2, greatly improves upon the static risk-adjusted FV, V_1, in terms of capturing the low traded price in the baseline indefinite-horizon asset market (treatment A). However, there is still a noticeable gap between the estimated market FV and the actual market price. We, therefore, continue to search for additional/alternative explanations for the final market 3 traded prices. A second factor that we explore is the possibility from cumulative prospect theory (Tversky and Kahneman (1992)) that subjects employ probability weighting in evaluating the lotteries that characterize the asset.[30] 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.

To isolate the role of probability weighting, we will calculate the market FV, assuming risk neutrality. We start with a short description about probability weighting. We then describe how to apply probability weighting to our experimental treatments. The estimation of risk-neutral FV under probability weighting follows a two-step procedure. The first step is to transform the probabilities of the lottery outcomes involved in our treatments. In the second step, we use the transformed probabilities to calculate the expected value of the lottery. Note that under the assumption of risk neutrality, the expected value of the lottery is also the market FV. Note also that while estimating the probability weighted FV, similar to the

[30]Probability weighting, together with loss aversion and reference dependence, are fundamental principles of prospect theory, an alternative to the 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.

consideration of risk attitudes, it is important to distinguish static versus dynamic FVs. For treatment A, we will estimate both; for the other two treatments, it is more appropriate to consider the static FV.

F.1 A Primer on Probability Weighting

We first provide a short description of probability weighting. Suppose agents face a risky prospect with n outcomes $x_1 < x_2 < x_i < ... < x_n$, with probability $p_1, p_2, ..., p_i, ..., p_n$. Probability weighting transforms the original probability p_i to w_i through

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

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 $q_i = \sum_{j=i}^{n} p_j$ is the cumulative probability of getting an outcome weakly better than x_i, i.e., $\Pr(x \geq x_i)$, and $q_{i+1} = \sum_{j=i+1}^{n} p_j$ is the the probability of outcomes strictly better than x_i. The transformed density probability π_i is derived from the transformed cumulative probabilities.

2. The transformed probabilities π_i satisfy $\sum_{i=1}^{n} \pi_i = 1$.

3. We say event i is overweighted if $\pi_i > p_i$ and underweighted if $\pi_i < p_i$. Note that since

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

whether event i is over or underweighted 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 $w'(q_i) < 1$.

F.2 Transform Probabilities of Lottery Outcomes

To transform the probabilities of the lottery outcome, we set $\gamma = 0.71$, following Wu and Gonzalez (1996).[31]

In treatment A, at the end of each period after the dividend payment of 5 points, a random draw 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, the dividend payment stops, and with probability 0.9, the 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

[31] 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.

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 example,

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

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 event i is over or under weighted can be approximated by whether $w'(q_i) > 1$. In figure F.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 F.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 45^0 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 are underweighted.

F.3 Estimate the Fundamental Value

In the case of the static lottery, the risk-neutral, probability-weighted market FV is the expected value of dividend payments using the weighted probabilities, $\pi(td) = w(\delta^{t-1}) -$

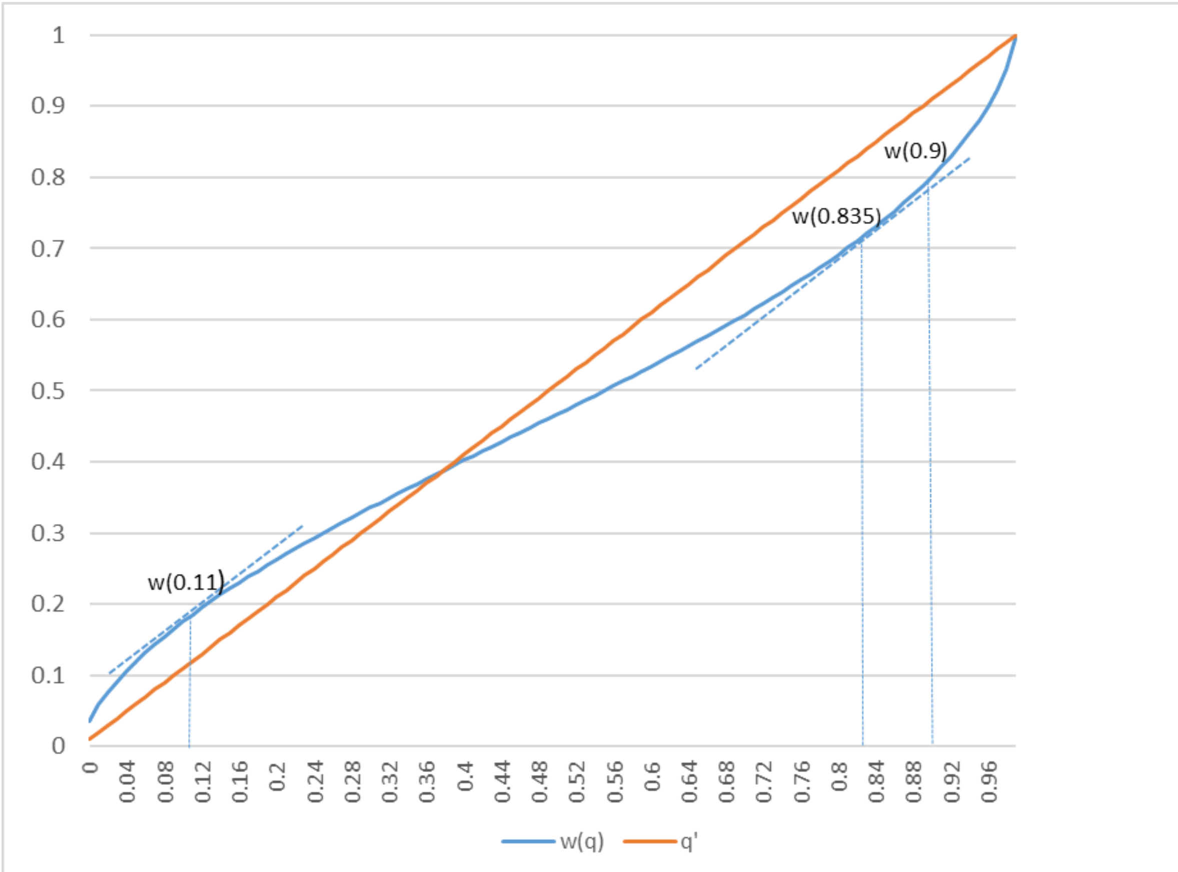

Figure F.1: Transformed Probabilities

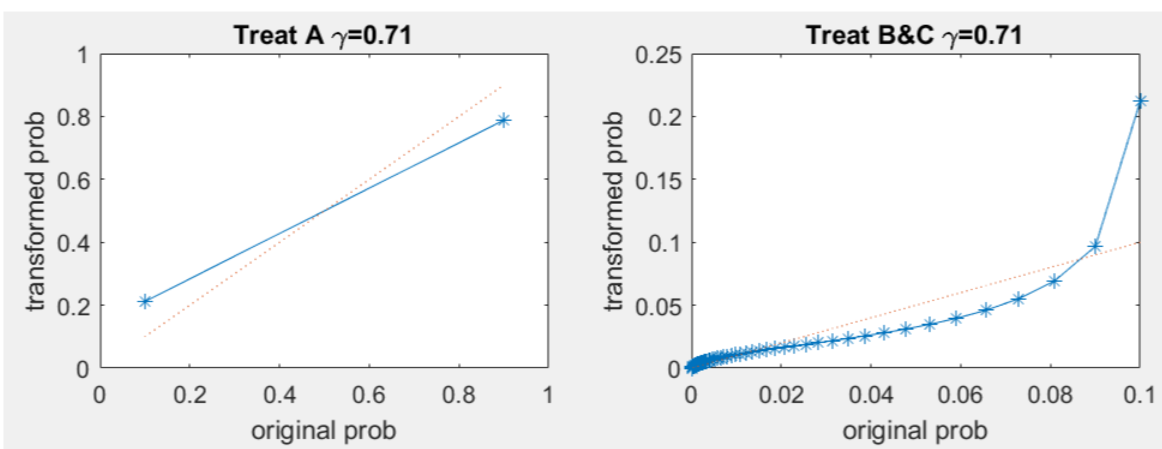

Figure F.2: Transformed Probabilities in Treatments

$w(\delta^t)$, in place of the original probabilities, $(1-\delta)\delta^{t-1}$:

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

The probability-weighted dynamic FV is given by

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

Table F.1: p-values from Wilcoxon Signed Rank Tests: Average Market 3 Prices against Risk-Neutral Probability-Weighted Market FVs

Treatment	V_1^{PW}	V_2^{PW}
A	0.008	0.742
B	0.109	
C	0.844	
No. of Obs.	8	8

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

Table F.1 lists the p-value of the signed rank tests between the session average traded price and the (risk-neutral) probability-weighted FV. The probability-weighted FV seems to capture the traded price in all three treatments reasonably well. For treatment A, the dynamic probability-weighted FV is 23.6, which is only slightly above the median of the session average price in market 3, 20. The signed rank test suggests that the average traded prices in market 3 of treatment A are not significantly different from the probability-weighted dynamic FV. The p-value for the test between probability-weighted dynamic FV and the average market 3 price in treatment A is 0.742. For treatments B and C, the probability-weighted static FV is 57.3, which slightly overshoots the median of the session average traded price in market 3 (50.6 in treatment B and 48.6 in treatment C). The p-value for the tests between the probability-weighted static FV and the average market price is 0.109 and 0.844, respectively.[32] We summarize the analysis in this section as the finding below.

Finding F.1 ***Market Price and Risk-Neutral, Probability-Weighted FV.***

1. *For treatment A, the traded price in market 3 is not significantly different from the probability-weighted dynamic FV.*

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

Similar to the exercise with the risk-adjusted FV in section 4, we show that the probability-weighted dynamic FV is also consistent with the convergent traded prices in asset markets, similar to the setup in Smith et al. (1988). For example, in one configuration used in Smith

[32] The $p-$values in table F.1 do not correct for multiple hypotheses. Doing so will not change the results.

et al. (1988), the asset lasts for a finite number of periods, and in each period, the dividend follows an iid distribution with four possible outcomes $\{0\ 4\ 8\ 20\}$ with equal probabilities. The standard FV is $= 8\times$ the number of remaining periods. The weighted probabilities assuming $\gamma = 0.71$ as above are $\{0.3611,\ 0.1783,\ 0.1677,\ 0.2929\}$. The probability-weighted dynamic FV is $7.9122\times$ the number of remaining periods, which is very close to (98.9% of) the standard FV.