

# Dynamic Inconsistency in Risky Choice: Evidence from the Lab and Field

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## ABSTRACT

Many economically important settings, from financial markets to consumer choice, involve dynamic decisions under risk. People are willing to accept risk as part of a sequence of choices—even when it is fair or has a negative expected value—while at the same time rejecting positive-expected value gambles offered in isolation. We use a unique brokerage dataset containing traders’ ex-ante investment plans and their subsequent decisions ( $N = 190,000$ ) and two pre-registered experiments ( $N = 940$ ) to study what motivates decisions to take risk in dynamic environments. In both settings, people accept risk as part of a “loss-exit” strategy—planning to take more risk after gains and stop after losses. Notably, this strategy generates a positively-skewed outcome distribution that is not available when the same gambles are offered in isolation. People’s actual behavior exhibits the *reverse* pattern, deviating from their intended strategy by cutting gains early and chasing losses. More individuals are willing to accept risk when offered a commitment to the initial strategy, which suggests at least partial sophistication about this dynamic inconsistency. We use our data to formally identify a model of decision-making that predicts both the observed deviations in planned versus actual behavior, as well as the discrepancy in risk-taking in static and dynamic environments. We then use this model to quantify the welfare costs of naïveté in our setting. Together, our results have implications for evaluating the welfare consequences of behavioral biases in dynamic settings, such as the disposition effect, and highlight potentially unintended effects of regulation mandating non-binding commitment.

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# I. Introduction

People are often confronted with risky decisions in dynamic environments, such as whether to purchase a stock or take out a loan. A crucial feature of such settings is that the initial decision includes the option to adjust and reevaluate one’s choices over time. For example, an investor can, after observing the stock’s performance, purchase more shares, sell them, or continue to hold the position. A borrower can repay the loan, roll it over, or borrow more.

Behavior in such dynamic environments—where people decide to take on risk knowing they can adjust their choices—appears to run counter to findings from one-shot, static settings. Individuals tend to avoid uncertainty when it is presented in isolation, overwhelmingly rejecting positive-expected-value gambles and displaying a seemingly anomalous preference for safer options (Kahneman and Tversky (1979)). At the same time, people appear risk-seeking when risk is offered as part of a sequence, even if the cumulative gamble has a zero or *negative* expected value. For example, investments in the retail foreign exchange market (FOREX) yield negative returns for the typical trader (e.g., Ben-David, Birru, and Prokopenya (2018); Heimer and Simsek (2019)), yet the daily market volume is roughly equivalent to the entire NYSE family of stock exchanges (King and Rime (2010)). Similarly, while casino and other forms of commercial gambling leave the average player with less money than when she started, the \$240 billion dollar industry is booming, collecting over \$70 billion dollar gambling revenues and breaking its revenue records year after year.<sup>1</sup> Studies in the lab have confirmed these patterns, with participants expressing a willingness to take on fair and negative expected-value gambles when they are presented as part of a dynamic sequence of choices (Andrade and Iyer (2009); Imas (2016)).<sup>2</sup> Risk-taking appears to be driven by a common motive across these settings, with recent work showing that people treat trading in financial markets as a substitute for gambling,

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<sup>1</sup> American Gaming Association annual report, 2018, <https://www.americangaming.org>.

<sup>2</sup> Note that this discrepancy between one-shot and sequential risk-taking is fundamentally distinct from risk-taking as a function of the evaluation period. Prior work has shown that people take on more risk when feedback on outcomes is provided less frequently. This phenomenon, termed myopic loss aversion (MLA; Gneezy and Potters (1997); Benartzi and Thaler (1995)), cannot explain the outlined differences in risk-taking in dynamic versus one-shot environments because 1) in dynamic environments feedback is provided after every choice and 2) an MLA agent would reject fair or negative expected-value risk regardless of feedback frequency (Langer and Weber (2008)).

and vice versa (Dorn, Dorn, and Sengmueller (2015); Kumar (2009); Gao and Lin (2015)).

This paper studies how particular features of dynamic settings—specifically, the ability to form contingent strategies—motivate people’s decisions to take risk in such environments. To do this, we leverage data from the field and the lab which allows us to compare planned risk-taking strategies to actual behavior in response to gains and losses. We find that indeed people are more likely to accept risk when it is presented as part of a dynamic sequence of choices than if the same gamble is offered in isolation. Results from both lab and field settings show that people are initially motivated to take risk as part of a “loss-exit” strategy, which involves continuing to take on risk after gains and to stop after losses. Notably, this strategy generates a positively-skewed outcome distribution not available when the gambles in a dynamic sequence are instead presented in isolation. Actual behavior follows the reverse pattern: people cut their gains early and chase losses. This dynamic inconsistency between planned and actual behavior, combined with data on demand for commitment, allows us to identify a theoretical framework. There, people are initially attracted to risk because of the positive skew generated by their ex-ante strategy, but deviate from it due to diminishing sensitivity to prospective gains and losses. The model rationalizes the discrepancy in risk-taking between dynamic and allows us to assess the welfare costs of dynamic inconsistency in our setting: a naïve agent would be better off taking one sure loss than being given the option to invest sequentially. Our results also shed light on a host of phenomena associated with sequential choice, such as the disposition effect (Odean (1998); Shefrin and Statman (1985); Weber and Camerer (1998)), the costly active trading of individual stocks (Barber and Odean (2000)), the tendency to ‘double-down’ on failed strategies (Heath (1995)), and have implications for welfare costs in dynamic settings that allow individuals to revise their risk-taking strategies.

We begin our investigation using a dataset from a large online brokerage with approximately 190,000 traders from over 150 countries. The unique feature of this data set is that the brokerage mandates that traders submit ex-ante strategies for every single position they open. When purchasing an asset, investors are required to submit an exit strategy after gains (take-profit limit) and after losses (stop-loss limit). Take-profit and stop-loss limits correspond to the most a trader is willing to gain or lose, respectively, before exiting the position. Importantly, the dataset also tracks all subsequent revisions to these limits until the asset is sold, as well as

whether positions are manually closed before triggering a gain or loss limit. The combination of initial limits, subsequent revisions, and manual sales allow us to directly characterize the traders' ex ante risk-taking strategies and to compare these strategies to actual behavior in response to gains and losses. For example, by placing a stop-loss limit of 10% and a take-profit limit of 20%, the trader opens the position with a risk-taking strategy that pairs a willingness to lose 10% for the chance of gaining 20%. She can revise this strategy by changing one of the limits after seeing gains and losses, e.g., moving the stop-loss limit to 20%, or by manually closing the position before the limits are hit, e.g., selling the asset after a 5% gain.

We document a significant discrepancy between planned and actual behavior. The majority of ex-ante strategies can be classified as “loss-exit” plans. The average stop-loss limit is smaller than the corresponding take-profit limit, which implies that traders open new positions with the intention of exiting after smaller losses relative to gains. At first glance, this strategy seems to contradict the well-known disposition effect, in which traders hold losers longer than winners (Odean (1998)). Traders' subsequent choices follow the *reverse* pattern of their intended plan. After experiencing losses, investors revise their loss limits to allow the price to further decrease. For example, when the position is currently at a 5% loss, a trader modifies her loss limit by lowering it from 10% to 20%. On the other hand, when experiencing gains, investors are most likely to manually exit the positive before the take-profit limit is triggered. For example, when the trader has set a 20% take-profit order and the position hits a 10% paper gain, she is most likely to manually close the trade at 10%. This pattern demonstrates a discrepancy between investors' “loss-exit” plans when opening a position and their subsequent behavior, which is instead consistent with a “gain-exit” strategy.

The financial setting is unique in allowing us to compare people's ex-ante risk-taking strategies to the choices that follow in an environment with significant stakes and frequent feedback. However, as is often the case when using real-world observational data, there is a tradeoff between external validity and the ability to control for potential confounds. Although the discrepancy between intention and behavior is suggestive of dynamic inconsistency, there may be alternative explanations such as beliefs about the data-generating process. We designed an experimental paradigm that generates data rich enough to identify dynamic inconsistency and formally test theories of dynamic decision-making under risk. As outlined formally in the

Appendix, this requires the experiment to have the following features: (i) the ability to elicit incentivized ex-ante strategies and compare them to ex-post behavior both within- and between-subject, (ii) elicit initial choices to begin taking risk—‘entry’ decisions—as a function of number of rounds and availability of commitment devices, and (iii) a long enough sequence of gambles such that strategies can significantly affect skew over final outcomes compared to the one-shot gamble (we employ 26 rounds, following the theoretical setup of Barberis (2012)).

In two pre-registered experiments ( $N = 940$ ), participants are offered the choice to accept or reject a sequence of fair symmetric gambles while being provided feedback after every decision and having the choice to stop anytime. We use a mixture of between-subject and within-subject designs to (i) test whether participants are more willing to take risk if offered a sequence of fair gambles than a gamble in isolation and (ii) understand the mechanism behind the discrepancy in risk-taking by comparing their ex-ante strategies before accepting risk to their actual behavior once outcomes are realized. The latter allows us to identify dynamic inconsistency in sequential risk-taking and quantify sophistication through demand for commitment. Participants are assigned to different treatments that vary the number of gambles they are presented with and whether we elicit their strategies prior to the initial choice. Similar to the field setting, strategies are elicited in the form of loss (gain) limits, which correspond to the most participants are willing to lose (gain) before refraining from taking on risk. Besides the advantage of being intuitive and easy to explain, under mild assumptions these limits are sufficient for fully characterizing participants’ risk-taking plans in our setting. In one treatment, the elicited strategies are binding; we refer to this condition as “hard commitment” because it provides participants with a guarantee that their preferred strategies will be followed. In the “soft commitment” treatment, participants are reminded of their initially preferred limits but can deviate from them, similar to the financial setting. Finally, in a separate ‘sequential’ treatment, participants make decisions without stating their ex-ante strategies.

The results show that participants are significantly more likely to accept risk when it is part of a larger sequence of gambles than in isolation. This confirms the puzzling discrepancy in risk-taking between static and dynamic settings within the same paradigm. Comparing ex-ante strategies to behavior allows us to identify the mechanism. The vast majority – more than 80% – of strategies can be classified as “loss-exit” plans; in contrast, only 7% of strategies can be

classified as “gain-exit.” Strikingly, the average participant initially accepts risk with a gain limit that is 3.81 times higher than her loss limit. In contrast, actual choices follow the *reverse* “gain-exit” pattern: participants are significantly more likely to stop after winning than after losing, replicating the behavioral pattern observed in the field. This deviation from planned behavior is costly. Cutting gains early and continuing to chase losses results in lower accumulated gains and higher accumulated losses both in an absolute sense, as well as relative to the outcomes implied by participants’ ex-ante strategies.

Our treatments also allow us to examine whether people are aware of their dynamic inconsistency or not. Following the time preference literature, we classify the former as ‘sophisticated’ and the latter as naïve. Differences in willingness to accept risk between treatments suggest that a portion of our participants are sophisticated about their dynamic inconsistency: people are significantly more likely to begin taking on risk when provided with a commitment opportunity. In contrast, there is no evidence for sophistication when comparing soft and hard commitment opportunities. Despite most people deviating from their strategies in a similar manner as when plans are not elicited, they are equally likely to take on risk when commitment is non-binding as when it is binding. This suggests that sophistication may be domain-specific: while a substantial portion of our participants appear aware of their dynamic inconsistency—displaying a demand for commitment—they nonetheless seem naïve about the effectiveness of soft commitment in disciplining behavior.

As we outline in Section IV and demonstrate formally in the Appendix, our pattern of findings is most consistent with the dynamic predictions of models that incorporate probability weighting and gain-loss asymmetry such as Cumulative Prospect Theory (CPT thereafter, Tversky and Kahneman (1992), Barberis (2012)), often matching not only the qualitative but also the quantitative predictions of the theory. We show that frameworks that incorporate diminishing sensitivity without a gain-versus-loss asymmetry (Expected Utility Theory, EUT thereafter) or probability weighting (Rank Dependent Utility, RDU thereafter; Quiggin (1982); Yaari (1987)) cannot rationalize the data. Barberis (2012) shows that dynamic CPT predicts that the same person will reject a single fair gamble while accepting the same gamble as part of a dynamic sequence of choices. The underlying mechanism that predicts this discrepancy also generates a dynamic inconsistency between ex-ante strategies and behavior. People begin

to take on risk with the plan of stopping after losses and continuing on after gains; actual decisions follow the reverse pattern, with a greater willingness to take on risk after losses than after gains.<sup>3</sup> Importantly, because actual behavior is consistent with the disposition effect while planned behavior is not, this implies that the well-studied phenomenon is a product of dynamic inconsistency. The framework also makes a prediction for the role of commitment in this setting. A person sophisticated about her dynamic inconsistency will be more likely to accept risk if she can commit to the “loss-exit” strategy than if no such commitment opportunities exist.

Having provided reduced-form evidence for a model with probability weighting and gain-loss asymmetry, we use simulations to quantify the welfare loss resulting from dynamic inconsistency. Naïve agents who accept the sequential gamble with the illusion that they will stick to their loss-exit plan incur a utility cost from participation. For a representative agent in our setting, the predicted cost of naïveté is equivalent to losing more than *one hundred and ten percent* of the one-shot investment with certainty. Section VII discusses recent work that micro-founds probability weighting as being driven by specific psychological processes (salience theory (Bordalo, Gennaioli, and Shleifer, 2012); efficient coding (Frydman and Jin, 2019); cognitive uncertainty (Enke and Graeber, 2019)). Importantly, these frameworks suggest that the extent of probability weighting and sophistication about dynamic inconsistency may be negatively correlated. This implies that welfare costs may be increasing in naïveté—those who are most prone to dynamic inconsistency may be least aware of it *ex-ante*.

Interpreting our empirical results through the lens of theory suggests that the option to stop taking on risk in response to gains and losses is a crucially appealing feature of dynamic environments—individuals begin to take on risk that they would avoid in isolation *because* they can condition future choices on past outcomes. However, dynamic inconsistency in *ex-post* behavior can potentially lead to welfare losses. This has significant implications for interpreting prior findings and policy design, as well as generating new predictions for the role of commitment. First, our results provide support for a mechanism that links seemingly disparate phenomena—e.g. differences in risk-taking between static and dynamic environments, the disposition effect—

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<sup>3</sup> The theoretical predictions regarding actual behavior after gains depend on whether the sequence is assumed to be finite (Barberis (2012)) or infinite (Ebert and Strack (2015)). A higher tendency to cut gains early is predicted for settings with finite number of rounds, such as our experimental paradigm.

within a unified framework. While the disposition effect has been one of the most widely studied (and replicated) phenomena in finance (see Kaustia (2010) for review), its costs are typically quantified in strictly financial terms. Our findings offer direct evidence for the hypothesis introduced by Barberis (2012) that the disposition effect is actually inconsistent with traders’ ex-ante preferences.<sup>4</sup> This is underscored in the field data, where traders who exhibit the disposition effect submit initial strategies that should generate the reverse behavioral pattern. As a result, the welfare consequences of the disposition effect potentially expand beyond calculating financial losses; Section VI shows that traders naïve about their dynamic inconsistency would be better off without the opportunity to take on risk in the first place.

Moreover, our findings suggest that loss and gain limits—which are prominent and oft-used features in financial markets— may serve the dual purpose of attracting investors through their perceived role as commitment devices. However, the vast majority of these limits can be adjusted ex-post. Such soft commitment also characterizes regulation aimed at limiting the scope for unintended losses. For example, the regulation on “depreciation reporting”, which is a part of the recently revised financial instruments regulation in European markets (MiFID II), essentially urges investors to think about a loss-exit strategy while leaving the loss-limit non-binding. Our experimental results show that the presence of soft commitment opportunities leads a substantial fraction of individuals who would have avoided risk absent commitment opportunities to accept it. This ‘illusion of commitment’ is costly, as these same individuals end up systematically deviating from their non-binding strategy. Our results suggest that policy and regulations employing non-binding commitment may backfire by encouraging investors to take on more risk than they otherwise would without effectively preventing them from chasing losses. On the other hand, providing ‘hard commitment’ opportunities that do not allow ex-post revision would not only increase naïvé-agents’ welfare, but also the welfare of sophisticated agents who correctly anticipate their dynamic inconsistency and do not accept sequential risks as a result. Hard commitment is valuable for these sophisticated agents because it enables them to accept risk as part of a utility-maximizing “loss-exit” strategy.<sup>5</sup>

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<sup>4</sup> As further evidence this mechanism, Bernard, Loss, and Weber (2020) show that the disposition effect amongst stock traders increases with skewness of the assets. In the lab, both Nielsen (2019) and Merkle, Müller-Dethard, and Weber (2019) show that loss-chasing is eliminated when risk is negatively skewed.

<sup>5</sup> As we show in Section VI, the opportunity for hard commitment is equivalent to a certain *gain* of up to one hundred



**Related Literature** We are not the first to examine ex-ante strategies in dynamic risk-taking environments. Andrade and Iyer (2009), Ploner (2017), and Dertwinkel-Kalt, Frey, and Köster (2020) find that people plan to bet more after a gain than a loss, while Barkan and Busemeyer (2003) find that people want to bet more after a loss than a gain. Moreover, Dertwinkel-Kalt, Frey, and Köster (2020) find that skewness preferences in static problems correlate with skewness preferences in the dynamic problem. However, these experiments were not designed to explore the motivation for risk-taking in static versus dynamic environments nor distinguish between theoretical models of choice under uncertainty. Hence the data cannot be used to rationalize the phenomena studied in this paper and precludes identification of the mechanism driving dynamic inconsistency.<sup>6</sup>

Our paper contributes to the literature on dynamic inconsistency between planned and actual behavior. A large literature explores systematic deviations from ex-ante strategies in intertemporal choice (Frederick, Loewenstein, and O’Donoghue (2002)). Sophistication about dynamic inconsistency and demand for commitment have been studied both theoretically (O’Donoghue and Rabin (1999)) and empirically (DellaVigna and Malmendier (2006)). The proposed mechanism for time inconsistency – hyperbolic discounting – is conceptually distinct from the driver of dynamic inconsistency in risky choice and cannot explain the behavioral patterns described here.<sup>7</sup> In contrast to the significant body of work on the former, few papers have explored the latter; and of those that do, the majority are theoretical rather than empirical (e.g. Barberis (2012); Ebert and Strack (2015)).

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and twenty percent of the static investment amount for some sophisticated agents who exhibit stronger non-linear probability weighting than the representative agent.

<sup>6</sup> In these studies, the decision to initially take risk was either forced (Ploner (2017); Barkan and Busemeyer (2003)) or coerced (Andrade and Iyer (2009)). Imas (2016) compares planned and actual behavior only in the domain of losses, using a within-subject hypothetical planning stage. All studies use four rounds or less, which can explain the somewhat contradictory results. Finally, Dertwinkel-Kalt, Frey, and Köster (2020) only look at strategies rather than ex-post revisions, and do not explore the initial decision to take on risk.

<sup>7</sup> Unlike a dynamic framework with probability weighting and diminishing sensitivity, models of time inconsistency do not predict outcome-specific deviations between planned and actual behavior. While it may be possible to generate deviations where people gamble for longer than they intended, frameworks such as present-biased preferences (O’Donoghue and Rabin (1999)) would not predict the discrepancy between “loss-exit” strategies and “gain-exit” behavior observed in our data.

Finally, our findings are linked to the work on using prospect theory to explain market anomalies. Theoretical work has studied the implications of prospect theory for asset pricing (Barberis, Huang, and Santos (2001); Barberis, Mukherjee, and Wang (2016); Barberis and Huang (2008)) and as an explanation for the disposition effect (Li and Yang (2013)). In particular, Barberis and Xiong (2009) demonstrates how the standard static version of prospect theory fails to predict a robust disposition effect. Barberis and Xiong (2012), Ingersoll and Jin (2013), and An et al. (2019) show that incorporating realization utility into prospect theory does generate a disposition effect. Importantly, however, these static models do not link the effect to a trader’s ex-ante preferences, making it difficult to assess its impact from a welfare perspective.

The rest of the paper proceeds as follows. Section II describes the field setting and presents results on risk-taking behavior. Section III describes the experimental design. Section IV outlines the theoretical predictions in this setting. Section V presents the results and Section VI describes the potential welfare consequences. Section VII outlines the implications of our findings. Section VIII concludes. Finally, Appendix A formally compares the predictions of various models of dynamic choice under uncertainty.

## II. Dynamic Inconsistency in the Field

We begin our investigation by looking at the dynamics of risky decision-making in the field. To do this, we employ trading data from a large international online brokerage from June 2013 and August 2015. The data contains 187,521 traders from over 150 countries, 84% of whom are male. The brokerage enables its clients to trade contracts for difference (CFD). CFDs are derivatives contracts that pay the difference between the open and close price of an instrument and involve no actual receipt of the underlying asset. Traders can open long or short positions in the assets and all transactions are self-initiated (non-advised). The majority of the transactions during this sample period are for CFDs in major currencies (e.g, EUR/USD, USD/JPY and GBP/USD). The majority of trades are levered at the time of purchase using margin provided by the brokerage (the median (average) leverage of the trades is 100:1 (163:1)).

A unique feature of our setting is that the brokerage requires all traders to set loss and gain limits (stop-loss and take-profit orders, respectively) for every position that they open and records *revisions* to these limits for all assets held by the trader.<sup>8</sup> Each gain (loss) limit corresponds to the most a trader is willing to gain (lose) as part of her ex ante strategy when buying an asset. For example, the investor may purchase a stock while setting the gain limit at 20% and a loss limit at 10%. Once a limit is hit (e.g. the price declines by 10%), the position is closed automatically at the price specified by the order.

These features allow us to accurately capture traders’ ex-ante strategies and ex-post revisions in a real-world setting. While traders are required to enter gain and loss limits when they open a position, these limits are not binding — after opening the position, traders can revise their limit orders after experiencing gains and losses. These order revisions are at the traders’ discretion, are not influenced by the brokerage, and can be revised as much as the trader desires until she closes the position manually or one of the limits is triggered.

We observe every revision of the limits, which allows us to test for the link between gains versus losses and the decision to close a position. Second, the holding period of the transactions is short with a median of 3.6 hours (average of 3.5 days); hence, informational shocks are less likely to play a role relative to settings with longer holding lengths. Third, the CFD of currency pairs have been shown to yield negative expected returns for active retail traders (Heimer and Simsek (2019)); in turn, the initial willingness to rake on risk in this setting cannot arise from return aggregation as in Benartzi and Thaler (1995).

## A. Results

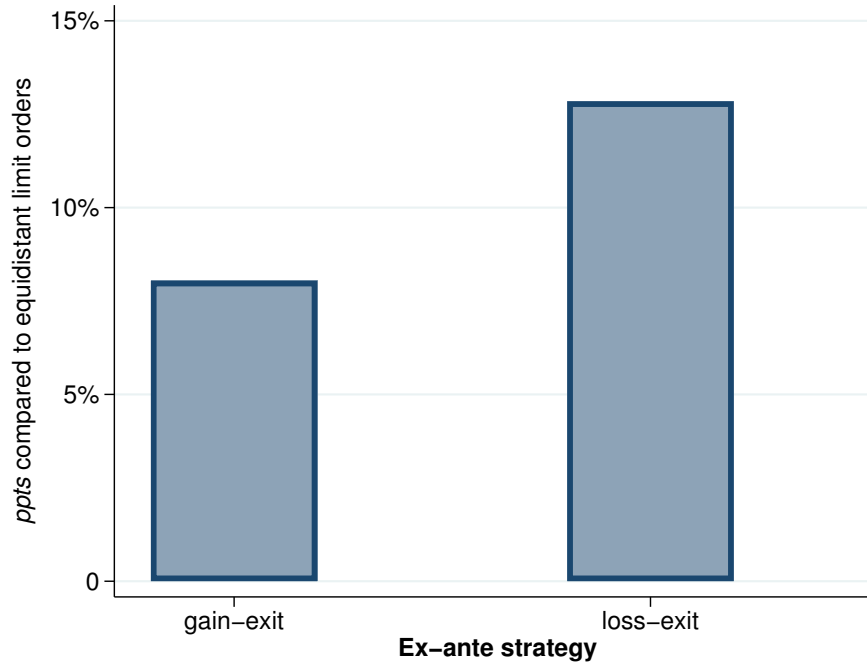
We define a strategy as the combination of a gain and loss limit order that traders submit when they initiate a position. Strategies are categorized as “loss-exit” (“gain-exit”) if the loss limit (gain limit) is closer to the reference level than the gain limit (loss limit). Strategies with loss and gain limits equidistant from the reference level are termed ‘neutral.’ We take the

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<sup>8</sup> These features distinguish the data set from others used in the literature (e.g., Barber and Odean (2001); Linnainmaa (2010)).

reference level to be the opening quoted price of the asset. This assumption is plausible because the brokerage displays position-level gains and losses relative to the opening quote.

The default limit order specified by the brokerage is the ‘neutral’ strategy of setting the loss and gain limits equidistant from the spot price—these constitute around 25% of all strategies. The majority of positions—40%—are opened as part of a “loss-exit” strategy. Figure 1 shows the distribution of ex-ante strategies relative to the ‘neutral’ strategy. The figure shows that the proportion of “loss-exit” strategies is significantly higher than the proportion of positions opened as part of a “gain-exit” plan (unless otherwise noted, all comparisons are significant at the  $p < .01$  level). Table I shows that traders’ propensities to employ “loss-exit” strategies is highly robust to the inclusion of a wide range of controls. The constant coefficient is reliably above 50%, and substantially so for some specifications. Panel A illustrates that trader characteristics, such as gender and host country, do not moderate the difference. Surprisingly, the propensity to use a “loss-exit” strategy increases as traders become more experienced. Panel B shows that the result is also robust to trade-based characteristics, such as the position’s leverage, direction, capital, and instrument.



**Figure 1. Ex-ante strategies** This figure illustrates the proportion of gain-exit and loss-exit strategies relative to the baseline ‘neutral’ strategy of setting equidistant gain and loss limits. A loss-exit strategy corresponds to a loss limit that is closer to the opening price than the contemporaneously submitted gain limit. A gain-exit strategy corresponds to a stop-loss limit that is further away from the opening price than the corresponding gain limit.

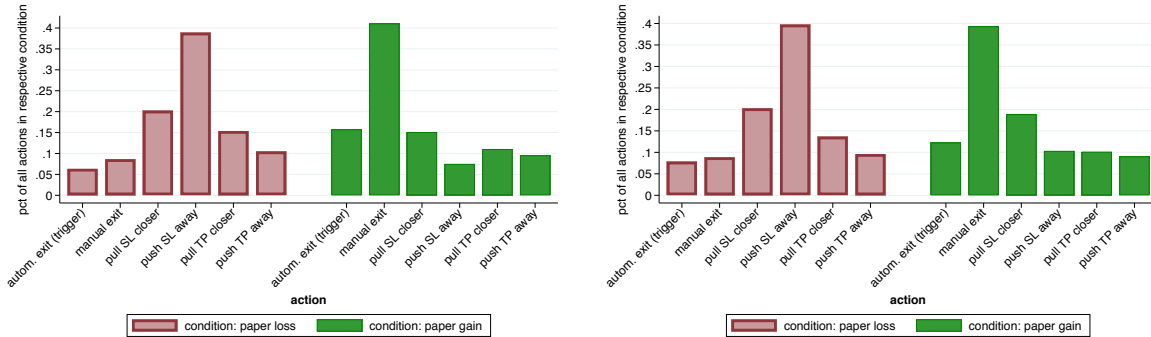
Figure 2 illustrates traders’ behavior in response to paper (i.e. unrealized) gains and loss.<sup>9</sup> Panel A of the figure displays the distribution of actions for all traders as a function of accumulating a (paper) gain on a position compared to accumulating (paper) loss. We find that the most frequent response to a paper loss is to revise the planned exit by lowering the loss limit, e.g. intending to limit losses to 10% but lowering it to 15%; downward revisions are nearly 20% more likely to be observed than the next most common choice. This is in contrast to behavior in response to a gain: when seeing a price increase, investors are most likely to manually close the position before the gain limit has been reached. Manually selling a winning

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<sup>9</sup> Gains and losses are evaluated in real-time using all trades on the online broker’s platform to estimate the bid and ask quotes of each underlying on a ten-minute frequency. The figure illustrates the distribution of different actions conditional on undertaking any action. This condition is necessary as we do not have any data on when traders are paying attention to their trading account.

position is nearly 25% more likely to be observed than the next most frequent action. These manual exits are rare for positions in the loss domain.

This pattern of results is also observed in the subsample of traders whose ex-ante strategies are categorized as “loss-exit.” As shown in Figure 2 Panel B, the pattern of ex post behavior in this sub-sample is the same as in the full sample: compared to their initial strategies, the majority extend their loss limits to allow for larger losses to accumulate and manually realize gains too early.



Panel A. All Positions

Panel B. Positions with loss-exit strategies

**Figure 2. Ex-post behavior** This figure illustrates the distribution of actions undertaken by traders in response to experiencing paper gains and losses. Paper gains and paper losses are calculated based on respective bid and ask prices constructed from the trading activity on the platform. Panel A shows the traders’ reaction to paper gains and paper losses in all positions. Panel B includes only positions that were started with a loss-exit strategies (i.e. initial loss limit closer to opening price than initial gain limit).

In sum, we find that traders allow larger losses to accumulate and realize gains too early compared to their initial “loss-exit” plans. These decisions result in a distribution of outcomes that skews in the *opposite* direction of traders’ original intentions.

### III. Experimental Design

Results from the field setting show a substantial discrepancy between people’s risk-taking intentions and actual behavior in dynamic settings. We developed an experimental design that allows us to identify whether this discrepancy is generated by an underlying dynamic

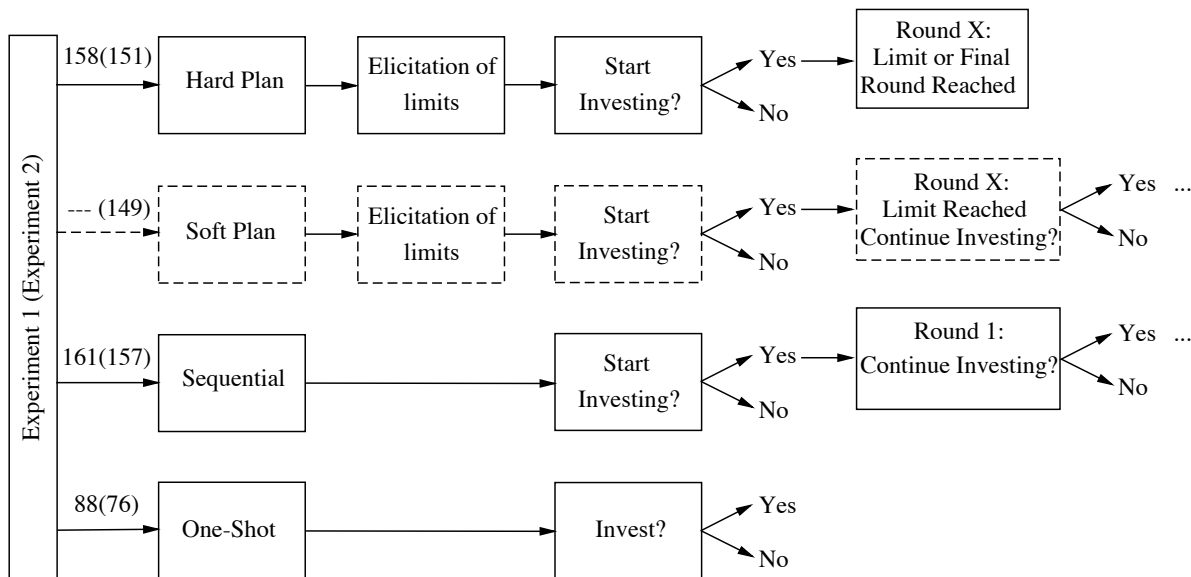
inconsistency, as well as formally test and distinguish between models of decision-making under risk. We conduct two preregistered experimental studies with a total of 940 subjects.<sup>10</sup> These experiments were designed to: (i) elicit incentivized initial strategies and compare them to subsequent behavior both within the same participant and across subjects, (ii) examine ‘entry’ decisions—the initial choice to take on risk or not, as a function of number of rounds and access to commitment devices, and (iii) study sophistication about dynamic inconsistency given the availability of ‘hard’ and ‘soft’ commitment devices.

Participants face binary choices of whether or not to invest a portion of their endowment in fair symmetric gambles that have an expected value of zero. Each gamble features a simple 50/50 chance that the investment either doubles or is lost. If the participant chooses not to invest, she keeps that portion of the endowment. We ensure that subjects understand the gamble by having them draw ten observations from a stratified sample before deciding (for the benefits of sampling for the understanding of probabilities see, e.g., Kaufmann, Weber, and Haisley (2013) and Hogarth and Soyer (2015)).

There are 3 (4) between-subject treatments in Experiment 1 (Experiment 2), as illustrated in Figure 3. Both experiments feature treatments with fewer rounds (one-shot) and treatments with multiple rounds. Experiment 1 has two multi-round treatments: a sequential treatment, in which participants begin taking on risk knowing that they will receive feedback after every round and adjust their choice accordingly, and a hard commitment treatment, in which participants commit to an ex-ante strategy. Experiment 1 allows us to test whether the decision to take on risk is affected by the number of prospective opportunities, test for dynamic inconsistency, and examine participants’ sophistication about it. Experiment 2 replicates the three treatments in Experiment 1, and includes a soft plan treatment which elicits participants’ ex-ante strategies similar to the hard commitment treatment but allows them to deviate after deciding to take on risk. This treatment tests for the effectiveness of a realistic, non-binding commitment device and participants’ sophistication about it.

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<sup>10</sup> Both experiments were preregistered: <https://aspredicted.org/blind.php?x=x954rp> and <https://aspredicted.org/blind.php?x=tn4dt4>.



**Figure 3. Experimental design and sample size.** This figure shows the experimental design of Experiments 1 and 2. The sample sizes in each between-subject treatment in Experiment 1 (Experiment 2) are displayed (in parentheses).

In the One-Shot treatment, participants receive an endowment of 10 cents and decide whether or not to invest in a single gamble. In the multi-round treatments (i.e., Sequential, Hard Plan and Soft Plan), participants face a sequence of the same investment decisions over a maximum of 26 rounds. This number of rounds was chosen for theoretical considerations as it allows us to differentiate between different models of dynamic decision-making under risk.<sup>11</sup> Each participant received an initial endowment of \$2.60 at the beginning of the experiment and decides whether to invest 10 cents in each round or to keep it, such that every investment decision was equivalent to the One-Shot treatment.<sup>12</sup> Once the participant chooses to stop

<sup>11</sup> As initially outlined in Barberis (2012) and discussed further in the Appendix, 26 is the number of rounds where, for a representative agent, Cumulative Prospect Theory can be differentiated from other models of decision-making. Previous experimental studies by Andrade and Iyer (2009) and Barkan and Busemeyer (1999) analyze dynamics of risk-taking over only two rounds, where the initial choice to gamble is either coerced or forced. This number of rounds is insufficient to distinguish between different theories of decision-making.

<sup>12</sup> In order to rule out that differential endowments would drive differences in entry rates between treatments, we ran a separate study with the One-Shot treatment as described here, a modified One-Shot treatment, and the Hard Plan treatment. In the modified One-Shot treatment, participants were given a \$2.60 initial endowment as in the multi-round treatment, but made the same single investment decision as in the original One-Shot treatment. Results, which



investing, she cannot re-enter and the main part of the experiment is over.

In the Sequential treatment, participants made decisions round by round with feedback on the previous outcome (gain or loss) in between. Specifically, each participant first decided whether or not to invest in the first round; we refer to this as the ‘entry’ decision. If she decides to invest, the outcome for the first round is revealed and she decides whether or not to invest in the next round, and so forth. Participants are informed about the total gains or losses they have accumulated since the beginning alongside the outcome of the last round.

The Commitment treatments have the same structure as the sequential treatment. The main difference is that participants first enter their desired risk-taking strategy before making the ‘entry’ decision. Strategies are elicited by asking participants to indicate their gain limit (i.e., minimum gain where they would prefer to stop gambling rather than continue) and loss limit (i.e., maximum loss where they would prefer to stop gambling rather than continue). After entering both limits, participants decided whether or not to begin taking risk. In the Hard Plan treatment, each was informed that she would automatically stop investing if either one of her limits is triggered—hence, the limits correspond to a binding commitment device. In the Soft Plan treatment, participants are informed that they will be notified as soon as either one of their limits is triggered and would then have the chance to decide whether or not to continue investing; hence, their limits correspond to a non-binding commitment device. Should the participant decide to continue investing, she will be notified again in every round when either one of her limits is triggered. The limits cannot be revised for the entire duration of the experiment.<sup>13</sup>

We choose a fair gamble to further distinguish our dynamic setting from research on how differential timing of feedback affects risk-taking, such as in the studies examining myopic loss

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are described in the Appendix, are unchanged: entry rates in both One-Shot treatment were lower than in the Hard Plan treatment. If anything, entry rates in the modified One-Shot treatment were lower than in the original where participants had a lower endowment.

<sup>13</sup> Fischbacher, Hoffmann, and Schudy (2017) propose optional and amendable gain and loss limits as an intervention to reduce the disposition effect. In contrast to the previous study, the limits in our experiments are not optional to prevent any selection effects and cannot be revised to ensure that they accurately measure participants’ ex-ante strategies.

aversion. In these studies, participants make risky choices over positive expected-value gambles either individually or in blocks. In the former treatments, feedback is provided after every decision and participants can revise their next choice accordingly; in the latter treatments, choices within a block cannot be revised and only cumulative feedback across decisions within a block is provided (Gneezy and Potters (1997); Benartzi and Thaler (1995)). Since the expected value of each gamble is positive, presenting cumulative feedback leads to a greater likelihood that the participant sees a positive outcome than if feedback is presented after every round. The authors explain this result through loss aversion and narrow bracketing: a loss-averse individual would prefer to avoid seeing negative information, so the gambles with cumulative feedback are more attractive. This mechanism can explain the Samuelson paradox where a person would reject a single positive expected-value gamble but be willing to accept multiple plays (Samuelson (1963)). However, this mechanism cannot explain any differences in willingness to accept a *fair* gamble in isolation versus as part of a sequence in our setting. First, feedback is provided after every round. Moreover, even if only cumulative feedback was provided, investing in fair gambles for a fixed number of rounds does not increase the probability of seeing a positive cumulative outcome compared to a single play; rather, it generates greater variance without providing a greater risk premium.

Both experiments were conducted online on Amazon’s Mechanical Turk in four batches to isolate potential day-of-week effects. Participants in Experiment 1 were excluded from the subject pool for Experiment 2. Both experiments consist of an entry-level questionnaire that elicits demographic characteristics (e.g., age, gender, highest level of education) as well as self-reported level of statistical skills. After the main task, participants complete an exit-level questionnaire that elicits other control variables <sup>14</sup> Fewer than 5% of participants exited the experiment after being randomized into treatment, hence there is little room for selective attrition. Table II presents participant demographics. Except for participants in Experiment 2 reporting higher perception of their own statistical skills, there are no significant differences in demographic characteristics between Experiments 1 and 2.

[INSERT TABLE II ABOUT HERE]

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<sup>14</sup> A list of all variables included in the paper is provided in Appendix B.

## IV. Theoretical Predictions

Note that, by design, the only way for subjects to achieve a skewed outcome distribution is through an outcome-dependent dynamic strategy. This is because gains and losses in the individual rounds are linearly compounded, which is why investing longer would not result in a positively skewed outcome distribution.

In this section, we provide the intuition for the dynamic predictions of Cumulative Prospect Theory (CPT) in our setting. Appendix A presents the formal derivation and compares them to the predictions of other models of dynamic choice under uncertainty, such as Rank Dependent Utility (RDU) and Expected Utility Theory (EUT). As discussed further in Section VII, models that microfound gain-loss asymmetry and probability weighting through specific psychological mechanisms, such as salience theory (Bordalo, Gennaioli, and Shleifer (2012)) and efficient coding (Frydman and Jin (2019)), would make similar predictions in our setting.

How does CPT rationalize risk-taking when there is no risk premium in the single gamble? When considering sequential choices, the decision-maker evaluates which strategy is most attractive in expectation. Strategies are evaluated as a function of the initial choice and the future choices she is planning to make in response to realized outcomes. For example, a trader may follow a “loss-exit” strategy, where she initially invests in a stock, reinvests if its price increases by 10 percent, and closes the position if its price falls by 5 percent ((Barberis, 2012)); she may decide differently—e.g., not invest at all—if the subsequent investment opportunities were not available. Compared to a “gain-exit” strategy or any outcome-independent strategy, a “loss-exit” plan generates greater positive skewness in the probabilities over final outcomes; “loss-exit” plans can even create positive skew when each individual gamble has no skew at all.

To illustrate the intuition, consider a decision-maker facing a sequence of fair gambles. She makes a choice to accept or reject the first gamble as part of a strategy. A strategy that does not depend on prior outcomes generates the same level of skew over final wealth as the individual gamble; on the other hand, a “loss-exit” plan—exiting earlier after losses than after gains—generates a positive-skewed lottery over final wealth. For example, a “loss-exit” strategy over two 50:50 gambles, each with an upside of  $G$  and downside of  $-G$  generates the following

lottery over final wealth,  $(2G, 1/4; 0, 1/4; -G, 1/2)$ . This lottery has substantially more positive skew than the single gamble, or a non-contingent strategy of accepting both gambles regardless of outcome,  $(2G, 1/4; 0, 1/2; -2G, 1/4)$ .

Even though the strategy does not change the expected value of the outcome distribution, which remains zero, the transformed skewness of the outcome distribution does make it more attractive to those who prefer positively skewed risk. There is substantial evidence that, holding other things constant, people are more willing to accept risk as it becomes more positively skewed (Dertwinkel-Kalt and Köster (forthcoming); Dertwinkel-Kalt, Frey, and Köster (2020); Eraker and Ready (2015)). This phenomenon has typically been explained either through non-increasing absolute risk aversion in Expected Utility Theory (Kraus and Litztenberger (1976); Arditti (1967)) or through non-linear probability weighting which leads to the overweighting of small likelihoods—one of the main components of CPT (e.g., Barberis and Huang (2008)). In turn, accepting the gamble as part of a “loss-exit” plan with the option—but no obligation—to take on a second gamble is more attractive to an individual with CPT preferences than accepting the gamble in isolation: the “loss-exit” plan generates a low likelihood of a large gain while limiting the potential downside. This generates the following predictions for our experimental setting:

***Prediction 1:*** *The decision-maker is more likely take on risk when it is part of a sequence of gambles than if the same gamble is presented in isolation.*

By design, the only way for participants to achieve a skewed outcome distribution is through an outcome-dependent dynamic strategy. This is because gains and losses in the individual rounds are linearly compounded, which is why investing longer would not result in a positively skewed outcome distribution. Our second prediction follows.

***Prediction 2 :*** *The decision-maker takes on risk as part of an ex-ante “loss-exit” strategy, where the loss limit is smaller than the corresponding gain limit.*

Importantly, CPT also generates a dynamic inconsistency between a person’s ex-ante strategy and actual behavior once she starts taking on risk. Standard models of risky decision-making such as EUT assume that, all else equal, people will stick to their contingent strategies after

seeing the realized outcomes: the trader who plans to sell after a loss and double down after a gain will stick to this strategy. In contrast, diminishing sensitivity of the value function—which generates risk-seeking in the loss domain and risk-aversion in the gain domain—leads a decision maker with CPT preferences who accepts the first bet as part of a “loss-exit” strategy to systematically deviate from this plan by stopping too early after winning and continuing on too late after losing (relative to her plan). To illustrate the intuition, consider what happens after seeing a gain. The plan that involves accepting the next gamble does not generate as much positive skewness as the one which included the previous gamble because there is one less round to play and the skewness depends on the number of outstanding rounds. In the above example, the decision-maker is now looking at a prospect with even odds. Since the skewness decreases sequentially round by round and the agent is risk-averse in the gain domain, she will eventually deviate from her plan to stop taking on risk. After losing, the decision-maker faces the choice of accepting the loss with certainty or potentially compensating for it by continuing to take on risk. Risk-seeking in the loss domain predicts that she will chase her losses and accept more risk.

***Prediction 3*** : *The decision-maker’s ex-post behavior will exhibit a “gain-exit” strategy, exiting earlier after gains than after losses.*

As we formally demonstrate in Appendix A, we also show that the specific pattern of dynamic inconsistency—“loss-exit” strategy and “gain-exit” behavior—is uniquely predicted by a model with gain-loss asymmetry and probability weighting, such as CPT. Specifically, we first show that such dynamic inconsistency is not predicted by Expected Utility Theory, which does not incorporate probability weighting. Consistent with our results Barseghyan et al. (2013) find that probability weighting plays a key role in explaining the risky choice of deductibles in households’ insurance contracts. Second, we show that probability weighting alone does not suffice as RDU, which only features non-linear probability weighting, cannot rationalize our experimental findings.

Finally, the framework also makes predictions on how awareness of dynamic inconsistency will affect behavior. Sophisticated individuals will only accept the first gamble if provided with an opportunity to commit to their strategy; naïve individuals will be equally likely to accept

the first gamble in a sequence whether or not they have a commitment opportunity. Standard models in decision theory predicts no such demand for commitment: in a market setting, a trader who is dynamically consistent will take on the same amount of risk regardless of whether she can commit to this plan through, for example, a stop-loss or take-profit order, or not. This generates our final prediction.

**Prediction 4** : *Sophisticated decision-makers will be more likely to accept risk when given the opportunity to commit to an ex-ante strategy.*

We do not make any explicit predictions on differences between the Hard Plan and the Soft Plan treatments, as this depends on participants' sophistication about the efficacy of 'soft commitment' devices. We now proceed to present our empirical findings and compare them to these predictions.

## V. Experimental Results and Discussion

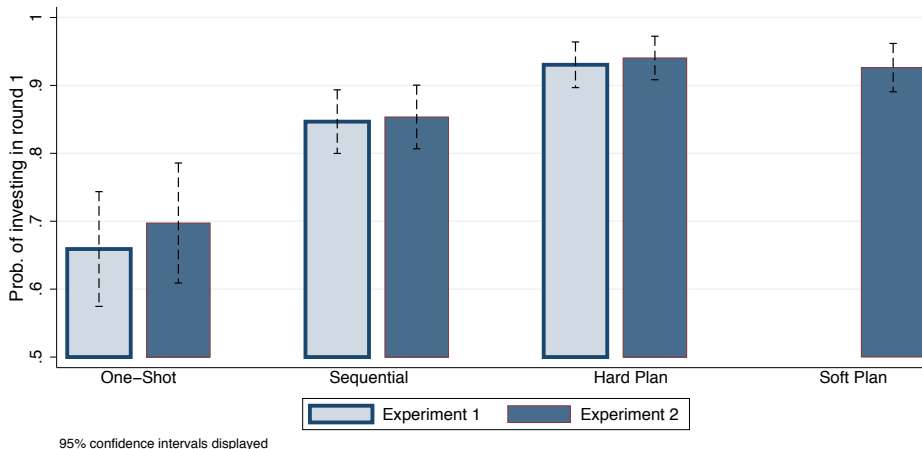
### A. Accepting a Fair Gamble (Entry Decision)

We begin by examining participants' initial willingness to accept risk, i.e., the *entry decision*. First, we aim to learn whether participants are more likely to take risk if it is part of a dynamic sequence of choices. Second, we look at whether participants accept risk as part of a "loss-exit" ex-ante strategy as in the field setting, or whether other strategies are predominant. Third, we analyze whether participants value the availability of a commitment device, which would provide the first piece of evidence for potential dynamic inconsistency and the extent of their sophistication about it. Finally, we examine potential differences between binding and non-binding commitment devices.

Consistent with Prediction 1, we find that participants are more likely to accept the fair gamble as part of a sequence than in isolation once. Figure 4 displays the proportion of participants who accept risk in the first round across each of the treatments. We see that the entry rate is substantially lower in the One-Shot treatment compared to any of the multi-round

treatments. Table III, Panel A, displays the marginal fixed effects (mfx) of Probit regressions of the binary entry decision across both Experiment 1 and 2. The main independent variables are dummy variables for each of the multi-round treatments (i.e., Sequential, Hard Plan and Soft Plan treatments). The mfx measures the difference between the probability to accept the gamble in the respective multi-round treatment compared to the One-Shot treatment, which is the reference treatment in Panel A. We display all regressions with and without demographic control variables.

Differences between the multi-round and the One-Shot treatments are all significant at the 1% level in both experiments. It is important to note that, by design, taking the fair gamble many times does not result in a higher expected value nor a lower probability of experiencing losses. Thus, the higher tendency to accept risk for multiple rounds cannot be explained by loss aversion and narrow bracketing, as in the case of positive-expected-value gambles (see, Gneezy and Potters (1997)). As outlined in Section IV and Appendix A, these differences cannot be explained by EUT with skewness preferences because at any level of risk-aversion, agents would not accept the one-shot nor the multi-round gamble. RDU can only explain this result under the assumption that participants' wealth levels outside of the experiment are very low. Assuming realistic levels of wealth would lead participants to accept the gamble independent of whether it is one-shot or multi-round.



**Figure 4. Entry decision.** This figure shows the percentage of participants in each treatment who accept risk in the first round.

[INSERT TABLE III ABOUT HERE]

Second, we find that participants are more likely to accept the multi-round fair gamble if they can commit to an ex-ante strategy. This result is demonstrated in Figure 4 and Table III, Panel B. The latter presents the marginal fixed effects (mfx) of Probit regressions of the binary entry decision excluding the One-Shot treatment; the reference treatment is the Sequential treatment, in which participants do not report their ex-ante strategy and can revise their choices round by round. Consistent with our fourth prediction, we find that participants are significantly more likely to initially accept risk if they can commit to an ex-ante strategy with a binding commitment device. Notably, entry rates are also higher in the Soft Plan treatment. We discuss the implications of this latter result in the next subsection.

One alternative explanation is that the complexity of the main task differs between the commitment treatments and the sequential treatment. In particular, since the commitment treatments restrict the strategy-choice set to strategies that can be described by a pair of limits, it may be the case that the perceived task-complexity is lower than the task-complexity of the sequential treatment, and may explain why subjects in the commitment treatments have a higher tendency to enter. To test this claim, in Experiment 2 we elicit the perceived complexity of the main task using the four-item score of Maynard and Hakel (1997). In contrast to this explanation, we find that perceptions of complexity, if anything, go in the opposite direction. A related alternative explanation is that the higher entry rate in the commitment treatments is due to decision aversion as the number of decisions to be made in those treatments (i.e., 3) is on average smaller than the number of decisions in the sequential treatment. However, if decision aversion was driving differences in initial risk-taking, we should have seen the highest entry rates in the One-Shot treatment, which is not the case.

### *B. Dynamics of Risk Taking: Ex-Ante Exit Plan versus Ex-Post Behavior*

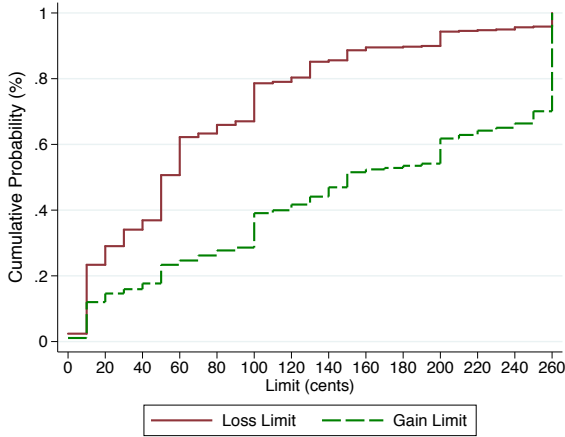
In this section, we examine what dynamic strategies participants choose ex-ante. We then examine whether participants are dynamically inconsistent by looking at their ex-post behavior in the absence of a commitment device. The specific pattern of deviations allow us to distinguish



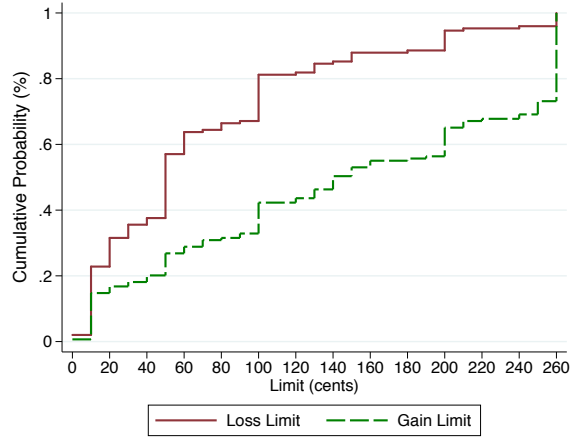
between different theoretical explanations. Specifically, if the majority of participants deviate from an ex-ante “loss-exit” strategy by following a “gain-exit” strategy ex-post (Predictions 2 and 3), this would provide strong evidence in favor of CPT. In the subsections that follow, we analyze the ex-ante strategies and the ex-post behavior both in a between-subject setting (i.e., by comparing the Sequential and the Hard Plan treatments) and in a within-subject setting (i.e., ex-ante versus ex-post behavior in the Soft Plan treatment).

### *B.1. Ex-Ante Strategies*

Figure 5 illustrates the cumulative distribution of gain and loss limits in our sample. Panel A reports results from the Hard and Soft Plan treatments across both experiments, whereas Panel B displays only the limits from the Soft Plan treatment. The differences in loss and gain limits are striking: the distribution of gain limits first-order stochastically dominates the distribution of loss limits. Table IV further shows that the average participant who accepts the initial gamble sets a gain limit that is 3.81 times higher than her loss limit. This corresponds to an average difference that is more than 30% of the total endowment. Participants can be classified according to their ex-ante strategy as “loss-exit” (i.e., loss limit closer to the reference level than gain limit), “gain-exit” (i.e. gain limit closer to the reference limit than loss limit), or neutral “symmetric” (both limits are equidistant). The table shows that the overwhelming majority of participants (80.8%) begin taking risk as part of a “loss-exit” strategy, whereas only 7% do so as part of a “gain-exit” strategy.



Panel A. All Subjects



Panel B. Soft Plan Treatment (Exp. 2)

**Figure 5. Ex-ante strategy.** This figure illustrates participants’ strategies in the Hard Plan and Soft Plan treatments. It shows the cumulative distribution of loss and gain limits. Panel A reports results from both experiments and commitment treatments. Panel B reports results from the Soft Plan treatment only.

[INSERT TABLE IV ABOUT HERE]

The prevalence of the loss-exit strategy leads to a positive skewness (0.31) of the expected final outcome distribution, as shown in Table IV. To calculate this number, we run 100,000 independent outcome paths for each participant in our sample and determine the individual expected final outcome distributions, which we then aggregate to form the expected final outcome distribution of the representative participant. Note that a positive skewness, by design, can only result from an outcome-dependent dynamic strategy, as we use a symmetric gamble and the outcomes are linearly compounded across rounds. The skewness of the realized outcome distributions of final outcomes in the Hard and Soft Plan treatments is close to the skewness of the expected outcome distributions—between 0.247 and 0.471. In Table V, we report the skewness of the realized outcome distribution among all participants in the Hard and Soft Plan treatments (Panel A), only amongst those who enter (Panel B), and the hypothetical outcome distribution if participants in the Soft Plan treatment would have stuck to their ex-ante strategies (Panel C). In all cases, skewness is positive and statistically significant at the 5% level. The table further shows that skewness in the Sequential treatment is close to zero and not statistically significant at the 10% level, unlike skewness of outcomes generated by ex-ante strategies in the Hard and

Soft Plan treatments. Importantly, we find that the *actual* outcome distributions of participants in the Soft Plan treatment does not exhibit any significant skewness, in contrast to the outcome distributions generated by their ex-ante strategies. These results suggest that within-subject behavior of those in the Soft Plan treatment deviates from their desired “loss-exit” strategies. In the following subsection, we explore this deviation in greater detail.

[INSERT TABLE V ABOUT HERE]

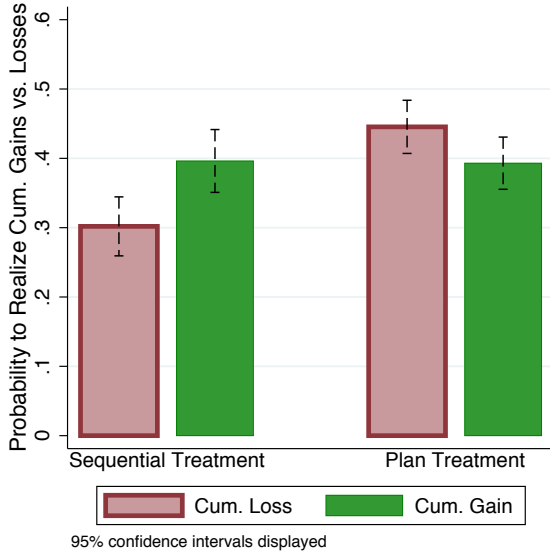
### B.2. *Ex-Post Behavior*

We now proceed to analyze the ex-post behavior and compare it to participants’ ex-ante strategies. In particular, we study whether participants’ ex-post decisions are outcome-specific (i.e., different after gains versus losses) and whether this asymmetry is consistent with their ex-ante “loss-exit” plans.

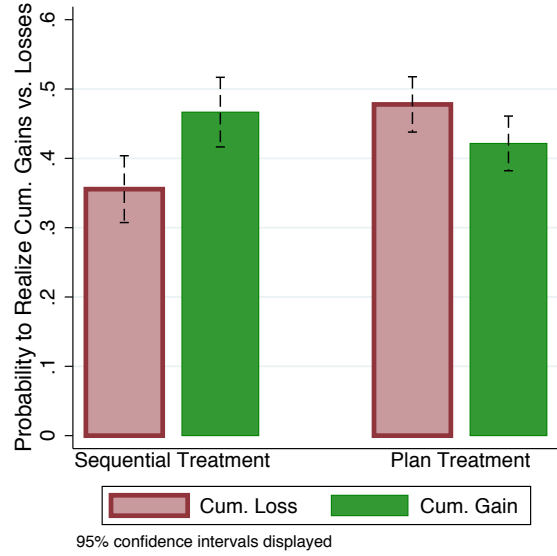
First, we analyze the probability of exiting after gains versus losses in the Sequential treatment. Figure 6 shows that participants in the Sequential treatment are more likely to end up with a cumulative gain than a cumulative loss even though the gamble is symmetric (Panels A and B). This is partly due to participants being 20 percentage points more likely to stop taking risk if the outcome of the first round is a gain than a loss (Panel C). Behavior in the first round represents direct causal evidence of losses increasing the likelihood of taking on risk because the outcome after the first round is random and thus orthogonal to any subsequent choices. This is consistent with our third prediction that participants’ ex-post behavior will follow a “gain-exit” strategy.

Critically, the “gain-exit” ex-post strategy is the reverse of the one implied by participants’ ex-ante strategies, implying a dynamic inconsistency between planned and actual behavior. Table VI, Columns (1) and (2), compare the probability of realizing a cumulative gain versus a cumulative loss. The table displays the marginal effects of Probit regressions with and without demographic controls and with cluster-robust standard errors. We find that the probability of realizing a cumulative gain is 8.9 - 9.8 percentage points higher in the Sequential treatment than

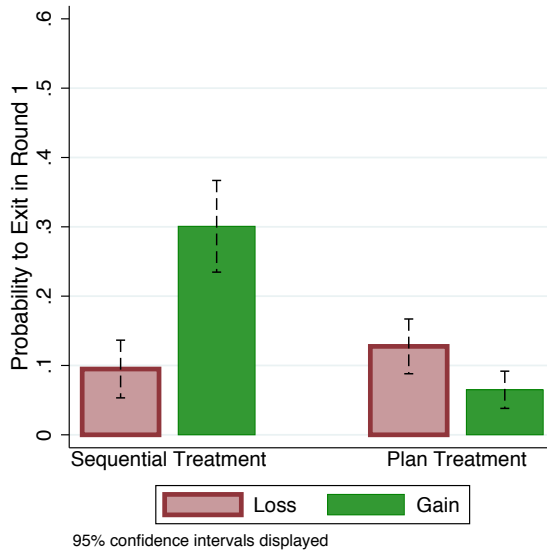
in the outcomes generated by participants' ex-ante strategies. The cleanest test for dynamic inconsistency comes from comparing ex-ante strategies to behavior after feedback in the first round—before endogenous exit decisions have a chance to accumulate. Here, the decision to exit can be conditioned on the simple chance outcome of experiencing a gain or a loss. Table VI, columns (3) and (4), displays these results using OLS regressions with main effects of the Sequential treatment compared to the commitment treatments, a Gain dummy, and the treatment-outcome interaction. The analysis shows that the higher probability of exiting after a gain than a loss represents a substantial deviation from participants' ex-ante strategies in response to first round outcomes. The difference, as measured by the interaction term, is statistically significant at the 1% level. This presents direct evidence for dynamic inconsistency in risky choice (Prediction 4).



Panel A. All Participants



Panel B. Participants Who Enter

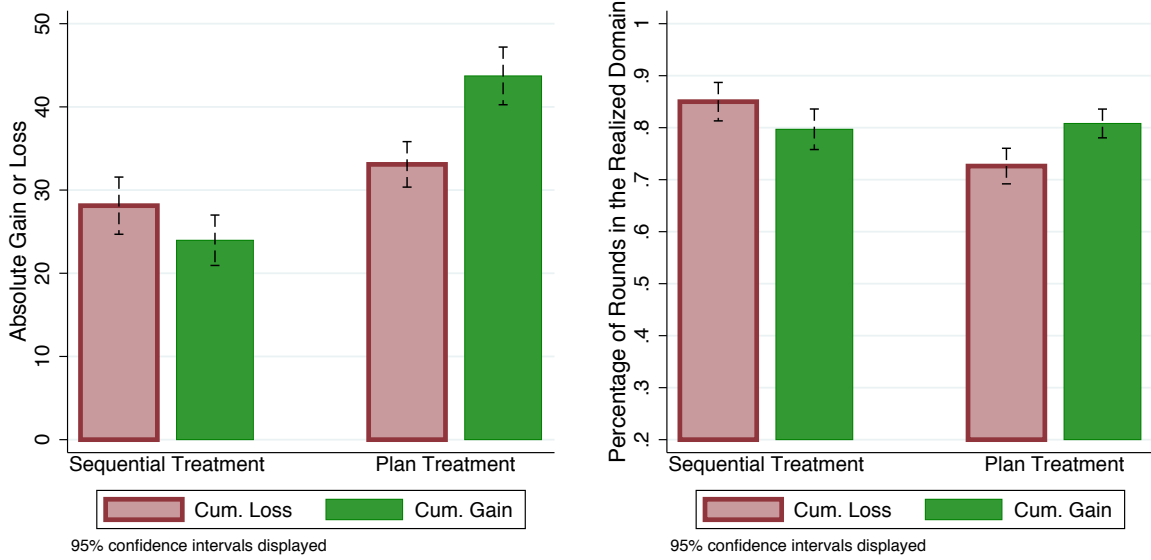


Panel C. Round 1 Exit

**Figure 6. Probability of realizing a gain versus loss — ex-ante versus ex-post.** This figure illustrates the ex-post behavior in the Sequential treatment compared to the ex-ante strategies in the commitment treatments as a function of prior gains and losses. The commitment treatments includes the hypothetical cumulative outcomes of the participant in the Soft Plan treatment. Panel A shows the percentage of participants who earn a cumulative gain versus a cumulative loss across Experiments 1 and 2. Panel B excludes participants who choose not to enter. Panel C shows the percentage of participants who enter and then stop investing after feedback in the first round.

[INSERT TABLE VI ABOUT HERE]

It is important to note that a higher probability of realizing gains does not imply that participants in the Sequential treatment earned more money on average—in fact, the opposite is true. As the gamble is fair and the individual draws are iid, participants can only achieve a higher probability of gains if they cut their gains early and chase their losses longer, thus earning small gains and accumulating large losses. Figure 7 shows that this is indeed the case in our data. It compares the absolute cumulative gains and the absolute cumulative losses in the Sequential treatment and the commitment treatments (Panel A). It further shows what percentage of rounds participants are willing to experience gains versus losses before rejecting further risk. For both measures, the pattern between gains and losses in the Sequential treatment is the reverse of the one in the commitment treatments. In the commitment treatments, participants leave more room for large gains and restrict the scope of their losses (Panel A). To achieve that, they allow for larger gains to accumulate compared to losses, which are cut sooner (Panel B). Table VII shows that the difference-in-difference in both measures is statistically significant at the 1% level, providing evidence that the dynamic inconsistency between planned and actual behavior is potentially costly in a financial sense.



Panel A. Absolute Cum. Gains/Losses

Panel B. Realization Reluctance

**Figure 7. Cummulative Gains and Losses— ex-ante versus ex-post.** This figure illustrates differences in the outcomes and behavior between participants who realize a cumulative loss versus gain in the commitment versus sequential treatments (ex post) across Experiments 1 and 2. The commitment treatments includes the hypothetical cumulative outcomes of participants in the Soft Plan treatment; hence in case the participant deviates from her plan we replace the actual outcome with the outcomes at the point of time when her limits were first triggered. Panel A shows the absolute cumulative gains/losses in Sequential versus commitment treatments. Panel B illustrates differences in participants’ reluctance to realize their final cumulative outcome as measured by the percentage of rounds the participants’ cumulative gain has been in the domain that they ended up realizing.

[INSERT TABLE VII ABOUT HERE]

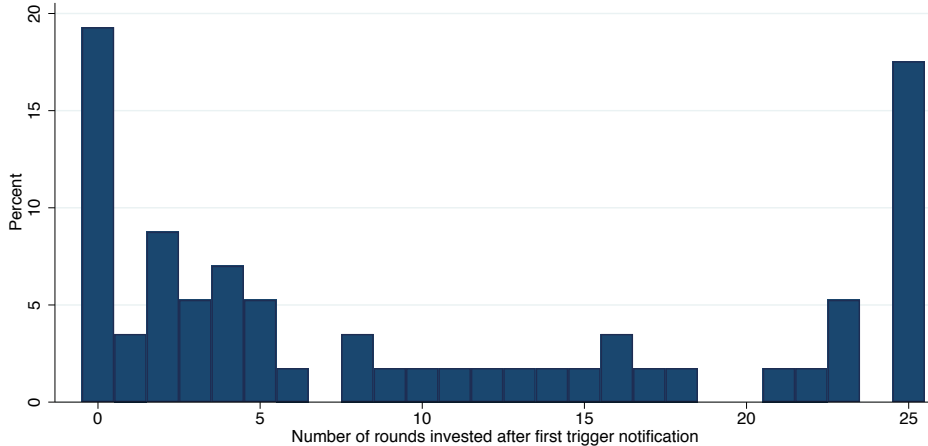
Critically, the ex-post deviation is also present in the Soft Plan treatment, where participants are allowed to revise their decisions after being notified that a limit has been reached. From the 57 participants whose limits were triggered, 80.7% decide to continue investing and thus deviate from their ex-ante strategies, as shown in Figure 8. The majority (70.2%) of the triggered limits are loss limits.<sup>15</sup> Strikingly, the most common type of deviation is to do so from the beginning until the end, thus repeatedly revising the ex-ante strategy. This pattern replicates the findings from the field, where people are significantly more likely to revise their

<sup>15</sup> This should be expected given that most participants set loss limits closer than the gain limits.

loss limit down compared to their gain limits.

Going back to the decision to take on risk, the difference in entry rates between the commitment and Sequential treatments suggests that participants are at least partially sophisticated about their dynamic inconsistency. However, people may be aware of their dynamic inconsistency but ignorant about the efficacy of soft commitment for restraining future deviations. To measure the scope of sophistication across both domains, we examine entry rates under binding and a non-binding commitment opportunities. Figure 4 and Table III, Panel B, show that a non-binding commitment opportunity also significantly increases the likelihood that participants accept initial risk. The entry rate for non-binding commitment is roughly the same as with binding commitment (the difference is not significant at the 10% level). However, as shown here, soft commitment is not effective in mitigating dynamic inconsistency. Non-binding commitment is frequently offered in many real-world settings. For instance, traders in our field setting can revise their loss and gain limits to prevent them from triggering. Similarly, the recently introduced MiFID II regulation in Europe requires that advisors and portfolio managers inform their clients immediately in case their portfolio depreciates by more than 10% from the beginning of the quarter (i.e., depreciation reporting). Such reporting rules can be viewed as non-binding commitment devices: they correspond to a particular type of dynamic strategy, namely to take action in case of a loss, that the investor may ex-ante intend to follow but fail to execute ex-post. Whether such real-world commitment devices have unintended, adverse effects on risk-taking behavior depends on whether people believe that the devices are effective in disciplining ex-post behavior. Our results on entry decisions suggest that people presume that non-binding commitment is similarly effective as binding commitment, which does not seem to be the case.





**Figure 8. Deviations in Soft Plan treatment** This figure shows the sample distribution of the duration of investment (in rounds) after a limit has been triggered for the first time. The data for this figure consists of 57 observations of participants in the Soft Plan treatment whose limits are triggered during the experiment. A duration of zero indicates that the participant sticks to her ex-ante plan. The maximum duration is 25 rounds.

The presented patterns of deviations allow us to distinguish between different theoretical explanations for the observed dynamic inconsistency. Taken together, our findings are most consistent with the predictions of CPT. The theory predicts that agents with an ex-ante “loss-exit” plan (majority of our sample) will exhibit “gain-exit” behavior ex post. This prediction is unique to CPT, as RDU predicts that representative agents will end up taking risk until the end, independent of the outcome. This runs counter to our findings, as outcome valence (gain versus loss) causally affects participants’ decision to continue taking on risk.

## VI. Welfare Implications

In the following, we discuss welfare implications of the observed dynamic inconsistency in risky choice. To this end, we rely on the CPT model as its predictions are most consistent with our empirical findings. In the CPT framework, being dynamically inconsistent results in two types of potential welfare losses, which affect naïve and sophisticated agents differently. Some naïve agents begin investing because of a mistaken belief that they will stick to their

ex-ante strategy. For sophisticated agents aware of their dynamic inconsistency, the utility of investing in the first gamble is lower than rejecting it. As a result, naïve agents who accept the gamble and deviate from their intended strategy incur a larger welfare loss compared to sophisticated agents, who reject the gamble from the beginning. We refer to this form of welfare loss as the *cost of naïveté*. Both naïve and sophisticated agents can potentially incur another type of welfare loss, which stems from the opportunity cost of not having access to binding commitment opportunities. For dynamically inconsistent agents, binding commitment is the only method of implementing their ex-ante utility-maximizing strategy. We refer to the utility difference between implementing the preferred ex-ante strategy through binding commitment and rejecting risk due to a lack of commitment opportunities as the *value of commitment*. We now proceed to employ the CPT framework to capture these two types of welfare.

We measure the welfare loss resulting from dynamic inconsistency for our experimental setting in which the distribution of the gamble and the maximum length of the sequence is known. Utility is calculated for sets of CPT parameters  $\{\alpha, \delta, \lambda\}$ , where  $\alpha$  corresponds to the diminishing sensitivity parameter,  $\delta$  corresponds to the probability weighting parameter, and  $\lambda$  corresponds to loss aversion. To measure welfare, for every set of CPT preference parameters we calculate the certainty equivalent of the aggregate outcome distribution resulting from the ex-ante strategy and the ex-post behavior, respectively. Outcome distributions are obtained from simulations as described in Appendix A, where the one-round investment amount is a numeraire. Hence, certainty equivalents are measured as multiples of the one-round investment amount. We refer to a CPT agent with preference parameters  $\{\alpha, \delta, \lambda\} = \{0.88, 0.65, 2.25\}$ —median estimates from Tversky and Kahneman (1992)—as a ‘representative agent.’

Figure 9 reports the certainty equivalents of the ex-ante strategy (i.e., value of commitment) and the ex-post behavior (i.e., cost of naïveté). Loss aversion is taken as fixed at the ‘representative’ level of 2.25, while levels of probability weighting and diminishing sensitivity are allowed to vary. A positive value in Panel A indicates how much a sophisticated agent would be willing to pay for a binding commitment device which guarantees execution of her ex-ante strategy.<sup>16</sup> Agents with stronger skewness preferences (i.e., lower  $\delta$ ) and higher sensitivities (i.e.,

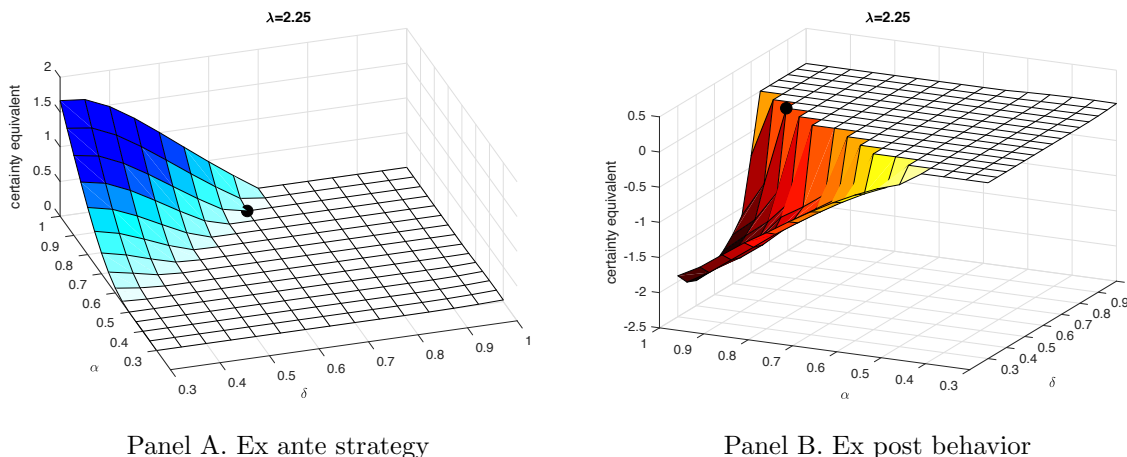
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<sup>16</sup> Note that the value of commitment for the ‘representative agent’ is close to zero by construction. This is because the maximum number of rounds was deliberately chosen such that this agent would be close to indifferent between

higher  $\alpha$ ) than the ‘representative agent’ would be willing to pay up to 166% of the one-round endowment depending on the parameter combination. In the absence of a commitment device, both naïve and sophisticated agents incur a welfare loss corresponding to the value of commitment reported in Panel A. Naïve agents incur another potential welfare loss because they are unaware of their inability to implement their ex-ante strategy and accept the initial gamble rather than rejecting it. These costs of naïveté are illustrated in Figure 9, Panel B. Notably, all CPT agents who would optimally select a “loss-exit” strategy incur costs of naïveté as indicated by the negative certainty equivalents for all parameter combinations with high skewness preferences and low sensitivity. Around the parameter region of the representative agent, the costs of naïveté are over 110% of the one-round endowment amount. Importantly, the costs of naïveté are even higher for CPT agents with greater probability weighting and lower sensitivity. Depending on the parameter combination, a CPT agent may incur a cost that corresponds to a certain loss of up to 208.5% of the one-round endowment. As discussed further in the next Section, the relationship between probability weighting and naïveté is important from a policy perspective—a positive relationship would imply that those who bear the highest costs of dynamic inconsistency are also the ones most prone to it.

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accepting or rejecting the first gamble ((Barberis, 2012))



**Figure 9. Welfare implications of dynamic inconsistency: value of commitment and costs of naïvete.** This figure illustrates the certainty equivalent of agents with CPT preferences with different levels of probability weighting ( $\delta$ ) and diminishing sensitivity ( $\alpha$ ), i.e. the extent to which agents are risk-averse in the gain domain and risk-seeking in the loss domain. Loss-aversion is taken as fixed at  $\lambda = 2.25$ , corresponding to the ‘representative’ level as estimated by Tversky and Kahneman (1992). The certainty equivalent is measured as a multiple of the one-round investment amount (which corresponds to  $1/26$  of the total endowment). Panel A reports the certainty equivalents of the outcome distribution which would be generated by the agent’s ex-ante plan. It can be interpreted as the *value of commitment* from the point of view of a sophisticated agent, who would begin taking risk if she could commit to her ex-ante strategy, and would reject risk otherwise. Panel B reports the certainty equivalent of the ex-post outcome distribution. It can be interpreted as *costs of naïvete* that agents endure if they begin to take on risk without a commitment device as opposed to rejecting it.

Note that whether a participant incurs costs of naïveté also depends on the type of commitment device that is available. People may be sophisticated about their dynamic inconsistency but naïve about the effectiveness of soft commitment in disciplining behavior. The results in Section V suggest that a substantial number of participants are sophisticated about dynamic inconsistency but fail to appreciate the difference between hard and soft commitment. When assessing welfare, the introduction of soft commitment devices may thus lead a significant proportion of people to incur significant cost of naïveté. Hence, regulation that introduces soft commitment devices in dynamic risky environments should consider these potential costs.

## VII. Discussion

In this Section, we discuss the relationship between sophistication and probability weighting and consider the theoretical implications of the planning horizon.

### *A. Probability Weighting and Sophistication*

As noted in the previous Section, the link between probability weighting and naïveté is important for welfare because a positive relationship would imply that those most prone to dynamic inconsistency would also bear the highest costs. Although the current paper does not collect data on this relationship, recent theoretical work proposing a psychological foundation for probability weighting may shed light on this question.

Salience Theory (Bordalo, Gennaioli, and Shleifer (2012)) derives probability weighting from the principle of “local thinking”, where agents focus and put greater weight on the most salient states (e.g., see evidence on the overweighting of unlikely but salient causes of death Heimer, Myrseth, and Schoenle (2019)). This follows from the proposition that unlikely states are more salient, leading to low probability events being overweighted and high probability events being underweighted in judgment. The authors argue that the degree of “local thinking” is likely related to an individual’s ability to pay attention to multiple states at the same time and cognitive capacity in general. The theory of efficient coding and risky choice (Frydman and Jin (2019)) proposes that cognitive constraints lead the brain to encode a coarse representation of stimuli such as payoffs and probabilities. This coarse representation leads to insensitivities and generates the inverse-S shaped probability weighting function. They provide empirical evidence on the relationship between coarseness in mental representations and insensitivity to changes in values. This implies that greater cognitive constraints will lead to more extreme probability weighting. Finally, recent work on cognitive uncertainty (Enke and Graeber (2019)) argues that people’s subjective uncertainty about the optimal action leads them to rely on mental defaults; in the case of probabilities, this leads to a compression around the 50:50 norm and generates probability weighting. The authors show that indeed, greater cognitive uncertainty is associated with more pronounced probability weighting.

To the extent that cognitive capacity, constraints, and uncertainty are related to sophistication about dynamic inconsistency, all three frameworks suggest a positive relationship between naïveté and probability weighting. It should be noted, however, that Dimmock et al. (2018) find a positive relationship between numeracy, financial literacy, and probability weighting. This highlights the importance of research that further explores the link between probability weighting and sophistication about one’s own dynamic inconsistency.

### *B. Planning Horizon*

Theoretical work on the dynamics of CPT under an infinite planning horizon has shown that agents are predicted to continue gambling independent of the outcome all their wealth is spent. This result is driven by the fact that if the planning horizon is long enough, the agent can always generate a strategy with enough skewness to justify taking on more risk, irrespective of whether she is in the gain or loss domain. A finite planning horizon, in contrast, restricts the potential skewness of a dynamic “loss-exit” strategy. As the number of remaining investment decisions decreases, so does the CPT agent’s willingness to continue gambling if she is in the gain domain. However, unlike our experimental setting, people’s planning horizons are likely long. And since gambling until bankruptcy is rarely observed, the infinite horizon predictions can be interpreted as a negative result for the empirical relevance of the dynamic predictions of CPT.

Nonetheless, despite the lack of any explicit binding restriction on holding time, we find that traders in our field setting behave according to the dynamic predictions of CPT under a finite horizon. We believe these results suggest that finite planning horizons are a realistic assumption for most real-world settings. In dynamic models of CPT, the relevant horizon corresponds to the time before the reference point resets. Even in contexts where instrumental factors imply a long time horizon, psychological factors that lead to reference point resetting may lead to substantially shorter time horizons in practice. The prevalence of such psychological factors—e.g. the realization of gains and losses (Imas (2016); Barberis and Xiong (2012)), temporal markers (e.g. end of the week Dai, Milkman, and Riis (2014)), and attention-based narrow bracketing (Koszegi and Matejka (2018); Evers and Imas (2019))—highlights the empirical validity of CPT

as a positive model of dynamic decision-making under risk.

## VIII. Conclusion

We show that people are dynamically inconsistent when taking risks repeatedly while knowing that they have the option to stop whenever they like. In particular, they take ‘bad’ risks too often because they plan to stop as soon as they make small losses and continue as long as they win to reap large gains. However, they fail to execute their ex-ante plan and behave in an opposite way ex-post if they cannot fully commit to an ex-ante plan. Even though subjects are partially sophisticated to the extent that they reject taking risks in the absence of any commitment device, they are easily lured into accepting risk if non-binding commitment devices are provided. Non-binding commitment devices are ineffective, leading to a similar pattern of behavior as when no commitment devices are provided.

Our results shed light on prior findings in sequential risky choice and suggest scope for policy in these settings. For example, the propensity to realize gains and hold on to losses (Odean (1998)), and the underperformance of investors due over-trading in response to prior outcomes (Barber and Odean (2000)) may run counter to their ex-ante strategies when they begin to trade. Heimer and Imas (2019) document the outcomes of a policy that restricted the amount of leverage available to retail FOREX traders. Counter to the predictions of the standard model, but consistent with dynamic inconsistency, decreasing traders’ choice sets in this manner actually *improved* their outcomes.

In the real world, people sometimes have commitment devices at disposal but they are often non-binding. Our findings of a dynamic inconsistency taken together with people’s prevailing naïvete about the effectiveness of non-binding commitment devices highlights the need for regulation to address the discretion of industry (e.g., casinos, credence goods providers, financial brokers etc.) to design and, in particular, to soften the commitment devices available to their clients.

Particularly, the results highlight the need for regulation of consumer financial product to

be based on evidence to prevent unintended adverse effects. For example, consider the recently introduced “depreciation reporting rule”, which is a part of the revised European market in financial instruments regulation (MiFID II) that came into force in January 2018.<sup>17</sup> The rule requires all wealth manager, brokers and financial advisers in Europe to immediately notify their clients in case their portfolio exhibits a loss of 10% or higher from the portfolio value at the beginning of the quarter. Although the intention behind it might have been different, the rule ultimately constitutes an exogenous non-binding loss limit at the level of 10%. Following our results, the notifications will be utterly redundant for the majority of investors as they are likely to ignore it. More importantly, however, the rule might change investors’ ex ante perspective on investing as they would anticipate receiving notifications ex ante. Our results suggest that investors might be more likely to take risks after the introduction of the rule, most importantly even investing in assets with zero or negative risk premium, because they might erroneously presume that they will reduce or close their positions after receiving a notification, thus limiting their losses at 10%. Instead of helping investors make better financial decisions, the regulation may pave the way into higher share of speculative trades and more (costly) dynamic inconsistency on the part of naïve investors. In addition, the finance industry provides investors with a variety of alert subscriptions, notifications and reminders on trading and information platforms, which may be used as non-binding limits and are currently largely unsupervised and unregulated. In light of our findings, regulation should address the finance industry’s discretionary power to design and provide such tools to their clients.

Our findings also relate to the work on self-control, impulsivity, and financial decision-making. Papers have linked proxies for impulsivity such as propensity to smoke (Uhr, Meyer, and Hackethal (2019)), drink alcohol (Ben-David and Bos (2017)), or procrastinate (Brown and Previtero (2016)) to increased trade frequency and inferior financial performance. The form of dynamic inconsistency studied in the current paper may or may not be linked to the types of self-control proxies considered in these papers. An important avenue of future research would link dynamic inconsistency in choice under uncertainty to other measures of impulsivity, which would potentially increase the scope for targeted policy interventions.

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<sup>17</sup> See Directive 2014/65/EU of the European Parliament on the market in financial instruments (MiFID II). For European legislation see <https://eur-lex.europa.eu/>.



## IX. Figures and Tables

**Table I**  
**Traders' ex-ante strategies**

This table reports the coefficients of OLS regressions using brokerage data. The dependent variable equals one if the trade has an ex-ante “loss-exit” strategy in which the stop-loss order is a smaller distance from the spot price than is the take-profit order. Panel A includes independent variables that reflect trader characteristics. Panel B includes independent variables related to the characteristics of each trade. Standard errors, in parentheses, are clustered by trader \*, \*\* and \*\*\* indicate statistically significant at the 10%, 5%, and 1% level, respectively.

<i>Panel A</i>				
	Ex-ante strategy (loss-limit = 1)			
	(1)	(2)	(3)	(4)
Constant	0.533*** (0.0050)	0.534*** (0.0056)	0.521*** (0.0042)	0.535*** (0.0074)
female		-0.00480 (0.012)		
trader location (Africa omitted)				
Asia			0.00158 (0.0076)	
Europe			0.00440 (0.0054)	
N Amer			0.0225*** (0.0058)	
Oceania			0.0206** (0.0098)	
S Amer			0.0920* (0.048)	
trading experience <sup>2</sup> (years)				0.00324** (0.0014)
trading experience (years)				-0.0102 (0.0069)
R2	-8.1e-11	0.000012	0.0022	0.00023
N	11,465,145	11,322,186	11,437,756	11,465,145

**Table I**  
**Traders' ex-ante strategies**

<i>Panel B</i>				
	Ex-ante strategy (loss-limit = 1)			
	(5)	(6)	(7)	(8)
Constant	0.540*** (0.0052)	0.531*** (0.014)	0.569*** (0.0026)	0.582*** (0.024)
long position	-0.0140*** (0.0039)			
currency pair groups (EUR/USD omitted)				
USDpairs		-0.00224 (0.014)		
EURpairs		0.00874 (0.014)		
JPYpairs		0.0242* (0.014)		
position leverage (400:1 omitted)				
2:1			-0.222 (0.21)	
5:1			0.161*** (0.058)	
10:1			-0.0608*** (0.0068)	
25:1			-0.0886*** (0.0049)	
50:1			-0.0566*** (0.0034)	
100:1			-0.0408*** (0.013)	
200:1			-0.0163** (0.0082)	
log(position capital)				-0.0158** (0.0062)
R2	0.00020	0.00019	0.0042	0.0021
N	11,465,145	11,465,145	11,465,145	11,465,145

**Table II**  
**Overview of Demographics**

This table reports sample statistics of demographic characteristics elicited with an entry-level questionnaire before the main experimental task. Dummy variables are indicated with “(D)” and the range of categorical variables is indicated in parentheses. Columns (1) and (2) present the sample statistics of Experiment 1, while columns (3) and (4) show the respective results for Experiment 2. The  $z$ -statistic of a nonparametric Mann-Whitney test is reported in column (5).

	Experiment 1		Experiment 2		Mann-Whitney
	(1)	(2)	(3)	(4)	(5)
	$\mu$	$\sigma$	$\mu$	$\sigma$	$z$ -stat ( $\mu_1 - \mu_2 = 0$ )
Age	34.55	10.34	34.88	11.00	0.04
Male (D)	0.60	0.49	0.56	0.50	1.18
Statistical Skills (1-6)	3.31	1.29	3.52	1.30	-2.59
Study Business (D)	0.14	0.35	0.17	0.38	-1.14
Study Comp Sciences (D)	0.18	0.39	0.18	0.38	0.16
Study Econ (D)	0.04	0.19	0.04	0.19	-0.20
Study Math (D)	0.02	0.15	0.02	0.14	0.16
Study Statistics (D)	0.00	0.05	0.00	0.06	-0.35
Study Psychology (D)	0.04	0.21	0.06	0.23	-0.83
Highest Education (1-6)	3.42	1.02	3.53	1.03	-1.56

**Table III**  
**Sequence and Commitment Effects on Entry Decision**

This table reports the coefficients of Probit regressions of the decision whether or not to start investing in round 1. The main independent variables are dummy variables for Sequential treatment ( $D^{seq}$ ), hard and soft plan treatment ( $D^{hardplan}$  and  $D^{softplan}$ ). Panel A shows results including the One-Shot treatment as a reference group. Panel B shows results excluding the One-Shot treatment, hence the reference group is the Sequential treatment. Columns (1) and (2) show results based on the combined dataset of Experiments 1 and 2 where the soft commitment treatment, which is unique for Experiment 2, is excluded. We include demographic variables elicited in an entry-level questionnaire. These variables are age, gender, study field (dummies), highest level of education, self-reported statistical skills. Standard errors are cluster-robust.  $t$ -statistics are in parentheses. \*, \*\* and \*\*\* indicate statistically significant at the 10%, 5%, and 1% level, respectively.

<i>Panel A</i>						
	Experiments 1 & 2		Experiment 1		Experiment 2	
	(1) mfx	(2) mfx	(3) mfx	(4) mfx	(5) mfx	(6) mfx
$D^{seq}$	0.125*** (4.418)	0.125*** (4.433)	0.136*** (3.409)	0.139*** (3.586)	0.102*** (2.775)	0.097*** (2.710)
$D^{hardplan}$	0.230*** (7.351)	0.229*** (7.356)	0.241*** (5.511)	0.239*** (5.695)	0.198*** (4.765)	0.195*** (4.784)
$D^{softplan}$					0.177*** (4.399)	0.174*** (4.386)
Demographics	No	Yes	No	Yes	No	Yes
Pseudo $R^2$	0.077	0.090	0.080	0.130	0.071	0.093
N	791	791	407	407	533	533
<i>Panel B</i>						
	Experiments 1 & 2		Experiment 1		Experiment 2	
	(1) mfx	(2) mfx	(3) mfx	(4) mfx	(5) mfx	(6) mfx
$D^{hardplan}$	0.088*** (3.435)	0.089*** (3.520)	0.087** (2.397)	0.087** (2.553)	0.083** (2.462)	0.083** (2.522)
$D^{softplan}$					0.065** (2.006)	0.065** (2.030)
Demographics	No	Yes	No	Yes	No	Yes
Pseudo $R^2$	0.029	0.044	0.027	0.086	0.027	0.040
N	627	627	319	319	457	457

**Table IV**  
**Ex-Ante Strategies**

This table illustrates the ex-ante strategies in the Hard and Soft plan treatments across Experiments 1 and 2. Panel A reports the share of participants who have a loss-exit, gain-exit, or symmetric neutral strategies. A loss-exit (gain-exit) strategy is defined as lower (greater) loss limit than gain limit. Column (1) to (4) reports the results for all participants. Columns (5) to (8) reports the results only for those who initially choose to take on risk. Panel B reports aggregate statistics to illustrate the magnitude of the difference between gain and loss limits. “Ratio” refers to the ratio between the gain and loss limit ( $\frac{gain}{loss}$ ) and “Difference” refers to their difference ( $gain - loss$ ).  $t$ -statistics of Wald tests for  $H_0 : Ratio = 1$  and  $H_0 : Diff = 0$ , respectively, are in parentheses. Panel C reports the mean and the skewness of the aggregate outcome distribution that results from participants’ gain and loss limits in expectation. The outcome distribution for each participant (each set of gain and loss limits) results from 100,000 independently simulated outcome paths.

Experiment	All Subjects				Entered Lottery			
	(1) 1&2	(2) 1	(3) 2 (hard)	(4) 2 (soft)	(5) 1&2	(6) 1	(7) 2 (hard)	(8) 2 (soft)
N	458	158	151	149	427	147	142	138
<i>Panel A. Strategy Categorization</i>								
Lossexit	80.3%	85.4%	78.1%	77.2%	80.8%	86.4%	78.9%	76.8%
Symmetric	12.7%	10.1%	14.6%	13.4%	12.2%	8.8%	14.1%	13.8%
Gainexit	7.0%	4.5%	7.3%	9.4%	7.0%	4.8%	7.0%	9.4%
<i>Panel B. Aggregate Statistics</i>								
Ratio	3.81*** (10.71)	3.67*** (6.17)	4.51*** (6.45)	3.24*** (6.19)	3.63*** (10.11)	3.56*** (5.79)	4.25*** (6.11)	3.05*** (5.87)
Difference	80.26*** (19.67)	85.00*** (13.84)	81.06*** (10.51)	74.43*** (10.13)	79.98*** (19.01)	86.26*** (13.63)	80.14*** (10.22)	73.12*** (9.52)
<i>Panel C. Expected Outcome Distributions</i>								
Mean	-0.03	-0.15	0.10	0.14	0.04	-0.09	-0.07	0.01
Skewness	0.31	0.30	0.33	0.33	0.31	0.28	0.32	0.29

**Table V**  
**The Effect of Commitment on Outcome Distributions**

This table reports sample distribution parameters of the realized outcome distributions across the different treatments. The outcome is the cumulative gain or loss from the beginning of the sequential lottery until the participant chooses to stop investing. Panel A compares the Hard and Soft Plan treatments from Experiments 1 and 2 to the Sequential treatment. For the Soft Plan treatment in Experiment 2, we take the outcome at the point of time when one of the limits was triggered for the first time. In case no limit was triggered, we take the final outcome. Panel B shows the results for participants who choose to initially take on risk. Panel C focuses only on the Soft Plan treatment and compares the hypothetical outcome that would have been reached with the limits (i.e. ex ante) to the actual outcome that was reached at the end (i.e. ex post). We report the  $p$ -values of Wald tests comparing the means of the distributions to zero. In addition, we use Jarque-Bera test for the skewness of the outcome distribution. \*, \*\* and \*\*\* indicate statistically significant at the 10%, 5%, and 1% level, respectively.

<i>Panel A: Between-Subject Test (Experiment 1 and 2)</i>			
	N	Mean	Skewness
Commitment Treatment	458	2.445 (0.217)	0.268** (0.019)
Sequential Treatment	318	1.006 (0.515)	0.060 (0.656)
<i>Panel B: Between-Subject Test (Experiment 1 and 2)</i>			
	N	Mean	Skewness
Commitment Treatment	427	1.185 (0.515)	0.247** (0.037)
Sequential Treatment	270	2.623 (0.217)	0.037 (0.798)
<i>Panel C: Within-Subject Test (Experiment 2)</i>			
	N	Mean	Skewness
Soft Commitment (Ex Ante)	138	1.812 (0.618)	0.471** (0.023)
Soft Commitment (Ex Post)	138	2.319 (0.569)	0.280 (0.166)

**Table VI**  
**Probability of Realizing Gain versus Loss — Ex-Ante versus Ex-Post**

This table reports the coefficients of OLS and the marginal fixed effects of Probit regressions. The dependent variable in Columns (1) and (2) is a dummy variable that equals one if the participant’s final outcome is a cumulative gain as opposed to a cumulative loss (zeros are excluded). In Columns (3) and (4), the dependent variable is a dummy variable that equals one if the participant stops investing in Round 1 after the first outcome of the gamble is revealed (excluding participants who did not start investing at all). The main independent variables are dummy variables for Sequential treatment ( $D^{seq}$ ), drawing a gain versus loss in Round 1 ( $D^{1gain}$ ). The commitment treatments includes the hypothetical cumulative outcomes of the participant in the Soft Plan treatment; hence in cases where the participant deviates from her plan we replace the actual outcome with the outcomes at the point of time when her limits were first triggered. We include demographic variables elicited in an entry-level questionnaire. These variables are age, gender, study field (dummies), highest level of education, self-reported statistical skills. Standard errors are cluster-robust.  $t$ -statistics are in parentheses. \*, \*\* and \*\*\* indicate statistically significant at the 10%, 5%, and 1% level, respectively. The results of this table are illustrated in Figure 6.

	Realizing a Cum. Gain versus Cum. Loss		Stop Investing in Round 1	
	(1)	(2)	(3)	(4)
$D^{seq}$	0.098** (2.376)	0.089** (2.154)	-0.099*** (-2.615)	-0.112*** (-2.960)
$D^{1gain}$			-0.081** (-2.312)	-0.092*** (-2.653)
$D^{seq} \times D^{1gain}$			0.287*** (4.884)	0.305*** (5.203)
Demographics	No	Yes	No	Yes
Pseudo $R^2$	0.007	0.017	0.040	0.060
R2			0.040	0.060
N	606	606	697	697

**Table VII**  
**Cumulative Gains and Losses**

This table reports the coefficients of OLS regressions. The dependent variables are the absolute cumulative gains/losses (Columns (1) and (2)), and the participants' reluctance to realize a gain or a loss (Columns (3) and (4)). The reluctance to realize gains or losses is measured by the percentage of rounds the participant has had a paper cumulative gain (loss) conditional on her realizing a cumulative gain (loss) at the end. The main independent variables are dummy variables for Sequential treatment ( $D^{seq}$ ), a dummy variable for realizing a cumulative gain versus loss ( $D^{gain}$ ). The commitment treatments include the hypothetical cumulative outcomes of the participant in the Soft Plan treatment; hence in case the participant deviates from her plan we replace the actual outcome with the outcomes at the point of time when her limits were first triggered. We include demographic variables elicited in an entry-level questionnaire. These variables are age, gender, study field (dummies), highest level of education, self-reported statistical skills. Standard errors are cluster-robust.  $t$ -statistics are in parentheses. \*, \*\* and \*\*\* indicate statistically significant at the 10%, 5%, and 1% level, respectively. The results of this table are illustrated in Figure 7.

	Absolute Cumulative Gain/Loss		Realization Reluctance	
	(1)	(2)	(3)	(4)
$D^{gain}$	10.634*** (3.979)	11.295*** (4.327)	0.082*** (3.078)	0.085*** (3.165)
$D^{seq}$	-4.963* (-1.875)	-4.016 (-1.506)	0.124*** (4.079)	0.126*** (4.036)
$D^{seq} \times D^{gain}$	-14.791*** (-3.852)	-15.937*** (-4.124)	-0.135*** (-3.224)	-0.135*** (-3.173)
Demographics	No	Yes	No	Yes
R2	0.087	0.119	0.030	0.046
N	606	606	606	606



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## Appendix A. Theoretical Predictions

In this section, we formally derive the predictions of Cumulative Prospect Theory (CPT), Rank Dependent Utility (RDU), and Expected Utility Theory (EUT) on dynamic inconsistency in sequential risk-taking.<sup>18</sup>

### Cumulative Prospect Theory

Our analysis of CPT largely follows Barberis (2012). A decision-maker considers the following gamble  $L = (p_{-m}, x_{-m}; \dots; p_{-1}, x_{-1}; p_0, x_0; p_1, x_1; \dots; p_n, x_n)$ , where  $p_i$  corresponds to the likelihood of attaining outcome  $x_i$ . Outcomes are ordered such that  $-m \dots -1$  correspond to those below the reference point  $x_0$ , here assumed to be the status quo, and  $1 \dots n$  correspond to those above the reference point. We follow Tversky and Kahneman (1992) in assuming that utility derived from this gamble can be represented by:

$$V(L) = \sum_{-m}^n \pi_i^{CPT} v(x_i), \tag{A1}$$

where

$$\pi_i^{CPT} = \begin{cases} w(p_i + \dots + p_n) - w(p_{i+1} + \dots + p_n) & \text{for } 0 \leq i \leq n, \\ w(p_{-m} + \dots + p_i) - w(p_{-m} + \dots + p_{i-1}) & \text{for } -m \leq i < 0, \end{cases} \tag{A2}$$

We also follow Tversky and Kahneman (1992) in assuming the following form for the probability weighting function:

$$w(p) = \frac{p^\delta}{(p^\delta + (1-p)^\delta)^{1/\delta}} \tag{A3}$$

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<sup>18</sup> Note that CPT is a special case of the generalized formulation of RDU as proposed by Quiggin (1982) and Yaari (1987). Here, we derive predictions of RDU without the assumption of reference dependence or loss aversion using the formulation employed in Polkovnichenko (2005) .

and value function

$$v(x) = \begin{cases} x^\alpha & \text{for } x \geq 0, \\ -\lambda(-x)^\alpha & \text{for } x < 0 \end{cases} \quad (\text{A4})$$

where  $\alpha, \delta \in (0, 1)$  and  $\lambda \geq 1$ .

In our setting,  $L = (1/2, -10; 1/2, 10)$ . The decision-maker faces a sequence of choices. In each round  $t \in \{0, \dots, 26\}$ , she can accept or reject the gamble. If she rejects the gamble, no more gambles are offered. If she accepts it, the outcome is revealed and the decision-maker is offered the same choice again (up through round 26, when the sequence ends). When evaluating this choice problem, the decision-maker chooses a plan  $s$  from the set of available plans  $S_{t,j}$  in round  $t$  and outcome node  $j$ . For a given  $(t, j)$ , the subscript  $j \in \{1, t + 1\}$  corresponds to the distance of the outcome node  $(t, j)$  from the top node of a column in a binomial tree of all potential outcomes that could have occurred by that round  $t$ . For example,  $S_{1,2}$  corresponds to the set of available plans available after the decision-maker accepted the first gamble and lost. Each plan  $s \in S_{t,j}$  is a mapping from every potential outcome of the sequence of gambles from round  $t$  onward to actions  $a \in \{\text{continue}, \text{exit}\}$ .

Each  $s$  generates a random variable  $\tilde{G}_s$ , which corresponds to the accumulated gains or losses conditional on  $s$  being carried out. For example, take  $s \in S_{0,1}$  where the decision maker plans to accept the first gamble, continue if she wins in  $t = 1$  and then exits regardless of the next outcome in  $t = 2$ , and exiting in  $t = 1$  if she loses the first gamble. This plan corresponds to  $\tilde{G}_s \sim (1/2, -10; 1/4, 0; 1/4, 20)$ . She chooses plan  $s$  which maximizes utility,  $\max_{s \in S_{t,j}} V(\tilde{G}_s)$ . Absent a commitment device, in each round  $t$  the decision-maker evaluates the choice problem and re-optimizes given her set of available plans.

Non-linear probability weighting makes it difficult to solve the problem analytically; there is no known analytical solution for a dynamic setting with an arbitrary  $T$ . We follow Barberis (2012) in solving the decision problem numerically.

We run simulations to determine the ex-ante optimal plan (in  $t = 0$ ) and the ex-post behavior (in  $t > 0$ ) of each agent. An agent is defined by a unique parameter combination of probability weighting ( $\delta$ ), diminishing sensitivity of the value function ( $\alpha$ ), and loss aversion ( $\lambda$ ).



Following the design of the commitment device described in Section III, we define an ex-ante strategy as a combination of a loss limit and a gain limit. For each agent we simulate 10,000 independent paths, each consisting of 26 iid draws from a fair symmetric gamble. A strategy transforms the simulated paths into an outcome distribution.

The optimal plan  $s^*$  for each agent is the one that is connected to the outcome distribution with the highest expected value among all possible strategies, as given by the objective function in Equation A1. The agent accepts the sequential gamble if the expected value of the optimal strategy is higher than the value of exiting, which is normalized to zero. If the agent accepts the gamble in the first round, she revisits her decision in every subsequent round. For this purpose, the agent compares the expected value of continuing to accept the gamble, assuming that she will adhere to the ex-ante optimal strategy, with the value of exiting. The value of continuing to gamble is determined by running 10,000 new simulations to determine the updated outcome distribution. The value of exiting is given by the value of the accumulated gains or losses since the beginning. We assume that the reference point is the initial endowment of \$2.6, hence the agent does not update the reference point until the final period when the outcome is paid out.<sup>19</sup> This assumption is consistent with prior experimental evidence (see Imas (2016)).

### *Results (CPT)*

Figure A1, Panels A, C, and E present the findings on the ex-ante optimal plan in  $t = 0$ . Though the figures illustrate results across a broad range of parameters, we focus on the representative agent with  $\alpha = .88$ ,  $\delta = .65$  and  $\lambda = 2.25$ , as estimated in Tversky and Kahneman (1992). Note that in the presence of dynamic inconsistency, the ex-ante decision depends not only on the preference parameters but also on agents's sophistication and the availability of commitment devices. In the following, we analyze the ex-ante decisions of naïve agents, who erroneously believe that they will stick to their ex-ante optimal strategy, as well as sophisticated agents who have a commitment device at their disposal to make sure that they will stick to their ex-ante optimal strategy. Later in this section we discuss how the ex-ante decisions of these two types of agents differ from the ex-ante decision of sophisticated agents without commitment devices. Several findings are obtained.

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<sup>19</sup> We present results when this assumption is relaxed below.

First, the agent would accept the first gamble in a sequence with endogenous exit even though she would reject the same gamble in isolation.

Second, the combination of non-linear probability weighting, diminishing sensitivity and loss aversion determines the ex-ante optimal plan  $s^*$ . The optimal plan can be classified as a “loss-exit” strategy for the representative agent. This plan is also optimal for agents with moderate non-linear probability weighting and diminishing sensitivity. In contrast, agents who weigh probabilities close to linearly and have high levels of diminishing sensitivity ( $\alpha \ll 1$ ), the optimal strategy is a “gain-exit” strategy. Loss aversion plays a straightforward role in determining the proportion of agents who accept the first gamble as part of an optimal plan, as opposed to not entering in the first place.<sup>20</sup>

Figure A1, Panels B, D, and F present the findings on the ex-post behavior. First, agents who accepted the first gamble as part of a “loss-exit” plan deviate from this strategy. Notably, this includes the representative agent. Instead of exiting after initial losses, they end up chasing the losses further by accepting subsequent gambles. These agents exit too early after experiencing small gains (relative to their strategy). Note that while ex-ante strategies are largely determined by the extent of probability weighting, the deviation in ex-post behavior is driven by diminishing sensitivity, i.e. the extent to which agents are risk-averse in the gain domain and risk-seeking in the loss domain. Critically, agents who accept risk as part of a “loss-exit” strategy end up with an outcome distribution that has a *lower* value than rejecting the first gamble in  $t = 0$ . This represents substantial dynamic inconsistency between planned and actual behavior in this setting.<sup>21</sup>

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<sup>20</sup> Note that this result and the estimated parameter combinations that accept the sequential gamble largely overlap with the findings of Barberis (2012) even though we restrict the choice set of ex-ante strategies to include only strategies that can be expressed as a combination of two limits, whereas Barberis (2012) optimizes over all possible strategies that can be expressed using a binomial tree. This indicates that our experimental design choice to simplify the plan elicitation is not very restrictive.

<sup>21</sup> They also exit after breaking even if the remaining number of rounds is below an agent-specific minimum required number of rounds to enter the gamble. This type of deviation does not affect the skewness of the outcome distribution but reduces its standard deviation and increases its kurtosis compared to the distribution of the ex-ante optimal plan. Note that the resulting deviation between the value of the ex-ante and ex-post outcome distributions cannot explain why agents with an ex-ante “loss-exit” strategy would regret accepting the first gamble ex-post.

The predicted dynamic inconsistency generates predictions on initial choices as a function of sophistication and the availability of opportunities to commit to a plan. Agents with “loss-exit” optimal plans but who are aware that they will deviate also understand that the choice to enter yields less utility in expectation than rejecting the first gamble. These agents will only accept the first gamble if offered the opportunity to commit to their optimal plan. Agents who are naive about their dynamic inconsistency will accept the first gamble regardless of commitment opportunities. If the proportion of sophisticated agents is high enough, this leads to the prediction that a greater number of participants will begin gambling when offered an opportunity to commit to a loss or gain limit than when no such opportunities are available.

It is important to highlight that our assumption that the agent does not update the reference point until the final round is critical for predictions on ex-post behavior. An alternative assumption where the reference point updates after every round would not predict an asymmetrical response after accumulated gains and losses. This is because the agent would be in a similar situation as in  $t = 0$  in every round, but with a fewer number of prospective rounds. Due to the lower number of prospective rounds, the expected value of a “loss-exit” strategy is lower than it was in the beginning of the sequence. Once the number of rounds falls below the agent-specific number that would prompt her to accept the first gamble, she exits. This leads to the prediction that the agent is just as likely to exit after a loss as after a gain. For instance, for the representative CPT agent, the agent-specific minimum required number of rounds is 26, hence she would exit after the first round independent of the outcome because the number of remaining rounds is too low. In general, the closer an agent is to the white-colored area in Figure A1, Panel A, the higher is her agent-specific number of minimum required periods, hence the sooner the agent would exit the lottery independent of its outcome. As outlined in Section V, the prediction that subjects exit the lottery independent of their gains and losses is not borne out in the data.

### Rank-Dependent Utility

Rank-Dependent Utility (RDU) was introduced by Quiggin (1982) and Yaari (1987). We follow Polkovnichenko (2005) and assume the following functional form:

$$\sum_{-m}^n \pi_i^{RDU} u(W + x_i), \quad (\text{A5})$$

where  $W$  denotes the initial wealth before the first round,  $u(\cdot)$  is a power utility function of the form

$$u(W + x) = \begin{cases} \frac{(W + x)^{1-\gamma}}{1-\gamma} & \text{for } \gamma \geq 0 \text{ \& } \gamma \neq 1, \\ \ln(W + x) & \text{for } \gamma = 1, \end{cases} \quad (\text{A6})$$

and

$$\pi_i^{RDU} = w(p_{-m} + \dots + p_i) - w(p_{-m} + \dots + p_{i-1}) \quad (\text{A7})$$

For consistency, we assume the probability weighting function  $w$  is the same as in (3).

The simulations of the RDU ex-ante optimal plans and ex-post behavior are conducted in a similar way to those for CPT. In contrast to CPT, RDU requires an additional assumption regarding the agents' wealth. Linking this analysis to our experiment, we assume that the agent's wealth comprises their initial endowment of \$2.6. To illustrate how the model's predictions depend on the wealth assumption, we also run the simulations assuming that subjects have additional wealth of \$1,000.

### *Results (RDU)*

Figure A2, Panels A and C present the findings on the ex-ante behavior for an RDU agent. Two main results are obtained. First, as in the case of CPT, some agents would accept the sequential fair gamble with endogenous exit even though they would not accept a single play of the gamble in isolation. Note that this result depends critically on the wealth assumption. Assuming a wealth level of \$2.6, only agents with low levels of risk aversion and strongly non-linear probability weighting would accept the gamble for a single round. In contrast, assuming a wealth level of \$1,000 prior to the experiment leads to the prediction that all agents in Figure A2 with  $\delta < 0.9$  would also accept the gamble in isolation. Second, all agents who accept the first gamble do so as part of a "loss-exit" strategy.

Figure A2, Panels B and D present the findings on the ex-post behavior for an RDU agent. The main result is that while RDU does predict deviations from the “loss-exit” strategy for some agents, the deviations are always symmetric in response to gains and losses. This is in contrast to the results from CPT which predict asymmetric deviations, such that the agent is more likely to stop after a gain than after a loss.

There are two main types of deviations under RDU, which we refer to as ‘type 1’ and ‘type -1’. In the ‘type 1’ deviation, some decision-makers who accept the first gamble deviate from their “loss-exit” strategy to continue investing until the final round independent of the gamble outcomes. From an ex-ante perspective, the utility of this type of deviation is lower than from the “loss-exit” strategy for some agents (marked red in Figure A2). However, for a significant proportion of agents, the ‘type 1’ deviation still generates an outcome distribution which yields greater utility than rejecting the first gamble. This includes agents with preference parameters in the region of estimates from prior studies (e.g., Tversky and Kahneman (1992) and Camerer and Ho (1994)).<sup>22</sup> ‘Type -1’ deviations comprise all other types of deviations, such as the agent exits when the initial wealth is reached and the number of remaining rounds is sufficiently low.

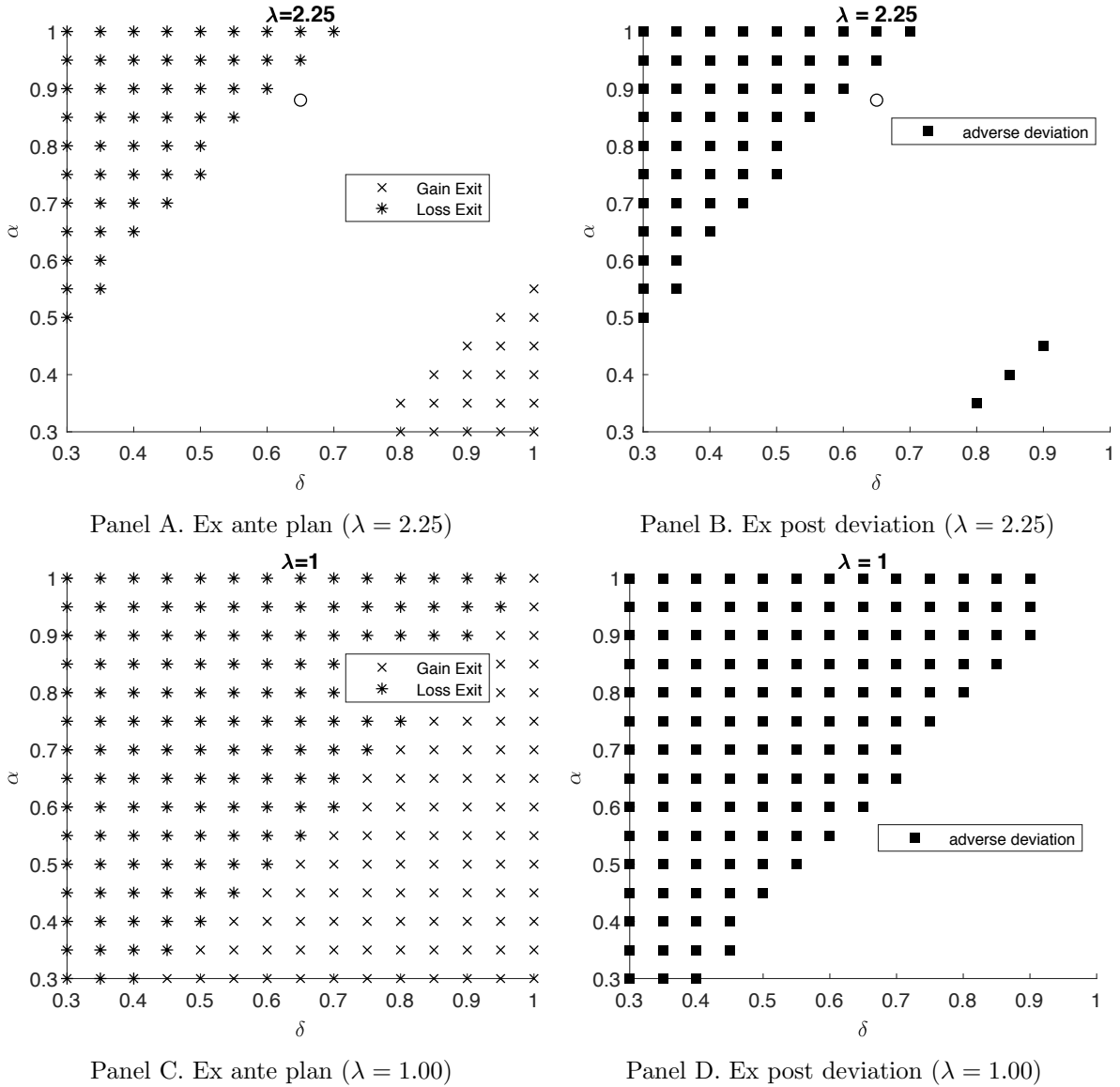
### Expected Utility Theory

Expected Utility Theory (EUT) is a special case of RDU for  $\delta = 1$ . The utility function for  $\delta = 1$  is characterized by constant relative and decreasing absolute risk aversion with skewness preferences (see Arditti (1967)). Predictions for both ex-ante plans and ex-post behavior are illustrated in Figure A2. It is clear that EUT with skewness preferences does not predict that participants will accept the first gamble in a sequence while rejecting the gamble in isolation. It also follows trivially that EUT does not predict any dynamic inconsistency.<sup>23</sup>

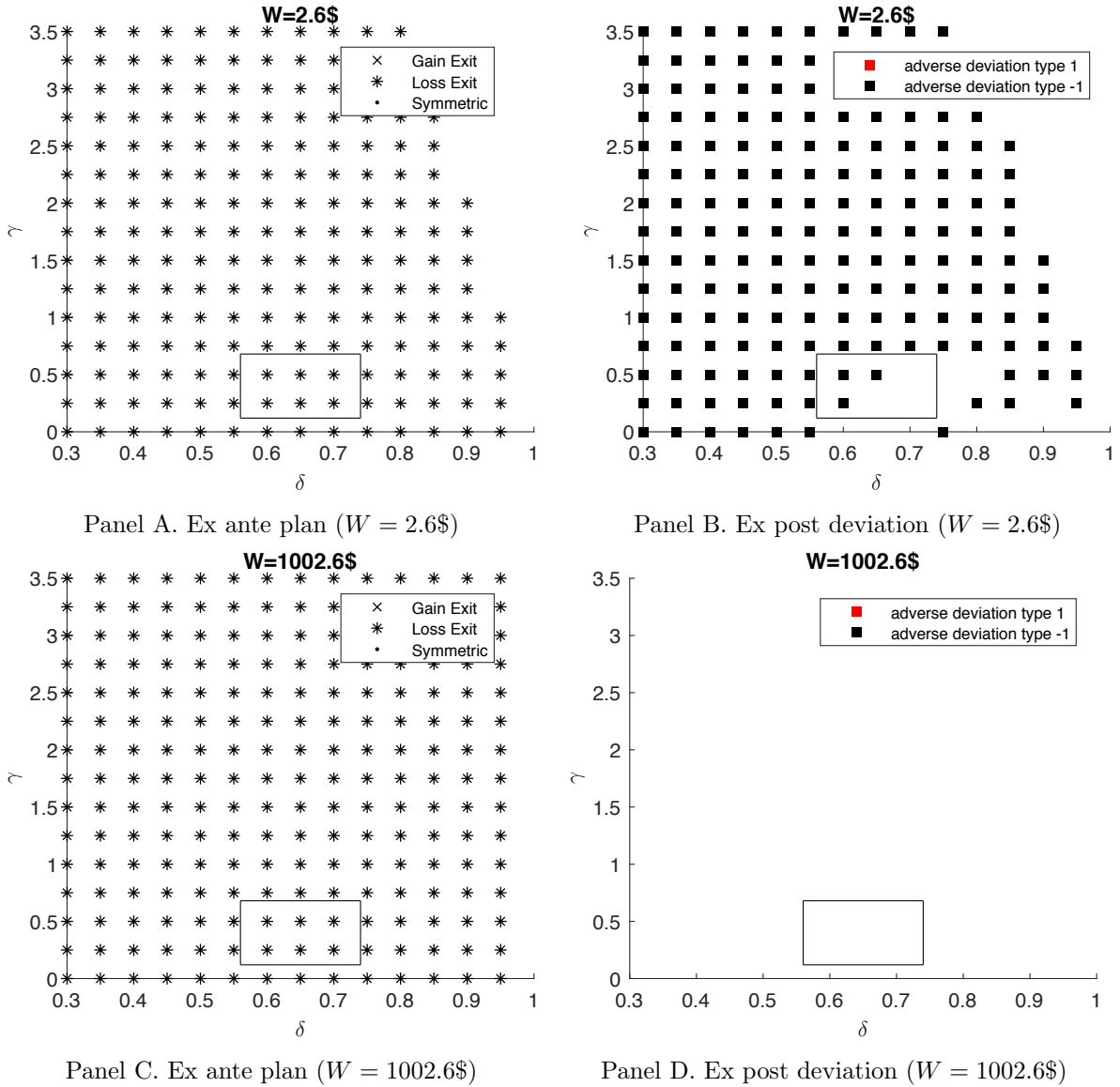
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<sup>22</sup> This result is dependent on the assumption about initial wealth. Assuming initial wealth \$1,000, all agents in Figure A2 who accept the initial gamble will continue until the end, independent of the outcome.

<sup>23</sup> For the case of gambles with positive expected value, Peköz (2002) shows that skewness preferences in combination with endogenous exit can explain the Samuelson paradox (Samuelson (1963)) as subjects will follow a “loss-exit” strategy to generate positive skewness. This is not the case for the fair gamble which is used in our experiments.



**Figure A1. Theoretical predictions of Cumulative Prospect Theory.** This figure illustrates the ex ante plan (Panel A and C) and the ex post deviation (Panel B and D) of agents with CPT preferences with different levels of probability weighting ( $\delta$ ) and diminishing sensitivity ( $\alpha$ ), i.e. the extent to which agents are risk-averse in the gain domain and risk-seeking in the loss domain. Panels A and B report the results for loss-averse agents (i.e., positive  $\lambda$ ), while Panels C and D report the results for agents who are not loss-averse (i.e.,  $\lambda = 1$ ). Ex ante plans are categorized as “gain exit” (“loss exit”), which implies that the gain limit is closer to (further away from) the reference point. Ex post behavior is categorized as adverse deviation if the ex-post outcome distribution has a lower value than rejective the gamble at the beginning, in  $t = 0$ . The representative agent as estimated by Tversky and Kahneman (1992) is marked by a circle in Panels A and B.



**Figure A2. Theoretical predictions of Rank Dependent Utility.** This figure illustrates the ex ante plan (Panel A and C) and the ex post deviation (Panel B and D) of agents with RDU preferences with different levels of probability weighting ( $\delta$ ) and risk aversion ( $\gamma$ ). Ex ante plans are categorized as “gain exit” (“loss exit”), which implies that the gain limit is closer to (further away from) the initial wealth than the loss limit, and “symmetric”, which implies equidistant limits. Ex post behavior is categorized as adverse deviation if the ex-post outcome distribution has a lower utility than the utility of rejecting the gamble at the beginning, in  $t = 0$ . In addition, ‘type 1’ deviation implies that the agent almost certainly continues investing until the final round. Other types of deviation are denoted as ‘type -1’.  $W$  indicates the assumption about initial wealth. The parameter-region estimated from previous experimental studies is marked by the box.

## Appendix B. List of Variables

Variable	Description
Age	Demographic variable elicited in entry-level questionnaire elicited in entry-level questionnaire.
Male	Dummy variable that equals one for male.
Statistical skills	Categorical variable elicited as follows: “How would you rate your statistical knowledge? Please choose a category between 1 (“very bad”) and 6 (“very good”).”
Study field	Categorical variable elicited as follows: “Your field of study?”
Highest education	Categorical variable elicited as follows: “Your highest level of education: 1 (below high school), 2 (high school), 3 (college), 4 (bachelor), 5 (master), 6 (PhD or above).”
Entry decision	Dummy variables which equals one if the subject accepts the gamble before the first round.
$D^{seq}$	Dummy variable that equals one for sequential treatment
$D^{hardplan}$	Dummy variable that equals one for hard plan treatment
$D^{softplan}$	Dummy variable that equals one for soft plan treatment
$D^{1gain}$	Dummy variable that equals one for drawing a gain in round 1 conditional on accepting the gamble.
$D^{gain}$	Dummy variable that equals one for realizing a cumulative gain and zero for realizing a cum loss.
Complexity	Equally-weighted average response to four questions regarding the perceived complexity of the main task following Maynard and Hakel (1997): “I found this to be a complex task”; “This task was mentally demanding”; “This task required a lot of thought and problem-solving”; “I found this to be a challenging task”. The responses are elicited on a Likert-type scale from 1 “totally disagree” to 7 “totally agree”. The perceived complexity is elicited after the main task.



## Appendix C. Experimental Instructions

### *Appendix CI. One-shot Treatment*

Screen: Instructions

You have 10 cents. You can choose to invest 10 cents in the following lottery or to keep it:

With a chance of  $1/2$  (50%) the lottery will "succeed" and you will earn an additional 10 cents, for a total of 20 cents. With a chance of  $1/2$  (50%) the lottery will "fail" and you will lose the 10 cents you invested.

Click "Start" to make several random draws from the distribution of the lottery: [The subject is required to make 10 draws from an individual stratified sample before proceeding to the next screen.]

Screen: Investment decision

You can now choose whether or not to invest 10 cents in the lottery.

Do you want to invest? [Yes]/[No]

## *Appendix CII. Sequential Treatment*

### **Screen: Instructions (1)**

You can choose to invest 10 cents in the following lottery or to keep it:

With a chance of  $1/2$  (50%) the lottery will "succeed" and you will earn an additional 10 cents, for a total of 20 cents. With a chance of  $1/2$  (50%) the lottery will "fail" and you will lose the 10 cents you invested.

Click "Start" to make several random draws from the distribution of the lottery: [The subject is required to make 10 draws from an individual stratified sample before proceeding to the next screen.]

### **Screen: Instructions (2)**

The experiment consists of 26 successive rounds. You have 260 cents in total to invest with. You can invest 10 cents per round in the lottery for up to 26 rounds. At the beginning you will choose whether or not to invest in the first round. After learning the outcome of your investment (whether you won or lost), you will choose whether to invest again or not. You can stop investing at any time. Once you decide to stop investing, this part of the experiment will end.

Your earnings for this part of the experiment are as follows: At the end, we will count the number of rounds you have won ( $n$ ) and the number of rounds you have lost ( $m$ ). Your total gain or loss is given by the difference between these numbers multiplied by your investment per round which is 10 cents.

- If  $n \geq m$ , you have earned a total gain of  $(n - m) \times 10$  cents. In this case, you will receive your initial endowment plus the amount of your total gain.
- If  $n < m$ , you have endured a total loss of  $(m - n) \times 10$  cents. In this case, you will receive the rest of your initial endowment after deducting the amount of your total loss.

Please click "Next" to proceed with the first round.

Screen: Round 1 of 26: Investment decision

You can now choose whether or not to invest 10 cents in the lottery in round 1.

Do you want to invest? [Yes]/[No]

dots

Screen: Round X of 26: Result

[This screen is displayed conditional on investing in this round.]

In round X you have earned a gain/endured a loss of [...] cents. [The outcome is colored in red or green for loss or gain, respectively.]

In the first X rounds you have earned a total gain/endured a total loss of [...] cents. [The outcome is colored in red or green for loss or gain, respectively.]

Please click "Next" to proceed to the next round.

*Appendix CIII. Hard and Soft Plan Treatments*

Screen: Instructions (1)

You can choose to invest 10 cents in the following lottery or to keep it:

With a chance of  $1/2$  (50%) the lottery will "succeed" and you will earn an additional 10 cents, for a total of 20 cents. With a chance of  $1/2$  (50%) the lottery will "fail" and you will lose the 10 cents you invested.

Click "Start" to make several random draws from the distribution of the lottery: [The subject is required to make 10 draws from an individual stratified sample before proceeding to the next screen.]

Screen: Before we move on...

Please think of two arbitrary numbers (integers) between 0 and 260. [Note: Your earnings do not depend on your responses to this question.]

My first number:...

My second number:...

Screen: Instructions (2)

You have 260 cents in total to invest with. You will choose whether or not to invest 10 cents in the lottery over a series of up to 26 rounds. But first we ask you to indicate what is the maximum amount of losses or gains you would be willing to take before stopping. These are your loss limit and your gain limit. If you choose to start investing 10 cents, you will keep investing 10 cents in each subsequent round until your total gain or loss reaches your gain limit or loss limit respectively.

- You can think of the **loss limit** as the most of your endowment that you are willing to lose.

- You can think of your **gain limit** as the amount of gains you would be happy to walk away with, without having to risk any more.

Example: At the beginning of the experiment we asked you for two arbitrary numbers and you gave us the numbers  $[y_1]$  and  $[y_2]$ . Let us assume, your loss limit is  $[y_1]$  cents and your gain limit is  $[y_2]$  cents. After every round, we will count the number of rounds you won and the number of rounds you lost so far to determine your total gain or loss. Your loss limit is reached if your total loss reaches  $[y_1]$  cents. In other words, it is reached as soon as you have lost  $[y_1/10]$  rounds more often than won. Your gain limit is reached if your total gain reaches  $[y_2]$  cents. In other words, it is reached as soon as you have won  $[y_2/10]$  rounds more often than lost.

Please note, that there is no guarantee that your gain limit or your loss limit will be reached during the course of the experiment as the lottery outcomes are completely random and independent.

Your earnings for this part of the experiment are as follows: At the end, we will count the number of rounds you have won (i.e.,  $n$ ) and the number of rounds you have lost (i.e.,  $m$ ) before you stopped investing.

- If you have earned a total gain (if  $n > m$ ), you will receive your initial endowment of 260 cents plus the amount of your total gain of  $(n - m) \times 10$  cents.
- If you have endured a total loss (if  $m > n$ ), you will receive the rest of your initial endowment after deducting the amount of your total loss of  $(m - n) \times 10$  cents.

Please indicate your loss limit and your gain limit. [Note: You will choose whether or not to start investing afterwards.]

Loss limit (in cents):...

Gain limit (in cents):...

Screen: Instructions (3)

[This screen is displayed conditional on being in the **soft plan treatment**.]

Your gain and loss limits are not binding and will not be enforced if you start investing. This means that we will inform you immediately if either your gain limit of [...] cents or your loss limit of [...] cents is reached before the final round. You will then choose whether to continue or stop investing.

This part of the experiment ends if:

- you decide not to invest in the first round (see next page), or
- you start investing and you decide to stop investing after being informed that one of your limits is triggered, or
- you reach the final 26th round.

Click "Next" to proceed.

Screen: Instructions (3)

[This screen is displayed conditional on being in the **hard plan treatment**.]

Your gain and loss limits are binding and will be enforced if you start investing. This means that you will automatically stop investing if either your gain limit of [...] cents or your loss limit of [...] cents is reached before the final round.

This part of the experiment ends if:

- you decide not to invest in the first round (see next page), or
- you start investing and either your gain limit or your loss limit has been reached or exceeded, or
- you reach the final 26th round.

Screen: Round 1 of 26: Investment decision

[This screen is displayed conditional on being in the **soft plan treatment**.]

You can now choose whether or not to start investing 10 cents in the lottery over a series of up to 26 rounds.

Do you want to start investing? [Yes]/[No]

Screen: Investment decision

[This screen is displayed conditional on being in the **hard plan treatment**.]

You can now choose whether or not to start investing 10 cents in the lottery over a series of up to 26 rounds until you automatically stop.

Do you want to start investing? [Yes]/[No]

Screen: Round X of 26: Result

[This screen is displayed conditional on being in the **soft plan treatment**.]

Your gain limit/loss limit was triggered in round X.

For the first X rounds you have earned a total gain/endured a total loss of [...] cents. [The outcome is colored in red or green for loss or gain, respectively.]

Screen: Round X+1 of 26: Investment decision

[This screen is displayed conditional on being in the **soft plan treatment**.]

You can now choose whether or not to continue investing 10 cents in the lottery. In case you continue, we will inform you as soon as either one of your limits is triggered again or the final round is reached.

Do you want to continue investing? [Yes]/[No]