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# How Financial Advisors Can Support Clients Through Market Volatility and Uncertainty

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Financial Advisors must face challenging market environments alongside their clients. In fact, helping clients withstand uncertain markets is one of the most valuable services an advisor provides.



In our research, we develop a grounded approach for guiding clients through rocky markets. We captured the experiences of top advisors who have guided clients through uncertainty. By collecting their experiences and lessons we have extracted insights you can use with your own clients.



But there are some problems...

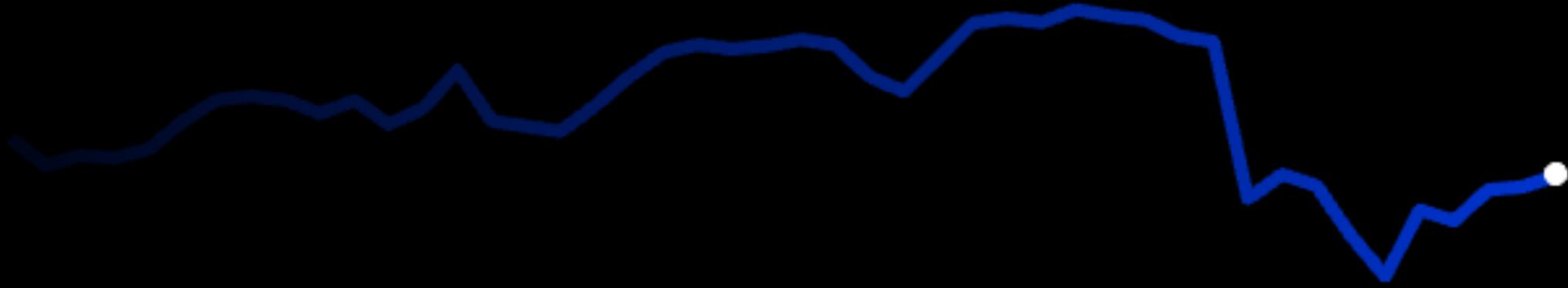


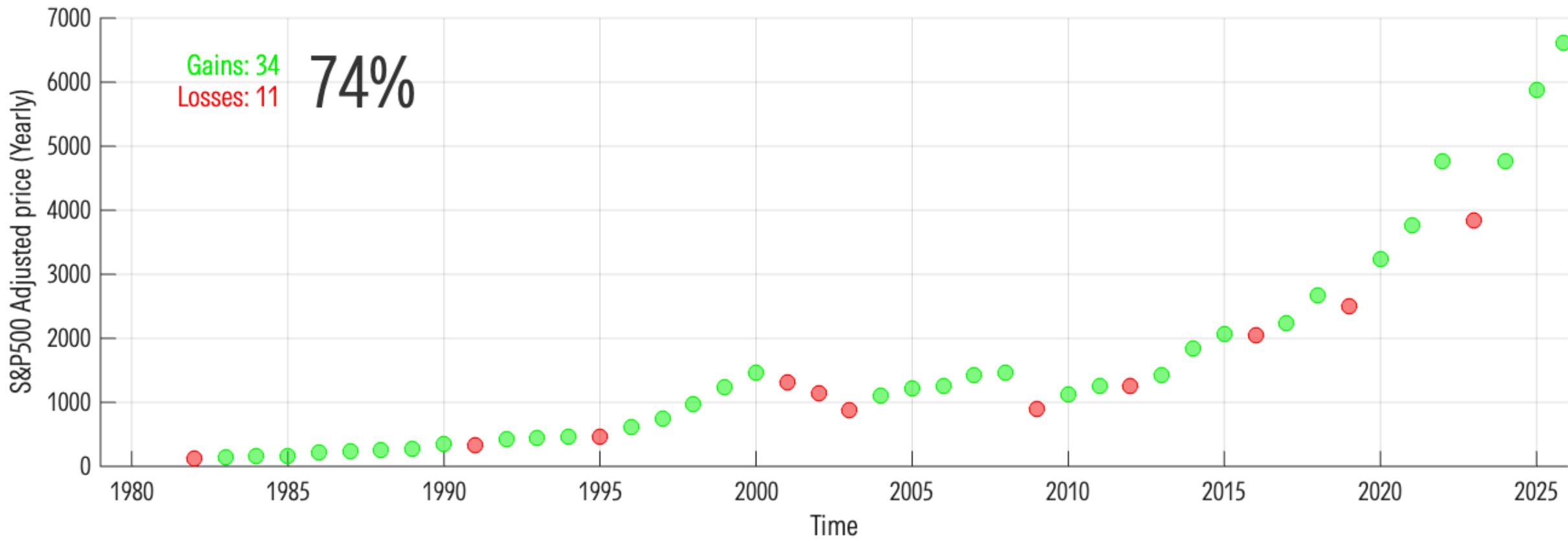


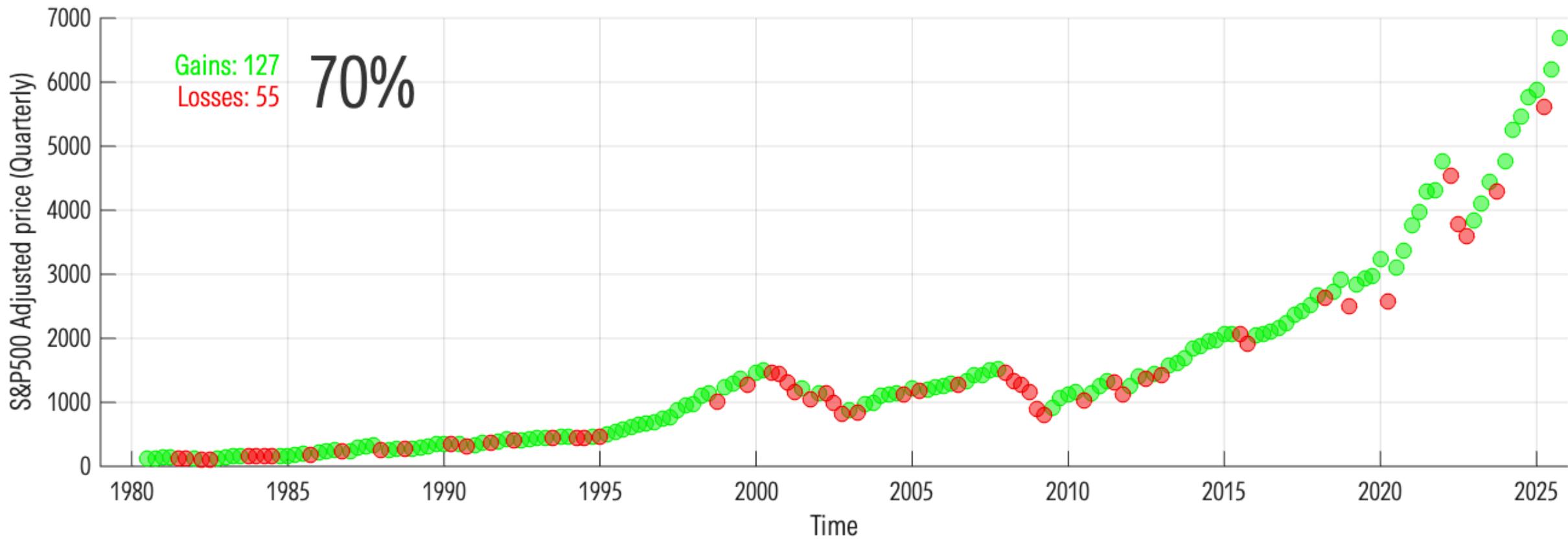
Distractions are abundant

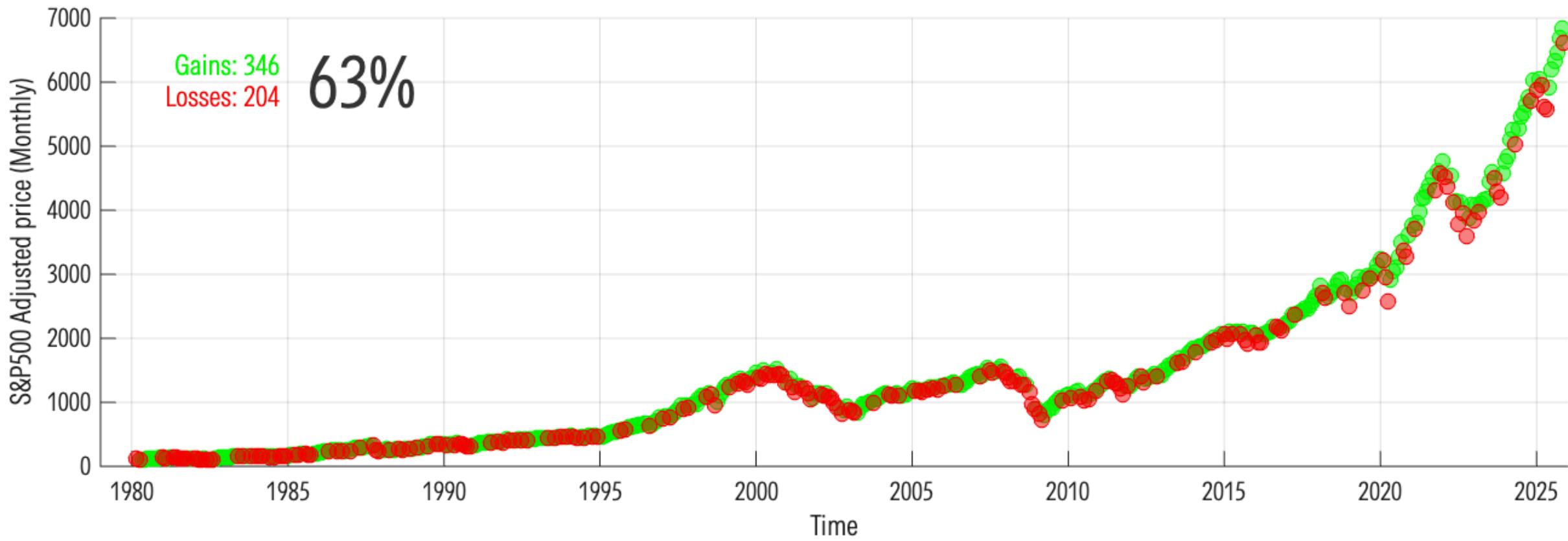
Your brain is a pattern recognition system (in overdrive)

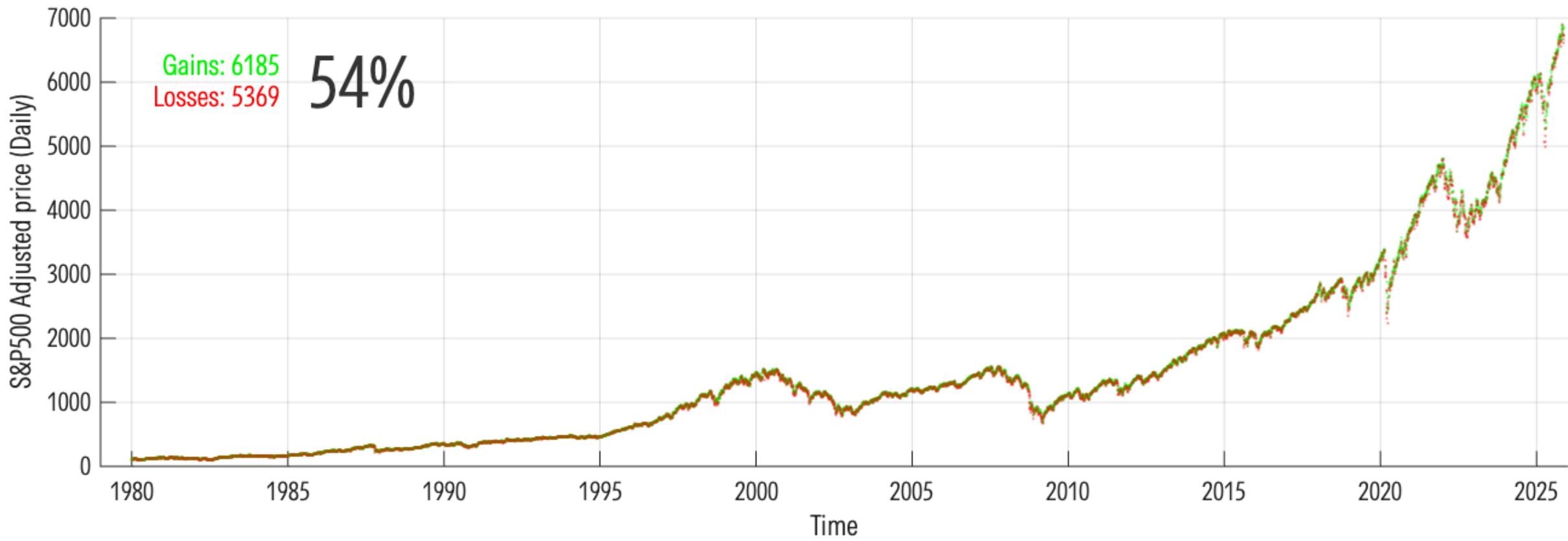
Feelings are associated with ups and **downs** (loss aversion)

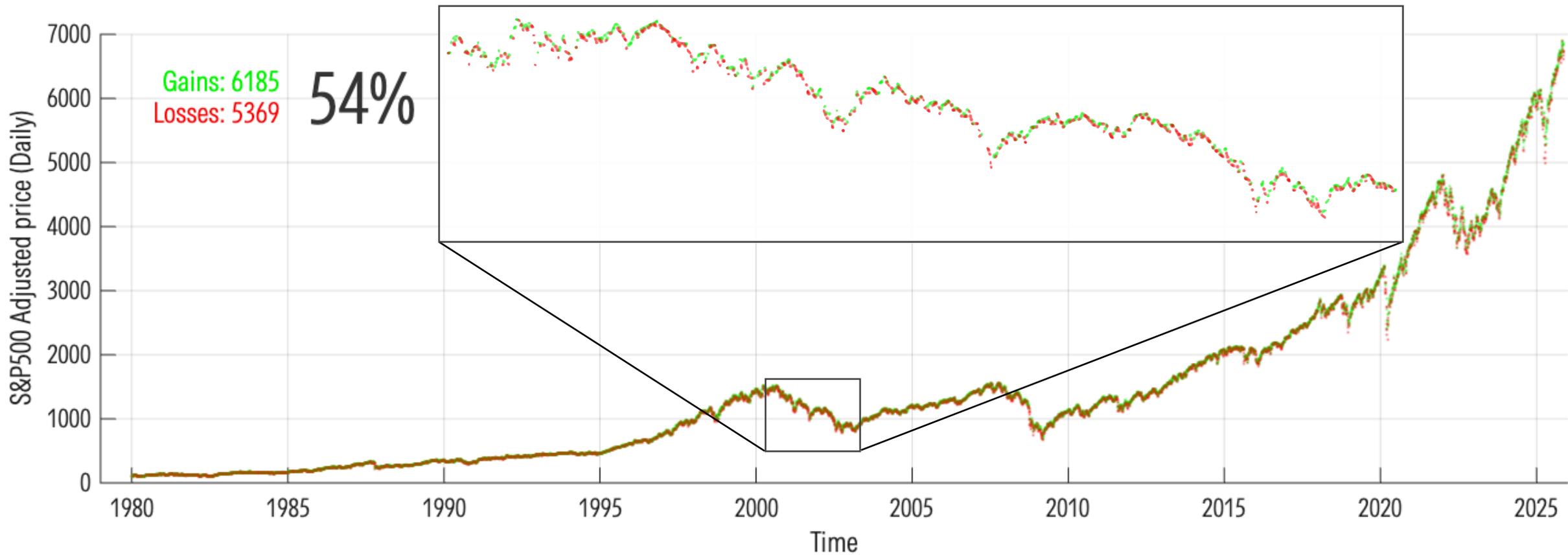


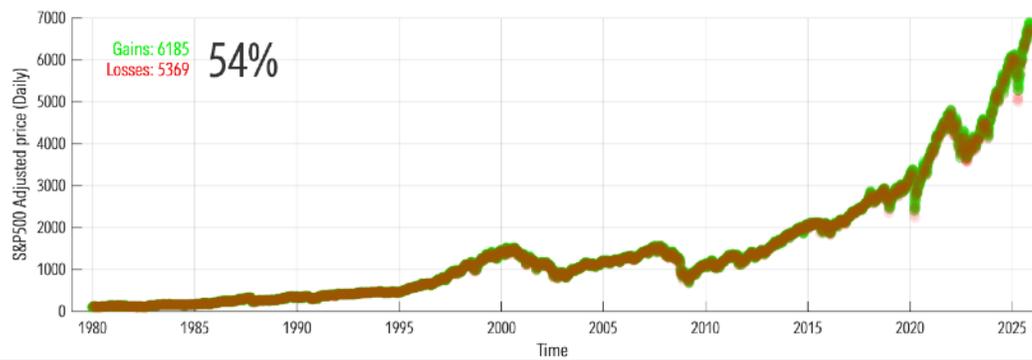
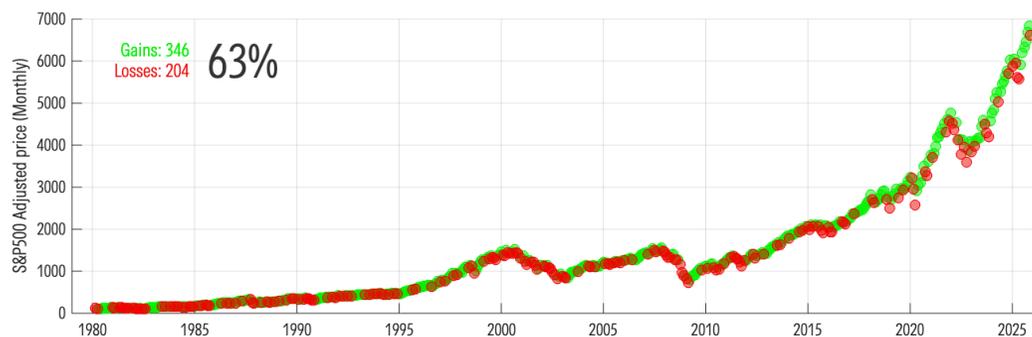
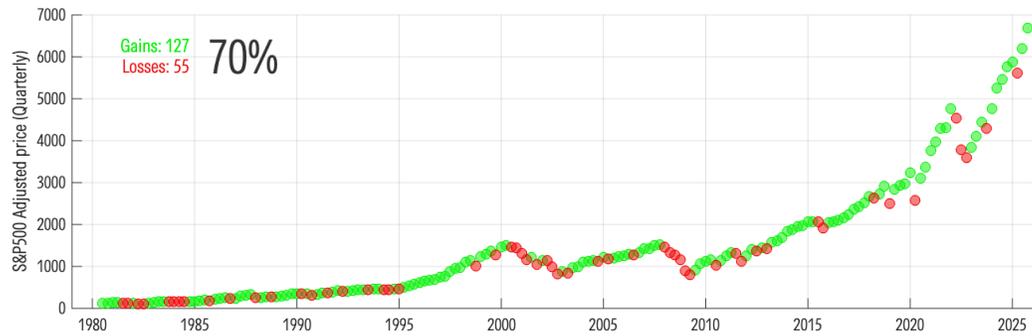
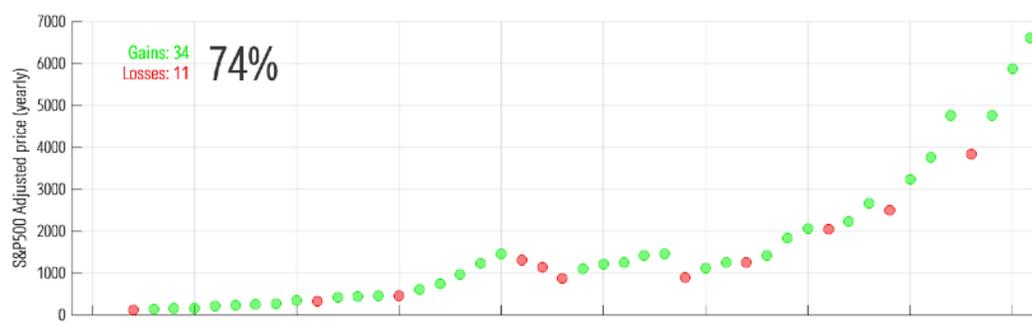








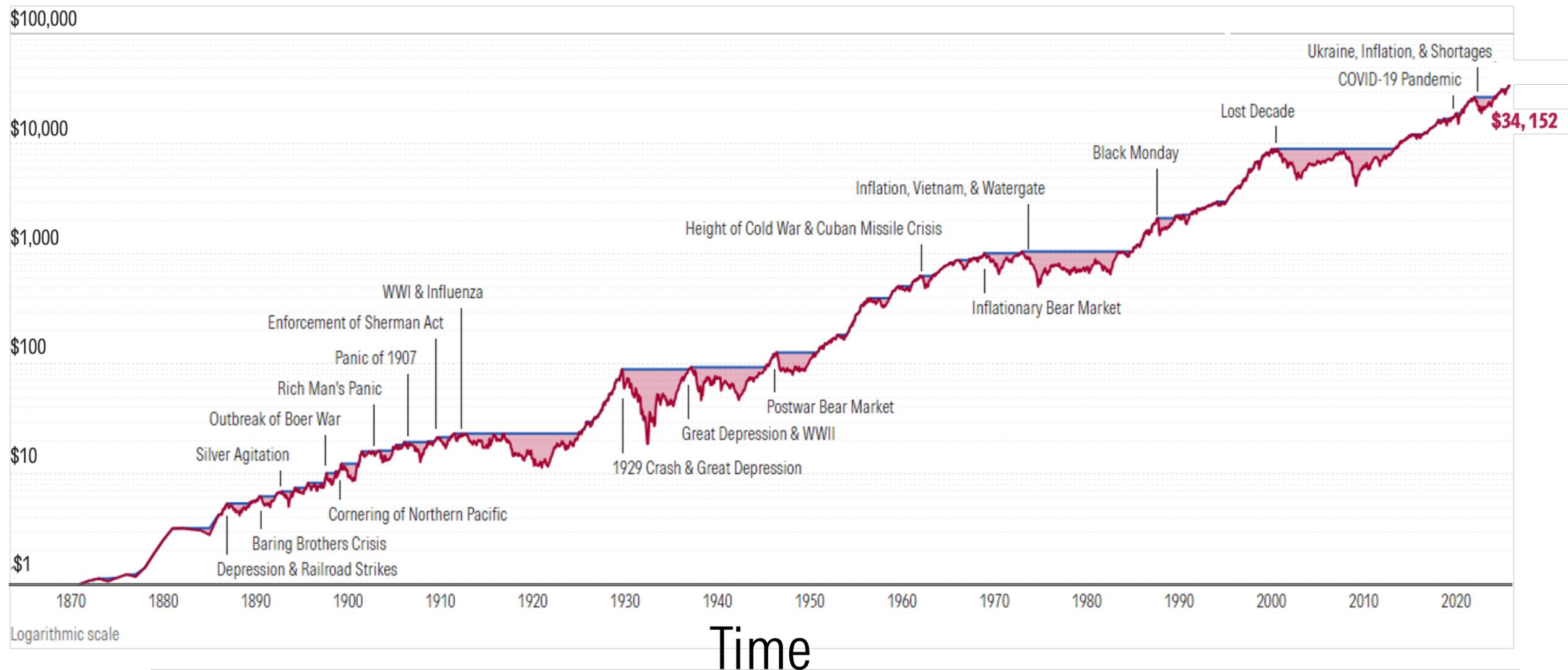




The more often people look  
the more volatility people see  
(and feel, and maybe act on)  
Loss aversion amplifies this



# A long view on markets



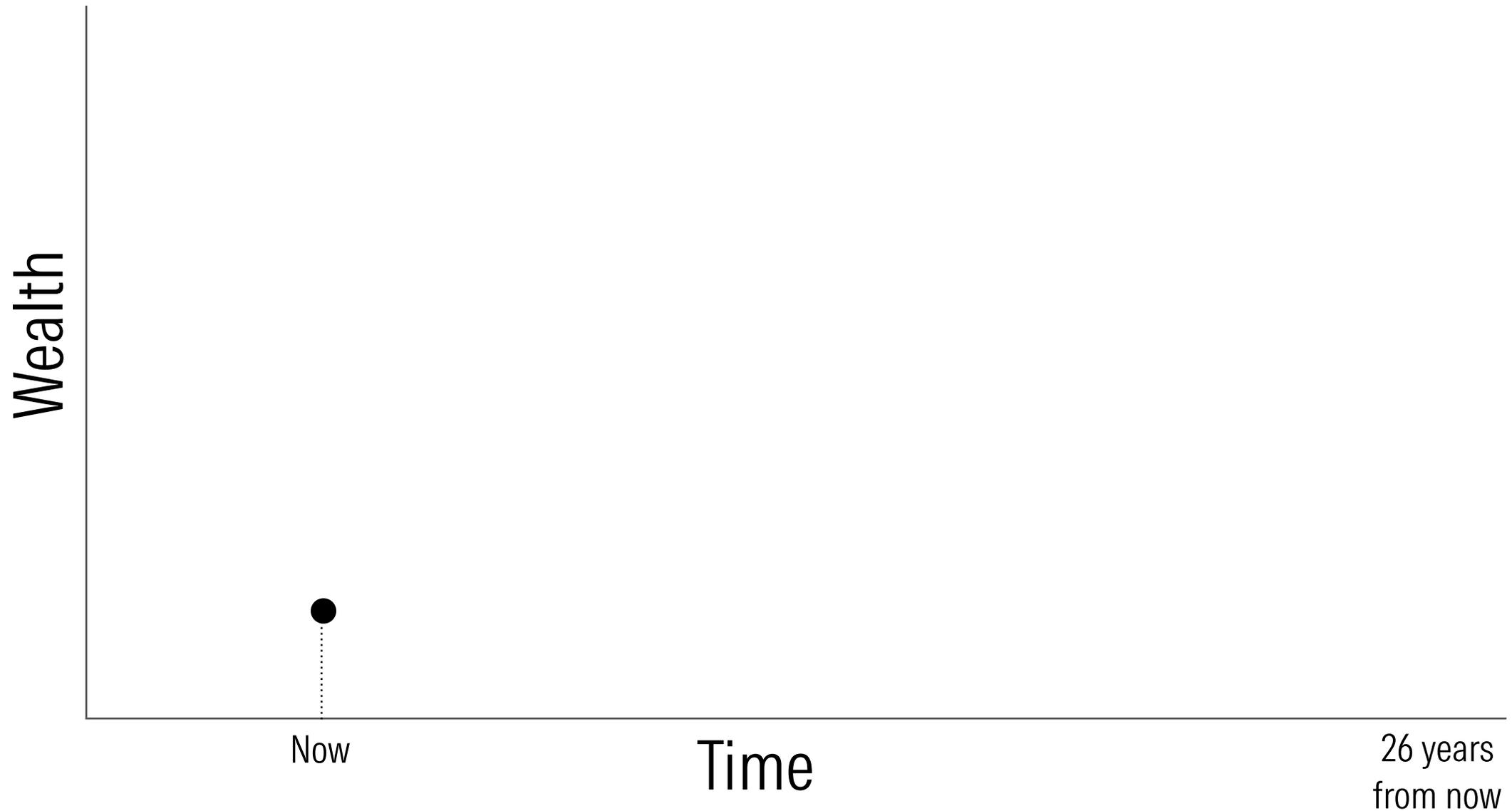
Source: Kaplan et al. (2009); Ibbotson (2023); Morningstar Direct; Goetzmann, Ibbotson, and Peng (2000); Pierce (1982); [www.econ.yale.edu/~shiller/data.htm](http://www.econ.yale.edu/~shiller/data.htm), Ibbotson Associated SBBI US Large-Cap Stock Inflation Adjusted Total Return Extended Index, S&P 500 (2025), Bureau of Labor Statistics, Non-Seasonally Adjusted Consumer Price Index (2025). Data as of Sep. 30, 2025.

What you can do about it (before it happens)

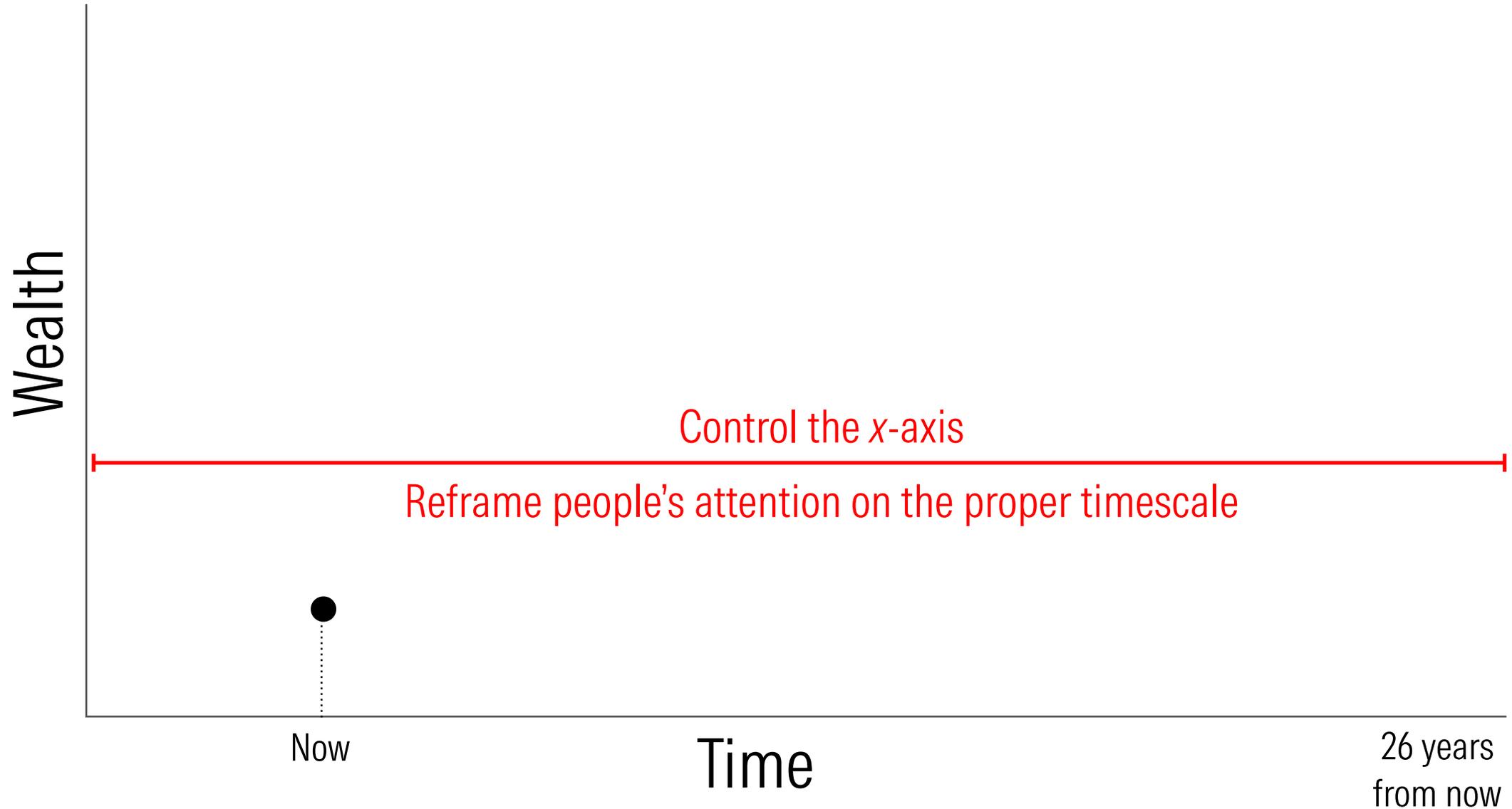
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Time

# What you can do about it (before it happens)



# What you can do about it (before it happens)





# Prospect Theory Reflects Selective Allocation of Attention

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**Keywords:** process tracing, cumulative prospect theory, risky choice, individual differences, attention

**Supplemental materials:** <http://dx.doi.org/10.1037/xge0000406.supp>

In 1654, an exchange of letters on gambling problems between French mathematicians Blaise Pascal and Pierre Fermat gave rise to the concept of *mathematical expectation* (Hacking, 1984). A decision under risk was thought to be rational if it maximized the decision maker's expected value (EV). In modern notation, EV is defined as

$$EV = \sum_{i=1}^n p_i x_i, \quad (1)$$

where  $p_i$  and  $x_i$  are the probability and the amount of money, respectively, associated with each possible outcome ( $i = 1 \dots n$ ) of that option.

It soon became clear that people's actual decisions violate the predictions of EV theory (e.g., the St. Petersburg paradox). Modifications of EV theory were proposed to account for these violations. For instance, objective amounts of money were replaced by subjective utilities (expected utility [EU] theory; Bernoulli, 1738/1954) or objective probabilities by subjective ones (Savage, 1954). Formally, these modifications were implemented by introducing functions with adjustable parameters that denote by how much the objective magnitudes are distorted when transformed into their subjective counterparts. For instance, in EU theory, the subjective value of an option can be defined as

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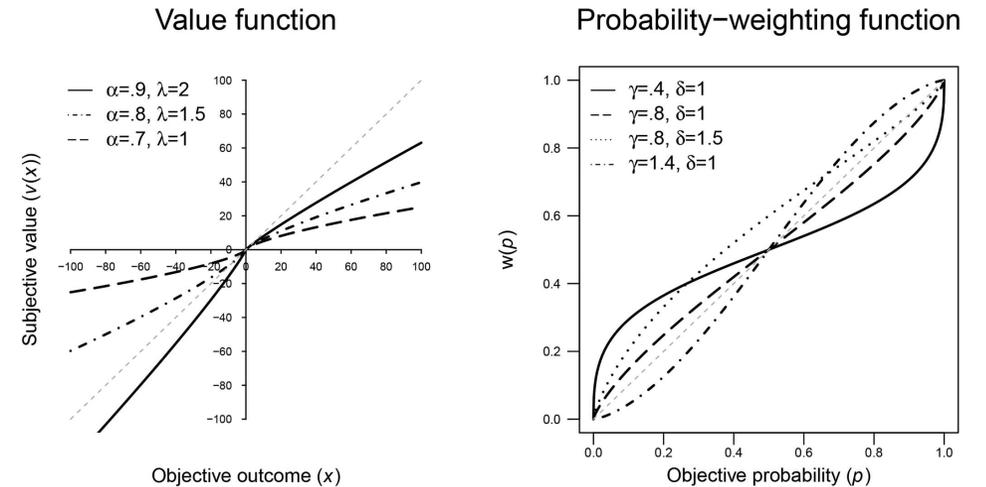


Figure 2. Cumulative prospect theory's value function for different values of the outcome-sensitivity ( $\alpha$ ) and loss-aversion ( $\lambda$ ) parameters (left) and the probability-weighting function for different values of the probability-sensitivity ( $\gamma$ ) and elevation ( $\delta$ ) parameters (right).

space. It separates the curvature of the probability weighting function from its elevation (e.g., Gonzalez & Wu, 1999) and is defined as follows:

$$w^+ = \frac{\delta^+ p^{\gamma^+}}{\delta^+ p^{\gamma^+} + (1-p)^{\gamma^+}} \text{ for } x, \quad (6)$$

$$w^- = \frac{\delta^- q^{\gamma^-}}{\delta^- q^{\gamma^-} + (1-q)^{\gamma^-}} \text{ for } y,$$

with  $\gamma^+$  and  $\gamma^-$  (both  $\geq 0$ ) governing the curvature of the weighting function in the gain and loss domains, respectively. Lower values on  $\gamma^+$  and  $\gamma^-$  indicate greater curvature and thus lower sensitivity to probabilities. The parameters  $\delta^+$  and  $\delta^-$  (both  $\geq 0$ ) govern the elevation of the weighting function for gains and losses, respectively, and are often interpreted as indicating the degree of optimism or pessimism (e.g., Gonzalez & Wu, 1999). We estimated a single  $\gamma$  parameter across gains and losses (i.e.,  $\gamma^+ = \gamma^-$ ) because probability sensitivity is typically found to be very similar across domains (Fox & Poldrack, 2014; Glöckner & Pachur, 2012; Tversky & Kahneman, 1992). In contrast, because, for instance, a high value on the elevation parameter implies opposite risk attitudes in the gain and loss domains (optimism vs. pessimism), we estimated this parameter separately for gains and losses. In a model comparison, this partly constrained implementation of CPT has been shown to outperform the unconstrained one (Pachur & Kellen, 2013). The right panel of Figure 2 depicts probability-weighting functions for different values of the  $\gamma$  and  $\delta$  parameters.

To derive predicted choice probabilities from CPT, we used an exponential version of Luce's choice rule (also known as softmax or logit function), which defines the probability that a gamble A is chosen over a gamble B as

$$P(A, B) = \frac{1}{1 + e^{-\theta(V(A) - V(B))}}, \quad (7)$$

where  $\theta$  ( $\geq 0$ ) is a scaling (or choice-sensitivity) parameter. With a higher  $\theta$ , the probability of choosing the gamble with the higher  $V$  approaches 1; with  $\theta = 0$ , choices are random.

In this implementation, CPT has six adjustable parameters (see Equations 3–7): outcome sensitivity ( $\alpha$ ), loss aversion ( $\lambda$ ), probability sensitivity ( $\gamma$ ), separate elevations for gains ( $\delta^+$ ) and losses ( $\delta^-$ ), and scaling ( $\theta$ ). The parameters were estimated for each participant, separately for the two sessions, using a hierarchical Bayesian approach (Nilsson et al., 2011; Scheibehenne & Pachur, 2015). In Bayesian parameter estimation, parameter estimates are initially represented in terms of prior distributions and then updated to posterior distributions based on the observed data. The advantage of a hierarchical approach is that individual parameters are partially pooled through group-level distributions, thus yielding more reliable estimates than does the traditional, nonhierarchical approach. The priors for the parameters on the individual level were set to distributions spanning a reasonable range that excluded theoretically impossible values but included parameter values found in previous research. Specifically, the ranges were 0–5 for  $\theta$ ,  $\lambda$ ,  $\delta^+$ , and  $\delta^-$  and 0–2 for  $\alpha$  and  $\gamma$ . The group-level parameters were linked with the individual level (assuming normal distributions on both levels) through probit transformations (see Rouder & Lu, 2005; Scheibehenne & Pachur, 2015). This transformation yields a range from 0 to 1 on the individual level. To extend the range of these distributions from 0 to 5 for  $\theta$ ,  $\lambda$ ,  $\delta^+$ , and  $\delta^-$  and from 0 to 2 for  $\alpha$  and  $\gamma$ , we interposed an additional linear linkage function. All hierarchical group-level means were assumed to be normally distributed with a mean of 0 and a variance of 1. The

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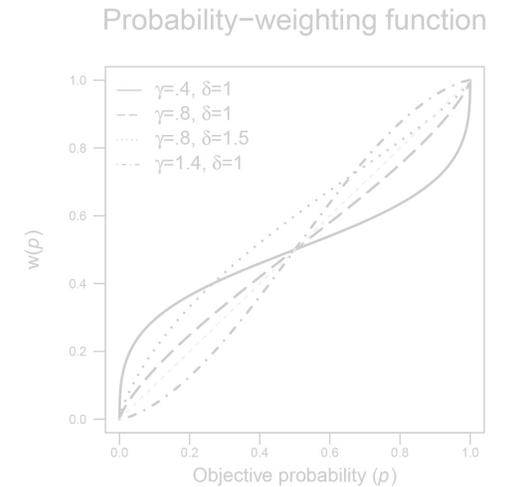
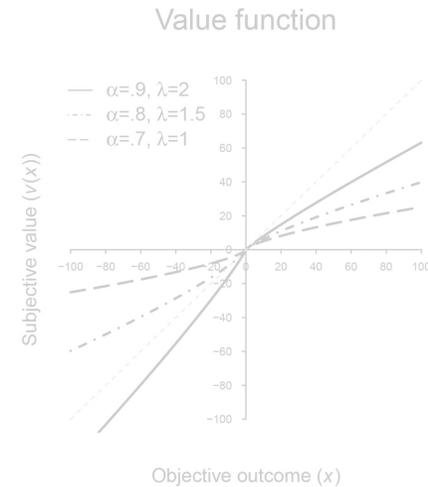


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$$w^+(p) = \frac{p^\gamma}{p^\gamma + (1-p)^\delta}, \quad \text{for } p \in [0, 0.5] \\ w^-(p) = \frac{p^\gamma}{p^\gamma + (1-p)^\delta}, \quad \text{for } p \in (0.5, 1]$$

with  $\gamma^+$  and  $\gamma^-$  (both  $\geq 0$ ) governing the curvature of the weighting function in the gain and loss domains, respectively. Lower values on  $\gamma^+$  and  $\gamma^-$  indicate greater curvature and thus lower sensitivity to probabilities. The parameters  $\delta^+$  and  $\delta^-$  (both  $\geq 0$ ) govern the elevation of the weighting function for gains and losses, respectively, and are often interpreted as indicating the degree of optimism or pessimism (e.g., Gonzalez & Wu, 1999). We estimated a single  $\gamma$  parameter across gains and losses (i.e.,  $\gamma^+ = \gamma^-$ ) because probability sensitivity is typically found to be very similar across domains (Fox & Poldrack, 2014; Glöckner & Pachur, 2012; Tversky & Kahneman, 1992). In contrast, because, for instance, a high value on the elevation parameter implies opposite risk attitudes in the gain and loss domains (optimism vs. pessimism), we estimated this parameter separately for gains and losses. In a model comparison, this partly constrained implementation of CPT has been shown to outperform the unconstrained one (Pachur & Kellen, 2013). The right panel of Figure 2 depicts probability-weighting functions for different values of the  $\gamma$  and  $\delta$  parameters.

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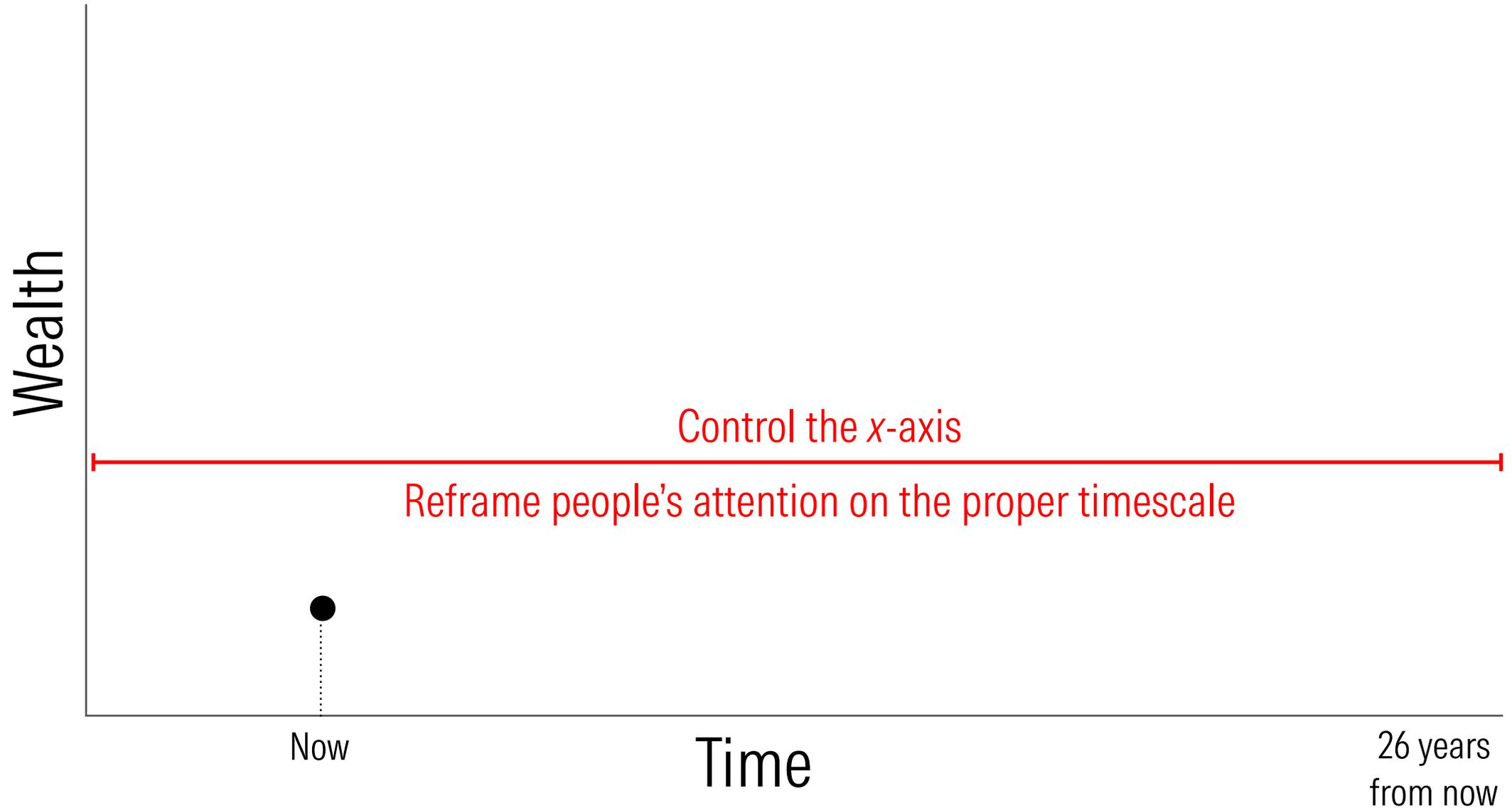
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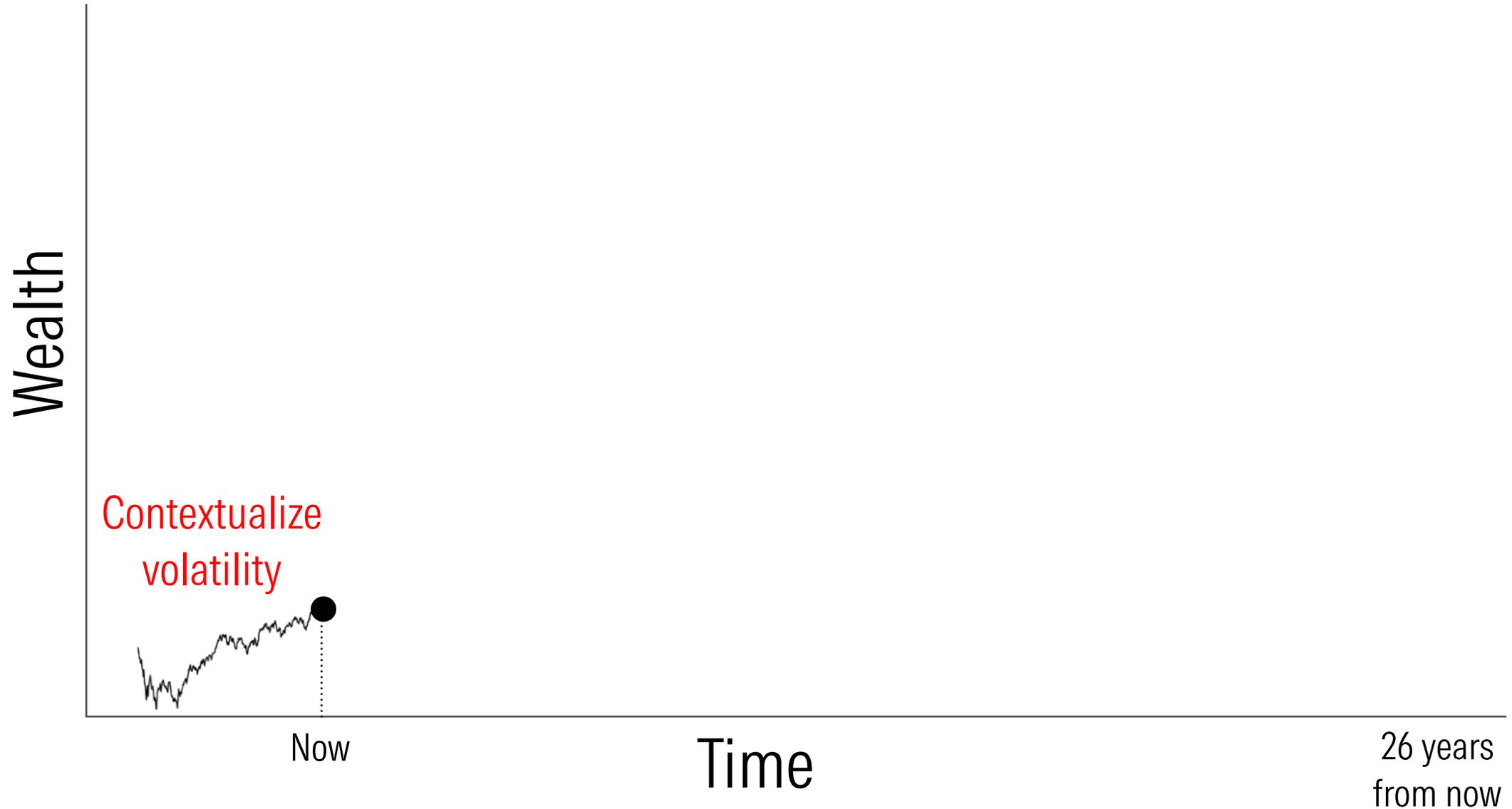
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# You can help overcome people's loss aversion by changing what they pay attention to.

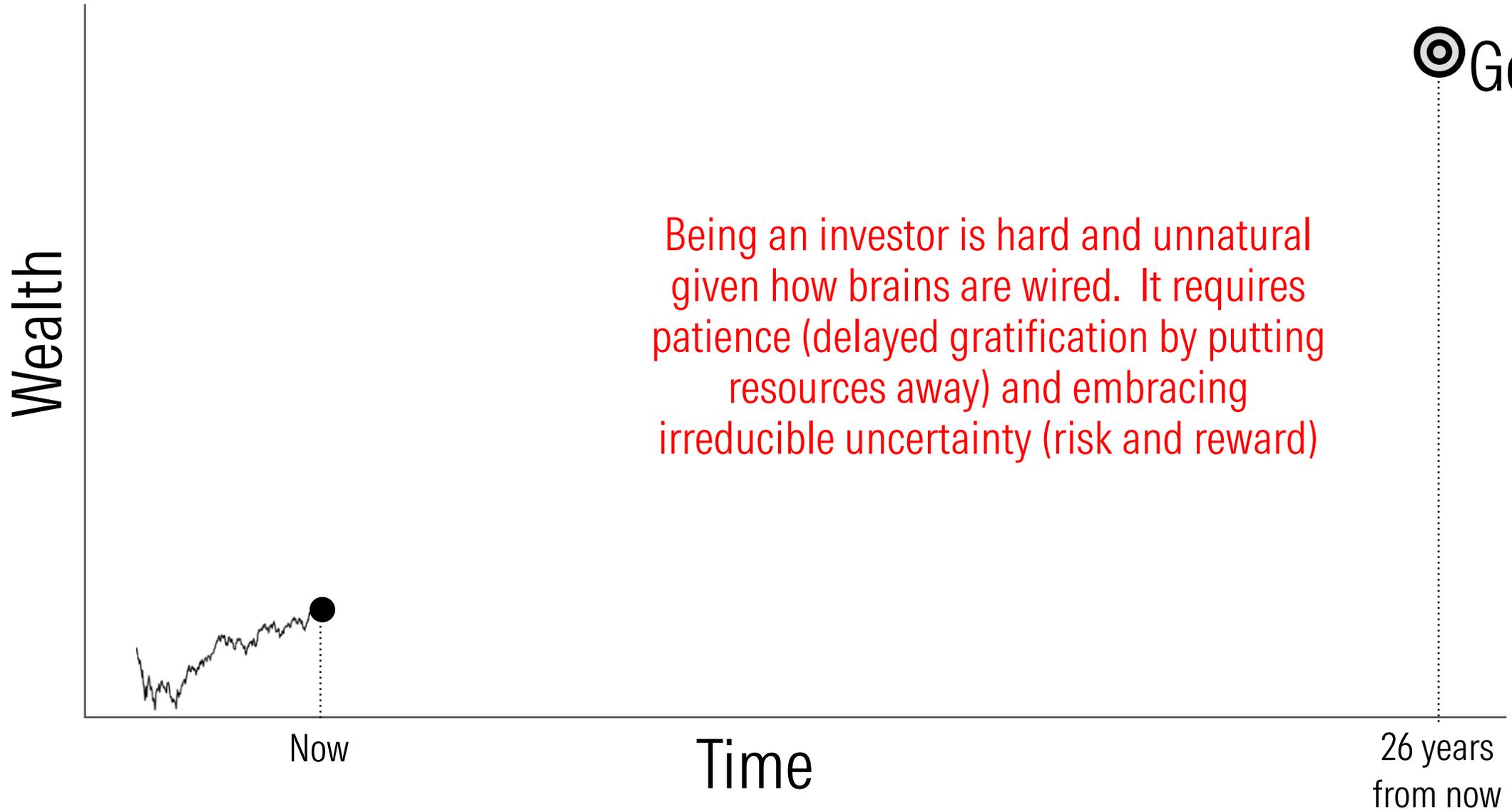
# What you can do about it (before it happens)



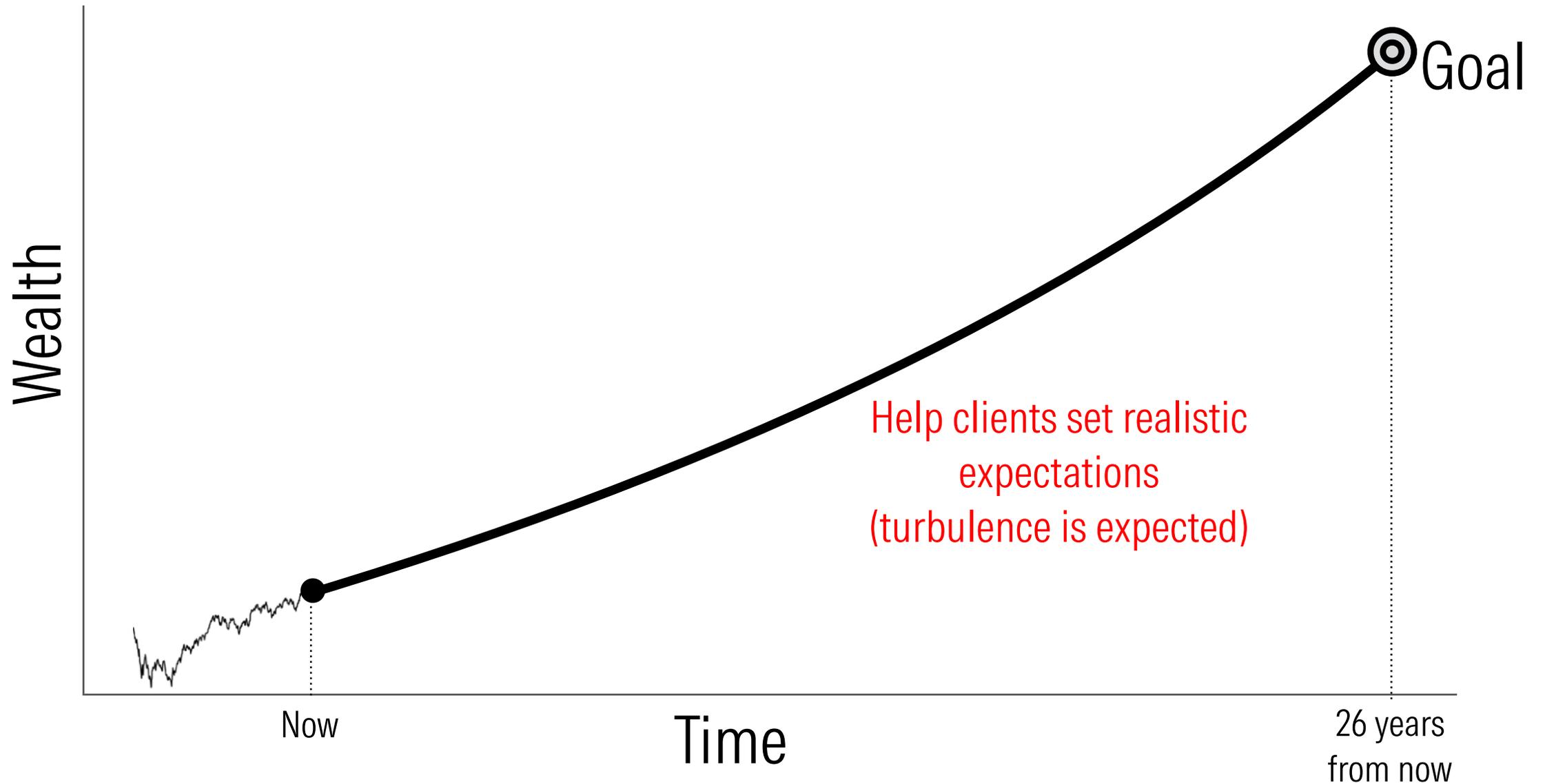
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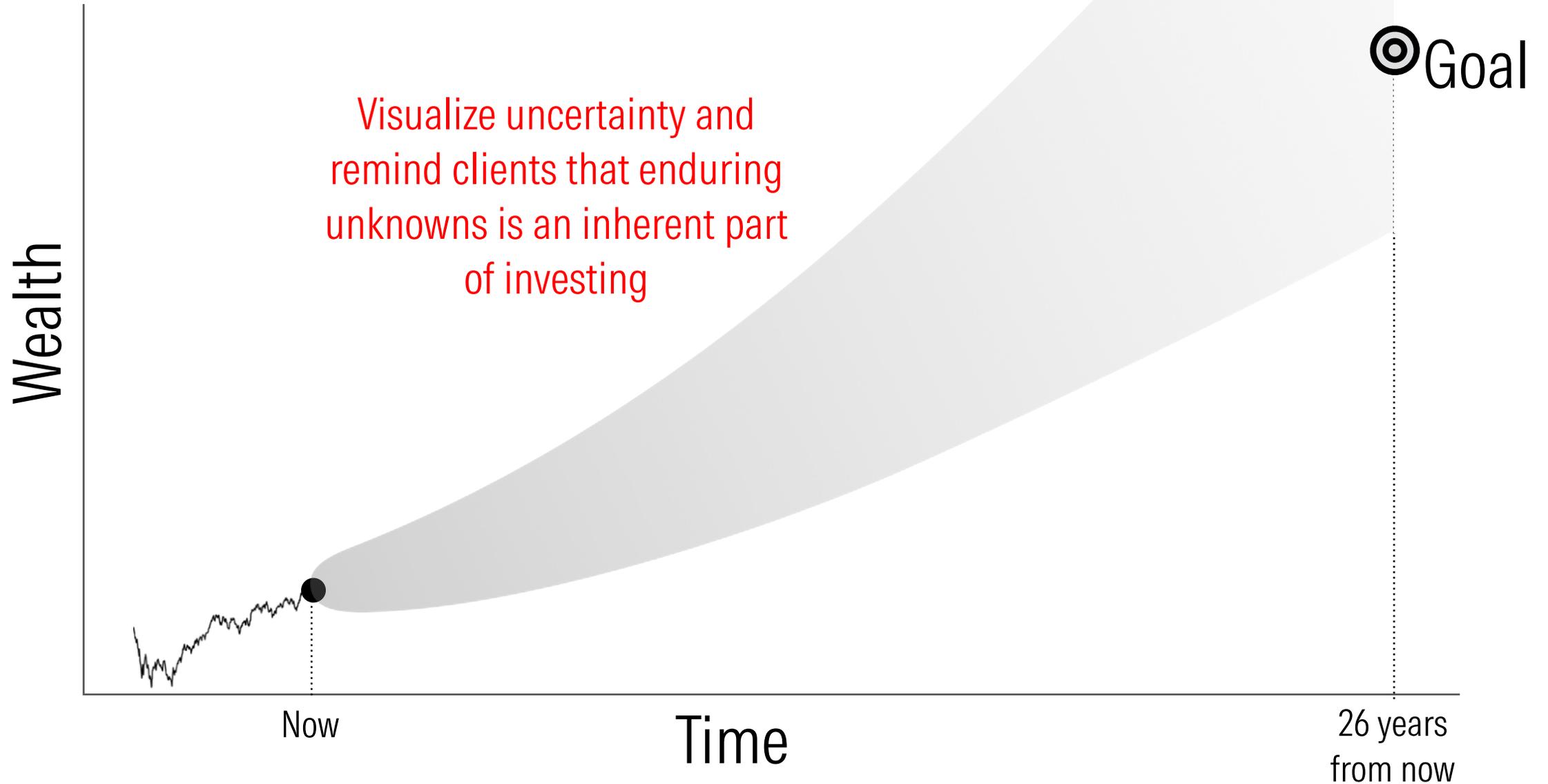
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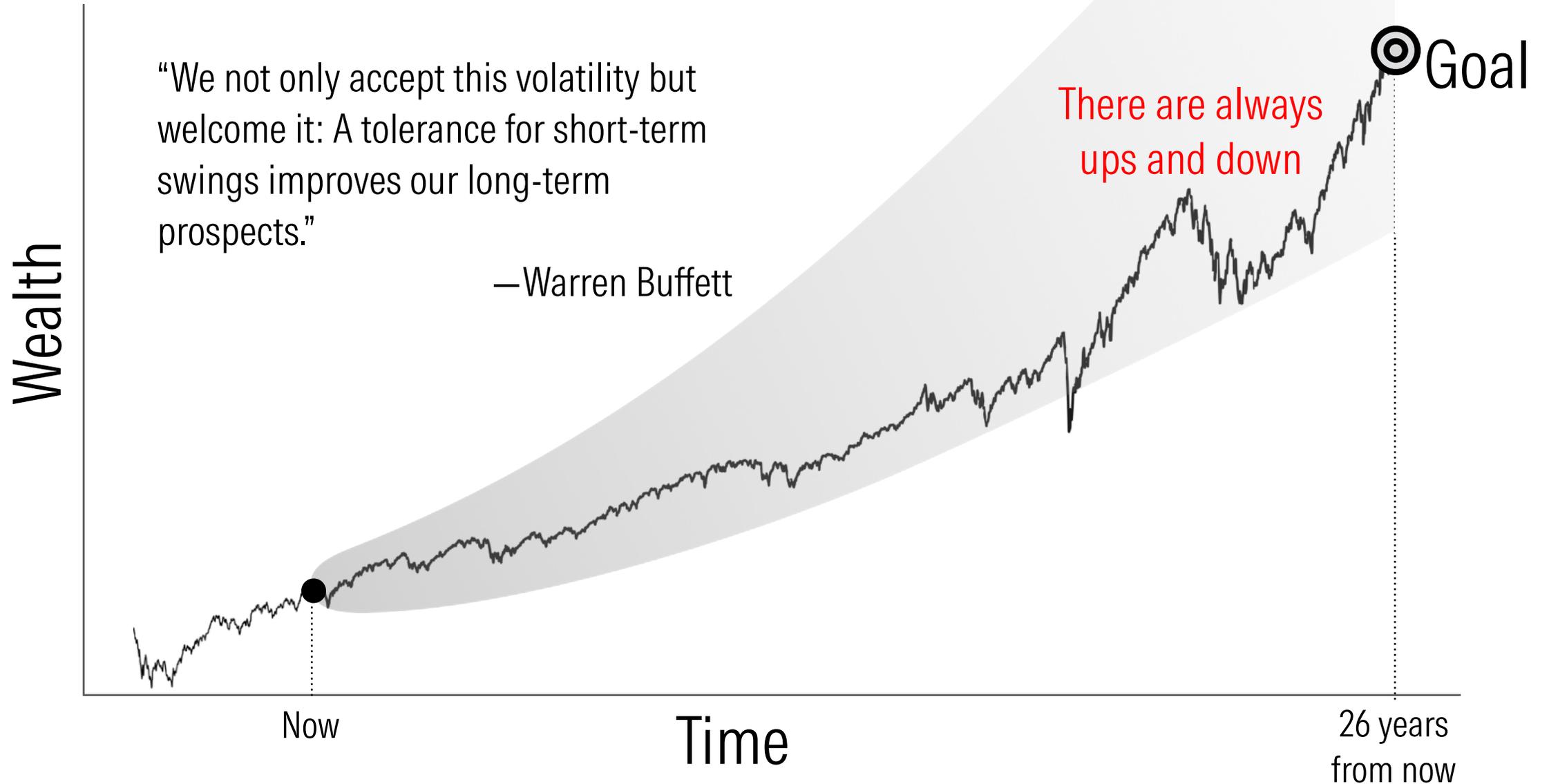
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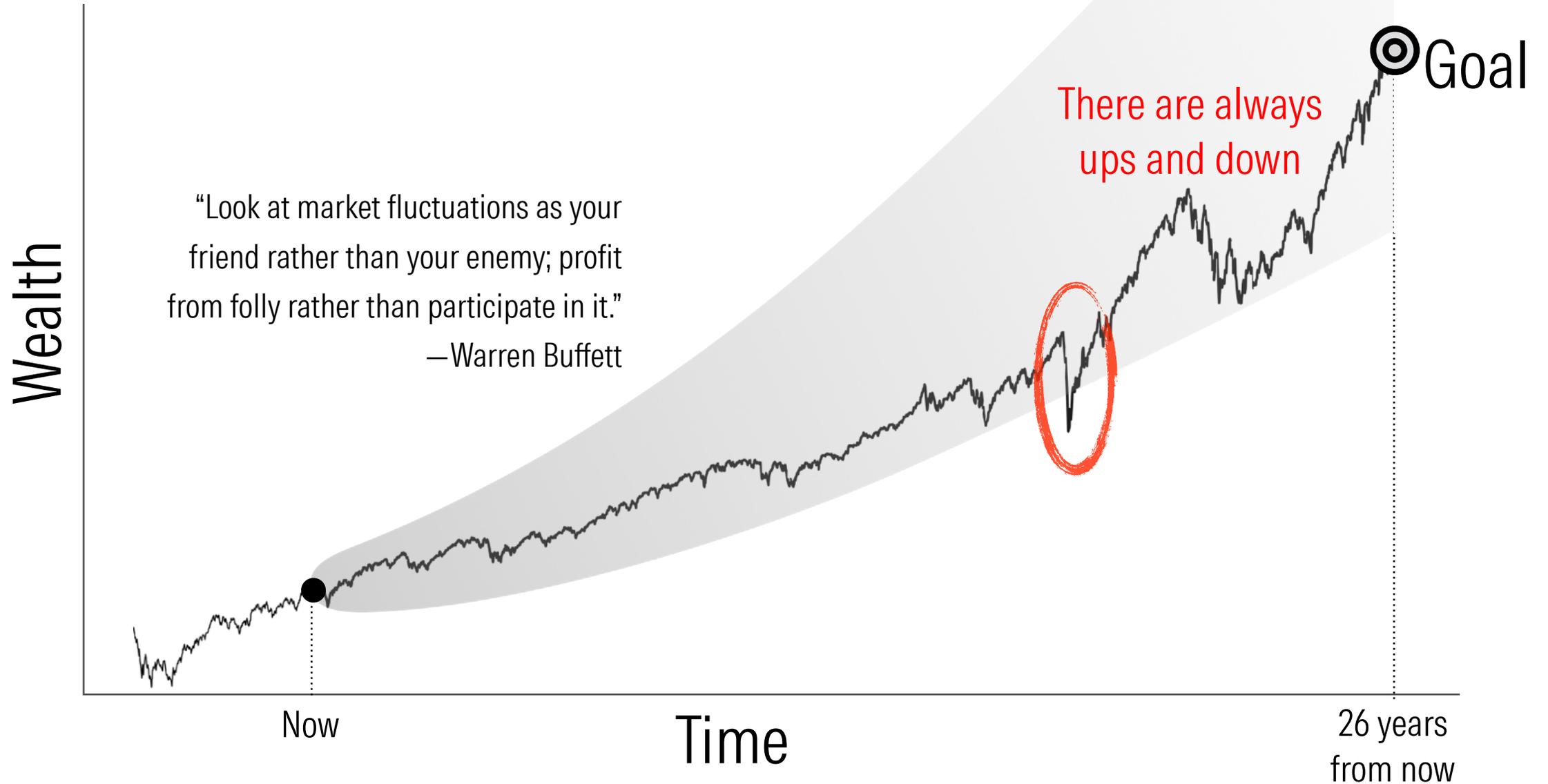
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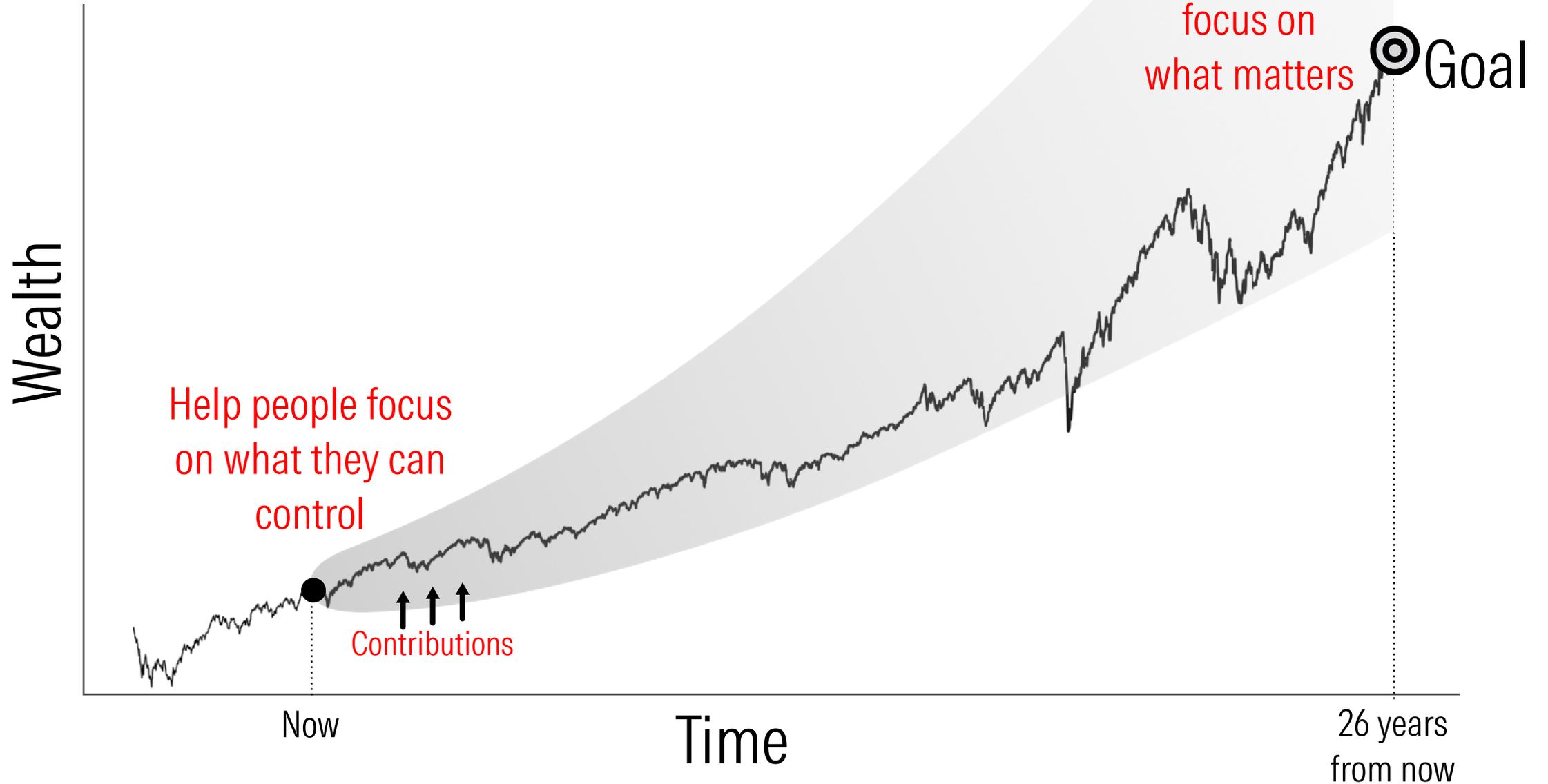
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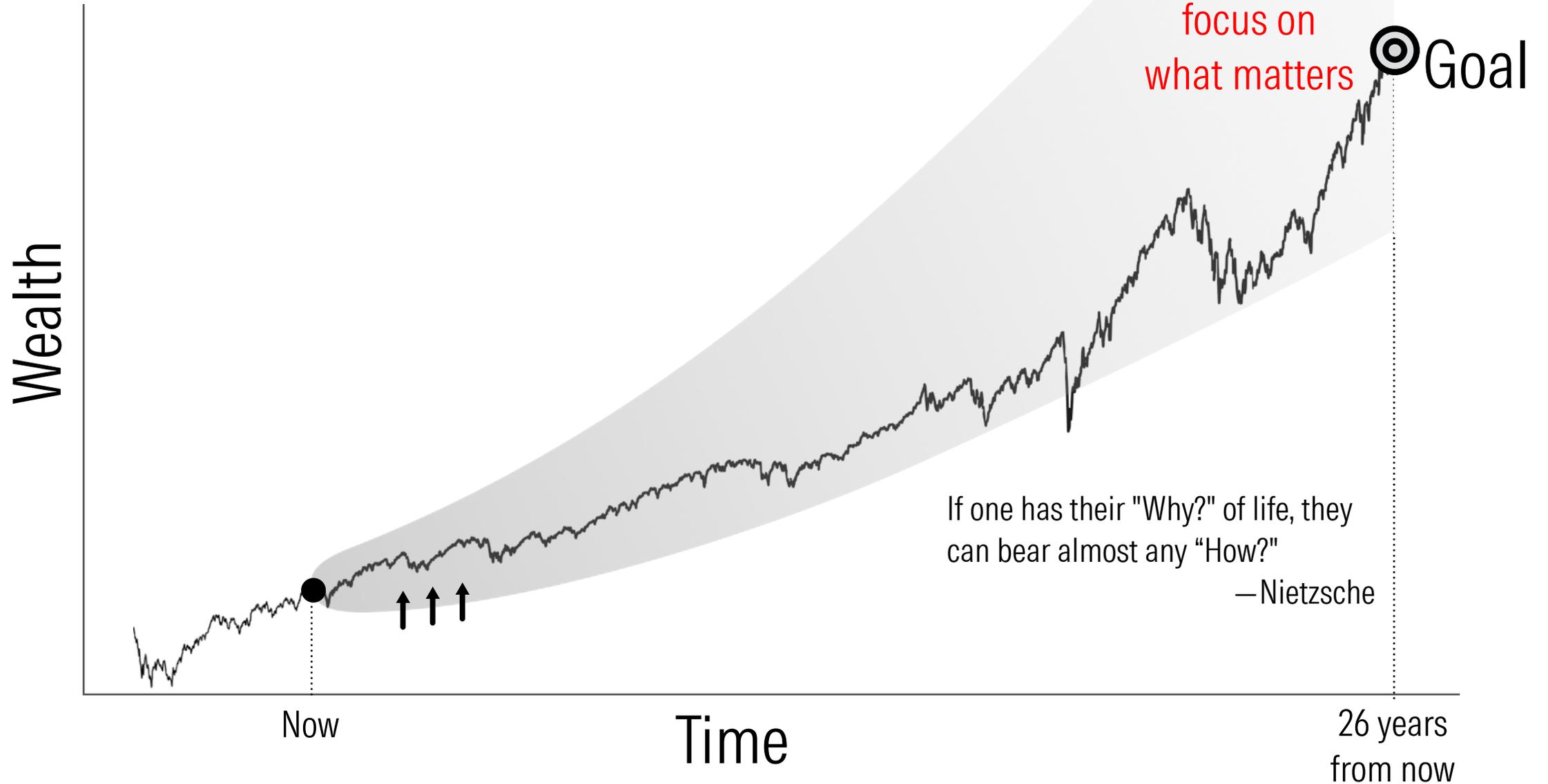
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# What you can do about it (before it happens)



# What you can do about it (before it happens)





# Study details

Morningstar Advisor Panel

Asked about their experiences with clients regarding volatility

47 established financial advisors (US, CA, UK, AUS, SA)

Mean age of 50, average of 19 years of experience

Average of about \$250M-\$500M AUM



## Before- Education and inoculation

Not **if** there will be a recession/downturn...  
...but how many.

Basic expectation management (good portfolios, over the long run, lose money about 4-5 months every year). That's normal.

Volatility is the ticket to ride and there is an opportunity to foster a contrarian mindset

Pre-commit- when there is a downturn,  
what are we going to do?

Help people understand what their  
anticipated volatile will look like and  
remind them this is normal.

“Be fearful when others are greedy, and  
greedy when others are fearful.”  
-Warren Buffett

# During volatility

## Who reaches out

### ***Patterns in Types of Clients Who Reach Out***

*Percent of advisor participants reporting each client type*

Inexperienced clients who are either new to investing or new to the practice

**34%**

Clients who are relying on their investments for income

**28%**

Clients who are worriers or overly cautious

**24%**

Client who are influenced by media or social connections

**14%**

Clients who are concerned about risk

**7%**

Clients who have recently made significant changes to their portfolios

**3%**

Clients who manage their own funds

**3%**

# During volatility

## What do they talk about

### Topics Brought Up by Cliets

Percent of advisor participants reporting topic

**Market Dynamics:** Questions about causes of volatility

47%

**Performance:** Inquire about how their own investments are faring

31%

**Lifestyle:** Concern about the maintenance of their financial security and lifestyles

17%

**Market Expectations:** Ask your opinion on future market performance

14%

**Adjustments:** Ask if they should modify their investments

14%

**Opportunities:** Seek guidance on how to take advantage of volatility

6%

**Goals:** Ask whether volatility will affect their long-term goals and plans

3%

# During volatility

What do they feel

**In general, how would you characterise your clients when they talk about market volatility?**

● Advisor response  
◆ Average advisor response

SCARED



WORRIED



OPPORTUNISTIC



CURIOUS



←-----→  
Describes none of my clients      Describes roughly half of my clients      Describes most of my clients

# During volatility

## What advisors can do

### TACTIC

Proactive Education About Volatility

Education During Volatility

Encourage Long-Term Investing

Let Client Lead

Strategic Review/Adaptation of Client Financial Situation

Reframe Volatility as an Opportunity

Decision-Making Support

### DESCRIPTION

Educates clients about potential market fluctuations and discusses strategies before volatility occurs.

Educates clients about market volatility and historical performance during volatility. It can be in the form of providing clients with educational resources such as market commentary presentations, newsletters, and articles.

Emphasizes the importance of maintaining a long-term perspective when it comes to investing.

Focus on listening or allowing clients to lead discussions about their concerns.

Work with a client to review the plan and adjust where necessary based on current market conditions (for example, considering clients' asset allocation, income needs, life stage, and time horizon).

Encourage clients to view market volatility as an investing opportunity.

Help clients make decisions by managing factors that might affect their decisions, such as their emotions, behaviors, values, personality, and temperament.

# After volatility

What advisors have learned to do differently given their experiences

## CHANGES

Shifted From Investment Focus to Advisory Role

Increased Confidence in Managing Conversations

Enhanced Reassurance Tactics

Improved Communication Skills

Focused on Education and Preparation

Increased Confidence in Investing Expertise

## DESCRIPTION

Shifted conversations to focus less on investments and more on as advisor's role as a financial guide/coach

Improved their ability and confidence when anticipating and managing client needs and concerns during periods of market volatility

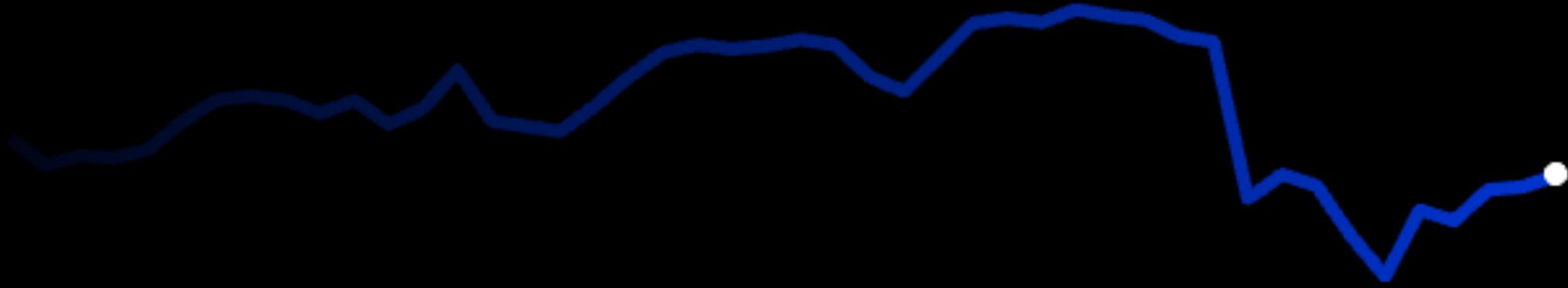
Refined their methods of reassuring clients during volatility (for example, leveraging personalized data and conducting proactive outreach)

Improved their communication techniques (for example, prioritizing empathy, active listening, using less jargon, and tailoring conversations to the client's understanding)

Prioritized educating and preparing clients for market volatility

Improved their own understanding of market volatility and investing strategies, allowing them to be more confident in their own investing approach

# Volatility and uncertainty are inherent parts of investing



Inoculate, Reframe, Refocus, Assuage, and Adapt

# Support Clients Through Market Volatility and Uncertainty

Advisors (not clients) initiate most volatility conversations, highlighting the value of proactive interventions

Clients focus on market mechanics and portfolio impact—but rarely on opportunities or long-term goals, revealing a need for advisors to foster contrarian thinking and goal-based framing during volatility

Advisors who rely on decision-making support and market education, and those incorporating behavioral coaching, see more opportunistic (and less reactive) clients

Experienced advisors shift from investment management toward communication, reassurance, and coaching

Developing a repeatable process for volatility conversations strengthens client outcomes and practice consistency, helping advisors scale their major value effectively

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# How Financial Advisors Can Support Clients Through Market Volatility and Uncertainty

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