Timing Risk and Valuation

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Abstract

I show that the pricing of timing risk is conceptually distinct from the pricing of outcome risk, deriving no-arbitrage characterizations and updating foundational valuation results for risk-adjusted discount rates, capital budgeting, and scenario analysis. For example, risk-adjusted discount rates move with idiosyncratic timing risk and generally increase even when timing risk increases valuation, creating a wedge relative to systematic risk based estimates. Capital budgeting techniques which are theoretically suboptimal for outcome risk satisfy desirable properties under timing risk. Despite theoretical timing-outcome differences, real world valuation treats the timing as more similar to outcomes than the no-arbitrage theory would suggest, yielding a theory-practice gap in the valuation of timing risk.

1 Introduction

Consider receiving money in 1 day. Which is valued higher: \$5 with 50% probability and \$10 with 50% probability, or \$7.50 for sure? The immediate answer from baseline valuation is \$7.50 for sure.

Now flip dollars and days and ask the same question. Consider receiving \$1 for sure. Now which is valued higher: receiving that \$1 in 5 days with 50% probability and in 10 days with 50% probability, or in 7.5 days for sure?

The first question is about outcome risk: how much will be paid. The second is about timing risk: when the payment will arrive.

This paper studies the pricing and valuation of timing risk. Both timing and outcomes can be represented by Arrow-Debreu states. But I show that they are different kinds of states. In particular, I show theoretically that timing has conceptual differences for pricing relative to outcomes, which yields results that update pedagogy and intuition for valuation elements. Yet, real-world valuation treats time as more similar to outcomes than these general conceptual differences would predict.

The conceptual time-outcome differences I derive are as follows. The only assumption I use for the results is no-arbitrage. Because these results therefore apply universally, it is all the more surprising that these timing-outcome differences do not appear to be fully incorporated in standard valuation tools and real-world valuation. First, I prove that pricing frameworks imposes more restrictions on state space for timing than for outcome risk. In particular, both outcome risk and timing risk admit a continuum of assets. However, I show that simplifications of the state space which are possible for pricing idiosyncratic outcome risk do not preserve prices for all assets with timing risk. Second, I show that all systematic risk can be decomposed into timing and outcome risk. This simple decomposition lends intuition for why these can be considered separate dimensions of risk and how they formalize. I characterize the differential impact of timing vs. outcomes for a wide class of SDFs in the case of aggregate risk. Third, I show that the price of timing risk is characterized by the risk-free yield curve.

I then prove theoretically that these simple no-arbitrage findings change the usual interpretation of foundational corporate finance elements across a wide range of settings. First, risk-adjusted discount rates are typically thought to reflect only systematic risk (Myers and Turnbull, 1977). This statement is certainly true for outcome

risk; however with timing, idiosyncratic risk also moves the risk-adjusted discount rate. Calibrations in empirical settings find that for a project with an expected time to completion of 5 years and a timing standard deviation of 3 years, idiosyncratic timing risk changes the risk-adjusted discount rate by 5% for typical moderately upward sloping yield curves; 1.4% for nearly flat yield curves; and 72 basis points for downward sloping yield curves. With a timing standard deviation of 5 years, the impact of idiosyncratic timing risk on the risk-adjusted discount rate becomes 14.4% for moderately upward sloping yield curves; 3.8% for near-flat yield curves; and -64 basis points for downward sloping yield curves. In addition, timing risk and outcome risk yield difference comparative statics. With outcome risk, a higher present value indicates a lower risk-adjusted discount rate. With timing, I further prove that it is possible to have higher present value and higher risk-adjusted discount rates – unlike for outcomes. As a result, incorporating timing risk predicts that risk-adjusted discount rates should typically be higher than predicted by systematic risk, providing one possible rationale for buffers relative to the rate required by systematic risk (Graham, 2022).

Second, capital budgeting techniques' appropriateness changes with timing risk. While the payback period method is commonly used in practice, it has long been maligned for lacking theoretical justification under outcome risk (Prabhala and Li, 2007; Graham, 2022). In contrast, I show that payback satisfies natural dominance properties for timing risk. Payback always satisfies first-order stochastic timing dominance, and empirically usually satisfies second-order stochastic timing dominance in ranking projects.

Third, whereas simple approaches to valuation such as thinking through a finite number of variables can work for outcome risk (Iyer and Schoar, 2024), I show any finite discretization approach is not able to correctly price all timing risk.

Together, these theoretical results show a general timing-outcome differences for pricing and foundational valuation elements.

I then check whether real-world financial markets obey the no-arbitrage timing-outcome results. Four pieces of market and valuation evidence collectively suggest that timing is not always priced as the no-arbitrage theory would predict. Together, they indicate three theory-practice gaps for the valuation of timing risk.

First, real-world valuation compresses timing in a manner similar to outcomes. The Securities and Exchange Commission, in its regulation for calculating the fair

value of an employee stock option, requires using the average historical within-firm time to exercise. While innocuous for outcome risk, this compression is not innocuous for timing risk. Collecting data on all employee stock option exercise, I compute fair value using both the SEC required compression and using the full historical within-firm timing distribution. The difference across firms in fair value is 4.6% on average, indicating a regulation-driven valuation gap from not having timing valued more closely to the no-arbitrage theory. Similarly, practitioner guides for valuing innovation companies, and in particular biotech, use expected time rather than using the full timing distribution. Re-calculating baseline valuations taking the full timing risk distribution into account changes valuation upwards as the no-arbitrage theory would predict, by 16%.

Second, real-world valuation features a default tilt towards valuing certainty higher, even when the no-arbitrage theory would predict otherwise. I directly elicit valuations for timing and outcome risk for over 400 finance experts: those with a higher education degree specializing in finance, who are at the highest financial literacy level per the Lusardi and Mitchell (2014) measures. I find that these experts largely adhere to theory for outcome risk, respecting dominance and making weakly risk averse choices. However, they depart from the no-arbitrage benchmark for timing risk. Across three different empirical yield curves, no more than 65% choose the project with the objectively highest valuation. A structural model reveals that one source of departure is a default propensity to tilt towards certainty. This is in contrast to the theory, because Theorem 2 says that risk attitudes, time of resolution, intertemporal considerations, and so on, should not matter once the yield curve is revealed. I estimate that the default propensity is 46% towards certainty, 39% towards uncertainty, and 15% towards indifference. Prices in derivatives markets, comparing otherwise identical options with and without timing risk to each other, are consistent with a higher valuation of timing certainty after controlling for frictions (Muravyev, 2016).

Third, real-world valuation is responsive to, but in an insensitive way, no-arbitrage pricing theory. The direct valuation exercises find a strictly positive ($p < 0.01$) insensitivity parameter: experts update towards the correct answer, but only partially.

The paper contributes to valuation theory and intuition. These topics are commonly taught in textbooks (Berk and DeMarzo, 2011), though finance theory does not always translate to real world valuation (Graham, 2022). Here, I formalize timing risk as a distinct dimension of pricing and provide evidence that both standard intuition

and real-world valuation do not always correctly reflect timing-outcome differences, leading to a tension between theory and practice. The gap between theoretical optimality and real-world valuation has been extensively studied by Graham (2022), who finds that capital budgeting methods used in practice often do not have theoretical grounding. The study of timing risk provides a partial theoretical justification. This explanation for payback is distinct from optionality type explanations (Nanda, 2015): here, the firm is on the receiving end of timing risk.

The paper utilizes only no-arbitrage, similar to Modigliani and Miller (1958), Hansen and Jagannathan (1991), and Giglio et al. (2016). The reliance on minimal assumptions allows the paper's results to apply to a wide variety of settings. In particular, the results apply regardless of whether valuation is friction-based (Krishnamurthy, 2010), factor-based (Barber and Lyon, 1997; Bryzgalova, 2026), constraint-based (Chen, 2010), preference-based (Viceira, 2001; Xu, 2021), or otherwise – so long as no-arbitrage holds. Unlike the study of bond pricing (Krishnamurthy, 2002; Chen, 2010), which often relies on uncertainty about interest rates, my results for timing risk apply even when interest rates are deterministic.

Timing risk is relevant across financial settings, including in early-stage valuation, employee-compensation valuation, and option markets. Prior work studies early-stage firms and innovation valuation (Nanda, 2009; Berk et al., 2004; Lo, 2021), executive compensation and fair value (Starks, 1987; Chidambaran and Prabhala, 2003), and early exercise and frictions in options markets (Berk, 1999; Kapadia and Willette, 2012; Muravyev, 2016; Bryzgalova et al., 2024). Taking the distribution of cash-flow dates as given, I ask whether and how empirical timing risk affects valuation.

Iyer and Schoar (2024) and Puri (2025) have studied simplified approaches towards valuation, and textbooks routinely teach scenario analysis (Graham et al., 2017). As the third characterization theorem shows, one possible reason for the compression of timing risk into its expected component is that the simplified compression of the world into a finite number of states, while largely innocuous for idiosyncratic outcome risk, removes the ability to correctly price all timing risk.

The study of timing risk is conceptually distinct from other literatures on time-related concepts such as duration-based pricing (Giglio et al., 2015), the elasticity of intertemporal substitution (Vissing-Jorgensen, 2002) and resolution period effects (Lerner and Nanda, 2020). One way to see this is that here payment is held fixed and timing varied, whereas these other literatures hold timing fixed and vary outcomes.

They then study outcome risk pricing implications of different fixed times, parametric values, and information arrival, respectively. Prior work on timing risk is in biology (Kacelnik and Bateson, 1996) and decision theory (Chesson and Viscusi, 2003; Onay and Onculer, 2007; DeJarnette et al., 2020); here, I use a more general no-arbitrage approach to study both theoretical and practical valuation implications for pricing.[1]

The paper proceeds as follows. Section 2 introduces and derives the theoretical differences between timing and outcome risk, both for no-arbitrage pricing and for foundational valuation elements. Section 3 considers the valuation of timing risk in practice. Section 4 considers theoretical extensions. Section 5 concludes.

2 Theory

2.1 No-Arbitrage Time-Outcome Differences

I start with an overview of the theoretically general time-outcome differences I derive, before proceeding to corporate theory for foundational valuation elements. A fully formal and precise treatment, with additional details, is deferred to Section 4.

For a conceptual time-outcome difference, I start with a simple decomposition of all priced risk into timing and outcome risk (Theorem 1). Conceptually, systematic outcome risk is how much payoffs move with the pricing kernel, while systematic timing risk measures whether payoffs arrive at times that are better or worse. This decomposition provides a conceptual intuition for why timing and outcome risk are distinct and how they formalize when forced to be orthogonal to one another.

To provide directionality results for valuation, I prove that for small aggregate shocks, for a wide class of microfounded pricing kernels (made precise in Section 4), timing risk increases valuation for positive shocks and reduces valuation for negative shocks (Corollary 1), where a positive shock is gaining money (e.g., gaining \$10 but the timing is uncertain) and a negative shock is losing money (e.g., losing \$10 but

[1] A comparison of pricing for different risk types (e.g., idiosyncratic, systematic, and the effects of diversification) is possible only within a pricing framework. Because my study is fully general, it nuances the findings of prior results in the literature that assume specific functional forms or immovable consumption. For example, the yield curve characterization shows that for pricing, certainty vs. uncertainty can reasonably go any way. Similarly, Perrakis (1975) studies the certainty equivalent method under specific functional forms for timing and concludes that 'it is obvious' that risk-averse valuation implies a lower valuation of projects with timing risk. As I show, this is not obvious at all: for any pricing kernel including risk averse ones, timing risk can add reasonably value.

the timing is uncertain). However, for large shocks which include systematic risk, the effect of timing risk will generally depend on time- and risk-relevant parameters.

Theorem 1 (Priced Risk Decomposition)**.** *Consider an asset that has both timing and outcome risk. At each time t, its priced risk can be decomposed as:*

$$Cov(M_{0\to t}, X_t) = \underbrace{P(\tau = t) \cdot Cov(M_{0\to t}, Y \mid \tau = t)}_{\textit{Systematic Outcome Risk at } t} + \underbrace{Cov\left(\mathbb{E}[M_{0\to t} \mid \tau], \mathbf{1}_{\{t=\tau\}} \cdot \mathbb{E}[Y \mid \tau]\right)}_{\textit{Systematic Timing Risk at } t}$$

Corollary 1. *Suppose there is a single asset in the economy that generates all consumption. When this asset has only timing risk (e.g. systematic outcome risk as defined in Theorem 1 is zero), then for a wide class of microfounded pricing kernels, valuation increases with the amount of risk for small positive shocks, and decreases with the amount of risk for small negative shocks.*

A natural question is whether anything can be said about shocks in general, not just small shocks, without taking any stance on factors affecting pricing. Using only no arbitrage, I prove a sufficient statistics result: for idiosyncratic risk, the price of timing risk is characterized by the risk-free term structure (Theorem 2). In particular, even though timing risk is a kind of risk, its price when idiosyncratic is not affected by risk-related parameters. Nor is it possible to separate the risk-free term structure from the pricing of timing risk. This result will lead to valuation implications for the key valuation elements of risk-adjusted discount rate and payback period. In addition, although the result formally proves irrelevance for *all* idiosyncratic timing risk, the valuation examples in practice will find that stated risk attitudes do appear to affect pricing of timing risk, one aspect of the theory-practice gap.

Theorem 2 (Timing Risk: Risk-Free Term Structure Characterization)**.** *Consider any asset with timing risk, whose risk is purely idiosyncratic. Its price must be equivalent to the price of a portfolio of zero coupon bonds, with portfolio weights equal to the timing risk asset's stopping time probabilities.*

Finally, finance typically defines assets with uncertain outcomes as mappings from states to the real line. Assets with timing risk instead hold fixed the payoff (for example, \$10), with risk arising from a random stopping time. As a result, although a continuum of both types of assets is possible, outcome risk assets admit a degree of freedom in standard pricing frameworks that timing risk assets do not. As a result, I

prove that simplifications which are innocuous for outcome risk do not work for timing risk (Theorem 3). In particular, thinking through a finite number of states can still price all outcome risk, but any finite simplification will fail to price all timing risk. This result will have relevance for the corporate valuation element of finite scenario analysis.

Theorem 3. *Suppose that, in reality, it is possible to price all possible assets with timing risk and with outcome risk, e.g. it is possible to price an asset that puts arbitrary probabilities on any n dates (timing risk), and on any n states within a date with arbitrary payoffs (outcome risk), $n = 1, 2, ...$ Then there exists a finite simplification of the state space that preserves price for all outcome risk assets; but no finite simplification can preserve price for all timing risk assets.*

2.2 No-Arbitrage Theory for Corporate Valuation

We now turn to deriving theoretical effects of timing risk for foundational corporate valuation elements. I show that timing risk updates standard intuition, in some cases pointing in the opposite direction from canonical outcome risk.

2.2.1 Risk-Adjusted Valuation

Corporate finance says that to adjust net present value for risk, adjust the discount rate (Graham et al., 2017). A typical intuition is that the discount rate reflects the project's systematic risk: the risk free rate plus a systematic risk adjustment (Berk and DeMarzo, 2011; Brealey et al., 2020). Consequently, textbooks teach that when two projects within the same firm have different systematic risk, or when the systematic risk changes over time, different adjusted discount rates should be used.

This is surely correct for outcome risk, but when the project has timing risk, this intuition is incomplete. There are two updates. First, idiosyncratic timing risk also affects the discount rate. As a result, the widely taught intuition of Myers and Turnbull (1977) – that the discount rate used should only be changed if the systematic risk changes – while correct for outcome risk, is not complete for timing risk. Proposition 1 states and proves this.

The second difference concerns comparative statics. The standard intuition for outcome risk is that when present value increases, the risk-adjusted rate should decrease, because a more valuable project is naturally summarized by a lower risk-

adjusted number (Graham et al., 2017). This intuition is certainly correct for outcome risk. However, as Proposition 2 shows, with timing risk, it is possible for both present value and the risk-adjusted discount rate to increase simultaneously. As a result, the presence of timing risk generally creates a positive wedge in the risk-adjusted discount rate relative to what outcome risk would predict.

Proposition 1. *Consider any asset X and its risk-adjusted discount rate r_x, defined such that $\sum_{t=0}^{\infty} \frac{E[X_t]}{(1+r_x)^t} = E\left[\sum_{t=0}^{\infty} M_{0\to t} X_t\right]$.*

When asset X has pure outcome risk, e.g. it pays off at some time t', r_x is a function of the risk-free rate from 0 to t' plus an adjustment for the asset's systematic risk.

However, when asset X has pure timing risk, r_x is a function of the zero-coupon bond portfolio with maturities where the asset pays out with positive probability with portfolio weights equal to the physical stopping time probabilities, plus an adjustment for the asset's systematic risk. In particular, the higher-order moments of the stopping time, even when risk is purely idiosyncratic, affect the risk-adjusted discount rate.

The proof sketch is as follows. If a single rate is meant to summarize the value of the project, then because the value of the project is affected by idiosyncratic timing risk – thanks to Theorem 2 – the risk-adjusted discount rate is affected too.

Proposition 2. *Consider any asset X and its risk-adjusted discount rate r_x.*

When asset X has pure outcome risk, then when the asset's value increases (resp. decreases), the risk-adjusted discount rate weakly decreases (resp. weakly increases).

In contrast, when asset X has timing risk, when the asset's value decreases, the risk-adjusted discount rate increases; but when the asset's value increases, the risk-adjusted discount rate may increase or decrease.

The next example and subsection illustrate the quantitative magnitude of these timing-outcome differences for risk-adjusted discount rates in a series of calibrations. The impact of timing risk on risk-adjusted discount rates is between 4-16% for a typical empirical upward sloping yield curve.

I start with a textbook example to illustrate changes to pedagogy before proceeding to empirical yield curves.

Example 1 (Textbook Numbers)**.** *To illustrate using textbook numbers, consider the yield curve from Brealey et al. (2020) Table 3.5: spot rates of $r_1 = 3\%$, $r_2 = 4\%$,*

$r_3 = 5\%$, *and* $r_4 = 6\%$, *etc. Consider a project that pays a single \$1 payoff at time* 5. *To incorporate systematic outcome risk, assume that* $Cov(M_{0\to t}, X_t) = -0.15$ *for all* $t \in T$, *to obtain, as derived below, a risk-adjusted discount rate of about 12% as used in Brealey et al. (2020) Chapter 9.*

The risk-adjusted discount rate r_x *for this project without timing risk satisfies*

$$\frac{1}{(1+r_x)^5} = \frac{1}{1.07^5} - 0.15.$$

Solving yields $r_x = 12.24\%$.

Now add idiosyncratic timing risk. Suppose that the cash flow of 1 comes at time 3 with 50% probability and at time 7 with 50% probability, independent of any systematic economic variables. The new risk-adjusted discount rate $r_x^{(timing)}$ *must solve:*

$$\frac{1}{2}\frac{1}{(1+r_x^{(timing)})^3} + \frac{1}{2}\frac{1}{(1+r_x^{(timing)})^7} = \frac{1}{2}\left(\frac{1}{1.05^3} - 0.15\right) + \frac{1}{2}\left(\frac{1}{1.09^7} - 0.15\right)$$

Solving yields $r_x^{(timing)} = 13.24\%$ *– a full percentage point of difference in the risk-adjusted discount rate.*

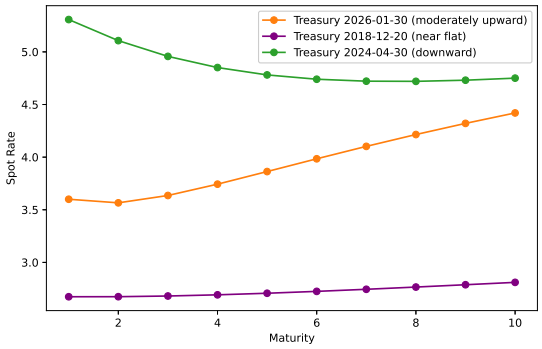
There are two mechanisms pushing the risk-adjusted discount rate up with idiosyncratic timing risk. The first is the yield curve adjustment. Because the yield curve in this example is steeply upward sloping, the present value with idiosyncratic timing risk is lower than without, which pushes the risk-adjusted discount rate up.

The second mechanism pushing it up comes from Proposition 2: even for a vanishingly small amount of idiosyncratic timing risk – say the payment comes at time $t+d$ *with probability 1/2 and at time* $t-d$ *with probability 1/2, and take* d *to zero –* $r_x^{(timing)}$ *needs to satisfy* $\frac{1}{2}\frac{1}{(1+r_x^{(timing)})^{t+d}} + \frac{1}{2}\frac{1}{(1+r_x^{(timing)})^{t-d}} = \frac{1}{(1+r_x)^t}$. *The left hand side is effectively a flat yield curve, so from Theorem 2 and its later implications (Corollary 4) in Section 4, if we were to set* $r_x^{(timing)} = r_x$, *the left side would be larger than the right side. As a result,* $r_x^{(timing)}$ *increases to make the left hand side smaller.*

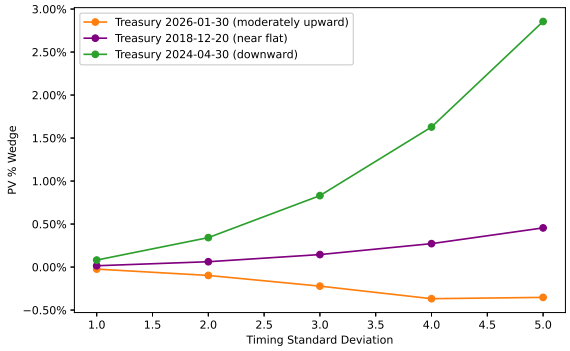
The next subsection further develops this intuition by illustrating comparative statics for different types of empirical yield curves.

Comparative Statics Intuition Consider three empirical yield curves. The first is a moderately upward sloping yield curve; I use the empirical Treasury January 30, 2026 yield curve as illustration. The second is a near-flat yield curve, with the

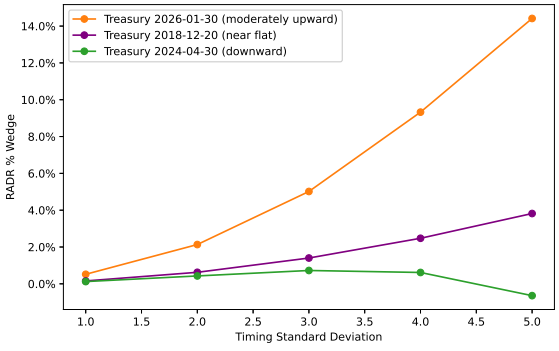
FIGURE 1: Comparative Statics Intuition



(A) Sample Yield Curves



(B) Present Value (% Difference)



(C) Risk-Adjusted Discount Rate (% Difference)

Note: Figure (A) plots sample yield curves. The orange is the empirical January 30, 2026 yield curve. The purple is the empirical December 20, 2018 yield curve. The green is the empirical April 30, 2024 yield curve. The empirical Treasury spot rates depicted for each curve come from Gurkaynak et al. (2006). Figures (B) and (C) compare the difference, as a percentage, for the relevant outcome variable for a project with a cash flow of \$1 arrives at time $5-d$ with 50% probability and at time $5+d$ with 50% probability; the project is assumed to have no systematic risk. The x-variable in both graphs is this d (e.g. the timing dispersion variable). One can calculate that d is also the standard deviation in the time domain of the project paying at $5-d$ and $5+d$ with equal probability.. The y-variable in Figure (B) is $\frac{PV_{timing,d}-PV_{det}}{PV_{det}} * 100$, where $PV_{timing,d}$ is the value of a project paying \$1 at time $5-d$ with 50% probability and at time $5+d$ with 50% probability, and PV_{det} is the value of a project paying \$1 at time 5. The y-variable in Figure (C) is $\frac{r_{timing,d}-r_{det}}{r_{det}} * 100$, where $r_{timing,d}$ is the risk-adjusted discount rate for the project paying \$1 at time $5-d$ with 50% probability and at time $5+d$ with 50% probability; and r_{det} is the risk-adjusted discount rate for a project paying \$1 at time 5.

December 20, 2018 Treasury yield curve used as illustration. The third is a moderately downward sloping yield curve, the empirical April 30, 2024 yield curve.

I compute the present value and the risk adjusted discount rate of a project paying \$1 at time $5-d$ with 50% probability and $5+d$ with 50% probability, setting both systematic outcome and timing risk to zero to cleanly demonstrate comparative statics. Therefore, all risk is purely idiosyncratic; standard intuition from Myers and Turnbull (1977), which adjusts only for systematic risk, would indicate that the risk-adjusted discount rate should be the risk-free rate at the relevant horizon.

As illustrated in Figures 1b and 1c, this is not the case. Figure 1b takes 50% time $5+d$, 50% time $5-d$, varying the timing standard deviation d from 1 to 5 years, and computes the percentage difference in the present value relative to receiving the cash flow in year 5 for sure ($\frac{PV_{timing}-PV_{det}}{PV_{det}} \times 100$). The effect on present value ranges from -2 to 8 basis points for a timing standard deviation of one year, to a -35 bps difference for the 2026 yield curve, a 45 bps difference for the 2018 yield curve, and a 2.8% difference for the 2024 yield curve, for a timing standard deviation of 5 years. Notice that the absolute value of the percent difference increases with dispersion, that is, as d increases in this example. As predicted by Theorem 2 and Corollary 4, idiosyncratic timing risk raises value for flat and, in this case, for the downward sloping yield curve; it reduces value for this upward sloping yield curve.

Figure 1c performs the same procedure, but now for the risk-adjusted discount rate; the y-axis is $\frac{r_x^{(timing)}-r_x}{r_x} \times 100$. Unlike for present value, more dispersion increases the risk-adjusted discount rate for all yield curves at nearly all horizons, from 13-52 basis points for a timing standard deviation of 1 year, to 61 bps - 9.4% for a timing standard deviation 4 years; the impact on the risk-adjusted discount rate is negative only for the downward sloping yield curve (a -64 bps impact), and only at a timing standard deviation of 5 years. The impact of increased timing dispersion on the risk-adjusted discount rate for the downward sloping yield curve is not monotonic. It increases from 12 to 72 basis points from a timing standard deviation of 1 year to 3 years, but then decreases to -64 basis points at a timing standard deviation of 5 years.

The reason that timing risk typically raises the risk-adjusted discount rate, even when it can push present value in any direction, is similar to that in Example 1: the risk-adjusted discount rate is affected by two forces. The first is the present value which, as in outcome risk, would tend to push the risk-adjusted discount rate down

when present value goes up, and up when present value goes down. The second force, from Proposition 2, is an uncertainty effect that is not present for outcome risk. Which force wins out depends on the relative strength of the two effects. For the April 2024 yield curve, the convexity effect tends to win out, as shown in Figure 1c; however, for a deeply steeply downward sloping yield curve, such as Volcker era yield curves, the present value effect wins out, as shown in Appendix B.

Overall, unlike for outcome risk, idiosyncratic timing risk affects risk-adjusted discount rates; and timing risk in general, whether idiosyncratic or systematic, tends to push risk-adjusted discount rates upward, even in cases where it raises present value. This mechanism suggests one timing-risk interpretation of hurdle-rate buffers relative to systematic-risk-based estimates of the cost of capital (Graham, 2022).

2.2.2 Capital Budgeting

The payback period method evaluates a project by the expected time it takes to recover the initial investment, and rejects projects whose payback period exceeds a fixed cutoff time (Berk and DeMarzo, 2011). Despite its widespread use in practice (Graham, 2022), payback is usually criticized in corporate finance because it ignores cash flows after the cutoff date and can incorrectly rank projects with larger positive net present value below those with lower net present value (Berk and DeMarzo, 2011; Graham et al., 2017).

I show that timing risk provides a partial theoretical foundation for this otherwise puzzling practice. The central point is that payback is especially well suited to comparing projects that differ in when, rather than how much, they pay. Proposition 3 shows that payback always respects first-order timing dominance: if one project probabilistically pays sooner than another, holding investment and cash flows fixed, then payback and NPV give the same ranking whenever forward rates are nonnegative. Thus, in the most direct timing-risk comparison, payback is not merely a rough heuristic; it is exactly aligned with value maximization.

Proposition 4 shows that payback also has an empirically relevant robustness property for second-order timing dominance. When the present value function is convex, payback cannot strictly favor the project with lower true value. Historical Treasury term structures satisfy this convexity or approximate-linearity condition most of the time, especially at medium and long horizons. Payback can therefore be understood as a simple rule that is particularly reliable when the central uncertainty

concerns the timing of cash flows.

This interpretation suggests that payback should be more attractive in settings where timing risk is important. Early-stage and smaller firms may face greater uncertainty about when cash flows will arrive because customers, suppliers, or counterparties often control the timing of payment. Non-manufacturing firms may also face more timing uncertainty than manufacturing firms with standardized production processes. Consistent with this prediction, the surveys in Graham (2022) find greater use of payback among small firms and non-manufacturing firms. The theory suggests that future empirical work on capital budgeting may wish to distinguish between different forms of project risk and examine whether payback is used especially when timing risk is salient.

Payback Always Respects First Order Timing Dominance We now prove the results. Our setup is the following.

Definition 1 (Projects with Timing Risk)**.**
At time 0, an initial cost I is incurred. After some idiosyncratic random stopping time τ – the timing uncertainty – the project deterministically pays $c_0(\tau)$ at time τ, then $c_1(\tau)$ at time $\tau + 1$, etc., with all $c_i \geq 0$. A project with timing risk is therefore characterized by a tuple $(I, \tau, \{c_i(\tau)\})$.

Definition 2 (Timing First-Order Dominates)**.**
Say that project $X_1 = (I^{(1)}, \tau^{(1)}, \{c_i^{(1)}(\tau)\})$ timing dominates project $X_2 = (I^{(2)}, \tau^{(2)}, \{c_i^{(2)}(\tau)\})$ if project X_1 probabilistically pays weakly sooner: $P(\tau_1 \leq t) \geq P(\tau_2 \leq t)$ for all times t. Say in addition that X_1 timing dominates project X_2 holding all else equal if X_1 timing dominates project X_2 and $I^{(1)} = I^{(2)}$, $c_i(\tau_1)^{(1)} = c_i(\tau_2)^{(2)}$ for all i.

Proposition 3 (Payback and NPV Rankings Agree on Timing Dominance Projects)**.**
Let X_1 and X_2 be projects with timing risk where X_1 timing dominates X_2, holding all else equal. Whenever spot rates are weakly positive, the payback ranking of projects is identical to the NPV ranking of projects.

The result is useful because it identifies a class of comparisons in which payback has exactly the same directional content as NPV. If one project shifts the distribution of cash-flow arrival earlier without changing the investment cost or the cash-flow sequence, then both criteria prefer the earlier project. Payback therefore does not make

a ranking mistake in first-order timing-dominance comparisons; it simply implements the same higher valuation for earlier cash-flow realization in a cruder form.

Payback Usually Respects Second Order Timing Dominance Proposition 4 identifies a simple condition under which payback is directionally reliable. When the present value function is convex, a project whose cash-flow start date is more dispersed is weakly preferred in NPV terms. In that case, payback may fail to distinguish between projects, but it cannot strictly favor the project with lower true value. Thus, under convex discounting, payback respects the NPV ranking implied by second-order timing dominance.

The empirical relevance of this condition depends on how often observed discount functions are convex. Figure 2 plots the average present value curve implied by Treasury risk-free spot rates from 1961-2026. The average curve is convex, implying that Proposition 4 applies directly under the average historical term structure.

The condition also holds frequently period-by-period. Appendix C classifies the present value curve implied by the Treasury term structure at each date. The discount function is convex or approximately linear in 72% of observations at a 5-year horizon, 91% at a 10-year horizon, and 98% at a 30-year horizon. Since approximate linearity makes the projects nearly value-equivalent under NPV, these cases are not ones in which payback produces a strict value reversal. By contrast, the cases in which the curvature condition clearly fails are concentrated at short horizons: concavity appears in 28% of 5-year observations, 6% of 10-year observations, and essentially never at 30 years.

These results suggest that the theoretical condition in Proposition 4 is not knife-edge. For historically observed risk-free term structures, payback is usually operating in the region where it either agrees with the NPV ranking or, in approximately linear cases, selects among projects with very similar present values. The scope for payback to be strictly wrong in this particular ranking problem is therefore empirically limited, especially for medium- and long-horizon projects.

Proposition 4. *Consider two projects X_1 and X_2 with the same annual cash flow $A > 0$ once cash flows start being generated, the same expected time T for cash flows to be generated, but the timing at which the cash flows start being generated is more dispersed (e.g. a mean-preserving spread) for project X_1 than for project X_2. Suppose the manager's present value function is convex. Then:*

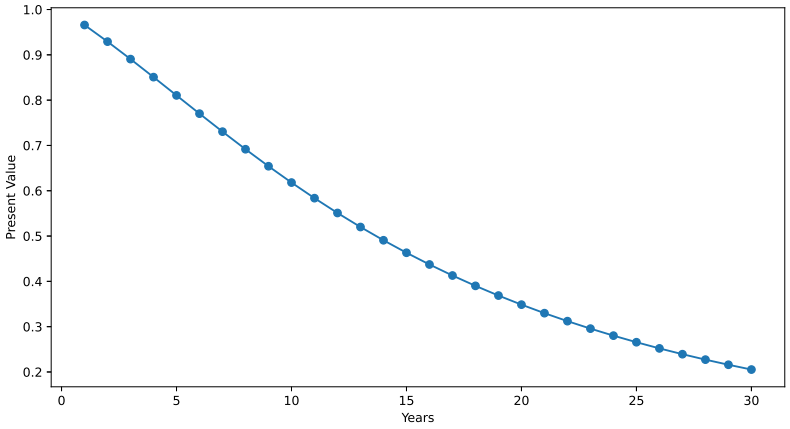


FIGURE 2: Average Present Value Curve Derived From Treasury Spot Rates, 1961-2026

Note: This figure shows the average present value curve. The risk-free term structure here is taken from Gurkaynak et al. (2006), who provide widely-used spot rates from Treasury data from 1961-2026. A given day is kept in the dataset only if all spot rates (from 1 year to 30 years) are not missing. Given each day in the dataset, the yield curve is translated to a present value curve. The figure then takes, for each year, the average of the present value calculations over all days in the dataset.

- *Payback either selects X_1 over X_2, selects both, or selects neither.*
- *Whenever payback selects X_1 over X_2, the true net present value of X_1 is higher than the true net present value of X_2.*

2.2.3 Scenario Analysis and Simplified Valuation

A natural heuristic, often used in real-world valuation and recommended by corporate finance (Graham et al., 2017; Iyer and Schoar, 2024; Puri, 2025), is to consider a finite number of states. For example, when doing scenario analysis, a firm might consider only a handful of scenarios, and within them, change only a few state variables in a discrete way.

This simple valuation approach can work well for outcome risk. However, it does not work for timing risk.

Corollary 2 states this formally. The result is a direct application of Theorem 3. Intuitively, although both outcome risk and timing risk form a continuum, pricing frameworks have an additional degree of freedom present for outcome risk which is not present for timing risk.

Corollary 2. *Finite scenario analysis can correctly price all idiosyncratic outcome risk; it fails to correctly price all idiosyncratic timing risk.*

3 Practice

Having shown how timing risk differs from outcome risk for foundational valuation elements, we now turn to examining how timing risk is valued in practice.

Four financial settings collectively suggest that real-world valuation treat time as more similar to outcomes than the no-arbitrage theory would imply.

The four settings comprise two settings with statements of direct valuation; one with elicited valuations; and one with market prices. First, the Securities and Exchange Commission issues guidelines for the fair value of an employee stock option. I study these guidelines and their valuation implications for how they treat timing risk. Second, in valuing innovation firms with clinical trials, such as biotechnology firms, practitioner valuation guides detail how benchmark assessments treat uncertainty over outcomes and over time. Third, direct valuation exercises through a survey of finance-educated professionals reveal valuation procedures for timing risk. Fourth, option markets provide a setting in which to compare derivatives with and without timing risk.

The benefit of real-world and market settings (Section 3.2.1, 3.2.2, and 3.2.4) is that they reflect behavior in the wild. The benefit of a direct survey is that it allows for clean, precise, and targeted tests of valuation behavior.

Each subsection below describes each setting and its implications for timing risk in detail. Together, they indicate the following three theory-practice gaps in valuing timing risk.

3.1 Theory-Practice Gaps in Valuing Timing Risk

I provide a summary of the three theory-practice gaps suggested by the data, before describing each setting in more detail.

Fact #1: Real-world valuation often compresses timing in a manner similar to outcomes. For outcome risk, a canonical fact is that only expectation matters when risk is purely idiosyncratic (Graham et al., 2017). For timing risk, in contrast, as Theorem 2 shows, the full distribution affects valuation even when risk is idiosyncratic. As a result, compression of the distribution to its expectation, while innocuous for outcome risk, is not correct for timing risk.

However, baseline valuation of biotechnology firms uses expected time to completion for clinical trials (Table 1). Collecting data on empirical clinical trial completions from all trials registered with clinicaltrials.gov, shown in Figure 4, I use calibrations to illustrate that using the full timing distribution for clinical trial completion, rather than expected time, increases baseline valuation by 16%. The increase and the effect on costs and revenues are predicted by the theory, in particular Corollary 4 in Section 4.

Similarly, US-wide regulation forces a compression of timing similar to outcomes. In particular, the SEC requires firms to calculate the fair value of employee stock options using expected time to exercise, typically taken to be average historical time to exercise within the firm. Collecting data on all stock option grants and exercises through SEC Form 4s (Figure 3), I calculate the within-firm valuation gap between using historical average time and the full distribution of historical time, and find it to be 4.6% on average across firms, with the distribution of dispersions across firms shown in Figure 3c. These empirical exercises illustrate that compression of timing occurs in important real-world settings and is not quantitatively innocuous.

Fact #2: Real-world valuation has a default tilt towards certainty for timing risk. When comparing timing certainty to timing risk, Theorem 2 shows that no-arbitrage theory predicts a tight relationship between the risk-free term structure and the value of timing risk. In particular, whether certainty or uncertainty has higher value should be entirely dependent on the yield curve. However, in the direct valuation exercises of Section 3.2.3, finance experts (e.g., those with a higher education degree, specializing in finance, at the highest financial literacy level per the Lusardi and Mitchell (2014) measures) display a default tilt towards certainty. Using a structural multinomial logit model, I calculate default propensities and sensitivity to yield curve conditions. The default propensity comes out to 46% towards certainty, compared to 39% towards uncertainty and 15% towards indifference.

Option markets provide further suggestive evidence. When early exercise is suboptimal, as it theoretically is for call options without dividends, American options should be valued weakly lower than European options. In reality, however, I document that American call options without dividends in their lifetime are valued more than otherwise identical European options, with the American price premium increasing with the amount of early exercise. Applying Theorem 1 empirically, I find

that early exercise in this context constitutes idiosyncratic risk, and the premium is therefore not due to systematic considerations. This pricing premium is also not fully explained by standard friction-based explanation such as liquidity, wildcard premia, adversarial thinking, re-investment risk, and other considerations but is consistent with a practical valuation of certainty.

Fact #3: Real-world valuation is responsive but insufficiently sensitive to no-arbitrage conditions. The direct valuation exercise of over 400 finance experts elicits valuations for different yield curve shapes. Table 2 shows the percentage answering correctly for each yield curve shape. For each yield curve, the correct answer is the mode, indicating some sensitivity to no-arbitrage conditions. However, for no yield curve is the percentage answering correctly statistically close ($p < 0.05$) to 100%; instead, the percentage correctly valuing timing risk according to no-arbitrage theory is 42% for the flat yield curve, 49% for the upward sloping yield curve, and 56% for the downward sloping yield curve. A structural model estimating default propensities and sensitivity finds corroborating evidence of limited sensitivity, with a strictly positive insensitivity parameter relative to the default propensity.

Option markets provide suggestive corroborating evidence to the direct tests, as the American-European pricing gap moves in a statistically significant way with the risk-free rate, though overall explanatory power is low.

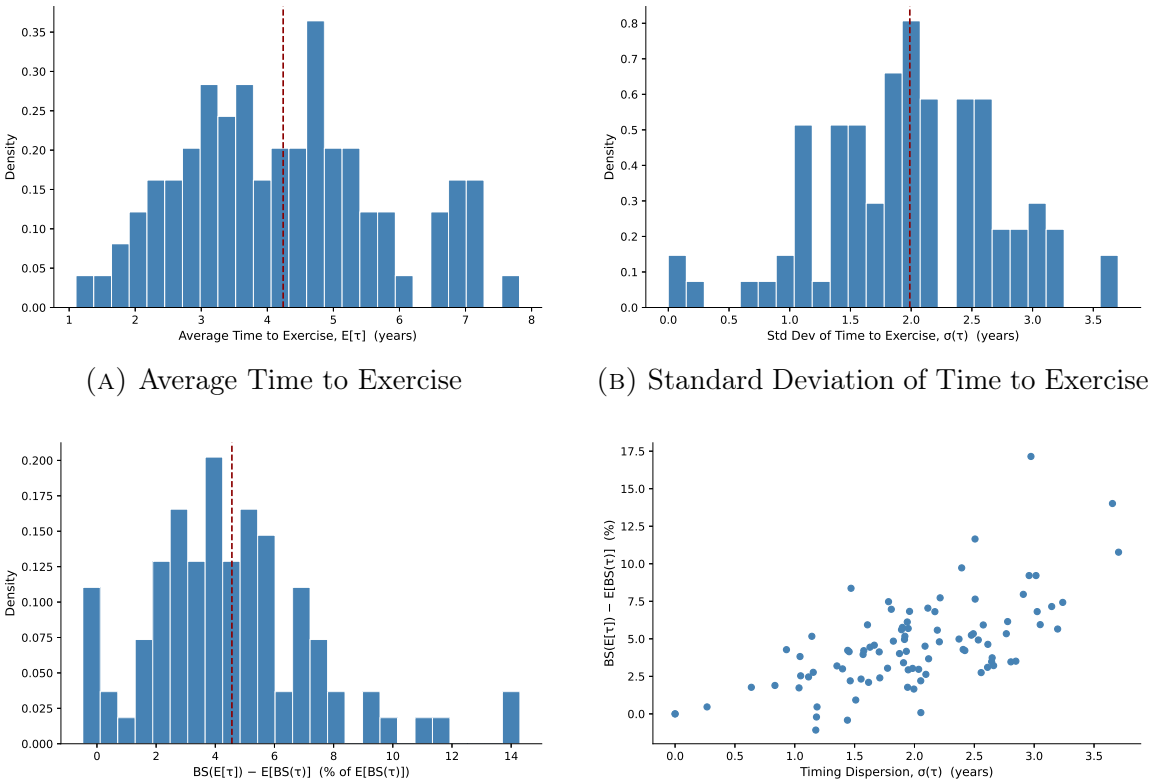
3.2 Valuation Settings

I now describe each valuation setting in more detail.

3.2.1 Regulation

The United States Securities and Exchange Commission (SEC) requires companies to measure and disclose the fair value of stock options granted to employees. To do so, the SEC follows the accounting rules that come from the Financial Accounting Standards Board (FASB). These rules use average time rather than the full timing distribution. In particular, they require reporting of the Black-Scholes or similar value using the expected time to exercise. The expected time to exercise is typically taken to be the average time to exercise historically. While a full real options approach may be too complex to report, a simple alternative to this regulatory guidance, that

FIGURE 3: Timing in Employee Stock Option Exercise



(A) Average Time to Exercise

(B) Standard Deviation of Time to Exercise

(C) Distribution of Valuation Gap

(D) Valuation Gap vs Timing Dispersion

Note: These figures plot data from the empirical time to exercise of the top 100 firms with employee stock option grants, as found in SEC Form 4 filings from 2005 to 2025. Figure (A) plots, across all firms, the average time to exercise. Figure (B) plots, across all firms, the standard deviation of the time to exercise. Figure (C) plots the difference between using the entire timing distribution and using just the expected time: $100 * \frac{BS(E(\tau)) - E(BS(\tau))}{E(BS(\tau))}$, where BS denotes Black-Scholes. Figure (D) plots this percentage difference against the standard deviation of time to exercise; each dot represents one firm. For each firm, the Black-Scholes parameters are taken to be the stock price at issuance, the strike price at issuance, the dividend yield computed over the past year, and the empirical stock volatility computed over the past year.

the theory (Theorem 2 and Proposition 1) indicates would be more accurate, would be to use the average Black-Scholes value over the entire historical empirical timing distribution, rather than Black-Scholes at the average time. In this section, I calculate whether that approach would quantitatively result in a different valuation. Note that this procedure simply takes the full empirical timing distribution into account; no position needs to be taken on whether exercise is optimal.

The SEC guidelines for calculating the fair value of an option state:

> The fair value of a stock option (or its equivalent) granted by a public entity shall be estimated using an option-pricing model (for example, the Black-Scholes or a binomial model) that takes into account as of the grant date the exercise price and **expected life** of the option, the current price of the underlying stock and its expected volatility, expected dividends on the stock (except as provided in paragraphs 32 and 33), and the risk-free interest rate for the expected term of the option.
>
> (FASB (2004), emphasis added)

Because stock options for employee compensation tend to be American-like in nature – they "typically allow exercise at any time after vesting and before expiration" (FASB, 2004) – the above regulatory guidance, which the SEC follows, replaces the empirical time distribution with the expected time of exercise.

I collect the grant and exercise times of stock options granted by all firms as filed in all SEC Form 4s from 2005 to 2025. Details of the data and analysis procedure are in Appendix E. To examine empirical exercise behavior, I then look at the 100 firms which granted the most stock options in the sample.

I calculate, for each firm, (1) the average time to exercise, (2) the dispersion of the time to exercise, and (3) the difference between the expected Black-Scholes value over the empirical exercise distribution relative to the Black-Scholes value at the average historical time to expiry. Thus, all analysis is done at the firm level.

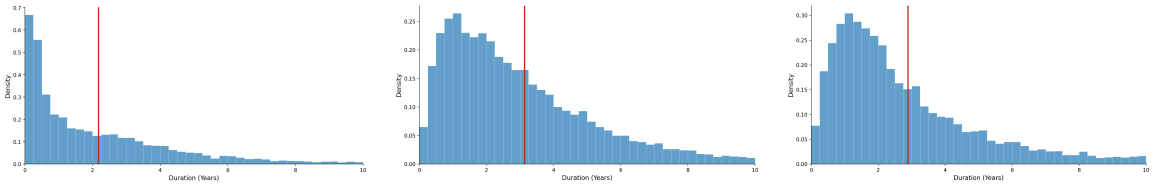
Figure 3a plots the mean time to exercise at the firm level, and Figure 3b the standard deviation of time to exercise at the firm level. Both within and across firm, dispersion in time to exercise is high. Figure 3b shows that, on average, within-firm dispersion is 2 years. Figure 3a shows that, across firms, mean time to exercise is not concentrated.

As a result, the firm-level gap between the theoretically better expected Black-Scholes value over the empirical timing distribution, and the regulation mandated Black-Scholes value at the expected time, is high. The gap is 4.56% on average, statistically significant at the $p < 0.01$ level. Figure 3c visually plots the distribution across firms.

Figure 3d finds that the larger the empirical timing dispersion at the firm level, the larger the gap. Intuitively, the larger the timing dispersion – even if idiosyncratic – the worse an approximation the average time is.

A regression of the percentage gap between the theoretically better and the regulatory mandated measure, on dispersion, with standard errors clustered at the firm level, yields a statistically significant ($p < 0.01$) slope: for every increase in standard deviation of one year, the valuation gap increases by 1.92%. Of course, the dependence on dispersion is not true for outcomes, where one can freely replace idiosyncratic risk with its expectation.

3.2.2 Innovation Firms



(A) Phase I (B) Phase II (C) Phase III

FIGURE 4: Empirical Distribution of Clinical Trial Completion Times

Note: This figure plots, in years, the density of empirical completion times of each phase for all trials registered with clinicaltrials.gov. Data is taken from the AACT registry publicly provided by clinicaltrials.gov. To match the date range in DiMasi et al. (2016), data includes all trials from 1990 to 2013. The mean completion time of each phase is depicted as a vertical brown line. The figure illustrates that innovation valuation involves a distribution of cash-flow dates, not only uncertainty over payoff amounts.

A typical intuition for valuation is to use net present value, adjusting for systematic risk through the CAPM (Graham et al., 2017; Brealey et al., 2020). Following this, an industry standard in biotech is to obtain a risk-adjusted discount rate through the CAPM, then apply expected values to obtain a baseline valuation (Chandra and Mazumdar, 2024). DiMasi et al. (2016) describes the average biotech startup and Chandra and Mazumdar (2024) use these numbers to illustrate a typical industry benchmark valuation for this average biotech startup; the numbers are reproduced

in Table 1, and the baseline valuation obtained is \$45.8M. Observe that the baseline valuation applies expected cash flows and expected time of each phase.

	Real Revenue (\$M)	Time to Next Stage (Yrs)	Discount Rate	Probability of Occurrence
Phase I	-20.8	2	10.5%	100.0%
Phase II	-53.8	3	10.5%	59.5%
Phase III	-240	3	10.5%	21.1%
NDA Submission	-2.4	2	10.5%	13.1%
Approval	2838	-	10.5%	11.8%

TABLE 1: Biotech Valuation Illustration

Note: This table is taken directly from Chandra and Mazumdar (2024), which in turn uses the average actual time and cost of biotech trials from DiMasi et al. (2016); the first four rows come directly from that paper's Table 3, and the final row comes from Equation (1) of the paper, computing the value at approval of the biotech startup given their assumptions on revenue and sales.

What the baseline valuation does not include is uncertainty in how long it will take to complete each phase. Instead, it uses mean times. From a prior where outcome risk is similar to timing risk, and risk is treated as idiosyncratic, this approach may seem reasonable. However, as Theorem 2 and Proposition 1 show, for timing risk unlike for outcome risk, the full timing distribution affects valuation when risk is idiosyncratic, while only expected outcomes matter when risk is idiosyncratic.

Augmenting the valuation table using the empirical range obtained from clinicaltrials.gov (which approximately matches DiMasi et al. (2016) on the mean time for each phase) gives the empirical distribution over phase times reported in Figure 4.[2] Notice that the empirical distributions at all phases are quite dispersed.

To illustrate the impact of timing risk only, I hold all else fixed (including the CAPM-based discount rate) and re-compute with the full empirical timing distribution. This changes the valuation from \$45.8M to \$53.0M, a difference of 16%. The change decomposes as a +\$8.24 adjustment from revenues being more timing dispersed and a −\$1.03 adjustment from costs being more timing dispersed.

Since there is more dispersion for revenue than for costs, as revenue accrues only after clinical trial cost expenditures are met, the theory (Corollaries 4 and 5 in Section 4) predicts, and we see demonstrated here, that timing risk amplifies revenues by more than it amplifies costs, increasing the overall value of the firm. An incorrect incorporation of timing risk may therefore contribute to the gap between what

[2]Note that this is the empirical distribution across all clinical trials; specific kinds of drugs may concentrate in different parts of the distribution. This exercise is meant to check whether idiosyncratic timing risk affects valuation.

founders believe their biotech firms are worth and what investors are willing to pay (Lo, 2019).

3.2.3 Direct Valuation

The benefit of real-world and market settings (Section 3.2.1, 3.2.2, and 3.2.4) is that they reflect behavior in the wild. The benefit of a direct survey is that it allows for precise and targeted tests of valuation behavior.

I design and implement an original survey of finance-literate individuals who hold higher education degrees with specialization in finance.[3] The key tension that emerges is that these finance experts adhere to theory for outcome risk: they respect dominance and are weakly risk averse. But, they make depart from the no-arbitrage theory for timing risk. Instead of valuing timing according to the no-arbitrage theory, they have a default tilt towards certainty – similar to outcomes – and then update towards the theoretically correct answer, but not in a fully sensitive way. The purpose of the survey is to examine theory-practice gaps for timing risk. I do not take a position on why these finance-literate individuals struggle more with timing than with outcomes, and various cognitive microfoundations may be possible (for example, overconfidence, asymmetries (Barber and Odean, 2013); etc.). As Sections 3.2.1 and 3.2.2 find, the theory-practice gap documented in the direct valuation exercises extends to regulation and to benchmark valuation, and are consistent with market prices (Section 3.2.4).

The survey was run in 2026 through Prolific, targeting respondents with a higher education degree who specialized in finance. To ensure data quality, I follow Stantcheva (2024) in including comprehension questions that respondents must answer correctly to proceed. These include questions on spot rate comprehension, the time value of money, and risk comprehension. In addition, I screen so that only respondents who score in the highest financial literacy category per the Lusardi and Mitchell (2014) measures are considered. The final sample totals 401 finance-literate individuals.

The timing risk questions used are taken from the theory section of the paper, and in particular Section 2.2.1. I provide participants with each of the three empirical yield curves depicted in Figure 1a, and ask them, for each yield curve, which project is valued higher: receiving \$100 in 5 years for sure; or in 2 years with 50% probability and in 8 years with 50% probability. Because Theorem 2 relies only on no-arbitrage, it follows that resolution period effects, risk attitudes, and other considerations, do

[3]Details of survey administration, and the questionnaire, can be found in Appendix F.

TABLE 2: Timing Risk Valuation Assessments: Practice vs. Theorem 2

Yield curve	Certainty	Equal	Uncertainty
Flat	37%	21%	42%
Upward	47%	16%	37%
Downward	38%	6%	56%

(A) Full Sample

Yield curve	Certainty	Equal	Uncertainty
Flat	31%	25%	44%
Upward	46%	20%	34%
Downward	32%	5%	63%

(B) Only Those Adhering to Outcome Risk Theory

Note: This table depicts, for each yield curve from Figure 1a, the percentage answering that certainty or uncertainty is valued higher, or if they are valued equally. The green boxes denote the no-arbitrage correct answer per Theorem 2, while red boxes denote incorrect answers. Respondents are financial experts from Prolific, with the properties described in Section 3.2.3.

not affect the objectively higher value choice once the yield curve is shown. As the theory (Section 2.2.1, Figure 1b, and Corollary 4) show, no-arbitrage predicts that for the upward sloping yield curve, certainty is objectively valued higher, and for the flat and downward-sloping yield curves, uncertainty is objectively valued higher.

In the full sample, respondents answer outcome risk questions correctly per standard theory, but do not adhere to theory for timing. Eighty percent and seventy-eight percent of respondents answer the outcome risk questions as weakly risk averse, and respecting dominance, respectively. Table 2a, in contrast, shows the proportion that get the timing risk questions right: 42% for the flat yield curve; 46% for upward sloping; and 56% for downward sloping.

Restricting only to the majority of respondents who answer all outcome risk questions correctly does not meaningfully move the timing risk numbers. Table 2b reports that the proportion answering timing risk valuation questions correctly in this outcome risk theory adhering subsample is 44% for the flat yield curve; 46% for upward sloping; and 63% for downward sloping.

What these tables hide is that the dollar payoff to getting the answer correct is highest for the downward sloping yield curve, second highest for the flat yield curve, and lowest for the upward sloping yield curve, as can be seen in Figure 1b. The fact

that a lower dollar payoff induces more participants to correctly answer for certainty (as in the upward sloping yield curve) than uncertainty (as in the flat yield curve) suggests that there may be a default propensity to tilt towards certainty when valuing timing risk.

To examine this hypothesis in a precise way, I fit a canonical rational inattention model, which for discrete choice is shown by Matejka and McKay (2015) to be equivalent to a multinomial logit specification:

$$P(c) = \frac{P_0(c)e^{\frac{v(c)}{\lambda}}}{\sum_{c' \in C} P_0(c')e^{\frac{v(c')}{\lambda}}}.$$

Here, $P(c)$ denotes the probability of choosing choice c, and P_0 the default propensity towards each choice; $v(c)$ denotes the no-arbitrage dollar value of choice c; and the parameter λ denotes inverse sensitivity, with $\lambda \to 0$ indicating that the agent is completely sensitive to economic conditions, in this case, the no-arbitrage pricing theory. Note that this model is simply being used to estimate a prior propensity and a sensitivity parameter; any number of neural microfoundations may be admitted, and the paper does not take a stand on which, if any, leads to the theory-practice gap for timing risk.

A maximum likelihood estimate reveals default propensities of $P_0 = 46\%$ for certainty, 39% for uncertainty, and 15% for indifference (defined in the model as a 50-50 chance of either certainty or uncertainty). In particular, the structural model finds a default tilt towards certainty, similar to what reduced form examination suggested. In addition, the inverse sensitivity parameter is $\lambda = 1.2$, statistically different from zero at the $p < 0.01$ level. Confirming indications from the reduced form examination, this parameter indicates some but not full sensitivity to no-arbitrage conditions for pricing timing risk.

3.2.4 Derivatives

We now turn to market data. Options provide a unique opportunity to compare otherwise identical traded products with and without timing risk. A benefit of this setting is that pricing can be observed. A limitation is that there are many factors that can affect pricing, and therefore, while I control for each to the extent possible, I interpret the evidence here as suggestive and consistent with a default practical

tilt towards certainty, similar to that found in the direct valuation exercise. The tilt towards certainty may arise for practical reasons, including hedging; the only point this subsection seeks to make is prices appear to be consistent with a valuation of certain timing in option markets, whether for practical or other reasons.

The traded options I consider are the OEX and XEO, options on the S&P 100 which the offering exchange, the Chicago Board Option Exchange (CBOE) explicitly state are identical except for exercise style in their filings with the SEC (Securities and Exchange Commission, 2007).[4] I consider only call options without dividends in their lifetime. Because early exercise is not theoretically optimal for such options (Merton, 1973), standard intuition would predict that American options should be valued the same as (or, if idiosyncratic early exercise occurs, weakly lower than) otherwise identical European ones. In practice, however, I document that American options are typically always more expensive than European options for both quotes and trades. The average midpoint difference is 28 cents ($p < 0.01$), driven largely by asks: the average difference is \$0.33 ($p < 0.01$) for asks and \$0.22 ($p < 0.01$) for bids. The average traded difference is \$0.04. As percentages of the average quoted and average traded European price, the midpoint and traded American price premium correspond to 35 basis points and 1.2% respectively. As Figure B.2 in Appendix G.2 shows, American options consistently trade at higher prices than otherwise identical Europeans throughout the lifetime of the sample. To the extent that one interprets the ask as the market equilibrium price to be short, and the bid as the equilibrium price to be long, the results suggest an American price premium driven at least partially by the short side.

Because there are many variables that can affect prices, I control explicitly for liquidity by considering only minutes and quotes where the liquidity of the American

[4]There also exist both American and European options on the S&P 500; in particular, American-style contracts on SPDR and European-style contracts on the S&P 500 index. However, these differ in at least three ways that OEX and XEO do not. First, the most liquid of the S&P 500 options, SPY and SPX, have different contract sizes. In contrast, OEX and XEO have the same contract size. Second, all S&P 500 index options have different CBOE trading fees than SPY, meaning that even after matching on contract size, one would not be able to differentiate fees from pricing premia (CBOE, 2024*a*). This is because it is not possible to see participant identity in the data, and the fees differ by participant type. In contrast, OEX and XEO have the same CBOE trading fees for all participants. Third, SPY versus SPX (and other S&P 500 index options) settle 15 minutes apart; that difference in settlement time can contribute to what is known as a wildcard premium (Fleming and Whaley, 1994), further affecting pricing. In contrast, OEX and XEO have the same settlement time, and other contract features (CBOE, 2024*b*,*c*).

and European option is within 5% of each other, with robustness checks for no threshold and different thresholds in Appendix G.2; I also test whether the price difference moves with the amount of early exercise, and test for a number of friction-based explanations. To impute a proxy for early exercise from the data, I use a combination of volume and open interest detailed in Appendix G.3. Intuitively, when volume is zero and open interest goes down, early exercise must have occurred.

To check whether early exercise constitutes idiosyncratic or systematic timing risk, I empirically implement a corollary of Theorem 1 that aggregates across time periods (Corollary 6), with details of implementation in Appendix G.4). Table 3, presented in dollar units, finds early exercise in this setting to constitute purely idiosyncratic risk, as neither systematic timing nor outcome risk achieve statistical significance. As a result, a higher American price in this setting is not compensation for systematic early exercise risk considerations.

TABLE 3: Early Exercise Constitutes Idiosyncratic Risk, Both in Outcomes and Timing: Applying Theorem 1 and Corollary 6

	Systematic Outcome Risk	**Systematic Timing Risk**
CAPM SDF	1.01	-1.66
	(1.10)	(1.42)
Fama-French SDF	-0.77	-1.49
	(2.32)	(1.97)

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Note: This table computes total systematic outcome risk and systematic timing risk per Theorem 1 and Corollary 6, using the explicit step-by-step procedure of detailed in Appendix G.4. The SDFs, computed based on a one year rolling basis, are derived from either the CAPM or the Fama-French three factor model; results are reported for both. Point estimates and standard errors are computed using 1000 bootstrap iterations where each draw is taken at the date level. Since both the SDF and the early exercise outcome distribution are computed in levels, the units in the table represent dollars per contract.

To test whether the amount of early exercise moves with the American price premium – the equilibrium payment and compensation for timing risk, in this interpretation – I regress the midpoint difference on the the amount of early exercise relative to total volume (total ee / (total ee + volume)) both with and without moneyness and volume controls, and find a statistically significant coefficient of \$0.002 - \$0.005 ($p < 0.05$): every 5% increase in the forward-looking total number of contracts exercised early relative to contract volume increases the American price premium by 1 to 2.5 cents (recall the total American price premium is on average 28 cents). To test sensitivity to the risk-free rate, as predicted by Theorem 2, I regress the midpoint price difference on the risk-free rate, and find a statistically significant co-

efficient ($p < 0.05$): a one basis point increase in the daily risk-free rate reduces the American price premium by \$0.47 on average. The negative effect is consistent with idiosyncratic early exercise objectively lowering American value, as standard intuition would suggest, and lowering it by more the higher the risk-free rate, since suboptimal early exercise is more valuable to the short side when re-investment opportunities are higher. However, the explanatory power is low, with an R^2 of no more than 5% across specifications. Together, the results are consistent with the direct valuation tests: a slight certainty tilt (which may occur for practical reasons) mitigated by some amount of sensitivity to economic conditions and the yield curve.

Appendix G.5 tests for standard friction-based explanations: the wildcard premium, re-investment risk, hedging considerations, inventory risk, adversarial thinking, and others, and finds that none can fully explain the American price premium for call options without dividends in their lifetime.

4 Theoretical Details and Extensions

This section provides a precise and formal microfoundation for the results in Section 2.1, as well as extensions for timing-outcome differences.

I start by formalizing the set up to study timing vs. outcome risk, using the general pricing framework (Duffie, 2001) with a set of states, Ω, and amount of information at each time $\{\mathcal{F}_t\}$, and a probability measure P. Assets or projects cannot reveal any more information than exists at time t (e.g., each project is a set of payoffs $X = (X_1, X_2, ...)$, where X_t is measurable with respect to $\mathcal{F}_t$). Say that a stochastic discount factor or pricing kernel $M_t = \{M_{t\to t'}\}_{t'>t}$ exists if, for all assets, the time t price of asset X is given by $Price_t(X) = E_{P_t}[\sum_{t'} M_{t\to t'} X_{t'}]$.

I then formalize different types of risk within the SDF framework. Pure outcome risk fixes the date and varies the payoff amount. Pure timing risk fixes the incremental payoff and varies the date. General timing-and-outcome risk allows both the date and the amount to vary, potentially with arbitrary correlation.

Definition 3 (Assets with Pure Outcome Risk)**.**
An asset with pure uncertain outcomes X is one which has non-zero payoffs at only one time $t \in T$.

Definition 4 (Stopping Time)**.**
A stopping time is a random variable $\tau : \Omega \to T$ such that for every $t \in T$, the event $\{\omega \in \Omega : \tau(\omega) \leq t\}$ is in the filtration F_t (e.g, the stopping time does not reveal any more information than exists at time t).

Say that τ is a non-trivial stopping time if there are at least two distinct times it takes on with positive probability: there exist $t_1 \neq t_2 \in T$ such that $P(\tau = t_1), P(\tau = t_2) > 0$.

The expected time of τ is given by $E_P[\tau]$.

Definition 5 (Assets with Pure Timing Risk)**.**
An asset with pure uncertain timing X is one whose payoff process is entirely characterized by some nontrivial stopping time τ. In particular,

$$X_t(\omega) = \begin{cases} c + a & \text{if } t = \tau(\omega) \\ c & \text{if } t \neq \tau(\omega) \end{cases}$$

for some $c, a \in \mathbb{R}$.

Example 2. *Suppose that the state space at time 0 is $\{G, B\}$, standing for good and bad. The state space at time 1 is then $\{(G,G),(G,B),(B,G),(B,B)\}$; at time 2 is $\{(G,G,G),(G,G,B),(G,B,G),(G,B,B),(B,G,G),(B,G,B),(B,B,G),(B,B,B)\}$; etc.*

An example of an asset with pure uncertain timing on this state space is one that pays out \$1 the first time the state space hits good only. This asset takes on a payoff value of 1 whenever the state is $(\underbrace{B, \ldots, B}_{\text{any number of times}}, G)$, and 0 in all other states.

An example of an asset with pure uncertain outcomes on this state space is one that pays out \$5 (in state B) or \$10 (in state G) at time 1, and 0 in all other times and states.

Definition 6 (Systematic vs. Idiosyncratic Risk)**.**
The time-t' systematic risk of an asset X from the perspective of period $t \leq t'$ is given by $Cov(M_{t \to t'}, X_{t \to t'})$.

An asset has purely idiosyncratic risk from the perspective of period t if its time-t' systematic risk is equal to zero at all times $t' \geq t$.

Definition 7 (Assets with Both Timing and Outcome Risk)**.**
An asset with uncertain timing and outcomes is characterized by a baseline payoff $c \in \mathbb{R}$, a stopping time τ, and a random shock $Y : \Omega \to \mathbb{R}$. The payoff process is

$$X_t(\omega) = c + \mathbf{1}_{\{t=\tau(\omega)\}} \cdot Y(\omega), \qquad t \in T.$$

This nests:

- *Pure timing risk: $Y(\omega) = a \in \mathbb{R}$ (constant shock);*
- *Pure outcome risk: $\tau(\omega) = t^*$ (fixed time) and $c = 0$.*

Remark 1 (Arbitrary Correlation Between Outcome and Timing Risk)**.** *For assets with uncertain timing and outcomes, any correlation structure between outcome risk Y and time risk τ is permitted by Definition 7; for example, it may be the case that the distribution of $Y|\tau = t_1$ differs from that of $Y|\tau = t_2$.*

Definition 8 (Valuation)**.**
The valuation of asset X at time t is given by $Price_t(X) = E_{P_t}[\sum_{t'} M_{t\to t'} X_{t'}]$.

Consider an asset with pure uncertain timing X which has associated stopping time τ. When $E_p[\tau] \in T$, define its certain-time equivalent,

$$X_t(\omega) = \begin{cases} c + a & \text{if } t = E_p[\tau] \\ c & \text{if } t \neq E_p[\tau] \end{cases}$$

Say that certain timing is valued higher (resp. lower) than uncertain timing if, for any asset with pure uncertain timing, its valuation is lower (resp. higher) than the valuation of its certain-time equivalent.

The results rely only on a no-arbitrage assumption, from which the Fundamental Law of Asset Pricing (re-derived for the timing risk case in Appendix A.1 for completeness) implies existence of an SDF. The theorems therefore can, and do, directly assume the existence of a stochastic discount factor that prices all assets. In the case that there are multiple admissible SDFs, as can occur for incomplete markets (Berk and DeMarzo, 2011), the theory holds for each SDF within the permissible SDF set.

4.1 Further Timing-Outcome Differences

From the three characterization theorems, a number of conceptual timing-outcome differences follow. Corollaries 3 and 4 leverage Theorem 2 to show that the higher order moments of idiosyncratic timing risk affect price, and that there is a gain-loss asymmetry present for timing that is not generally present for outcomes. Although some anomalies disappear with diversification (Bryzgalova, 2026), Theorem 4 shows that these conceptual timing-outcome differences survive diversification.

4.1.1 Idiosyncratic Risk and Higher Order Moments

In contrast to outcome risk, Corollary 3 shows that the higher order moments of timing risk affect price. This follows from Theorem 2.

Corollary 3 (Higher-Order Moments for Timing Risk)**.** *Consider an asset with pure uncertain timing, with associated stopping time τ which has purely idiosyncratic risk. The higher-order moments of τ affect the valuation of the asset.*

4.1.2 Gain-Loss Asymmetry

In contrast to outcome risk, Corollary 4 shows, as the valuation calibrations of Section 2.2 had indicated, that timing risk can raise or lower price. Applying Theorem 2, which occurs depends on the shape of the yield curve. Also in contrast to outcomes, Corollary 5 shows asymmetry: whenever timing risk raises value for positive shocks, it must lower value for negative shocks, and vice versa.

Corollary 4 (Certainty and Uncertainty)**.** *Consider any asset with uncertain timing with associated stopping time τ and payoffs $(c, c+a)$ which has purely idiosyncratic risk. Let $y(T)$ denote the yield to maturity at time T.*

Then uncertain timing has a higher (resp. lower) valuation than certain timing for $a > 0$ (resp. $a < 0$) if and only if

$$(y(T) + T \cdot y'(T))^2 > 2y'(T) + T \cdot y''(T) \quad \text{for all } T \in \mathcal{T}$$

In particular, uncertainty can be valued higher, lower, or the same as, certainty.

Corollary 5 (Asymmetry)**.** *Any SDF that has a higher valuation for uncertain timing than certain-time equivalents for positive shocks must have a higher valuation for*

certain-time equivalents than uncertain timing for negative shocks. Any SDF that has a higher valuation for certain-time equivalents than uncertain timing for positive shocks must have a higher valuation for uncertain timing than certain-time equivalents for negative shocks.

Remark 2 (Yield Curve Translation)**.** *Uncertain timing is always valued higher (resp. lower) than certain timing for positive (resp. negative) shocks when:*

- *The yield curve is flat and nonzero:* $y' = 0, y'' = 0, y \neq 0$.
- *The yield curve is downward sloping and weakly convex:* $y' \leq 0, y'' \leq 0$.
- *The yield curve does not rise too steeply:* $2y'(t) \leq ty''(t)$.

4.1.3 Diversification

One might expect idiosyncratic timing risk to disappear in diversified portfolios, just as idiosyncratic outcome risk does. Theorem 4 shows why this intuition is incomplete. Diversification can remove randomness in aggregate cash flows, but it does not remove the fact that the cash flows occur at different dates. Temporal dispersion can therefore remain valuation-relevant even after aggregate uncertainty is eliminated.

Theorem 4 (Diversification with Uncertain Timing)**.** *Let* $A_1, \ldots, A_n$ *be assets with purely idiosyncratic timing risk, where asset* i *pays* c_i *at every date plus* a_i *at random stopping time* τ_i*, with each* τ_i *sharing a common marginal distribution supported on* $S = \{t_1, \ldots, t_K\}$*. Suppose there exist portfolio weights* $p = (p_1, \ldots, p_n)$ *such that the portfolio cash flow is deterministic: it pays* c *at every date plus* s *at each date in* S*, almost surely.*

Then:

(a) *The portfolio is priced as a portfolio of zero-coupon bonds: its value equals*

$$c \sum_{u \in T} m(u) \; + \; s \sum_{j=1}^{K} m(t_j),$$

where $m(u) := \mathbb{E}[M_{0 \to u}]$.

(b) *The higher-order moments of the temporal dispersion of the shock dates* $\{t_1, \ldots, t_K\}$ *affect valuation.*

(c) *The portfolio value can be higher, lower, or equal to that of a certain-time equivalent paying Ks at $\mathbb{E}[\tau_1]$.*

(d) *If the valuation wedge relative to the certain-time equivalent is positive (resp. negative) when $s > 0$, it is negative (resp. positive) when $s < 0$.*

Remark 3 (Contrast with Outcomes)**.** *Combining perfectly negatively correlated assets with uncertain outcomes that pay at the same date creates a risk-free asset valued identically to the deterministic asset paying $\mathbb{E}[A_1]$. By contrast, Theorem 4 shows that even when aggregate timing is made deterministic, value generally differs from paying the same total amount at the average time. The wedge is a curvature effect of the SDF, not a risk premium, and the sign asymmetry of part (d) persists even in the absence of uncertainty.*

4.2 Characterization Theorems Detailed

4.2.1 Systematic Risk

Theorem 1 decomposed systematic risk into timing and outcome components. Corollary 6 aggregates these into overall systematic timing and outcome risk measures. Example 3 provides a numerical example of systematic timing vs. outcome risk.

Corollary 6 (Overall Systematic Risk Decomposition)**.** *Let the asset pay the shock Y at the (random) date τ. Then*

$$\operatorname{Cov}\left(\sum_t \mathbf{1}_{\{\tau=t\}} M_{0\to t}, Y\right) = \underbrace{\sum_t \mathbb{P}(\tau = t)\cdot \operatorname{Cov}(M_{0\to t}, Y \mid \tau = t)}_{\textit{Total systematic outcome risk}} + \underbrace{\operatorname{Cov}\left(\mathbb{E}\left[\sum_t \mathbf{1}_{\{\tau=t\}} M_{0\to t} \,\middle|\, \tau\right], \mathbb{E}[Y \mid \tau]\right)}_{\textit{Total systematic timing risk}},$$

where the first term exactly corresponds to the sum of similar terms in Theorem 1 and the second term is a probability weighted covariance over two random variables, where the probability weights are given by the stopping time τ's probabilities.

Example 3 (Numerical Example: Systematic Risk Decomposition)**.** *Consider a probability space with state space* $\Omega = \{GG, GB, BG, BB\}$*, times* $T = \{1, 2\}$*, and probability measure* P *given in the table below. Define an asset with uncertain timing and outcomes (Definition 7) with baseline* $c = 2$*, stopping time* τ*, and shock* Y *as follows:*

State ω	$P(\omega)$	$\tau(\omega)$	$Y(\omega)$	c	*Asset Payoff at Time 1*	*Asset Payoff at Time 2*	$M_1(\omega)$	$M_2(\omega)$
GG	0.30	1	13.0	2.0	15.0	2.0	0.90	0.85
GB	0.30	1	5.0	2.0	7.0	2.0	0.94	0.91
BG	0.25	2	2.0	2.0	2.0	4.0	0.96	0.93
BB	0.15	2	0.0	2.0	2.0	2.0	0.97	0.95

where $M_t(\omega) := M_{0\to t}(\omega)$ *denotes the stochastic discount factor from time 0 to time* t *in state* ω*.*

The asset's payoff process is:

$$X_t(\omega) = c + \mathbf{1}_{\{t=\tau(\omega)\}} \cdot Y(\omega) \quad \text{for } t \in \{1, 2\}.$$

We compute the time 1 systematic risk decomposition.

For systematic outcome risk, we calculate the covariance of the SDF with the shock conditional on the asset paying at time 1, times the probability of paying at 1. Conditional on $\tau = 1$*:*

$$P(GG \mid \tau = 1) = \frac{0.30}{0.60} = 0.5, \qquad P(GB \mid \tau = 1) = \frac{0.30}{0.60} = 0.5.$$

The conditional means are:

$$\begin{aligned} \mathbb{E}[M_1 \mid \tau = 1] &= 0.90 \cdot 0.5 + 0.94 \cdot 0.5 = 0.92, \\ \mathbb{E}[Y \mid \tau = 1] &= 13.0 \cdot 0.5 + 5.0 \cdot 0.5 = 9.0. \end{aligned}$$

The conditional covariance is:

$$\begin{aligned} \mathrm{Cov}(M_1, Y \mid \tau = 1) &= \mathbb{E}[M_1 Y \mid \tau = 1] - \mathbb{E}[M_1 \mid \tau = 1] \cdot \mathbb{E}[Y \mid \tau = 1] \\ &= (0.90 \cdot 13.0 \cdot 0.5 + 0.94 \cdot 5.0 \cdot 0.5) - 0.92 \cdot 9.0 \\ &= (5.85 + 2.35) - 8.28 = -0.08. \end{aligned}$$

Therefore, systematic outcome risk at time 1 is $P(\tau = 1) \cdot \mathrm{Cov}(M_1, Y \mid \tau = 1) = 0.6 \cdot (-0.08) = -0.048$*..*

We now compute systematic timing risk at time 1. Since there are two times at which the asset pays off with positive probability, create two mega-states: one where the asset pays at time 1 and one where it pays out at time 2. Then:

$$\begin{aligned}
\mathbb{E}[M_1 \mid \tau = 1] &= 0.92, \\
\mathbb{E}[M_1 \mid \tau = 2] &= \frac{0.96 \cdot 0.25 + 0.97 \cdot 0.15}{0.40} = 0.96375, \\
\mathbb{E}[Y \mid \tau = 1] &= 9.0, \\
\mathbb{E}[Y \mid \tau = 2] &= \frac{2.0 \cdot 0.25 + 0.0 \cdot 0.15}{0.40} = 1.25.
\end{aligned}$$

Computing the covariance and setting $\mathbb{E}[Y \mid \tau = 2]$ *to 0 using the indicator* $\mathbf{1}_{\{\tau=1\}}$*:*

$$\begin{aligned}
\mathbb{E}[\mathbb{E}[M_1 \mid \tau]] &= 0.92 \cdot 0.6 + 0.96375 \cdot 0.4 = 0.9375, \\
\mathbb{E}\big[\mathbf{1}_{\{\tau=1\}} \cdot \mathbb{E}[Y \mid \tau]\big] &= 9.0 \cdot 0.6 + 0.0 \cdot 0.4 = 5.4, \\
\mathbb{E}\big[\mathbb{E}[M_1 \mid \tau] \cdot \mathbf{1}_{\{\tau=1\}} \cdot \mathbb{E}[Y \mid \tau]\big] &= 0.92 \cdot 9.0 \cdot 0.6 + 0.96375 \cdot 0.0 \cdot 0.4 = 4.968.
\end{aligned}$$

Therefore, systematic timing risk at time 1:

$$\mathrm{Cov}\left(\mathbb{E}[M_1 \mid \tau], \mathbf{1}_{\{\tau=1\}} \cdot \mathbb{E}[Y \mid \tau]\right) = 4.968 - 0.9375 \cdot 5.4 = -0.0945.$$

The total systematic risk at time 1 is the sum of the two components:

$$\mathrm{Cov}(M_1, X_1) = -0.048 + (-0.0945) = -0.1425.$$

While the directional predictions for systematic risk will in general depend on the specific pricing kernel used, it is possible to obtain directionality results for aggregate risk for a wide class of SDFs. By aggregate risk, I mean that the timing risk asset is the only asset in the economy; without it, consumption is zero. Corollary 1 (Restated) characterizes directionality for aggregate risk in the special case of Kreps-Porteus utility-based SDFs; this nests many of the microfounded SDFs used in the literature (Hansen and Singleton, 1982; Tallarini, 2000; Routledge and Zin, 2010) because the Kreps-Porteus class has the generally attractive properties of being dynamically consistent, history independent, and having no probability distortions.[5]

[5]The result generalizes and brings to aggregate risk pricing prior results on special functional form cases for un-moveable consumption such as expected utility (Chesson and Viscusi, 2003), additive

Corollary 1 (Restated). *Suppose the SDF derives from a Kreps-Porteus representation with convex time discounting. Then for any asset with uncertain timing and payoffs* $(c, c + a)$*, where the representation is smooth at* c *and when the asset represents aggregate risk, uncertain timing is valued higher (resp. lower) than certain timing when* $a > 0$ *(resp.* $a < 0$*) for sufficiently small* $|a|$*.*

To circumvent nonlinear aggregation, which can distort the price of risk in unpredictable ways, the proof uses a Taylor expansion. However, a limitation of the result is that this directionality holds only for small shocks. When shocks become large, it is possible for the nonlinear aggregator to move directionality in any way. A strength of Theorem 2 is that it applies for shocks of all sizes.

4.2.2 Risk-Free Term Structure Equivalence

As noted in Section 2.1, when risk is purely idiosyncratic, it is possible to characterize the price of timing risk for all timing risk assets. In particular, it is characterized by the risk-free term structure.

The intuition behind Theorem 2 is as follows. When writing out the price of an asset with uncertain timing which has purely idiosyncratic risk, the covariance between the SDF and the asset vanishes by virtue of the risk being idiosyncratic. What is left is a weighted sum over the expected value of the SDF at each point in time, where the weight on each time is exactly the stopping time probability.

4.2.3 Restrictions on the SDF State Space

Both outcome and timing risk admit a continuum of assets, but the two place that continuum in different locations, and this is what a finite state space can and cannot accommodate. The distinction is one of where the pricing-relevant degree of freedom resides.

The asymmetry can be stated compactly. Pricing idiosyncratic outcome risk is low-dimensional: one degree of freedom per date, the mean, suffices, and any finite discretization that preserves the discount function preserves prices. Pricing timing risk is irreducibly infinite-dimensional: the entire stopping-time distribution is payoff-relevant, and no finite discretization preserves prices for all assets. Theorem 3 (Re-

utility (Onay and Onculer, 2007), and Epstein-Zin (DeJarnette et al., 2020).

stated) makes this precise, while Theorem 3 was the simplified introductory statement.

Theorem 3 (Restated). *Let $\mathcal{E} = (\Omega, \mathcal{F}, P)$ be the true probability space, and let Price denote price under this space. Suppose there are a finite set of dates, and the stochastic discount factor M is such that it admits a unique expected value at each date: $E[M_t] \neq E[M_{t'}]$ when $t \neq t'$. Suppose that in this space, for any two dates t_1 and t_2, all assets of the form $x\%$ chance of paying \$1 at time t_1 and $1 - x\%$ chance of paying \$1 at time t_2, which have purely idiosyncratic risk, are representable. Call this set of assets binary idiosyncratic timing risk. Similarly, suppose in this space, all assets which pay on a deterministic date t, but may load arbitrarily on different states within that date, which have purely idiosyncratic risk, are representable. Call this set of assets idiosyncratic outcome risk assets. Then:*

- *Ω cannot be finite.*
- *There exists a finite discretization of the space, e.g. a finite Ω^F which is a coarsening of Ω with corresponding coarsenings $\mathcal{E}^F = (\Omega^F, \mathcal{F}^F, P^F)$ and a function such that all outcome risk assets with idiosyncratic risk maintain their price: there exists a mapping g from representable idiosyncratic outcome risk assets under $\mathcal{E}$ to representable idiosyncratic outcome risk assets under $\mathcal{E}^F$ such that for any outcome risk asset with idiosyncratic risk A_O in the original probability space, $Price(A_O) = Price^F(g(A_O))$.*
- *For any finite discretization of the space, it is not possible to correctly price all binary idiosyncratic timing risk assets. In particular, for any mapping g from representable binary idiosyncratic timing risk assets under $\mathcal{E}$ to representable binary idiosyncratic timing risk assets under $\mathcal{E}^F$, there exist two binary idiosyncratic timing risk assets A_1 and A_2 such that $Price(A_1) \neq Price(A_2)$ but $Price^F(g(A_1)) = Price^F(g(A_2))$.*

5 Conclusion

This paper contrasted the no-arbitrage pricing of timing risk with that of outcome risk, generally, for valuation elements, and in practice. Theoretically, the price of

idiosyncratic timing risk is characterized by the yield curve; systematic risk can be decomposed into systematic timing and systematic outcome risk, with aggregate risk signed for small shocks; and finite-state approaches work better for pricing outcome than pricing timing risk. These characterization results lead to other theoretical time-outcome differences, such as asymmetry for positive versus negative shocks, and the result that timing risk can amplify both investment cost and revenue potential.

Timing risk changes the standard intuition for risk-adjusted discount rates, both for idiosyncratic risk and comparative statics. Calibrations using empirical yield curves suggest the effect is non-trivial, and may help account for buffers in empirical hurdle rates relative to systematic risk based estimates. Capital budgeting techniques, in particular payback period, which are suboptimal under outcome risk satisfy more reasonable properties for timing risk. Finite scenario analysis can work for outcome risk but does not work as well for timing.

Despite these many theoretical timing-outcome differences, real world valuation across a number of settings treats the two as more similar than the theory would suggest. Direct valuation exercises find departures for theory for pricing timing relative to no-arbitrage theory, even when there are no departures from theory for pricing outcomes. There is a slight default tilt towards certainty with some but not complete sensitivity to updating pricing based on economic conditions. Real-world valuation in the realms of regulations for employee compensation, and for valuing innovation firms, compress timing in a manner similar to outcomes. Market prices are consistent with these results.

Future work on timing may wish to exploit the fact that timing risk and outcome risk are often lumped together; and separating them may lead to interesting insights. For example, it could be fruitful to study the pricing impact of timing risk vs. outcome risk in various real-world markets, such as mergers and acquisitions, or initial public offering timing, to better understand whether these follow the no-arbitrage theory or if, as found in this paper, there are theory-practice gaps.

References

Barber, Brad M., and John D. Lyon. 1997. "Firm Size, Book-to-Market Ratio, and Security Returns: A Holdout Sample of Financial Firms." *The Journal of Finance*, 52: 875–883.

Barber, Brad M., and Terrance Odean. 2013. "The Behavior of Individual Investors." In *Handbook of the Economics of Finance*. Vol. 2, 1533–1570. Elsevier.

Berk, Jonathan B. 1999. "A Simple Approach for Deciding When to Invest." *American Economic Review*, 89: 1319–1326.

Berk, Jonathan B., Richard C. Green, and Vasant Naik. 2004. "Valuation and Return Dynamics of New Ventures." *Review of Financial Studies*, 17: 1–35.

Berk, Jonathan B., and Peter M. DeMarzo. 2011. *Corporate Finance. The Prentice Hall series in finance*. 2., ed ed., Boston:Prentice Hall.

Brealey, Richard A., Stewart C. Myers, and Franklin Allen. 2020. *Principles of corporate finance. The McGraw-Hill/Irwin series in finance, insurance, and real estate*. Thirteenth edition, international student edition ed., New York, NY:McGraw-Hill Education.

Bryzgalova, Svetlana, Anna Pavlova, and Taisiya Sikorskaya. 2024. "Strategic Arbitrage in Segmented Markets." *Journal of Financial Economics, Forthcoming*.

Bryzgalova, Svetlana. 2026. "Spurious Factors in Linear Asset Pricing Models." *Working Paper*.

CBOE. 2024*a*. "Cboe U.S. Options Fee Schedules."

CBOE. 2024*b*. "OEX Options Product Specifications."

CBOE. 2024*c*. "XEO Options Product Specifications."

Chandra, Amitabh, and Sumon Mazumdar. 2024. "Biotech Asset Valuation Methods: A Practitioner's Guide." *Journal of Investment Management*, 22: 36–57.

Chen, Hui. 2010. "Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure." *The Journal of Finance*, 65: 2171–2212.

Chesson, Harrell W., and W. Kip Viscusi. 2003. "Commonalities in Time and Ambiguity Aversion for Long-Term Risks." *Theory and Decision*, 54: 57–71.

Chidambaran, N.K., and Nagpurnanand R. Prabhala. 2003. "Executive stock option repricing, internal governance mechanisms, and management turnover." *Journal of Financial Economics*, 69: 153–189.

DeJarnette, Patrick, David Dillenberger, Daniel Gottlieb, and Pietro Ortoleva. 2020. "Time Lotteries and Stochastic Impatience." *Econometrica*, 88: 619–656.

DiMasi, Joseph A., Henry G. Grabowski, and Ronald W. Hansen. 2016. "Innovation in the pharmaceutical industry: New estimates of R&D costs." *Journal of Health Economics*, 47: 20–33.

Duffie, Darrell. 2001. *Dynamic asset pricing theory.* . 3rd ed ed., Princeton (N.J.):Princeton university press.

FASB. 2004. "Statement of Financial Accounting Standards No. 123: Accounting for Stock-Based Compensation. Issued 1995, Revised 2004." Financial Accounting Standards Board.

Fleming, Jeff, and Robert E. Whaley. 1994. "The Value of Wildcard Options." *The Journal of Finance*, 49: 215–236.

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel. 2015. "Very Long-Run Discount Rates." *The Quarterly Journal of Economics*, 130: 1–53.

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel. 2016. "No-Bubble Condition: Model-Free Tests in Housing Markets." *Econometrica*, 84: 1047–1091.

Graham, John R., Scott B. Smart, Christopher Adam, and Brindha Gunasingham. 2017. *Introduction to corporate finance.* . 2nd Ed. ed., Australia ; Mason, Ohio:South-Western/Cengage Learning.

Graham, John R. 2022. "Presidential Address: Corporate Finance and Reality." *The Journal of Finance*, 77: 1975–2049.

Gurkaynak, Refet S., Brian Sack, and Jonathan Wright. 2006. "The U.S. Treasury Yield Curve: 1961 to the Present." *Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System.*

Hansen, Lars Peter, and Kenneth J. Singleton. 1982. "Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models." *Econometrica*, 50: 1269.

Hansen, Lars Peter, and Ravi Jagannathan. 1991. "Implications of Security Market Data for Models of Dynamic Economies." *Journal of Political Economy*, 99: 225–262.

Iyer, Rajkamal, and Antoinette Schoar. 2024. "Contracting when enforcement is weak: evidence from an audit study." *Review of Finance*, 28: 1513–1536.

Kacelnik, Alex, and Melissa Bateson. 1996. "Risky Theories-The Effects of Variance on Foraging Decisions." *American Zoologist*, 36: 402–434.

Kapadia, Nikunj, and Gregory Willette. 2012. "Equilibrium exercise of European warrants." *Review of Derivatives Research*, 15: 129–156.

Krishnamurthy, Arvind. 2002. "The bond/old-bond spread." *Journal of Financial Economics*, 66: 463–506.

Krishnamurthy, Arvind. 2010. "How Debt Markets Have Malfunctioned in the Crisis." *Journal of Economic Perspectives*, 24: 3–28.

Lerner, Josh, and Ramana Nanda. 2020. "Venture Capital's Role in Financing Innovation: What We Know and How Much We Still Need to Learn." *Journal of Economic Perspectives*, 34: 237–261.

Lo, Andrew. 2019. "Bridging the Valley of Death Through Financial Innovation." Testimony to the US House of Representatives Financial Services Committee, Washington D.C.

Lo, Andrew W. 2021. "Can Financial Economics Cure Cancer?" *Atlantic Economic Journal*, 49: 3–21.

Lusardi, Annamaria, and Olivia S. Mitchell. 2014. "The Economic Importance of Financial Literacy: Theory and Evidence." *Journal of Economic Literature*, 52: 5–44.

Matejka, Filip, and Alisdair McKay. 2015. "Rational inattention to discrete choices: A new foundation for the multinomial logit model." *American Economic Review*, 105: 272–298.

Merton, Robert C. 1973. "Theory of Rational Option Pricing." *The Bell Journal of Economics and Management Science*, 4: 141.

Modigliani, Franco, and Merton Miller. 1958. "The Cost of Capital, Corporation Finance and the Theory of Investment." *American Economic Review*, 48.

Muravyev, Dmitriy. 2016. "Order Flow and Expected Option Returns." *The Journal of Finance*, 71: 673–708.

Myers, Stewart C., and Stuart M. Turnbull. 1977. "Capital Budgeting and the Capital Asset Pricing Model: Good and Bad News." *The Journal of Finance*, 32: 321–333.

Nanda, Ramana. 2009. "Entrepreneurship and the Discipline of External Finance." *Harvard Business School Paper*.

Nanda, Ramana. 2015. "Experimentation and Real Options in Entrepreneurial Finance." *Harvard Business School Module Note 815-056*.

Onay, Selcuk, and Ayse Onculer. 2007. "Intertemporal choice under timing risk: An experimental approach." *Journal of Risk and Uncertainty*, 34: 99–121.

Perrakis, Stylianos. 1975. "Certainty Equivalents and Timing Uncertainty." *The Journal of Financial and Quantitative Analysis*, 10: 109.

Prabhala, Nagpurnanand R., and Kai Li. 2007. "Self-Selection Models in Corporate Finance." In *Handbook of Empirical Corporate Finance*. 37–86. Elsevier.

Puri, Indira. 2025. "Simplicity and Risk." *Journal of Finance*, 80: 1029–1080.

Routledge, Bryan R., and Stanley E. Zin. 2010. "Generalized Disappointment Aversion and Asset Prices." *The Journal of Finance*, 65: 1303–1332.

Securities and Exchange Commission. 2007. "Release No. 34-56191; File No. SR-CBOE-2007-79."

Stantcheva, Stefanie. 2024. "Why Do We Dislike Inflation?" National Bureau of Economic Research w32300, Cambridge, MA.

Starks, Laura T. 1987. "Performance Incentive Fees: An Agency Theoretic Approach." *The Journal of Financial and Quantitative Analysis*, 22: 17.

Tallarini, Thomas D. 2000. "Risk-sensitive real business cycles." *Journal of Monetary Economics*, 45: 507–532.

Viceira, Luis M. 2001. "Optimal Portfolio Choice for Long-Horizon Investors with Nontradable Labor Income." *The Journal of Finance*, 56: 433–470.

Vissing-Jorgensen, Annette. 2002. "Limited Asset Market Participation and the Elasticity of Intertemporal Substitution." *Journal of Political Economy*, 110: 825–853.

Xu, Nancy. 2021. "Procyclicality of the comovement between dividend growth and consumption growth." *Journal of Financial Economics*, 139: 288–312.