Do Firms Prefer An Early Resolution of Uncertainty?: A Structural Approach Using Recursive Utility*

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Abstract

We estimate firm-level managerial risk preferences using Epstein–Zin recursive utility and executive compensation data. By merging ExecuComp with CRSP for 1992–2023, we treat each listed firm as an economy in which managerial compensation growth serves as a proxy for consumption, while the firm's equity return represents the wealth portfolio. Using the Generalized Method of Moments (GMM) estimator, we obtain structural parameters that capture risk aversion, the elasticity of intertemporal substitution (EIS), and implied preferences regarding the timing of uncertainty resolution. Up to 73.6% of firms exhibit a preference for early resolution, with considerable heterogeneity in risk aversion and EIS among firms. Cross-sectional regressions reveal that the pricing of risk aversion and intertemporal substitution in stock returns is significantly influenced by managers' preferences regarding the resolution of uncertainty.

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1 Introduction

The risk preferences of corporations are closely related to those of the managers whom the shareholders appoint and delegate key decisions to. Through compensation contracts and control rights, boards try to shape executives' attitudes toward risk and intertemporal trade–offs, yet these preferences remain difficult to observe directly. Existing empirical work typically backs out managerial risk attitudes from option exercise behavior or contract calibration, or proxies for them using demographics, hobbies, or personality traits. Brenner (2015), for example, uses executives' stock option exercise patterns to infer moderate but highly heterogeneous coefficients of relative risk aversion at the individual level. Survey and field evidence further shows that more risk-tolerant CEOs choose riskier capital structures and policies and are compensated with more performance-sensitive pay (e.g., Cronqvist et al., 2012; Cain and McKeon, 2016; Graham et al., 2013). Despite these advances, we still lack direct, firm-level measures of managerial preferences in a dynamic environment and, in particular, of how managers value the timing of uncertainty resolution.

In modern macro–finance, preferences over risk, time, and the timing of uncertainty are most naturally modeled using Epstein and Zin (1989, 1991) recursive utility. By disentangling risk aversion from the elasticity of intertemporal substitution (EIS), this framework allows an agent to be very averse to risk yet relatively willing (or unwilling) to substitute resources across time, and implies a well-defined preference for early versus late resolution of uncertainty. In the canonical Epstein–Zin specification, the relation between relative risk aversion and the inverse of the EIS pins down whether early or late resolution is preferred. At the micro level, Brown and Kim (2014) show experimentally that most individuals choose parameter combinations consistent with a strict preference for early resolution of uncertainty, with relative risk aversion typically exceeding the reciprocal of the EIS. Household-finance studies similarly estimate recursive preferences using life-cycle portfolio and consumption data, documenting substantial heterogeneity in risk aversion and EIS across households. However, we know very little about whether corporate managers—who make repeated high-stake decisions under uncertainty—exhibit similar patterns, and whether their implied preferences regarding when uncertainty is resolved affect firm-level stock returns.

This paper asks four related questions. First, can we construct direct, firm-level measures of managerial risk preferences in a dynamic environment, rather than relying on static contract calibrations or behavioral proxies? Second, do firms—through the executives they hire—exhibit systematic preferences for early versus late resolution of uncertainty? Third, how heterogeneous are the underlying risk-aversion and intertemporal substitution parameters across firms when we allow for Epstein–Zin recursive utility? Finally, conditional on risk aversion and intertemporal substitution, how is the implied preference for the timing of uncertainty resolution associated with cross-sectional variation in stock performance?

To answer these questions, we embed Epstein–Zin preferences in a firm-level Euler-equation framework, in which the manager chooses an implicit "wealth portfolio" that loads on the firm's equity return. We assume that boards select managers whose risk and timing preferences are aligned with the firm's preferred risk profile, so that each firm can be characterized by a stable vector of preference parameters. Managerial "consumption" is proxied by the evolution of compensation, constructed from ExecuComp data, while the return on the wealth portfolio is proxied by the firm's own stock return from CRSP. We then estimate, at the firm level, both a benchmark constant-relative-risk-aversion (CRRA) model and a richer Epstein–Zin specification using generalized method of moments (GMM) applied to Euler equations for the firm's equity and test assets. This delivers structural estimates of relative risk aversion, the EIS, and the implied preference for early versus late resolution of uncertainty for each firm in the panel.

The CRRA benchmark serves two purposes. First, it provides a direct comparison to existing work that infers a single risk-aversion parameter for executives from options or contracts. Second, it highlights the limits of time-additive expected utility in a corporate setting. We show that estimated CRRA coefficients are highly heterogeneous across firms, spanning a wide range from near risk-neutrality to substantial risk aversion, and that standard J-tests reject the overidentifying restrictions for most firms. These rejections suggest that collapsing risk and intertemporal substitution into a single curvature parameter is too restrictive for describing managerial behavior in dynamic corporate environments.

Moving to the Epstein–Zin specification, we obtain joint firm-level estimates of risk aversion and the EIS, using them to classify firms according to the sign of the difference between relative risk aversion and the inverse of EIS. Following the theoretical mapping in Brown and Kim (2014), this classification yields three groups: firms whose managers prefer early resolution of uncertainty, firms that prefer late resolution, and firms that are approximately indifferent. We find that the majority of firms fall into the early-resolution region, consistent with experimental evidence on individuals, while a nontrivial minority exhibits parameter combinations consistent with late resolution or near indifference. These findings provide, to our knowledge, the first field evidence on the temporal resolution of uncertainty for corporate managers derived from actual compensation and stock return data, rather than hypothetical choices.

Finally, we link the estimated preference parameters to the cross-section of stock returns. We run firm-level regressions of average returns on risk aversion, the EIS parameter, and the implied resolution-of-uncertainty indicator. Two striking patterns emerge. First, the sign of the relation between risk aversion and returns depends on how the manager values the timing of uncertainty resolution: among firms whose managers prefer late resolution, higher estimated risk aversion is associated with higher average stock returns, whereas among firms whose managers prefer early resolution, higher risk aversion is associated with lower returns. Second, once we condition on the resolution-of-uncertainty preference, the EIS has little systematic explanatory power for returns. Together, these results suggest that the way managers prefer uncertainty to be resolved—early versus late—is an economically important, independent dimension of heterogeneity that helps organize the cross-sectional relation between managerial preferences and stock performance.

Our work contributes to several strands of literature. First, we bring Epstein–Zin recursive utility to the study of managerial behavior, providing micro-level structural estimates of risk aversion, intertemporal substitution, and uncertainty-resolution preferences for individual firms. This complements the existing experimental evidence on individuals and household-finance estimates of recursive preferences, and extends them to the domain of corporate decision-making. Second, we connect the executive-traits and corporate-policy literature—which emphasizes how CEO characteristics shape leverage, investment, and payout policies—to a structural asset-pricing framework that yields interpretable preference parameters. Third, methodologically, we show how to implement firm-level GMM estimation of recursive preferences using widely available executive-compensation and return data, providing a template for future work on managerial heterogeneity in dynamic settings. More broadly, our results speak to debates on managerial short-termism and risk-taking: they indicate that both the level of risk aversion and the preferred timing of uncertainty resolution matter for how firms are priced and how they bear risk in the capital markets.

2 Related Literature

Our paper is related to three branches of literature, which we briefly review below.

Recursive Utility and Asset Pricing

Our work builds on the macro–finance literature that models investor preferences and their implications for asset returns. Epstein and Zin (1989, 1991) introduce recursive preferences that disentangle risk aversion from the EIS. Under standard expected utility, these two features are tied together through curvature in the utility function; Epstein–Zin (EZ) preferences instead allow an agent to be highly risk-averse while still willing to substitute consumption intertemporally, or vice versa.

In EZ models, the intertemporal marginal rate of substitution (IMRS) typically takes the form

$$m_{t+1}(\lambda, \beta) = c_{t+1}^{-\lambda\beta} R_{a,t+1}^{\lambda-1}, \tag{1}$$

where c_{t+1} is gross consumption growth, $R_{a,t+1}$ is the return on aggregate wealth, and (λ, β) are preference parameters that jointly determine risk aversion, the EIS, and attitudes toward the timing of resolution of uncertainty. A large literature uses EZ preferences to address classic asset-pricing puzzles by allowing risk and time preferences to move independently.

At the individual level, Brown and Kim (2014) experimentally elicit risk, time, and intertemporal-substitution preferences and use the Epstein–Zin mapping to infer whether subjects prefer early or late resolution of uncertainty. They find that most individuals have relative risk aversion greater than the inverse of the EIS and therefore prefer early resolution, providing direct empirical content for the EZ framework and for the link between risk attitudes, intertemporal substitution, and the timing of uncertainty resolution.

Managerial Risk Preferences

An extensive empirical literature documents that CEOs' personal traits and risk attitudes correlate with corporate policies. Cronqvist et al. (2012) show that CEOs who take more personal leverage also run firms with higher corporate leverage, suggesting that personal risk tolerance extends to the corporate balance sheet. Cain and McKeon (2016) find that CEOs who engage in risky hobbies such as private aviation pursue riskier corporate policies—higher leverage, more frequent acquisitions, and more volatile stock returns. Survey evidence by Graham et al. (2013) further documents the links between managerial preferences and firm policies: more risk-tolerant CEOs are more likely to undertake mergers and acquisitions, while more risk-averse CEOs prefer safer corporate strategies and are paid primarily in fixed salary rather than equity-based compensation.

Structural estimation approaches have recently been applied to executive behavior. Page (2018) estimates a dynamic principal–agent model of CEO compensation and effort, allowing for heterogeneity in risk aversion and board influence, and shows that the cost of managerial risk aversion to shareholders can be substantial. Other papers infer risk aversion by calibrating optimal contracts to observed pay and firm policies (e.g., Dittmann and Maug, 2007; Dittmann et al., 2017). Text-based approaches use personality traits extracted from executive communications to proxy for inherent risk aversion and relate these to compensation structures (Hrazdil et al., 2019). Brenner (2015) complements this work by structurally backing out executives' risk aversion from large-scale option exercise data, documenting substantial heterogeneity in risk preferences across individual managers.

These studies collectively show that managerial preferences matter for both contract design and corporate risk-taking. However, existing work generally treats risk aversion and time preferences separately yet, within expected utility. To our knowledge, no prior study structurally estimates an Epstein–Zin-Weil recursive utility model that jointly recovers risk aversion, EIS, and uncertainty-timing preferences for corporate executives using field data. Our paper fills this gap.

Bridging Asset Pricing and Corporate Finance

Our paper integrates insights from aggregate asset pricing and executive-level corporate finance. On the asset-pricing side, we adopt EZ recursive utility and estimator structures inspired by GMM implementations on consumption and market returns. On the corporate side, we use executive compensation data and firm-level returns to construct a firm-specific consumption-based pricing kernel that reflects the executive's preferences. This approach complements existing contract-based structural models and broadens the empirical toolkit for studying managerial preferences, allowing us to connect micro-level preference parameters to the cross-section of stock returns and to firms' implied preferences over the timing of uncertainty resolution.

3 Data and Variable Construction

Our main panel is constructed by merging ExecuComp compensation data with CRSP stock returns at the firm (`GVKEY`)–year level. Using ExecuComp's `TDC2` as our proxy for managerial "consumption", we aggregate across top executives within a firm-year and compute the mean compensation for the top management team. Merging this with annual stock returns from CRSP yields a panel of approximately 64,000 firm-year observations for 4,100 distinct firms during 1992–2023. We restrict the GMM estimation sample to firms with at least 12 annual observations on compensation and returns, plus non-missing moments. This leaves 2,209 firms for the CRRA model and 2,210 firms for the EZ model.

3.1 Managerial Consumption

To estimate the Euler equation, we require a proxy for the executive's consumption stream. Following the structural corporate finance literature, we utilize the executive's total realized compensation (`TDC2` in ExecuComp) as a proxy for consumption. `TDC2` includes salary, bonus, the value of restricted stock grants, and crucially, the value of stock options *exercised* during the year. This measure better reflects the actual cash flow available to the manager for consumption than the grant-date value of pay (`TDC1`).[1] Let $C_{i,t}$ denote the real compensation for the CEO of firm i in year t. We deflate nominal compensation using the Consumer Price Index (CPI) to obtain real values.

3.2 The Wealth Portfolio

The Epstein-Zin Euler equation requires the return of an agent's total wealth portfolio, $R_{w,t+1}$. Given that CEOs and other upper echelons are typically under-diversified with significant human and financial capital tied to their firm (Hall and Murphy, 2002), we proxy the return on their wealth portfolios with the firm's annual total stock return. Data on annual returns are merged from CRSP.

[1] `TDC2` is a measure of total compensation, calculated as Salary + Bonus + Other Annual + Restricted Stock Grants + LTIP Payouts + All Other + Value of Options Exercised. `TDC1` is identical except that it uses Value of Option Grants instead of Value of Options Exercised, and thus is a measure of awarded value rather than realized value.

3.3 Sample Construction

We merge ExecuComp and CRSP data by `GVKEY` and fiscal year. To ensure the stability of the GMM estimation, we require firms to have a minimum number of consecutive observations (filtering out short time series of less than 12 years). The final full sample consists of 2,210 unique firms with an average time series length of 26 years.

Table 1 reports summary statistics for the firm-year distribution of managerial compensation and stock returns. Average annual firm-level stock returns are about 17.6% with substantial dispersion (interquartile range of approximately −13% to 35%). The mean top-management compensation (ExecuComp `TDC2`, averaged within a firm-year) is around \$3.1 million, with a median of roughly \$1.5 million and a wide right tail.

[Insert Table 1 About Here]

4 Model and Econometric Methods

In this section we describe the intertemporal preference specifications that underlie our asset pricing restrictions and the econometric procedures used to estimate the preference parameters. We first present a benchmark model with standard constant relative risk aversion (CRRA) expected utility, and then introduce Epstein–Zin (EZ) recursive preferences, which allow us to disentangle risk aversion from the elasticity of intertemporal substitution (EIS). For each specification we derive the stochastic discount factor (SDF) and the resulting moment conditions that are taken to the data using the Generalized Method of Moments (GMM).

4.1 CRRA Preferences and the Euler Equation

We begin with a manager (or representative decision maker) who has time-separable CRRA preferences over consumption (or, more generally, over a consumption proxy such as executive compensation). Period utility is given by

$$u(c_t) = \begin{cases} \dfrac{c_t^{1-\gamma}}{1-\gamma}, & \gamma \neq 1, \\ \\ \ln(c_t), & \gamma = 1, \end{cases} \tag{2}$$

where c_t denotes consumption at time t and $\gamma > 0$ is the coefficient of relative risk aversion. The corresponding marginal utility of consumption is

$$u'(c_t) = c_t^{-\gamma}. \tag{3}$$

Let $\delta \in (0, 1)$ denote the subjective time discount factor. In a frictionless environment with complete markets and no arbitrage, optimal intertemporal consumption and portfolio choice imply the standard Euler equation for any asset with gross return R_{t+1}:

$$\mathbb{E}_t \left[\delta\, R_{t+1} \left(\frac{c_{t+1}}{c_t} \right)^{-\gamma} \right] = 1. \tag{4}$$

The term

$$m_{t+1}^{\text{CRRA}} \equiv \delta \left(\frac{c_{t+1}}{c_t} \right)^{-\gamma} \tag{5}$$

is the stochastic discount factor implied by CRRA preferences. Equation (4) states that, under rational expectations, the discounted, marginal-utility–weighted payoff of any asset must be a martingale and therefore have conditional expectation equal to one.

In our empirical application, we do not observe true consumption for each manager. Instead, we follow the macroeconomics and finance literature in assuming that individual consumption is a constant fraction of wealth, and managerial wealth can be proxied by total compensation. Then, we can set

$$\frac{c_{t+1}}{c_t} \approx \frac{\text{Comp}_{t+1}}{\text{Comp}_t}. \tag{6}$$

Substituting this proxy into (4) and taking unconditional expectations over time yields

$$\mathbb{E}\left[\left(\frac{c_{t+1}}{c_t}\right)^{-\gamma}(R_{t+1} - R_{f,t})\right] = 0, \tag{7}$$

where $R_{f,t}$ is the risk-free rate. Equation (7) provides the basis for the unconditional moment conditions used in our GMM estimation. For a given set of test assets, any deviation of the sample analog of (7) from its theoretical value reflects a violation of the restrictions implied by CRRA preferences, and GMM chooses the parameter vector to minimize such deviations.

4.2 Epstein–Zin Recursive Preferences

The CRRA specification imposes the restriction that risk aversion and the elasticity of intertemporal substitution are tightly linked: the EIS equals $1/\gamma$. Epstein–Zin recursive preferences relax this restriction by allowing risk aversion and intertemporal substitution to be governed by distinct parameters. This additional flexibility is particularly useful in asset pricing applications where evidence suggests that the risk aversion required to match risk premia appears too high relative to the EIS inferred from macroeconomic data.

Let U_t denote the continuation utility at time t. Under Epstein–Zin preferences, utility evolves according to the recursive formulation

$$U_t = \left[(1-\delta) \, c_t^{\frac{\rho-1}{\rho}} + \delta \left(\mathbb{E}_t \left[U_{t+1}^{1-\gamma} \right] \right)^{\frac{\rho-1}{\rho} \cdot \frac{1}{1-\gamma}} \right]^{\frac{\rho}{\rho-1}}, \tag{8}$$

where $\delta \in (0,1)$ is the time preference parameter, $\gamma > 0$ is the coefficient of relative risk aversion, and $\rho > 0$ governs the elasticity of intertemporal substitution. The elasticity of intertemporal substitution is given by

$$\psi = \frac{1}{\rho - 1}, \tag{9}$$

so that large ψ corresponds to a high willingness to shift consumption intertemporally in response to changes in the intertemporal marginal rate of substitution.

Expression (8) nests the standard CRRA specification as a special case when $\gamma = \rho$. When $\gamma \neq \rho$, the agent's aversion to time variation in consumption (through ρ) can differ from the curvature of the aggregator over risky outcomes (through γ), generating nontrivial implications for risk premia and the term structure of interest rates even in environments with relatively smooth expected consumption growth.

Under Epstein–Zin preferences, the intertemporal marginal rate of substitution, or SDF, can be written in the following convenient parametric form:

$$m_{t+1} = \delta \left(\frac{c_{t+1}}{c_t} \right)^{-\lambda\beta} R_{a,t+1}^{\lambda-1}, \tag{10}$$

where $R_{a,t+1}$ denotes the gross return on the aggregate wealth portfolio (or a suitable proxy, such as a broad market index), and the parameters

$$\lambda = \frac{1-\gamma}{1-1/\psi}, \qquad \beta = \frac{1}{\psi}, \tag{11}$$

reparameterize the preference primitives in terms of risk aversion and the EIS. The parameter λ captures the degree to which the SDF is sensitive to both consumption growth and shocks to the return on aggregate wealth. Equation (10) emphasizes that under recursive preferences the SDF depends not only on consumption growth, as in the CRRA case, but also on the return on the wealth portfolio, which reflects news about future opportunities.

For any asset i with gross return R^i_{t+1}, absence of arbitrage implies the fundamental asset pricing condition

$$\mathbb{E}_t\left[m_{t+1}R^i_{t+1}\right] = 1. \tag{12}$$

Equivalently, if we consider a zero-cost portfolio that takes a long position in asset i and a short position in asset j, with payoff $R^i_{t+1} - R^j_{t+1}$, then (12) implies

$$\mathbb{E}_t\left[m_{t+1}\left(R^i_{t+1} - R^j_{t+1}\right)\right] = 0. \tag{13}$$

Equation (13) will be the starting point for our empirical moment conditions based on returns on difference portfolios formed from the available test assets.

4.3 Moment Conditions for GMM

Our empirical strategy is to use the pricing restrictions implied by Equation (12) (or (13)) in combination with observed asset returns and instrumental variables to construct a set of unconditional moment conditions. These moments are then exploited to estimate the preference parameters by GMM.

4.3.1 Epstein–Zin Model with Instruments

Let R_{t+1} denote a $K \times 1$ vector collecting the gross returns on K test assets (for example, portfolios sorted on observable characteristics) in period $t+1$. Let Z_t denote an $L \times 1$ vector of instruments that are measurable at time t. The instrument vector typically includes a constant and possibly lagged macroeconomic variables or lagged returns intended to capture time variation in conditional expected returns and conditional variances.

Under the null hypothesis that the Epstein–Zin model with parameter vector $\theta = (\lambda, \beta)'$ correctly prices the test assets, we have

$$\mathbb{E}\left[m_{t+1}(\lambda, \beta)\, R_{t+1} \otimes Z_t\right] = 0, \tag{14}$$

where $\otimes$ denotes the Kronecker product. Equation (14) stacks the K pricing restrictions in (12) for each asset and interacts them with each of the L instruments, generating $K \times L$ unconditional moment conditions. Intuitively, if the model is correct, then the pricing errors should be orthogonal to all information available at time t.

The sample analog of (14) is

$$g(\lambda, \beta) = \frac{1}{T} \sum_{t=1}^{T} m_t(\lambda, \beta) \left(R_t \otimes Z_t\right), \tag{15}$$

where T is the sample size and R_t denotes the vector of gross returns realized in period t. The vector $g(\lambda, \beta)$ has dimension $KL \times 1$; the empirical objective of GMM is to find parameter values that make this sample moment vector as close to zero as possible in a quadratic sense, taking into account the covariance structure of the moments.

4.4 GMM Estimation Procedure

Let θ denote the vector of parameters to be estimated. In the Epstein–Zin specification we focus on $\theta = (\lambda, \beta)'$, but the discussion applies more generally. Given a vector of sample moments $g(\theta)$ defined as in (15), the standard GMM estimator minimizes the quadratic form

$$J(\theta) = g(\theta)' W g(\theta), \tag{16}$$

where W is a positive definite weighting matrix. When the number of moments exceeds the number of parameters (an over-identified model), the choice of W affects the efficiency of the estimator. The optimal weighting matrix, in the sense of Hansen (1982), is the inverse of the long-run covariance matrix of the moment conditions.

In practice we implement a two-stage GMM procedure. The first stage uses a simple, fixed weighting matrix to obtain a preliminary consistent estimator. The second stage uses the residuals from the first stage to estimate the covariance matrix of the moment conditions and constructs an efficient weighting matrix.

4.4.1 Stage 1: Identity Weighting

In the first stage, we choose the identity matrix as a convenient initial weighting matrix,

$$W^{(1)} = I_{KL}, \tag{17}$$

where I_{KL} is the $KL \times KL$ identity matrix. The first-step GMM estimator solves

$$\hat{\theta}^{(1)} = \arg\min_{\theta} J^{(1)}(\theta), \qquad J^{(1)}(\theta) = g(\theta)' g(\theta). \tag{18}$$

Because the weighting matrix is fixed and does not depend on the unknown parameters, this step is straightforward to compute; it provides a consistent but generally not efficient estimate of θ under standard regularity conditions.

4.4.2 Stage 2: Optimal Weighting

In the second stage, we use the first-step estimator $\hat{\theta}^{(1)}$ to approximate the covariance structure of the sample moments. Let $h_t(\theta)$ denote the $KL \times 1$ vector of individual period-t moment functions such that

$$g(\theta) = \frac{1}{T} \sum_{t=1}^{T} h_t(\theta). \tag{19}$$

We estimate the long-run variance of the moment conditions by

$$S = \frac{1}{T} \sum_{t=1}^{T} h_t\big(\hat{\theta}^{(1)}\big) h_t\big(\hat{\theta}^{(1)}\big)', \tag{20}$$

possibly augmented with standard heteroskedasticity and autocorrelation consistent (HAC) adjustments in applications with serial correlation. For expositional simplicity, we present the case without HAC corrections. The optimal second-stage weighting matrix is

$$W^{(2)} = S^{-1}. \tag{21}$$

Using this updated weighting matrix, the efficient GMM estimator solves

$$\hat{\theta}_{\text{GMM}} = \arg\min_{\theta} J^{(2)}(\theta), \qquad J^{(2)}(\theta) = g(\theta)' W^{(2)} g(\theta). \tag{22}$$

Under suitable regularity conditions, $\hat{\theta}_{\text{GMM}}$ is consistent and asymptotically efficient within the class of estimators based on the chosen set of moment conditions.

4.4.3 Epstein–Zin Moment Calculation

For the Epstein-Zin model, the individual moment associated with asset $k \in \{1, \ldots, K\}$ and instrument $\ell \in \{1, \ldots, L\}$ at time t is

$$h_{t,k\ell}(\lambda, \beta) = m_t(\lambda, \beta)\, R_{t,k}\, Z_{t,\ell}, \tag{23}$$

where $R_{t,k}$ denotes the gross return on asset k in period t, and $Z_{t,\ell}$ is the ℓ-th element of the instrument vector. Stacking all such moments for a given t yields the $KL \times 1$ vector $h_t(\lambda, \beta)$. The sample moment vector is then

$$g(\lambda, \beta) = \frac{1}{T} \sum_{t=1}^{T} h_t(\lambda, \beta) \in \mathbb{R}^{KL}. \tag{24}$$

The GMM estimator chooses (λ, β) so that these sample moments are as close as possible to zero in the sense of (16) and (22). Inference in GMM relies on the Jacobian matrix of the moment conditions with respect to the parameters. Let

$$D(\theta) = \frac{\partial g(\theta)}{\partial \theta'}$$

denote the $KL \times 2$ Jacobian matrix in our Epstein–Zin specification, where $\theta = (\lambda, \beta)'$. Using (15), the Jacobian components can be written as

$$\frac{\partial g}{\partial \lambda} = \frac{1}{T} \sum_{t=1}^{T} \frac{\partial m_t}{\partial \lambda} \left(R_t \otimes Z_t\right), \tag{25}$$

$$\frac{\partial g}{\partial \beta} = \frac{1}{T} \sum_{t=1}^{T} \frac{\partial m_t}{\partial \beta} \left(R_t \otimes Z_t\right), \tag{26}$$

where $\partial m_t/\partial\lambda$ and $\partial m_t/\partial\beta$ follow directly from the SDF expression (10). Taking logarithms of (10) and differentiating yields

$$\frac{\partial m_t}{\partial \lambda} = m_t \left(-\beta \ln\left(\frac{c_{t+1}}{c_t}\right) + \ln\left(R_{a,t+1}\right) \right), \tag{27}$$

$$\frac{\partial m_t}{\partial \beta} = m_t \left(-\lambda \ln\left(\frac{c_{t+1}}{c_t}\right) \right). \tag{28}$$

We compute the Jacobian numerically by evaluating (25) and (26) at the estimated parameter vector $\hat{\theta}_{\text{GMM}}$. This Jacobian plays a central role in the asymptotic variance formula derived below.

4.4.4 Weighting Matrix Computation

For completeness, we briefly discuss the weighting matrix used in the GMM estimation. In the simpler CRRA case with a scalar moment condition, suppose the CRRA specification yields a scalar moment $h_t(\gamma)$ at each date, for example,

$$h_t(\gamma) = \left(\frac{c_{t+1}}{c_t}\right)^{-\gamma} X_t, \tag{29}$$

where X_t is some instrument. Denote by H the $T \times 1$ vector collecting $\{h_t(\gamma)\}_{t=1}^{T}$. The long-run variance of the moment condition is then estimated by

$$S = \frac{1}{T} H'H = \frac{1}{T} \sum_{t=1}^{T} h_t(\gamma)^2. \tag{30}$$

Because there is only one moment condition in this simple case, the optimal weighting matrix reduces to

$$W = \frac{1}{S}. \tag{31}$$

This illustrates how, in the scalar case, GMM effectively rescales the moment by its estimated variance.

In the Epstein-Zin setting with multiple assets and instruments, the moment vector has dimension KL, and we collect the corresponding individual moments in the $T \times KL$ matrix H, whose t-th row is $h_t(\hat{\theta}^{(1)})'$. The long-run variance of the stacked moment conditions is then estimated by

$$S = \frac{1}{T} H' H, \tag{32}$$

which corresponds to a sample covariance matrix of the KL-dimensional moment vector. The optimal weighting matrix is the inverse of this estimated covariance matrix,

$$W = S^{-1}. \tag{33}$$

In finite samples, especially when the number of moments is large relative to the sample size or when some moments are highly correlated, S may be nearly singular, and its inverse can be numerically unstable. To mitigate this issue, it is common to introduce a small ridge penalty on the diagonal of S, leading to the regularized weighting matrix

$$W = \left(S + \epsilon I_{KL}\right)^{-1}, \tag{34}$$

where $\epsilon > 0$ is a small scalar and I_{KL} is the identity matrix. This ridge adjustment stabilizes the inversion and has negligible impact on the asymptotic distribution when ϵ is sufficiently small.

Under standard GMM regularity conditions, including correct specification of the moment conditions, appropriate mixing conditions on the data, and smoothness of the moments in the parameters, the GMM estimator is asymptotically normal. Specifically,

$$\sqrt{T}\big(\hat{\theta}_{\mathrm{GMM}} - \theta_0\big) \xrightarrow{d} N(0, V), \tag{35}$$

where θ_0 denotes the true parameter vector and the asymptotic covariance matrix V is given by

$$V = (D'WD)^{-1} D'WSWD (D'WD)^{-1}. \tag{36}$$

Here $D = \partial g(\theta)/\partial \theta'$ is the Jacobian evaluated at θ_0 (in practice at $\hat{\theta}_{\mathrm{GMM}}$), S is the long-run variance of the moments defined in (20) or (32), and W is the weighting matrix used in the GMM criterion. When the efficient weighting matrix $W = S^{-1}$ is used in the second stage, the asymptotic covariance matrix simplifies considerably:

$$V_{\mathrm{eff}} = (D'S^{-1}D)^{-1}. \tag{37}$$

This expression underscores the role of the Jacobian in determining how informative the moment conditions are about the parameters: if the columns of D are nearly collinear, the covariance matrix becomes large and the parameters are weakly identified.

4.4.5 Standard Error Calculation

In empirical implementation we replace the population objects in (36) or (37) with their sample estimates. Let $\widehat{D}$ denote the Jacobian evaluated at $\hat{\theta}_{\mathrm{GMM}}$, and let $\widehat{S}$ and $\widehat{W}$ denote the estimated long-run variance and weighting matrix, respectively. The estimated asymptotic covariance matrix is

$$\widehat{\mathrm{Var}}(\hat{\theta}) = (\widehat{D}'\widehat{W}\widehat{D})^{-1}\widehat{D}'\widehat{W}\widehat{S}\widehat{W}\widehat{D}(\widehat{D}'\widehat{W}\widehat{D})^{-1}/T. \tag{38}$$

For the efficient GMM estimator with $\widehat{W} = \widehat{S}^{-1}$, this simplifies to

$$\widehat{\mathrm{Var}}_{\mathrm{eff}}(\hat{\theta}) = (\widehat{D}'\widehat{S}^{-1}\widehat{D})^{-1}/T. \tag{39}$$

The standard error associated with the j-th parameter $\hat{\theta}_j$ is then obtained as the square root of the corresponding diagonal element of the estimated covariance matrix:

$$SE(\hat{\theta}_j) = \sqrt{\left[\widehat{\mathrm{Var}}(\hat{\theta})\right]_{jj}}. \tag{40}$$

These standard errors are used to construct asymptotic t-statistics for individual parameters and to form confidence intervals under the assumption of asymptotic normality.

4.4.6 The J-Test for Overidentifying Restrictions

When the model is overidentified, meaning that the number of moment conditions q exceeds the number of parameters p, the GMM framework provides an internal specification test based on the minimized value of the objective function. The null hypothesis is that all moment conditions are correctly specified at the true parameter vector:

$$H_0 : \mathbb{E}[h_t(\theta_0)] = 0. \tag{41}$$

Let $\hat{\theta}_{\text{GMM}}$ denote the efficient GMM estimator and $g(\hat{\theta}_{\text{GMM}})$ the corresponding sample moments. The J-statistic is defined as

$$J = T\, g(\hat{\theta}_{\text{GMM}})' W\, g(\hat{\theta}_{\text{GMM}}), \tag{42}$$

where W is the weighting matrix used in the second-stage estimation (for efficient GMM, $W = \widehat{S}^{-1}$). Under the null hypothesis and standard regularity conditions, the J-statistic converges in distribution to a chi-squared random variable with degrees of freedom equal to the number of overidentifying restrictions:

$$J \xrightarrow{d} \chi^2_{df}, \qquad df = q - p. \tag{43}$$

The corresponding p-value is computed as

$$p\text{-value} = 1 - F_{\chi^2_{df}}(J), \tag{44}$$

where $F_{\chi^2_{df}}(\cdot)$ denotes the cumulative distribution function of the chi-squared distribution with df degrees of freedom. A low p-value provides evidence against the null that the imposed asset pricing restrictions are jointly consistent with the data, and may indicate misspecification of the preference model, an inadequate choice of test assets, or problems with the measurement of consumption (or its proxy) and returns.

5 Empirical Results

This section presents the results of firm-level GMM estimates of managerial risk preferences and examine how they relate to stock performance. We start with a one-parameter CRRA benchmark, and then move on to the Epstein–Zin specification that separates risk aversion from the elasticity of intertemporal substitution (EIS). Finally, we study how the implied preference for the timing of uncertainty resolution is priced in the cross section of firm returns.

Our estimation sample consists of ExecuComp firms with at least 12 consecutive years of compensation and return data between 1992 and 2023.[2] The raw merged ExecuComp–CRSP panel contains about 64,000 firm–year observations. After requiring sufficient time-series length and successful convergence of the GMM routine, we obtain CRRA estimates for 2,209 firms and Epstein–Zin estimates for 2,207–2,210 firms, depending on the specific specification and filters.

Relative to the macro-finance literature, which typically estimates a representative-agent CRRA or EZ model from aggregate consumption and returns (e.g., Hansen and Singleton, 1983; Epstein and Zin, 1989; Weil, 1990; Bansal and Yaron, 2004), our exercise treats each listed firm as a separate "mini-economy" governed by the preferences of its top executives, and we ask how far we can push standard Euler-equation logic at that level. Throughout this section we emphasize magnitudes, dispersion, and model fit.

[2]We also have a set of results requiring 20 consecutive years of compensation and return data. The number of firms in this sample is 1,121, and the estimation results are highly compatible to the benchmark case.

5.1 CRRA benchmark

As a starting point, we estimate the standard one-parameter CRRA Euler equation at the firm level. For each firm i, we estimate a coefficient of relative risk aversion γ_i from the unconditional moment condition

$$\mathbb{E}\left[\left(\frac{c_{i,t+1}}{c_{i,t}}\right)^{-\gamma_i}(R_{i,t+1}-R_{f,t})\right]=0,$$

using firm-level compensation growth as a proxy for the manager's consumption growth and the firm's stock return as the test asset.

Table 2 summarizes the cross-sectional distribution of the estimated CRRA coefficients. Across 2,209 firms, the mean risk-aversion estimate is about $\bar{\gamma} \approx 2.23$, with a standard deviation of about 4.04 (i.e., the t-statistics is about 25.9). The average risk aversion value is quite compatible with the calibration value used in the macroeconomics and macro-finance literature. However, the distribution is highly heterogeneous and fat-tailed: the 25th percentile is about 0.56, the median is 1.27, the 75th percentile is 2.49, and the full range spans from roughly 0.10 to 105.85. Average annual stock returns for these firms average about 16.6% with an interquartile range of roughly 9.9% to 21.0%.

To focus on reasonably well-identified cases, we define a "significant" subset based on GMM precision ($|t\text{-stat}(\gamma)| > 1.645$ and stable weighting matrices). This yields 531 firms. In this subset, mean risk aversion rises to about 2.89 (median $\approx$ 1.93), with the 75th percentile around 3.37 and a maximum near 47.4. These firms also earn higher average returns: mean and median annual returns are about 23.1% and 18.8%, respectively.

[Insert Table 2 About Here]

Despite these seemingly reasonable parameter estimates, the one-parameter CRRA model fares poorly in terms of formal model fit. The Hansen–J overidentification test rejects the CRRA Euler equation for essentially the entire cross section of firms. This echoes the classic empirical failures of the consumption-based CAPM estimated on aggregate consumption and broad asset returns, suggesting that simply moving to the firm level does not, by itself, resolve the standard Consumption-CAPM puzzles.

5.2 Epstein–Zin estimates and preference for uncertainty resolution

We next estimate Epstein–Zin recursive preferences at the firm level. Under Epstein–Zin utility, risk aversion and the elasticity of intertemporal substitution (EIS) are decoupled. We parameterize the Epstein–Zin stochastic discount factor at the firm level in terms of (λ_i, β_i) as

$$m_{i,t+1}(\lambda_i, \beta_i) = \left(\frac{c_{i,t+1}}{c_{i,t}}\right)^{-\lambda_i \beta_i} R_{A,i,t+1}^{\lambda_i - 1},$$

following Epstein and Zin (1989, 1991). The underlying preference parameters of interest—risk aversion γ_i and the elasticity of intertemporal substitution ψ_i—are then recovered via the Epstein–Zin mapping

$$\lambda_i = \frac{1-\gamma_i}{1-1/\psi_i}, \qquad \beta_i = \frac{1}{\psi_i},$$

so that

$$\gamma_i = 1 - \lambda_i(1-\beta_i), \qquad \psi_i = \frac{1}{\beta_i}.$$

Under this specification, the manager's preference over the timing of resolution of uncertainty is governed by the sign of $\gamma_i - 1/\psi_i$: if $\gamma_i > 1/\psi_i$, the manager prefers *early* resolution of uncertainty; if $\gamma_i < 1/\psi_i$, she prefers *late* resolution; and if $\gamma_i \approx 1/\psi_i$, she is near indifferent.

Table 3 reports the cross-sectional distribution of the estimated Epstein–Zin parameters, and Figures 1 and 2 plot the histogram and the kernel density of the estimated preference parameters γ and ψ, respectively. In the full EZ sample, we obtain valid estimates for 2,207 firms. The mean risk-aversion estimate is about 1.84 (median 1.42) with a standard deviation of 1.81. The interquartile range is roughly [0.78, 2.41], and the full range spans from about −3.68 to 10.9. The EIS estimates are stable on the low end but very heavy-tailed. When we truncate extreme values at 100 (as in the notebook), the mean EIS is about 28.3, the median is 3.67, the 25th percentile is about 0.87, and the 75th percentile is about 56.6.

Focusing again on a "significant" subset of 919 firms with more reliable EZ estimates, the mean risk aversion rises to about 2.39 (median 2.28) and the interquartile range for RRA is approximately [0.36, 3.74]. For this subset the EIS remains right-skewed, with the mean around 37.4 and median about 9.03. Average returns for the EZ sample are similar to the CRRA case: mean annual return around 15–17%, with medians near 14–15%.

[Insert Table 3, Figures 1 and 2 About Here]

The EZ estimates allow us to classify firms as preferring early or late resolution of uncertainty. Using the theoretical criterion $\gamma_i \gtrless 1/\psi_i$, we form two groups:

- **Early resolution firms:** $RRA_{EZ,i} > 1/\psi_i$. This group contains 1,401 out of 2,210 firms (63.4%). Their mean risk aversion is about 2.22 and mean EIS is about 40.7. Their average annual stock return is about 18.7%.

- **Late resolution firms:** $RRA_{EZ,i} \leq 1/\psi_i$. This group consists of 806 firms (36.5%). Their mean risk aversion is about 1.18 and mean EIS is about 6.70. Their average annual return is about 14.4%.

Only a negligible fraction of firms lies exactly on the boundary $RRA_{EZ,i} \approx 1/\psi_i$, consistent with the CRRA case who is indifferent to the speed of uncertainty resolution. Taken together, these results suggest that U.S. corporations tend to hire or evolve towards managers whose preferences imply a desire for the *early* resolution of uncertainty, consistent with recent experimental evidence on individual Epstein-Zin preferences. However, a nontrivial portion of hopeful firms exist who may bet on long-run uncertainty/risk.

Figure 3 reports the cross sectional distribution of J-statistics and their p-values. We can observe that all p-values are greater than 0.6, thus none of them are rejected at the 10% level, suggesting that the model fits the data well.

[Insert Figure 3 About Here]

5.3 Stock returns and managerial preference parameters

We next relate the estimated recursive-preference parameters to cross-sectional differences in average stock returns. Our baseline specification regresses the firm-level average annual return on Epstein–Zin estimates of relative risk aversion (RRA) and elasticity of intertemporal substitution (EIS):

$$\bar{R}_i \;=\; \alpha \;+\; \beta_\gamma\, \widehat{\mathrm{RRA}}_i \;+\; \beta_\psi\, \widehat{\mathrm{EIS}}_i \;+\; \varepsilon_i, \tag{45}$$

where $\widehat{\mathrm{RRA}}_i$ and $\widehat{\mathrm{EIS}}_i$ are the firm-level EZ estimates of γ and ψ for firm i, respectively. To capture the role of preferences over the timing of uncertainty resolution, we augment this baseline with an "early resolution" dummy and interaction terms:

$$\bar{R}_i \;=\; \alpha + \beta_\gamma\,\widehat{\mathrm{RRA}}_i + \beta_\psi\,\widehat{\mathrm{EIS}}_i + \beta_{\mathrm{Early}}\mathbf{1}_{\mathrm{Early},i} + \beta_{\Delta,\gamma}\,\widehat{\mathrm{RRA}}_i{\times}\mathbf{1}_{\mathrm{Early},i} + \beta_{\Delta,\psi}\,\widehat{\mathrm{EIS}}_i{\times}\mathbf{1}_{\mathrm{Early},i} + \varepsilon_i, \tag{46}$$

where $\mathbf{1}_{\mathrm{Early},i}$ is an indicator equal to one if firm i is classified as an early-resolution firm, i.e. if $\widehat{\mathrm{RRA}}_i > 1/\widehat{\mathrm{EIS}}_i$, and zero otherwise.

Table 4 shows how this classification splits the sample. In the full sample, roughly two thirds of firms are in the early-resolution region (63% early versus 36% late). The early-resolution share is similar after filtering out extreme EIS estimates (54% versus 46%) and rises further in the subset where the EZ parameters are statistically significant (about 74% and 68% early in the unfiltered and filtered significant samples, respectively). Thus, in our data, early-resolution preferences are the modal case at the firm level, mirroring prior evidence at the individual level which shows that most subjects exhibit relative risk aversion exceeding the reciprocal of the EIS and therefore prefer early resolution of uncertainty.

[Insert Table 4 About Here]

We begin with baseline regressions that omit the timing dummy and interactions. Columns (1)-(3) of Tables 5–8 report estimates of Equation(45) for the full sample, the subset with statistically significant EZ estimates, and the corresponding EIS-filtered subsamples. In the full sample, the coefficient on risk aversion is positive and statistically significant across specifications. For example, in the unfiltered full sample the RRA coefficient is about 0.006 in the joint specification with EIS (column (3) of Table 5), and it is slightly larger (0.0065) when we restrict to firms with $\widehat{\mathrm{EIS}}_i < 100$ (Table 7). In the significant subsamples, the point estimates are larger—around 0.011–0.013 in columns (1)–(3) of Tables 6 and 8—and highly statistically significant. In all four samples, EIS has little explanatory power in these baseline regressions: the EIS coefficient is small in magnitude and statistically indistinguishable from zero when included alongside risk aversion, whereas adjusted R^2 remains very low (on the order of 0.6%–3.8%). Taken together, these baseline results indicate that, on average and ignoring timing preferences, firms managed by more risk-averse managers tend to earn somewhat higher average returns, but the economic magnitude is modest and the overall fit is weak.

[Insert Tables 5 to 8 About Here]

The picture changes substantially once we allow returns to depend on the interaction between EZ parameters and the early-resolution indicator ($\mathbf{1}_{\text{Early}}$). Columns (4) and (5) of Table 5 to Table 8 estimate the specification of Equation(46). Introducing the early-resolution dummy alone (column (4)) already yields a sizeable and highly significant level effect: the coefficient on $\mathbf{1}_{\text{Early}}$ ranges from about 0.037 to 0.141 across samples, implying that early-resolution firms earn substantially higher average returns than late-resolution firms, conditional on the level of risk aversion and EIS. At the same time, the coefficient on EIS becomes negative and significant in the full-sample specifications without interactions, suggesting that, conditional on RRA, higher EIS is associated with lower returns once we distinguish between early and late timing types in levels. The adjusted R^2 increases from below 4% in the baseline models to between 2.3% and 16.6% when we simply add the early-resolution dummy. Figures 4 and 5 provide a visual representation of the results for a more intuitive understanding.

[Insert Figures 4 and 5 About Here]

Allowing for full interactions in column (5) reveals a systematic and robust pattern: the effect of risk aversion and EIS on returns is markedly different in early- versus late-resolution firms. Because $\mathbf{1}_{\text{Early}}$ enters both in levels and interacted with the EZ parameters, it is useful to write the implied marginal effects explicitly. For late-resolution firms ($\mathbf{1}_{\text{Early}} = 0$) we have

$$\frac{\partial \bar{R}_i}{\partial \widehat{\text{RRA}}_i} = \beta_\gamma, \qquad \frac{\partial \bar{R}_i}{\partial \widehat{\text{EIS}}_i} = \beta_\psi,$$

whereas for early-resolution firms ($\mathbf{1}_{\text{Early}} = 1$),

$$\frac{\partial \bar{R}_i}{\partial \widehat{\text{RRA}}_i} = \beta_\gamma + \beta_{\Delta,\gamma}, \qquad \frac{\partial \bar{R}_i}{\partial \widehat{\text{EIS}}_i} = \beta_\psi + \beta_{\Delta,\psi}.$$

In the unfiltered full sample (Table 5, column (5)), the estimates are $\beta_\gamma = 0.0181$ and $\beta_{\Delta,\gamma} = -0.0216$, both significant at the 1% level. Thus, for late-resolution firms the marginal effect of risk aversion on average returns is positive and economically meaningful: holding EIS fixed, an increase of one unit in $\widehat{\text{RRA}}_i$ is associated with roughly a 1.8 percentage point increase in the average annual return. For early-resolution firms, the marginal effect becomes slightly negative, $\beta_\gamma + \beta_{\Delta,\gamma} \approx -0.0035$. The difference in slopes across timing types, $\beta_{\Delta,\gamma}$, is itself large and precisely estimated, indicating that the pricing of risk aversion is strongly moderated by the timing preference. The same qualitative pattern holds in the other three samples. In the significant subset (Table 6), the late-resolution slope is about 0.0652 and the early-resolution slope is about -0.0072; in the filtered full and filtered significant samples (Tables 7 and 8) the late-resolution slopes are 0.0093 and 0.0613 and the early-resolution slopes are about -0.0033 and -0.0058, respectively. In every case, the interaction coefficient $\beta_{\Delta,\gamma}$ is negative and highly significant, so the marginal return to risk aversion is consistently larger (and positive) in late-resolution firms than in early-resolution firms.

The EIS coefficients exhibit a complementary pattern. In the full sample with interactions, we estimate $\beta_\psi = -0.0014$ and $\beta_{\Delta,\psi} = 0.0014$, again both statistically significant at the 1% level. This implies that among late-resolution firms, higher EIS is associated with lower average returns: an increase of one unit in $\widehat{\text{EIS}}_i$ reduces the average annual return by about 14 basis points. In contrast, for early-resolution firms the net marginal effect of EIS is essentially zero, $\beta_\psi + \beta_{\Delta,\psi} \approx 0$. Filtering out extreme EIS values amplifies this pattern. In the filtered full sample (Table 7, column (5)), the late-resolution EIS slope is sharply negative ($\beta_\psi = -0.0061$), while the interaction term is positive and of similar magnitude ($\beta_{\Delta,\psi} = 0.0068$), yielding again a weakly positive and statistically insignificant EIS effect in the early-resolution group. In the significant subsamples the EIS coefficients are smaller and individually insignificant once interactions are included, but the sign pattern persists: EIS matters, if at all, primarily through its negative association with returns in the late-resolution group, with little incremental effect in the early group.

The early-resolution dummy itself remains strongly positive and statistically significant in all interaction specifications. Evaluated at $\widehat{\text{RRA}}_i = \widehat{\text{EIS}}_i = 0$, the coefficient β_{Early} implies that early-resolution firms earn between about 3.9 and 13.9 percentage points higher average annual returns than otherwise comparable late-resolution firms, depending on the sample. Of course, actual firms have strictly positive RRA and EIS, so the relevant comparison combines this level effect with the group-specific slopes discussed above. Nevertheless, the magnitude and robustness of β_{Early} confirm that the EZ-based timing classification picks up a substantial cross-sectional return premium. Consistent with this, the adjusted R^2 rises further when interactions are added, reaching about 7.4% in the full sample, 21.6% in the significant sample, and around 6.1% and 18.6% in the filtered full and filtered significant samples, respectively. This is a sizeable improvement over the baseline models that use only

RRA and EIS.

Overall, these regressions show that firm-level recursive preferences are reflected in average returns not through RRA or EIS in isolation, but through their interaction with the manager's implied preference for the timing of uncertainty resolution. At the aggregate level, more risk-averse managers tend to be associated with higher-return firms, and EIS has limited standalone explanatory power. However, once we distinguish between early- and late-resolution firms, risk aversion commands a positive return premium primarily in late-resolution firms and a much weaker, even slightly negative, association in early-resolution firms, while EIS depresses returns in late-resolution firms but is largely neutral in early-resolution firms. These patterns underscore that the cross-sectional pricing of managerial preferences is inherently multidimensional: what matters for expected returns is not only how risk-averse or how willing to substitute intertemporally managers are, but also how these traits interact with their preferences for resolving uncertainty over time.

6 Conclusion

This paper provides a structural estimation of executive risk preferences using a recursive utility framework. By moving beyond the CRRA constraint, we document that U.S. executives exhibit moderate risk aversion but high elasticity of intertemporal substitution. The heterogeneity in preferences for uncertainty resolution—with a majority preferring early resolution—suggests a new dimension of managerial traits that should be accounted for in contracting and corporate governance research. Future work will examine how these structural parameters correlate with observable corporate policies such as R&D investment and leverage.

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Figure 1: **Distribution of Estimated Risk Aversion**

This figure shows the histogram and the kernel density of the estimated relative risk aversion parameters for each firm. RRA are from GMM estimates of Epstein-Zin parameters at the firm level. EIS is the implied coefficient of elasticity of intertemporal substitution under EZ utility, and the sample is truncated at 100 to mitigate the influence of extreme outliers. The significant subset collects firms with reasonably precise GMM estimates (e.g., $|t\text{-stat}(\gamma)| > 1.645$ and stable weighting matrices).

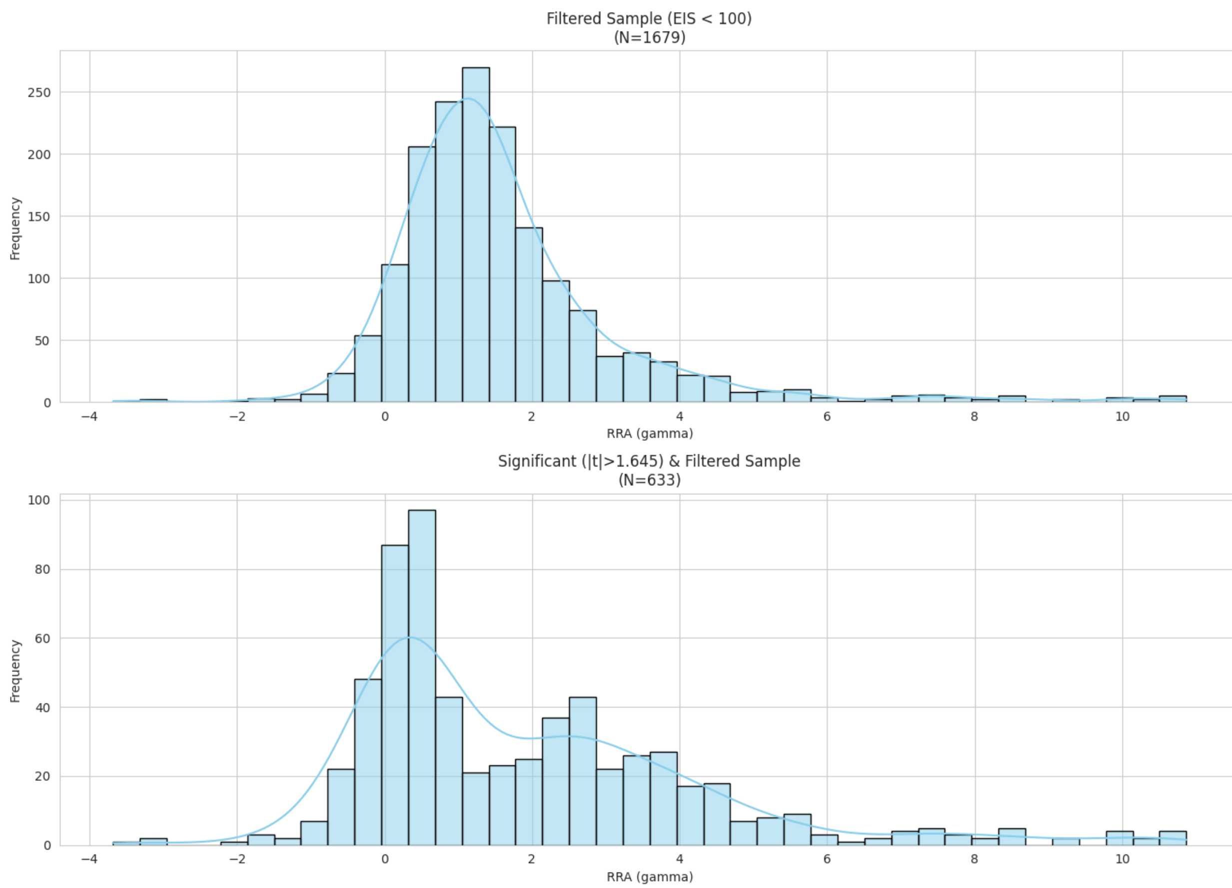

Figure 2: **Distribution of Estimated Elasticity of Intertemporal Substitution**

This figure presents the histogram and the kernel density of the estimated elasticity of intertemporal substitution parameters for each firm. EIS are from GMM estimates of Epstein-Zin parameters at the firm level, and the sample is truncated at 100 to mitigate the influence of extreme outliers. RRA is the implied coefficient of relative risk aversion under EZ utility. The significant subset collects firms with reasonably precise GMM estimates (e.g., $|t\text{-stat}(\gamma)| > 1.645$ and stable weighting matrices).

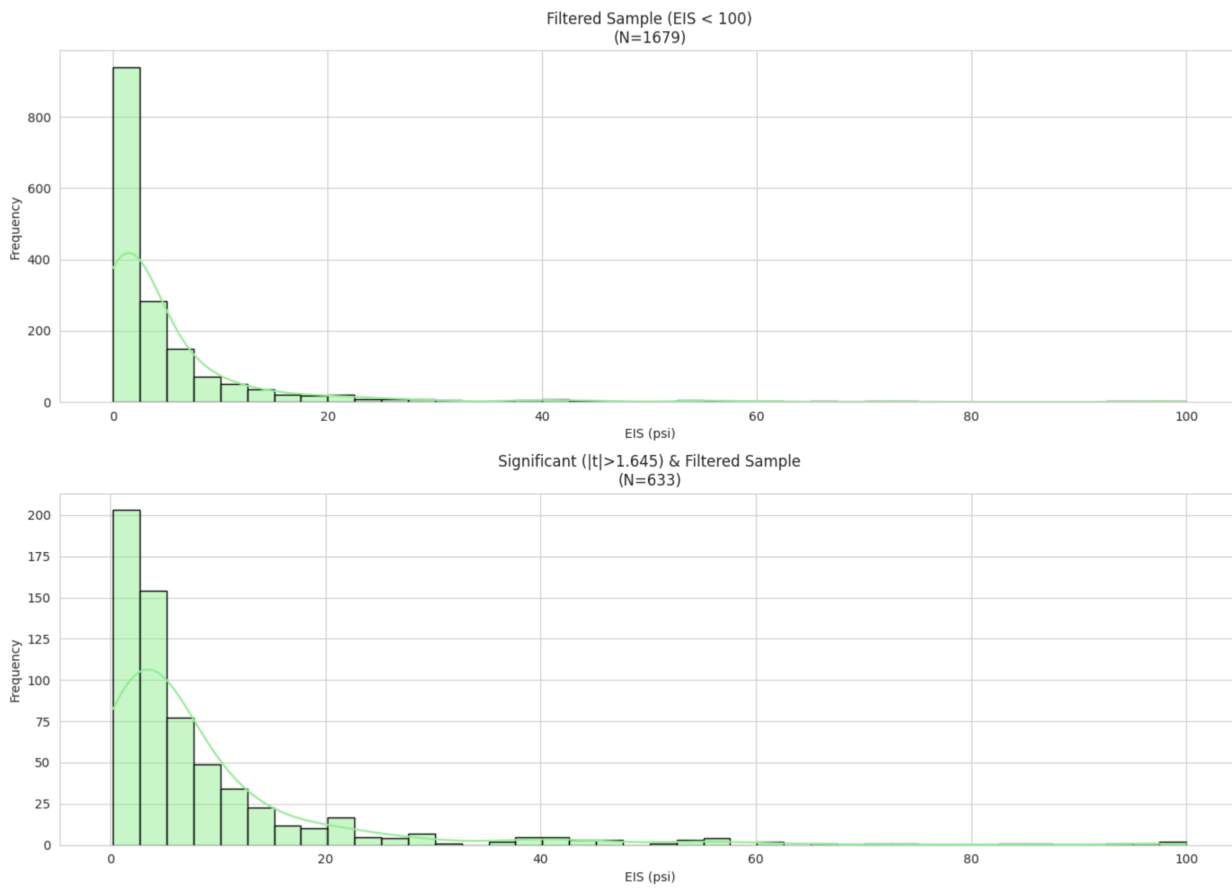

Figure 3: **Distribution of J-statistics of Epstein-Zin Model Estimation**

This figure presents the histogram and the kernel density of the J-statistics for overidentified models. The J-statistic is defined as $J = T\, g(\hat{\theta}_{\mathrm{GMM}})' W\, g(\hat{\theta}_{\mathrm{GMM}})$, where $\hat{\theta}_{\mathrm{GMM}}$ denotes the efficient GMM estimator, $g(\hat{\theta}_{\mathrm{GMM}})$ the corresponding sample moments, and W the weighting matrix used in the second-stage estimation. The null hypothesis is that all moment conditions are correctly specified at the true parameter vector. The corresponding p-value $= 1 - F_{\chi^2_{df}}(J)$, where $F_{\chi^2_{df}}(\cdot)$ denotes the cumulative distribution function of the chi-squared distribution with df degrees of freedom (df equals the number of overidentifying restrictions).

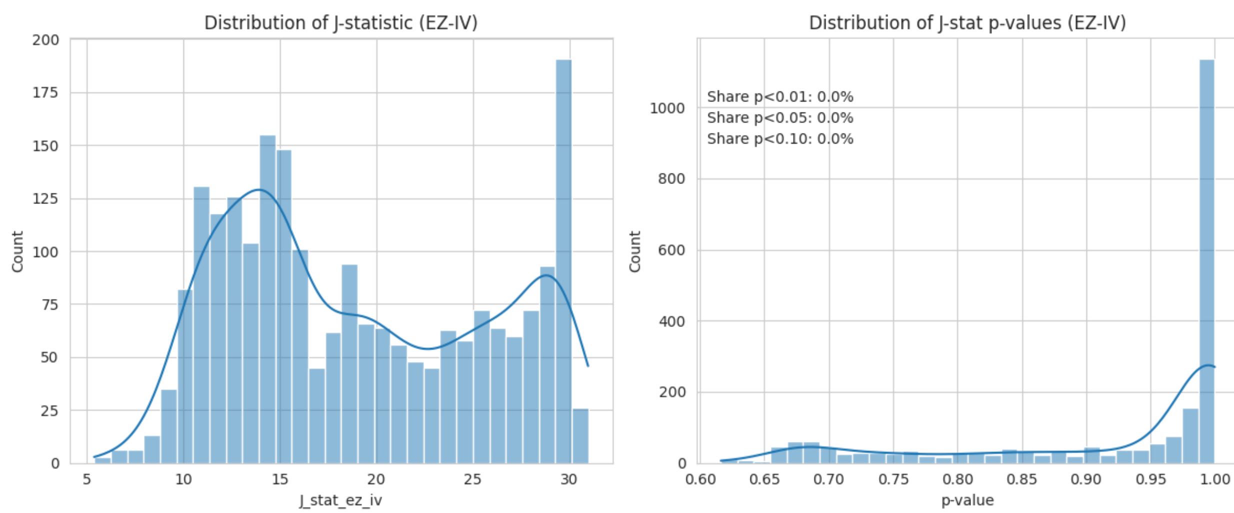

Figure 4: **Risk Aversion vs. Average Stock Returns According to Uncertainty Resolution Preference**

This figure presents the relation between Relative Risk Aversion (RRA) and firm annual stock returns. RRA are from GMM estimates of Epstein-Zin parameters at the firm level. Early Resolution is defined as $RRA > 1/EIS$ and Late Resolution as $RRA \leq 1/EIS$. EIS is the implied coefficient of elasticity of intertemporal substitution under EZ utility, and is truncated at 100 to mitigate the influence of extreme outliers.

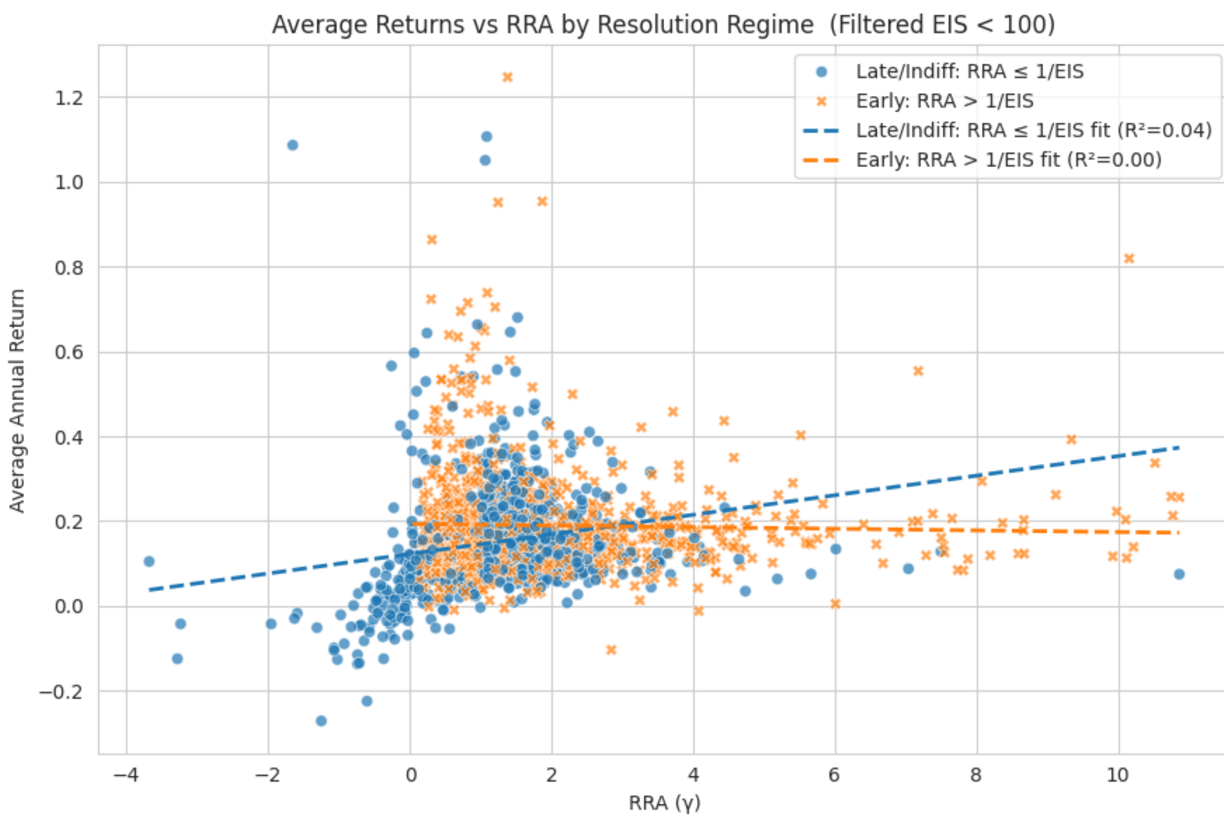

Figure 5: **Intertemporal Substitution vs. Average Stock Returns According to Uncertainty Resolution Preference**

This figure presents the relation between Elasticity of Intertemporal Substitution (EIS) and firm annual stock returns. EIS are from GMM estimates of Epstein-Zin parameters at the firm level, and is truncated at 100 to mitigate the influence of extreme outliers. Early Resolution is defined as $RRA > 1/EIS$ and Late Resolution as $RRA \leq 1/EIS$. RRA is the implied coefficient of relative risk aversion under EZ utility.

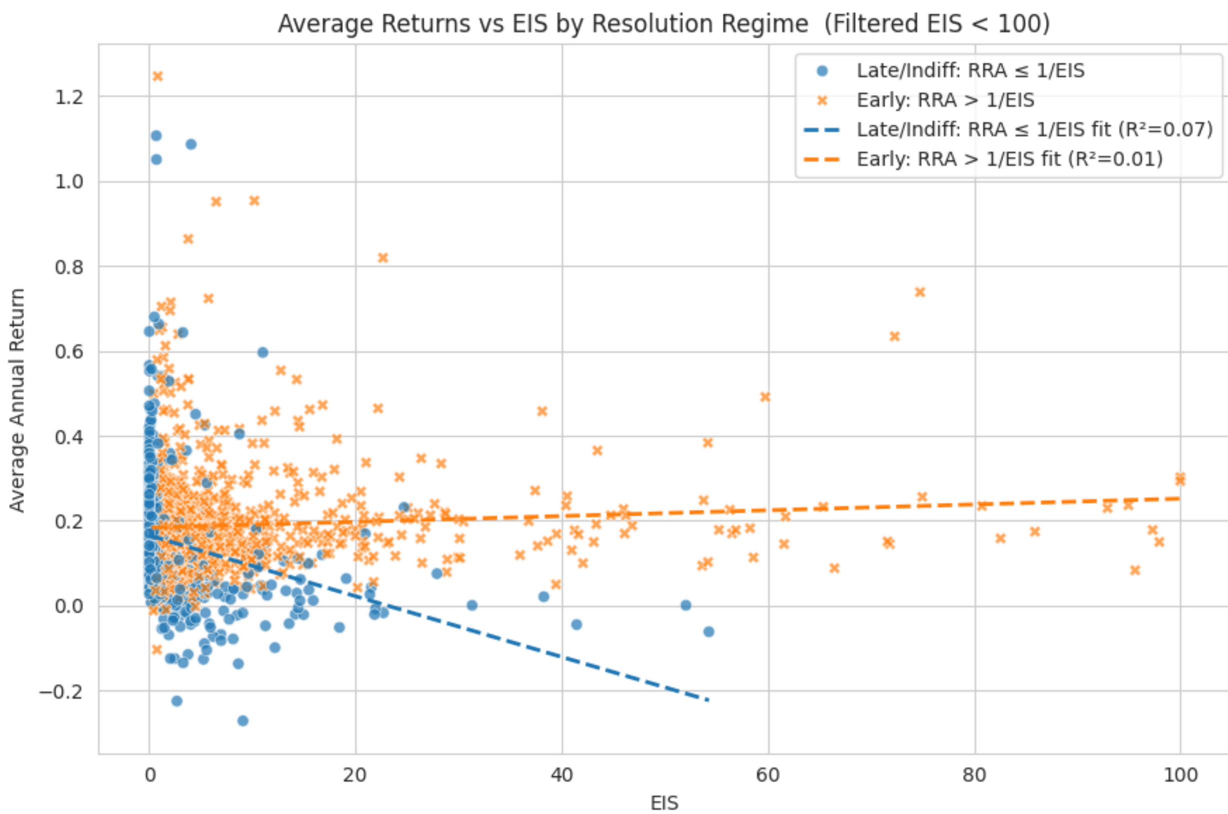

Table 1: Summary Statistics: Managerial Consumption Proxy and Returns

Variable	Mean	Stddev	P25	Median	P75	Min	Max	Obs
Executive Compensation	3,072.8	24,946.8	676.4	1,510.8	3,307.5	0.0	5,877,734	63,909
Annual Stock Return	0.18	0.64	-0.13	0.10	0.35	-0.99	26.19	61,583

Note: This table summarizes the firm-level average returns and observation counts for the sample used in the GMM estimation. Returns are real annual total returns. Executive Compensation is the average total compensation (TDC2 from ExecuComp) of top executives for each firm(gvkey)-year, in thousands of U.S. dollars.

Table 2: Firm-Level CRRA GMM Estimates

	Risk Aversion (γ)			Annual Return		N
Sample	Mean	Median	[P25, P75]	Mean	Median	(Firms)
Full sample	2.23	1.27	[0.56, 2.49]	16.6%	14.6%	2,209
Significant subset	2.89	1.93	[1.27, 3.37]	23.1%	18.8%	531

Note: This table reports GMM estimates of the CRRA coefficient γ from the firm-level Euler equation. The significant subset collects firms with reasonably precise GMM estimates (e.g., $|t\text{-stat}(\gamma)| > 1.645$ and stable weighting matrices). Returns are average annual stock returns for each firm over the estimation window.

Table 3: Firm-Level Epstein-Zin GMM Estimates

	Risk Aversion (γ)			EIS (ψ)			N
Sample	Mean	Median	[P25, P75]	Mean	Median	[P25, P75]	(Firms)
Full EZ sample	1.84	1.42	[0.78, 2.41]	28.28	3.67	[0.87, 56.59]	2,207
Significant EZ subset	2.39	2.28	[0.36, 3.74]	37.43	9.03	[2.99, 100]	919

Note: This table reports GMM estimates of Epstein–Zin parameters at the firm level. RRA is the implied coefficient of relative risk aversion under EZ utility; EIS is the elasticity of intertemporal substitution. EIS is truncated at 100 in the summary statistics to mitigate the influence of extreme outliers. The significant subset collects firms with more precise EZ estimates (e.g., $|t\text{-stat}(\gamma, \psi)| > 1.645$ and stable weighting matrices). Mean (Median) stock return for the Full EZ sample is 17.12 (15.18) and are 16.17 (14.98) for the Significant EZ subset, respectively. In comparison with the CRRA case, there are two cases in which estimation did not converge, affecting the final sample.

Table 4: Preferences for Early vs. Late Resolution of Uncertainty

Panel (a): Counts of Early vs. Late Resolution by Sample Type

		Counts		%	
Sample Description	Total (N)	Early	Late	Early	Late
Full Sample	2,210	1,401	806	63.39	36.47
Filtered Sample (EIS < 100)	1,676	909	767	54.24	45.76
Significant Sample	919	676	243	73.56	26.44
Filtered & Significant Sample	633	428	205	67.61	32.39

Panel (b): Summary Statistics by Resolution Type (Full Sample)

	Early (N=1,401)		Late (N=806)	
	Mean	Median	Mean	Median
RRA	2.22	1.62	1.18	1.24
EIS	40.70	9.24	6.70	0.34
Return (%)	18.71	16.32	14.37	12.79

Note: Early Resolution defined as $RRA > 1/EIS$ and Late Resolution as $RRA \leq 1/EIS$. RRA and EIS are GMM estimates of Epstein–Zin parameters at the firm level. EIS is truncated at 100 in the filtered samples to mitigate the influence of extreme outliers. Return (%) denotes the average annual stock return.

Table 5: Regression Results: Full Sample (N=2,207)

	Dependent Variable: Average Annual Stock Return ($\bar{R}_i$)				
	(1)	(2)	(3)	(4)	(5)
	RRA Only	EIS Only	RRA + EIS	+ Early	+ Interactions
Intercept	0.1609***	0.1715***	0.1622***	0.1414***	0.1317***
	(0.004)	(0.003)	(0.004)	(0.005)	(0.007)
RRA	0.0056***		0.0060***	0.0035**	0.0181***
	(0.001)		(0.002)	(0.002)	(0.004)
EIS		-0.0000	-0.0001	-0.0003***	-0.0014***
		(0.0001)	(0.0001)	(0.0001)	(0.0002)
Early				0.0490***	0.0631***
				(0.006)	(0.009)
RRA × Early					-0.0216***
					(0.004)
EIS × Early					0.0014***
					(0.0002)
Adj. R^2	0.0061	-0.0004	0.0061	0.0340	0.0735
Observations	2,207	2,207	2,207	2,207	2,207

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: This table reports regression results of firm returns on RRA, EIS, Early resolution and their interactions. RRA and EIS are GMM estimates of Epstein–Zin parameters at the firm level; RRA is the implied coefficient of relative risk aversion under EZ utility; EIS is the elasticity of intertemporal substitution. Early is an indicator variable equal to 1 if the firm prefers early resolution of uncertainty and zero otherwise. Early Resolution is defined as $RRA > 1/EIS$ and Late Resolution as $RRA \leq 1/EIS$.

Table 6: Regression Results: Significant Subset (N=919)

	Dependent Variable: Average Annual Stock Return ($\bar{R}_i$)				
	(1)	(2)	(3)	(4)	(5)
	RRA Only	EIS Only	RRA + EIS	+ Early	+ Interactions
Intercept	0.1362***	0.1601***	0.1405***	0.0725***	0.0798***
	(0.006)	(0.006)	(0.007)	(0.009)	(0.009)
RRA	0.0107***		0.0117***	-0.0025	0.0652***
	(0.002)		(0.002)	(0.002)	(0.011)
EIS		0.0000	-0.0002	-0.0002**	-0.0004
		(0.0001)	(0.0001)	(0.0001)	(0.0003)
Early				0.1413***	0.1387***
				(0.012)	(0.013)
RRA × Early					-0.0724***
					(0.011)
EIS × Early					0.0004
					(0.0003)
Adj. R^2	0.0356	-0.0009	0.0374	0.1661	0.2161
Observations	919	919	919	919	919

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: This table reports regression results of firm returns on RRA, EIS, Early resolution and their interactions. RRA and EIS are GMM estimates of Epstein–Zin parameters at the firm level; RRA is the implied coefficient of relative risk aversion under EZ utility; EIS is the elasticity of intertemporal substitution. Early is an indicator variable equal to 1 if the firm prefers early resolution of uncertainty and zero otherwise. Early Resolution is defined as $RRA > 1/EIS$ and Late Resolution as $RRA \leq 1/EIS$.

Table 7: Regression Results: Full Sample (Filtered EIS < 100, N=1,676)

	Dependent Variable: Average Annual Stock Return ($\bar{R}_i$)				
	(1)	(2)	(3)	(4)	(5)
	RRA Only	EIS Only	RRA + EIS	+ Early	+ Interaction
Intercept	0.1615***	0.1699***	0.1607***	0.1458***	0.1511***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)
RRA	0.0065***		0.0062***	0.0044**	0.0093**
	(0.002)		(0.002)	(0.002)	(0.004)
EIS		0.0004	0.0002	-0.0002	-0.0061***
		(0.0003)	(0.0003)	(0.0003)	(0.0010)
Early				0.0372***	0.0386***
				(0.007)	(0.010)
RRA × Early					-0.0126***
					(0.005)
EIS × Early					0.0068***
					(0.0010)
Adj. R^2	0.0059	0.0004	0.0056	0.0233	0.0607
Observations	1,676	1,676	1,676	1,676	1,676

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: This table reports regression results of firm returns on RRA, EIS, Early resolution and their interactions. RRA and EIS are GMM estimates of Epstein–Zin parameters at the firm level; RRA is the implied coefficient of relative risk aversion under EZ utility; EIS is the elasticity of intertemporal substitution. Early is an indicator variable equal to 1 if the firm prefers early resolution of uncertainty and zero otherwise. Early Resolution is defined as $RRA > 1/EIS$ and Late Resolution as $RRA \leq 1/EIS$.

Table 8: Regression Results: Significant Subset (Filtered EIS < 100, N=633)

	Dependent Variable: Average Annual Stock Return ($\bar{R}_i$)				
	(1)	(2)	(3)	(4)	(5)
	RRA Only	EIS Only	RRA + EIS	+ Early	+ Interact
Intercept	0.1374***	0.1570***	0.1378***	0.0814***	0.0841***
	(0.007)	(0.007)	(0.008)	(0.010)	(0.012)
RRA	0.0126***		0.0128***	-0.0009	0.0613***
	(0.002)		(0.003)	(0.003)	(0.013)
EIS		0.0005	-0.0001	-0.0001	-0.0011
		(0.0004)	(0.0004)	(0.0004)	(0.0012)
Early				0.1220***	0.1266***
				(0.014)	(0.016)
RRA × Early					-0.0671***
					(0.013)
EIS × Early					0.0016
					(0.0013)
Adj. R^2	0.0383	0.0005	0.0368	0.1416	0.1855
Observations	633	633	633	633	633

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: This table reports regression results of firm returns on RRA, EIS, Early resolution and their interactions. RRA and EIS are GMM estimates of Epstein–Zin parameters at the firm level; RRA is the implied coefficient of relative risk aversion under EZ utility; EIS is the elasticity of intertemporal substitution. Early is an indicator variable equal to 1 if the firm prefers early resolution of uncertainty and zero otherwise. Early Resolution is defined as $RRA > 1/EIS$ and Late Resolution as $RRA \leq 1/EIS$.