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Preference-Driven Contract Design: How Education Alters Risk, Patience, and Effort in Incentive Schemes

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Preference-Driven Contract Design: How Education Alters Risk, Patience, and Effort in Incentive Schemes *

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Abstract: Performance-contingent pay raises productivity, yet in the German Socio-Economic Panel (SOEP) only about 16% of workers report receiving performance pay, with the incidence being roughly seven percentage points higher among university graduates than among non-graduates. This coexistence of low aggregate take-up and a strong skill gradient is puzzling. This paper accounts for these twin facts with a principal–agent model in which the entire preference vector—risk aversion, probability weighting, time discounting, and effort cost—varies systematically with schooling. Endogenizing preferences yields two predictions: (i) optimal incentive slopes and induced effort increase with education-linked preferences; (ii) the productivity threshold for accepting performance pay falls with schooling, while heterogeneity in tastes keeps worker participation incomplete. A light calibration guided by documented schooling gradients reproduces modest overall incidence alongside a pronounced skill gradient. The key novelty is to treat the preference vector as an endogenous state variable that enters both sides of the principal–agent problem, shaping the optimisation problems of both the firm and the worker rather than being taken as a fixed primitive.

Zusammenfassung: Leistungsabhängige Vergütung steigert die Produktivität. Im Sozio-ökonomischen Panel (SOEP) berichten jedoch nur rund 16 % der Beschäftigten, leistungsbezogene Entlohnung zu erhalten. Zugleich liegt die Inzidenz unter Hochschulabsolventen um etwa sieben Prozentpunkte höher als unter Nicht-Absolventen. Dieses Nebeneinander aus geringer Gesamtverbreitung und ausgeprägtem Bildungsgradienten ist erklärungsbedürftig. Diese Arbeit erklärt beide Befunde in einem Prinzipal–Agenten-Modell, in dem der gesamte Präferenzvektor systematisch mit dem Bildungsniveau variiert. Die Endogenisierung von Präferenzen liefert zwei Implikationen: (i) optimale Anreizintensitäten und die induzierte Anstrengung steigen mit bildungsbezogenen Präferenzparametern; (ii) die Produktivitätsschwelle für die Akzeptanz leistungsabhängiger Vergütung sinkt mit dem Bildungsniveau, während Präferenzheterogenität die Teilnahme insgesamt unvollständig hält. Eine einfache Kalibrierung, welche sich an dokumentierten Bildungsgradienten orientiert, repliziert eine moderate Gesamtinzidenz bei gleichzeitig starkem Qualifikationsgradienten. Der Beitrag dieser Arbeit besteht darin, den Präferenzvektor als endogene Zustandsvariable zu modellieren, die die Optimierungsprobleme von Unternehmen und Beschäftigten gleichermaßen bestimmt, statt exogen vorgegeben zu sein.

Keywords: performance pay, incentives, risk preferences, time discounting, contract theory.
JEL classification: D81, D82, D86, J24, J33

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1 Introduction

Performance-contingent compensation—classically piece rates and increasingly bonus schemes in high-skill occupations—has been found to raise individual productivity (Lazear 2000; Lavy 2009). Yet in the German Socio-Economic Panel (SOEP, 2024) only about 16% of workers report receiving performance pay, and among university graduates the share is only about seven percentage points higher than among non-graduates. This is a puzzle: if stronger incentives "pay for themselves," why are they rare overall—and why concentrated in high-skill jobs? For firms, the problem is not whether incentives work on average, but when and for whom they are worth the risk and monitoring costs. Canonical principal–agent models with homogeneous, taste-invariant agents (e.g. Holmström 1979) can match one fact at a time (low take-up via noisy measurement, or a skill gradient via higher productivity) but struggle to generate both simultaneously. The bottleneck is the fixed-tastes assumption which the data increasingly suggest does not hold.

A growing body of evidence points directly to that channel: schooling (and cognitive ability) systematically shifts preferences. More education is associated with lower effective risk aversion and probability-weighting distortions, greater patience, and a lower disutility of effort. In short, education alters not only productivity but also the tastes that make incentives attractive. Ignoring these gradients makes it hard to reconcile low aggregate take-up of performance pay with a strong skill gradient and limits the ability of standard principal–agent models to account for observed heterogeneity in pay practices across jobs and skill levels.

This paper provides a theoretical resolution. I develop a tractable principal–agent model in which the entire preference vector—risk aversion, probability weighting, time discounting, and effort cost—is an explicit function of schooling. The firm observes workers' education (and thus their preference index) and conditions on cohort-level means of these preferences; it posts a menu of fixed and efficiency wages, individual-bonus, and team-bonus contracts, and workers sort given idiosyncratic tastes. The key novelty is to treat this preference vector as an endogenous state variable that enters both sides of the principal–agent problem, shaping the optimisation of both the firm and the worker rather than being taken as a fixed primitive.

Two sharp implications follow. First, optimal effort intensity rises with education-linked preferences (more patience, lower effective risk aversion, more linear probability weighting), making steeper incentives profitable for more-educated workers. Second, the productivity threshold for accepting performance pay falls with education, yet take-up remains incomplete because tastes vary idiosyncratically—even among the highly educated. Together, these mechanisms rationalise why performance pay is disproportionately chosen by high-skill workers while remaining uncommon overall.

The unified framework then generates testable predictions about which contract forms (fixed wage, efficiency wage, team bonus, individual bonus) emerge under different combinations of skill and output verifiability, and how changes in the workforce's skill composition—whether driven by education policy or technological change—translate into systematic adjustments in pay structures. Because workers' tastes differ idiosyncratically around the skill-linked average, the model also predicts that the boundary between contract types is smooth rather than sharp: even when strong incentives are on offer, some high-skill employees still opt for a flatter wage, while a minority of lower-skill workers accept variable pay. This "imperfect take-up" emerges endogenously and matches the partial adoption patterns observed in real-world data.

Although earlier research has shown that individual preference parameters can be endogenous, most studies isolate a single trait (e.g. Haubrich 1994 on risk; Plambeck & Zenios 2000 on time in dynamic models). A few structural studies estimate more than one parameter at a time—e.g. Fossen and Glocker (2014) jointly recover risk and time preferences from college choices—but even these do not model education as the common driver, nor do they embed the resulting preferences in a principal–agent contract. This paper contributes by showing that education-linked endogenous preferences provide a single mechanism that reconciles the twin facts of low aggregate performance-pay incidence and a pronounced skill gradient. Within a standard principal–agent environment, it endogenises the preference vector as a function of education and traces the implications for contract choice.[1]

2 State of the Literature

2.1 Preferences in Standard Economic Theory

In standard microeconomic models, agents maximise a von Neumann–Morgenstern expected-utility index with concave Bernoulli utility and exponential discounting; risk attitudes and time preferences are captured by fixed curvature and discount factors. A large literature in behavioural economics has relaxed this structure by introducing probability weighting, reference dependence and loss aversion, and present-biased or quasi-hyperbolic discounting (e.g. Kahneman and Tversky 1979; Tversky and Kahneman 1992; Laibson 1997).

[1]The same preference-aware logic naturally extends to deferred equity, flexible-work premia, and other contract features that trade off risk, timing, and effort.

Each of these departures alters the perceived trade-off between a guaranteed salary and a risky or deferred bonus. Probability weighting changes the subjective variance of pay, loss aversion makes downside risk especially painful, and present bias penalises contracts that postpone compensation. In consequence, incentive schemes that look optimal in a vNM-exponential world may be unattractive when these behavioural elements are present. Because recent evidence shows that risk attitudes, probability weighting, and time discounting vary systematically with education and cognitive ability, treating preference parameters as fixed primitives is increasingly hard to justify. The next subsection reviews that evidence and motivates an extended principal–agent framework in which schooling shapes both productivity and the very preferences that govern contract choice.

2.2 Education and the Endogeneity of Preferences

Until recently, preferences were treated primarily exogenously. However, a second strand of evidence shows that the parameters governing risk and time choice are not fixed, but vary systematically with schooling and cognitive skill. In an incentivised lottery experiment on a representative German sample, Dohmen et al. (2010) find that lower cognitive-ability respondents choose markedly safer lotteries, even after controlling for income and formal schooling, while the most able subjects select the riskier options—implying an inverse mapping from ability to the vNM coefficient of relative risk aversion. Similar gradients appear in the cross-country Global Preference Survey: across seventy-six nations, higher scores on a standard cognitive test "are uniformly positively linked to risk taking [...]" (Falk et al. 2018, p. 1647). Jung (2015) exploits the 1972 UK compulsory-schooling reform as an exogenous instrument for years of education and shows, in a sample of over 10 000 individuals, that each additional year of schooling reduces the estimated Arrow–Pratt coefficient of relative risk aversion significantly.

Schooling is likewise correlated with—and shapes—time preferences. In the same German data set used by Dohmen et al. (2010), cognitively able respondents display significantly lower personal discount rates in money-earlier-versus-later tasks. The Global Preference Survey replicates this pattern internationally: cognitive skill is "uniformly positively linked to patience" (Falk et al., 2018, p. 1647). Frederick (2005) shows that high Cognitive Reflection Test (CRT) subjects accept larger future payments much more readily than low-CRT subjects, consistent with lower β and higher δ in a quasi-hyperbolic specification. Part of this gradient appears causal. Exploiting a college-admission lottery in Mexico, Pérez-Arce (2017) finds that winning the lottery—and hence obtaining more schooling—makes young adults more willing to wait for future rewards. Becker and Mulligan's (1997) model offers a theoretical rationale: education invests in "future-oriented capital," enhancing an individual's ability to imagine and therefore value distant outcomes. Macro data are consistent with this micro evidence; countries with higher average years of schooling tend to post higher saving rates and greater support for long-term public projects (Falk et al., 2018).

Crucially, not all of these studies are merely descriptive. A first group can document only correlations between education and measured risk or time preferences, because their data are observational. A second, growing group, however, exploits plausibly exogenous variation in schooling and shows that preferences themselves move when education changes. In Jung's (2015) study, a compulsory-schooling reform shifts years of education and, in turn, estimated Arrow–Pratt coefficients; in Pérez-Arce (2017), a college-admission lottery induces additional schooling and makes winners more patient in incentivised intertemporal choices. Similar patterns arise in school-based interventions and field experiments (Alan and Ertac, 2018; Lührmann et al., 2018; Simunovic, 2024; Tawiah, 2022). Together with Schildberg-Hörisch's (2018) evidence that risk preferences evolve over the life cycle, these findings support the view that education does not only sort individuals by pre-existing tastes but also shapes those tastes.

Taken together, these studies justify treating the risk-aversion coefficient, the probability-weighting parameter, and the discount factor as decreasing or increasing functions of skill. My model embeds exactly that mapping, allowing education to influence contract choice not only through productivity x but also through the underlying preferences that determine how workers value a risky, deferred bonus versus a safe, immediate wage.

The final component of my preference vector concerns the taste for leisure, captured in the model by the disutility-of-effort parameter. Whereas risk and time preferences have received sustained empirical attention, the link between schooling and leisure valuation is less explored. It matters, however, for any contract that trades fixed income against (costly) on-the-job effort. If higher-skill workers intrinsically experience less disutility from labor, they will accept steeper incentives even at identical wage levels. Consequently, documenting how education correlates with labour-leisure trade-offs is essential for a complete preference-based account of contract choice. Historical time-use data indicate that educated Americans have gradually substituted work for leisure. Aguiar and Hurst (2007) show that between 1965 and 2005 the average male with only a high-school diploma gained roughly five hours of weekly leisure, whereas the typical college-educated male lost two hours. They furthermore report an 8–13-hour leisure gap in the early 2000s. Descriptive evidence by the Bureau of

Labor Statistics (2025) shows that within any given period tertiary educated workers log more hours than their lower skilled peers.

Chen and Chevalier (2008) exploit a natural comparison inside U.S. health care. Physicians—who undertake much longer training—work about one-third more hours than physician assistants (PAs) performing many of the same clinical tasks. Wage differences explain only part of this gap: calibrating a utility-of-leisure function, the authors show that a representative PA would require implausibly large pay to supply doctor-level hours, implying genuine heterogeneity in leisure tastes. The pattern fits a self-selection story: individuals with a high valuation of leisure choose the shorter education path, whereas those with a lower leisure weight commit to the physician track.

Two mechanisms can reconcile these facts. First, selection: people who derive high utility from leisure are less willing to invest in long, demanding education. Second, preference formation: schooling and professional socialisation may instill a stronger work ethic, lowering the psychic cost of effort (Arrow, 1973). Either channel supports modelling λ_L as decreasing in skill S. Incorporating that gradient lets my framework replicate both the observed hours differential and the contract sorting patterns: high-skill, low-λ_L workers self-select into performance-contingent pay; low-skill, high-λ_L workers gravitate toward fixed or efficiency wages. Standard labour models that assume a homogeneous taste for leisure cannot match these joint moments.

A common theme in these literatures is that the constellation of risk, time, and leisure preferences is not fixed: it tends to move systematically with human-capital accumulation. Experimental elicitations of lottery choices and intertemporal trade-offs (Dohmen et al., 2010; Frederick, 2005) and revealed labour-supply behaviour in large time-use datasets (Aguiar & Hurst, 2007) generally suggest more-educated, higher-skill individuals act as if they are less risk-averse, more patient, and more tolerant of work effort. Micro evidence within occupations (Chen & Chevalier, 2008) reinforces the view that such patterns cannot be attributed solely to wage substitution effects but reflect genuine preference heterogeneity. Theoretical contributions buttress this reading: Becker and Mulligan's (1997) model of 'future-oriented capital' predicts that schooling lowers effective discount rates, while on the effort side, one can think of schooling as imparting a 'work ethic': educational socialization and habit formation embed norms of diligence, which effectively lower the psychic cost of effort (Becker 1964; Benabou & Tirole 2003).

2.3 Incentives and Contract Menus

In economic thinking, a contract is a set of mutually agreed commitments that guides each party's decision-making—specifying who must do what, and under which contingencies—so that their individual choices converge on an outcome both regard as beneficial. In the employment setting, this abstract idea takes a concrete form: the firm pledges remuneration, the worker pledges effort, and either side may exit once those commitments no longer serve its interests.

The standard analytical lens for studying contractual incentives is the principal–agent model (Holmström, 1979; Grossman & Hart, 1983). In this framework, a risk-neutral principal cannot observe the agent's costly effort and therefore designs a compensation schedule to align the agent's private choices with the principal's objective. Three preference-driven trade-offs shape that schedule. First, stronger incentives expose the agent to greater income risk, so the allowable steepness depends on the agent's degree of risk aversion. Early calibrations of this trade-off appear in Haubrich (1994) as well as Grund and Sliwka (2010), who quantify the "insurance premium" required by a risk-averse worker to accept piece-rate pay. Second, any portion of pay that is deferred must be discounted by the agent (Plambeck & Zenios 2000), making the timing of compensation sensitive to the agent's rate of time preference. Third, the level of effort that can profitably be induced is limited by the agent's marginal disutility of labour. Together, these three preference coefficients determine which contract forms are feasible and which succeed in eliciting effort that is worthwhile for the firm.

Classical contract theory takes risk aversion, probability weighting and discount factors as fixed. In practice, however, these parameters co-move with education and cognitive skill as shown in section 2.2.

Empirically, variable-pay incidence rises with education. In Italy, managers with university degrees are significantly more likely to adopt and design high-powered bonus and profit-sharing schemes (Damiani & Ricci 2014). A global employee survey finds that, controlling for risk attitude and culture, more-educated workers prefer a larger share of variable pay (Scott et al. 2015).

When the preference map shifts with skill, optimal contracts shift as well. Faced with workers who are more patient, less averse to risk, and less sensitive to incremental effort, a firm can profitably post steeper, stronger incentives. Conversely, the same menu would fail with low-skill workers whose preferences place heavier weight on risk, delay, and fatigue.

Endogenising preferences helps reconcile three empirical regularities. At the lower end of the skill distribution—yet in jobs where output is readily observable— some firms still pay workers almost entirely by the piece: For instance, British-Columbia tree planters and California auto-glass installers earn unit-based wages because performance is easy to measure and, after an initial sorting period, the remaining workforce consists of high-productivity, relatively risk-tolerant individuals for whom the resulting earnings variance is acceptable (Paarsch & Shearer, 2000; Lazear, 2000). Where output remains verifiable but human capital is high, firms often rely on very large variable-pay packages: Oyer and Schaefer (2005) document that broad-based stock-option grants to middle managers far exceed what pure-incentive models predict—consistent with strong sorting and retention motives—while Aggarwal and Samwick (1999) show that CEO pay–performance sensitivity is systematically calibrated to output volatility, with steeper incentives where outcomes are more predictable. By contrast, when performance is noisy or team-based—complex R & D groups or many public-sector roles—firms rely on high baseline salaries that operate as efficiency wages: here measurement error, not risk aversion, caps the feasible incentive slope, so bonuses flatten even for highly skilled employees (Prendergast, 1999; Krueger & Summers, 1988, Holmstöm, 1982). A model that holds risk, patience, and effort costs fixed can capture at most one of these patterns, whereas allowing those parameters to evolve with skill accounts for all three within a single framework.

3 A Unified Principal–Agent Model

I build directly on the classic one-period hidden-action model (Holmström 1979; Grossman & Hart 1983), extending it by letting the agent's risk, time, and effort-cost parameters depend on her skill index.

3.1 Technology and Timing

Let $x \in \mathcal{X}$ denote the worker's *productivity ability* and $\phi \in \Phi$ denote their *preference index*. I assume both productivity ability x and preference index ϕ are influenced by schooling S and other background factors Z, via

$$x = f(S, Z), \quad \phi = g(S, Z),$$

so that more schooling typically raises both human-capital and alters preferences. At time $t = 0$ the agent chooses effort $e \geq 0$ at convex cost $k(e)$ (with $k' > 0$, $k'' > 0$). Output is

$$y = x\,e + \varepsilon, \quad \varepsilon \sim \mathcal{F}, \quad \mathbb{E}[\varepsilon] = 0,\ \mathrm{Var}(\varepsilon) = \sigma^2(m)$$

[2]. Here $\mathcal{F}(\cdot)$ and $f(\cdot)$ denote the cumulative distribution function and probability density function of ε, respectively.

Firms now offer *four* contracts:

- **Fixed contract** C_F: wage w_F paid at $t = 0$.
- **Efficiency contract** C_E: wage w_E paid at $t = 0$ (with $w_E > w_F$).
- **Individual performance contract** C_P: base salary a at $t = 0$, plus bonus $b\,y$ at $t = T$.
- **Team performance contract** C_T: base salary a at $t = 0$, plus bonus $r\,Y/n$ at $t = T$ with $Y = \sum_{j=1}^{n} y_j$.
- The agent has incurred a sunk schooling cost $S > 0$ prior to $t = 0$; it enters the reference point.

3.2 Outside Option, Feasible Pay, and IR

Workers have outside option utility $U_0 \in \mathbb{R}$ (e.g. from unemployment benefits or a flat outside job). Any admissible contract $C \in \{F, E, P, T\}$ must satisfy

$$V_C(x, \phi, \lambda_L) \ \geq\ U_0 \qquad \text{(individual rationality)}.$$

Limited liability and positivity of consumption. Utility is CRRA and defined on $\mathbb{R}_+$. To ensure consumption is strictly positive in all states, we impose:

(LL1) Output shocks are bounded: $\varepsilon \in [-\bar{\varepsilon}, \bar{\varepsilon}]$ and $\mathcal{E} \in [-\bar{\mathcal{E}}, \bar{\mathcal{E}}]$ with known finite bounds.

(LL2) Bonus formulas are non-penalising (no negative pay components). We therefore con-

[2]output variance and monitoring are introduced in section 3.6

strain slopes to $b \geq 0$ and $r \geq 0$ and set the realised payment to

$$c_P = a + b\,\max\{0,\, xe + \varepsilon\}, \qquad c_T = a + \frac{r}{n}\,\max\{0,\, nxe + \mathcal{E}\}.$$

(LL3) Bases are high enough that $c \geq c_{\min} > 0$ a.s.; e.g., $a \geq b\,\bar{\varepsilon} + \underline{c}$ and $a \geq \frac{r}{n}\,\bar{\mathcal{E}} + \underline{c}$ for some small $\underline{c} > 0$.

Under (LL1)–(LL3) we have $c > 0$ a.s., integrals are well defined, and IR is meaningful.[3]

3.3 Preferences

3.3.1 CRRA utility (risk aversion)

$$u\big(c; \rho(\phi)\big) = \begin{cases} \dfrac{c^{1-\rho(\phi)} - 1}{1 - \rho(\phi)}, & \rho(\phi) \neq 1, \\ \ln(c), & \rho(\phi) = 1, \end{cases} \qquad \rho'(\phi) < 0.$$

3.3.2 Reference dependence and loss aversion.

Let the reference point be $\Gamma = w_F + S$.

$$v\big(c \mid \Gamma; \rho(\phi), \psi(\phi)\big) = \begin{cases} u\big(c; \rho(\phi)\big) - u\big(\Gamma; \rho(\phi)\big), & c \geq \Gamma, \\ -\psi(\phi)\,\Big[u\big(\Gamma; \rho(\phi)\big) - u\big(c; \rho(\phi)\big)\Big], & c < \Gamma, \end{cases}$$

with $\psi(\phi) > 1$ and, if education attenuates loss aversion, $\psi'(\phi) \leq 0$.[4]

3.3.3 Time discounting.

Future bonus at $t = T$ is discounted by factor $\delta = \delta(\phi) \in (0, 1)$, increasing in ϕ (higher $\phi \Rightarrow$ more patient).

3.3.4 Probability weighting.

I adopt the one-parameter Prelec (1998) form

$$w_\phi(p) = \exp\{-(-\ln p)^{\theta(\phi)}\}, \quad 0 < p < 1, \qquad \theta(\phi) \in (0, 1), \qquad \theta'(\phi) \geq 0.$$

[3] All results extend if one prefers linear bonuses on y without the $\max\{\cdot\}$ truncation, provided bases satisfy $a > b\,\bar{\varepsilon}$ and $a > \frac{r}{n}\bar{\mathcal{E}}$.

[4] For functional form and comparative statics see Appendix B

Interpretation: for $\theta = 1$, $w_\phi(p) = p$ (no distortion). For $\theta \in (0, 1)$, w_ϕ is inverse-S: small probabilities are overweighted and large probabilities underweighted. Moreover,

$$\partial_\theta w_\theta(p) = w_\theta(p)\,(-\ln p)^\theta\left[-\ln(-\ln p)\right]\begin{cases} < 0 & \text{if } p < e^{-1}, \\ > 0 & \text{if } p > e^{-1}, \end{cases}$$

so raising θ attenuates the overweighting of rare events and moves decision weights toward linearity. In all expected-utility expressions the bonus component enters as a *Choquet integral*

$$\int v(c)\,d\big[w_\phi(\mathcal{F}(c))\big] \;=\; \int_{\text{supp}(c)} v(c)\;w'_\phi\big(\mathcal{F}(c)\big)\;f(c)\,dc.$$

Regularity conditions that justify density-form and differentiation are in Appendix C.

3.3.5 Leisure preference.

Effort incurs cost

$$k(e; \lambda_L(\phi)) = \frac{\lambda_L(\phi)}{1+\eta}\,e^{1+\eta}, \qquad \eta > 0.$$

Hence $k_e = \lambda_L e^\eta > 0$ and $k_{ee} = \eta\lambda_L e^{\eta-1} > 0$, guaranteeing a unique interior optimum. A higher λ_L *proportionally scales* the cost curve, so $\partial e^*_C/\partial\lambda_L < 0$: individuals with stronger leisure taste supply less effort. The quadratic case $\eta = 1$ yields $k(e) = \frac{\lambda_L}{2}e^2$ and the familiar linear closed-form solutions, but all results extend to any $\eta > 0$.

3.4 Agent's Optimisation

3.4.1 Fixed contract C_F.

$$U_F = v(w_F \mid \Gamma) - k(e; \lambda_L(\phi)) \quad \Rightarrow \; e^*_F = 0.$$

3.4.2 Efficiency contract C_E.

I assume a behavioural gift-exchange rule $e^*_E = \gamma\,(w_E - w_F)$ with $\gamma > 0$, $e^*_E > 0$,[5] taken as reduced-form. The firm anticipates this response when setting w_E.

Utility is

$$U_E = v(w_E \mid \Gamma) \;-\; k(e^*_E; \lambda_L(\phi))$$

[5] Microfoundation in Appendix D.

3.4.3 Individual contract $C_P = (a, b)$.

$$U_P(e) = v(a \mid \Gamma) - k(e; \lambda_L(\phi)) + \delta \int_{-\infty}^{\infty} v\big(a + b\,(xe + \varepsilon) \mid \Gamma\big)\, w'_\phi\big(\mathcal{F}_\varepsilon(\varepsilon)\big)\, f_\varepsilon(\varepsilon)\, d\varepsilon,$$

$$k_e\big(e^*_P\big) = \delta\, b\, x \int_{-\infty}^{\infty} v'\big(a + b\,(xe^*_P + \varepsilon) \mid \Gamma\big)\, w'_\phi\big(\mathcal{F}_\varepsilon(\varepsilon)\big)\, f_\varepsilon(\varepsilon)\, d\varepsilon.$$

3.4.4 Team contract $C_T = (a, r)$.

With symmetric co-workers let $\mathcal{E} = \sum_{j=1}^{n} \varepsilon_j$ denote the aggregated team shock, with CDF $\mathcal{F}_{\mathcal{E}}$ and PDF $f_{\mathcal{E}}$. Then

$$U_T(e) = v(a \mid \Gamma) - k(e; \lambda_L(\phi)) + \delta \int_{-\infty}^{\infty} v\Big(a + \tfrac{r}{n}\,\big(nxe + \mathcal{E}\big) \mid \Gamma\Big)\, w'_\phi\big(\,\mathcal{F}_{\mathcal{E}}(\mathcal{E})\big)\, f_{\mathcal{E}}(\mathcal{E})\, d\mathcal{E},$$

$$k_e\big(e^*_T\big) = \delta\, \frac{r}{n}\, x \int_{-\infty}^{\infty} v'\Big(a + \tfrac{r}{n}\,\big(nxe^*_T + \mathcal{E}\big) \mid \Gamma\Big)\, w'_\phi\big(\mathcal{F}_{\mathcal{E}}(\mathcal{E})\big)\, f_{\mathcal{E}}(\mathcal{E})\, d\mathcal{E}.$$

3.4.5 Certainty–equivalent utilities.

$$\left.\begin{aligned} e^*_C(x, \phi, \lambda_L) &= \arg\max_{e \geq 0} U_C\big(e; x, \phi, \lambda_L\big), \\ V_C(x, \phi, \lambda_L) &= U_C\big(e^*_C(x, \phi, \lambda_L); x, \phi, \lambda_L\big), \end{aligned}\right. \qquad C \in \{F, E, P, T\}.$$

Indifference cut-offs. In the *deterministic* benchmark (no taste shocks) define

$$x_E : \; V_E = V_F, \qquad x_T : \; V_T = V_E, \qquad x_P : \; V_P = V_T.$$

With the parameter ordering that makes $V_T \geq V_E \Rightarrow V_P \geq V_T$, the thresholds satisfy $x_F < x_E < x_T < x_P$.

3.4.6 Idiosyncratic taste shocks and contract choice.

Draw i.i.d. taste shocks $\varepsilon_C \sim \text{Gumbel}(0, \sigma_\varepsilon)$ for $C \in \{F, E, P, T\}$, independent of (x, ϕ, λ_L). Contract utilities are

$$U^C(x, \phi, \lambda_L) \;=\; V_C(x, \phi, \lambda_L) + \varepsilon_C.$$

Hence the choice probabilities are

$$\Pr_C(x, \phi, \lambda_L) = \frac{\exp\{V_C(x, \phi, \lambda_L)/\sigma_\varepsilon\}}{\sum_{D \in \{F,E,P,T\}} \exp\{V_D(x, \phi, \lambda_L)/\sigma_\varepsilon\}}.$$

As $\sigma_\varepsilon \downarrow 0$, $\Pr_C$ concentrates on the argmax of V_C (deterministic cutoffs). Larger σ_ε reflects greater unobserved taste heterogeneity and yields flatter shares. In the logit, $\partial \Pr_C / \partial V_C = \Pr_C(1 - \Pr_C)/\sigma_\varepsilon > 0$ and $\partial \Pr_C / \partial V_D = - \Pr_C \Pr_D / \sigma_\varepsilon < 0$ for $D \neq C$, so each probability is strictly increasing in its own utility. The deterministic ranking is recovered in the limit $\sigma_\varepsilon \to 0$, but for finite σ_ε occasional reversals can occur smoothing the sharp cutoffs.

IIA caveat. With i.i.d. Gumbel taste shocks, the multinomial logit entails IIA. Because $\{P, T\}$ (bonus) are likely closer substitutes than $\{F, E\}$ (non-bonus), Appendix E briefly outlines standard relaxations (nested logit and an error-components logit) that nest our baseline.

3.5 Comparative-Statics on Participation Cut-offs

- $\dfrac{\partial x_P}{\partial \rho} > 0$
  Intuition: higher risk aversion lowers the certainty-equivalent value of a risky bonus, so a worker needs higher productivity to find performance pay worthwhile.

- $\dfrac{\partial x_P}{\partial \delta} < 0$
  Intuition: greater patience increases the present value of the deferred bonus, lowering the productivity threshold for accepting it.

- $\dfrac{\partial x_P}{\partial \lambda_L} > 0$
  Intuition: a stronger preference for leisure (larger λ_L) raises the marginal disutility of effort, so the worker requires a larger bonus—hence higher x—to compensate.

- $\dfrac{\partial x_P}{\partial \theta} < 0$
  Intuition: As $\theta \in (0, 1)$ increases, Prelec weighting becomes more linear. For moderate/high success probabilities ($p > e^{-1}$) this raises the perceived value of the bonus. Therefore the productivity cutoff falls. [6]

[6] If the incremental appeal of C_P comes predominantly from *small-probability* upper-tail states (rare big gains), then increasing θ down-weights those events and the sign can flip to $\partial x_P / \partial \theta > 0$. The sign reversal boundary for $\partial_\theta w_\theta(p)$ is at $p = e^{-1} \approx 0.368$.

3.6 Firm's Contract Menu and Profit Maximisation

Firm's Problem. Upon hiring, a risk neutral firm observes each worker's skill level. Given that skill-level, the firm perceives the worker´s preference index ϕ_i as it knows the conditional distribution of the worker´s preference parameters - summarized by their means

$$(\mathbb{E}[\rho_i|\phi_i],\ \mathbb{E}[\delta_i|\phi_i],\ \mathbb{E}[\lambda_{L,i}|\phi_i],\ \mathbb{E}[\theta_i|\phi_i],\ \mathbb{E}[\psi_i|\phi_i])$$

but it cannot observe nor contract on the idiosyncratic deviations from those means. Taking this information set as given, the firm designs a contract menu

$$\Theta = (w_F, w_E, a, b, r, m) \in \mathbb{R}^6_+$$

that maximises expected profit over the distribution of unobserved preferences.

Monitoring cost. The firm chooses monitoring intensity $m \in [0,1]$ at quadratic cost $C_m(m) = \frac{\kappa}{2}m^2$. Monitoring improves the signal of performance: the output shock variance falls with m, $\sigma^2(m)$ with $\sigma'(m) < 0$. Accordingly, the density and CDF of the shock in the utility integrals are $f_\varepsilon(\cdot;\sigma^2(m))$ and $F_\varepsilon(\cdot;\sigma^2(m))$. For a team of size n, the aggregate noise is $\mathcal{E} \equiv \sum_{j=1}^{n} \varepsilon_j$ with mean 0 and variance $\mathrm{Var}(\mathcal{E}) = n\,\sigma^2(m)$ under independence; its density and CDF are $f_{\mathcal{E}}(\cdot;\, n\sigma^2(m))$ and $F_{\mathcal{E}}(\cdot;\, n\sigma^2(m))$.

Convex incentive-administration costs. Implementing steep piece–rates entails administrative overhead. I therefore introduce convex costs

$$C_b(b) = \frac{\eta_b}{2}\, b^2, \qquad C_r(r) = \frac{\eta_r}{2}\, r^2,$$

with $\eta_b, \eta_r > 0$.

3.6.1 Expected profit per worker.

Let $\Pr_C(x, \phi, \lambda_L; \Theta)$ be the logit choice shares for contract $C \in F, E, P, T$ and $e^*_C(x, \phi, \lambda_L; \Theta)$ the induced effort. Then given a pooled menu $\Theta = (w_F, w_E, a, b, r, m)$

$$\Pi(\Theta) = \underbrace{\mathbb{E}_\phi\Big[\mathbb{E}_{x,\lambda_L|\phi}\big\{\sum_C \Pr_C(x, \phi, \lambda_L; \Theta)\, x\, e^*_C(x, \phi, \lambda_L; \Theta)\big\}\Big]}_{\text{expected output}}$$

$$- \underbrace{\begin{aligned} \mathbb{E}_\phi\Big[\mathbb{E}_{x,\lambda_L|\phi}\big\{ & w_F \Pr_F(x, \phi, \lambda_L; \Theta) + w_E \Pr_E(x, \phi, \lambda_L; \Theta) \\ & + \Pr_P(x, \phi, \lambda_L; \Theta)\big(a + b\, x\, e^*_P(x, \phi, \lambda_L; \Theta)\big) \\ & + \Pr_T(x, \phi, \lambda_L; \Theta)\big(a + rx\, e^*_T(x, \phi, \lambda_L; \Theta)\big)\big\}\Big] \end{aligned}}_{\text{expected wage bill}}$$

$$- \frac{\kappa}{2}m^2 - \frac{\eta_b}{2}b^2 - \frac{\eta_r}{2}r^2.$$

All expectations are unconditional over the population distribution of (x, ϕ, λ_L).

3.6.2 Firm's programme.

$$\max_\Theta \; \Pi(\Theta) \quad \text{s.t. worker IC and logit shares.}$$

Closed-form FOCs are lengthy. The signs follow directly from the firm's FOC $\partial\Pi/\partial b = 0$ once we write it schematically as

$$\mathbb{E}\big[\Pr_P x \tfrac{\partial e^*_P}{\partial b}\big] - \mathbb{E}\big[\Pr_P b\, x\, e^*_P\big] - \mathbb{E}\big[(a + b\, x e^*_P)\, \tfrac{\partial \Pr_P}{\partial b}\big] - \eta_b\, b = 0,$$

and note how each parameter shifts the three components:

- **Risk aversion** ρ. A higher ρ increases the risk premium embedded in a, raising the marginal wage cost and lowering the optimal slope: $\partial b^*/\partial\rho < 0$.

- **Leisure parameter** λ_L. Greater disutility of effort shrinks $\partial e^*/\partial b$, so the output gain term falls: $\partial b^*/\partial\lambda_L < 0$.

- **Outcome variance** σ^2. More noise worsens the signal–to–noise ratio of incentives, again reducing b^*.

- **Preference index** ϕ. As ϕ rises, workers become more risk-neutral, more patient, and weight probabilities more linearly, lowering the risk premium and raising $\partial e^*/\partial b$ hence $\partial b^*/\partial \phi > 0$.

Analogous inequalities hold for the team-bonus parameter r^*; indeed, free-rider dilution typically implies $r^* < b^*$ in equilibrium.

Equilibrium: $(\Theta^*, \{e_C^*\})$ such that

1. Worker IC: e_C^* solves the FOC for each contract at Θ^*.

2. Contract shares $\Pr_C$ follow the logit rule with those V_C.

3. Θ^* maximises $\Pi(\Theta)$ given e_C^* and $\Pr_C$.

Numerical methods (e.g. simulated method of moments) recover (Θ^*, β) where β are structural parameters of u, v, w_ϕ, k from data on contract choice and effort proxies.

3.7 Intuition and Economic Narrative

Cast, timing, and information. **Stage 1.** A competitive, risk–neutral firm observes each applicant's preference index ϕ_i and knows the conditional distributions of $(x, \rho, \delta, \theta, \lambda_L)$ given ϕ_i. It cannot observe (or contract on) the idiosyncratic deviations around those conditional means. It posts a menu

$$\Theta = (w_F,\ w_E,\ a,\ b,\ r,\ m).$$

Stage 2. Each applicant observes Θ and her *own* trait vector, solves a private effort problem, and chooses a contract $C \in \{F, E, P, T\}$.

Taste shocks. To capture idiosyncratic fit, each contract utility receives an independent Gumbel error $\varepsilon_C \sim \mathrm{EV}(0, \sigma_\varepsilon)$, independent across contracts and workers. The resulting multinomial-logit shares are $\Pr_C(x, \phi, \lambda_L) \propto \exp\big(V_C(x, \phi, \lambda_L)/\sigma_\varepsilon\big)$.

Why some high-skill workers still reject performance pay. A steep bonus exposes income to risk and postpones part of remuneration. Workers with high loss aversion ψ, strong leisure taste λ_L, or sharply curved probability weighting θ need a larger productivity draw x before the bonus becomes as attractive as a flat wage. Deterministically this creates thresholds $x_F < x_E < x_T < x_P$; the Gumbel noise smooths these into strictly positive masses on *all* four contracts. This mirrors SOEP evidence that only 15,77% of German full-time employees receive individual performance pay.[7] (For probability weighting, the direction of the effect depends on whether the bonus loads mainly on rare vs. moderate/high-probability states; cf. Appendix A.2.5.)

Firm's first-order condition. Writing $\pi_P = \Pr_P(x, \phi, \lambda_L; \Theta)$ and $e_P^* = e_P^*(x, \phi, \lambda_L; \Theta)$, the exact FOC with expectations kept inside is

$$\frac{\partial \Pi}{\partial b} = \underbrace{\mathbb{E}\Big[\pi_P\,(1-b)\,x\,\tfrac{\partial e_P^*}{\partial b}\Big]}_{\text{net marginal incentive gain}} - \underbrace{\mathbb{E}\big[\pi_P\,x e_P^*\big]}_{\text{pass-through on current output}} + \underbrace{\mathbb{E}\Big[\big((1-b)\,x e_P^* - a\big)\,\tfrac{\partial \pi_P}{\partial b}\Big]}_{\text{sorting (net-surplus weighted)}} - \eta_b\, b = 0.$$

This says: a steeper slope increases output via the effort response (first term), but the firm must pass through more of output as bonus (second term), The third term refelcts the change in who selects into P, while incurring administrative cost $\eta_b b$.

The comparative statics follow directly:

$$\frac{\partial b^*}{\partial \rho} < 0, \qquad \frac{\partial b^*}{\partial \lambda_L} < 0, \qquad \frac{\partial b^*}{\partial \sigma^2} < 0, \qquad \frac{\partial b^*}{\partial \phi} > 0,$$

Higher ρ, λ_L, or σ^2 dampen $\partial e_P^*/\partial b$ and π_P, whereas a higher preference index ϕ (lower $\rho(\phi)$, higher $\delta(\phi)$, and more linear probability weighting with higher $\theta(\phi) \in (0,1)$) strengthens them. If monitoring is chosen, $\partial b^*/\partial \kappa < 0$ typically holds *indirectly* via a lower m^* that reduces incentive effectiveness.

Team incentives obey the same logic, with $r^* < b^*$ owing to free-rider dilution.[8]

Equilibrium summary. An equilibrium is $(\Theta^*, e_C^*, \Pr_C^*)$ such that (i) each worker best responds to Θ^*; (ii) contract shares follow the logit rule; and (iii) Θ^* maximises expected profit. Solving the fixed point numerically and matching moments—take-up, wages, output—to data identifies the structural preference parameters. In short, schooling reshapes

[7] SOEP v39, author's calculation.

[8] In team production, each worker's pay depends on total team output. Because any one worker enjoys only a small share of the gains from their own extra effort—while bearing the full effort cost—everyone has an incentive to "free-ride" on others. This under-provision of effort means a given team-bonus rate induces weaker effort than an individual bonus.

$\rho, \psi, \delta, \theta, \lambda_L$, and those endogenous tastes explain why (a) some high-skill workers still shun performance pay and (b) many firms choose moderate efficiency wages over high-powered incentives even in competitive talent markets.

4 Empirical Validation Strategy

The principal objective of this section is *conceptual verification*: I demonstrate that, even under a deliberately parsimonious parameterisation, the model can reproduce first–order empirical regularities in the German labour market. Two complementary pieces of evidence are brought to bear:

1. a reduced-form logit estimating the *conditional* effect of tertiary education on the probability of receiving performance pay as well as the effect of risk attitudes, and

2. a minimum-distance calibration that targets only two unconditional moments—overall incidence and the raw skill gap-yet delivers a schooling gradient as well as plausible take up rates.

The exercises are intentionally *suggestive* rather than exhaustive, they are intended to establish that the preference channel emphasized in the theory above is empirically plausible.

4.1 Reduced-Form Benchmark

Data and Descriptive Statistics I extract the 2016 cross-section of the German SOEP (SOEP, 2024).[9] The wave contains 13 265 full or part time employed respondents with a valid performance pay indicator. Listwise deletion of observations with missing controls leaves 12 383 individuals in the logit regressions reported below. Performance–pay[10] contracts are observed for 15.77 % of workers. The unconditional gap between university-educated and non-university workers is 7.32 pp (20.48 % vs. 13.16 %). These two moments—overall incidence and the raw skill gap—anchor the calibration in Section 4.2.

Logit specification. The dependent variable PPay_i equals one if the respondent reports being subject to performance contingent pay. The explanatory vector includes a tertiary-education dummy HighSkill_i, gender, firm size, public-sector status, seniority, East–West

[9] Sample restrictions: age $\geq$18; employment status `pgemplst` $\in \{1, 2\}$; complete covariate information.

[10] Because the dataset records only whether workers receive an individual performance-pay component, I observe only individual performance pay and fixed pay. The data do not identify efficiency wages or team bonuses.

indicator, a part time dummy and a self-reported risk attitude score (`plh0178`, 0–10) as well as its square.

I estimate

$$\Pr\big(\text{PPay}_i = 1\big) \;=\; \Lambda(\beta_0 + \beta_1 \text{HighSkill}_i + \boldsymbol{X}'_i \boldsymbol{\gamma}), \qquad \Lambda(z) = \frac{e^z}{1+e^z},$$

using heteroskedasticity-robust standard errors.

Results. The regression results show a clear and economically meaningful schooling gradient in the propensity to receive performance-contingent pay. The coefficients are shown as Average Marginal Effects in Table tab:ame. After controlling for firm size, public sector status, seniority region and part-time employment, individuals with a tertiary degree (ISCED $\geq$ 5) are estimated to be on average 5.83 percentage points more likely to hold a performance-pay contract than individuals without a university qualification. The direction and magnitude of the effect is consistent with the model´s premise that higher-skill agents find variable pay more attractive. Risk attitudes matter as well. The logit includes a linear and a quadratic term in the self-reported 0-10 risk-tolerance scale, the positive linear coefficient (AME = 0.013) and the negative quadratic coefficient (AME = -0.0013) together imply a monotonically increasing but gently concave relationship between risk tolerance and the predicted probability of performance pay. Marginal-effects calculations trace this profile as can be seen in Figure 1: the estimated probability rises from about 11 percent for the most risk-averse respondents (score 0) to about 24 percent for the most risk-loving (score 10), with each successive point adding slightly less than the previous one. Hence, greater willingness to bear risk systematically translates into higher performance-pay take-up, but the influence tapers off at the top of the scale.

Importantly, high-skill workers are not only more likely to be on performance pay, they also report higher risk tolerance in the first place. Kernel-density estimates of the risk scores, plotted separately by skill group, show the high-skill curves unit mass is to the right across nearly the entire support. Although both curves display pronounced spikes at round numbers (2, 5, 7) due to response heaping, the vertical gap between them is persistent. This can be seen in figure 2. A two-sample Kolmogorov–Smirnov test rejects the null of identical distributions ($D = 0.040, p < 0.001$), confirming that the difference is statistically significant. Taken together, the regression coefficients, the margins plot, and the distributional evidence form a coherent empirical pattern: education is associated with greater risk tolerance, and that elevated risk tolerance, in turn, predicts a higher likelihood of choosing contracts in

	AME	Robust s.e.
High skill	0.0583^{***}	0.0066
Female	-0.0365^{***}	0.0073
Risk tolerance	0.0131^{**}	0.0056
Risk tolerance^2	-0.0013^{**}	0.0005
Tenure	0.0019^{***}	0.0003
East Germany	-0.0292^{***}	0.0087
Part-time	-0.0323^{***}	0.0087
Establishment size	0.0583^{***}	0.0021
Public sector	-0.0549^{***}	0.0079
No. of observations	12 383	

Significance: *** $p < 0.01$; ** $p < 0.05$.

Dependent Variable. PPay = 1 if the respondent reports any performance-contingent pay (bonus/piece-rate); 0 otherwise.

Variables of interest. *High skill* is an indicator for tertiary education (ISCED ≥ 5). *Risk tolerance* is a self-reported 0–10 scale (higher = more willing to take risks); *Risk tolerance*^{2} allows nonlinearity.

Controls. *Establishment size* (categorical indicator of the number of employees in the current workplace), *Public sector* (=1 for public employer), *Tenure* (years with current employer), *East Germany* (=1 if resident in the East), *Part-time* (=1 if part-time employed).

Model. Logit; entries are *average marginal effects* (AMEs), i.e., the change in Pr(PPay = 1) averaged over all observations. For dummies, AME is the discrete change from 0 to 1; for continuous variables, the effect of a one-unit increase. AMEs are in probability units, so $0.050 \approx 5$ percentage points.

Robustness. Robust = Huber–White standard errors.

Table 1: Average marginal effects on performance–pay incidence

which pay is tied to performance. This chain of associations mirrors the core mechanism of the structural model and serves as suggestive validation of its behavioural premises.

4.2 Structural Calibration

Simulated economy. I simulate $N = 100$ workers. Schooling $S_i \sim \mathrm{U}[0.1, 1]$ maps into productivity and preference heterogeneity as

$$x_i \; = \; 1 + 0.5\, S_i + 0.2 Z_i, \qquad \phi_i \; = \; 1 + 0.3\, S_i + 0.1 Z_i, \qquad Z_i \sim \mathcal{N}(0, 1),$$

with truncation at 0.1 to avoid degenerate values. These scale factors (0.5 for productivity; 0.3 for the index) were tuned iteratively—i.e., by trial-and-error—so that the simulated skill gradient is of comparable magnitude to the empirical counterpart, subject to the plausibility bounds below. Monitoring intensity is normalised to $m = 0$ because (i) the two targeted moments—overall incidence and the unconditional education gap in performance pay—contain no direct information on monitoring, and (ii) adding m would absorb variance without improving identification. Accordingly, κ is omitted.

Plausible priors (working anchors). To keep the exercise suggestive rather than inferential, I anchor the working forms to broad plausible priors: risk aversion around 1.0; discount factors in [0.95, 0.995]; effort-cost scale near 0.8; probability-weighting curvature (Prelec-style) around 0.8; and loss aversion around 1.6. These priors discipline the search without pinning down functional forms.

Calibration bounds. Eight structural parameters

$$(\beta_\rho,\ \beta_\delta,\ \beta_\lambda,\ \beta_\theta,\ \beta_\psi,\ \eta_b,\ \eta_r,\ \sigma_\varepsilon)$$

are confined to economically plausible hyper-rectangles:

Objective function. Let $\hat{m} = (0.1577, 0.073)'$ collect the two data moments (overall incidence and the *unconditional* education gap), and let $m^{\text{sim}}(\theta)$ be the corresponding model moments. I minimise the identity-weighted distance

$$Q(\theta) = \big(\hat{m} - m^{\text{sim}}(\theta)\big)'\big(\hat{m} - m^{\text{sim}}(\theta)\big).$$

The search uses differential evolution (SCIPY v1.11.1; eight generations; population six; four parallel workers). Integrals are computed by 5-point Gauss–Hermite.

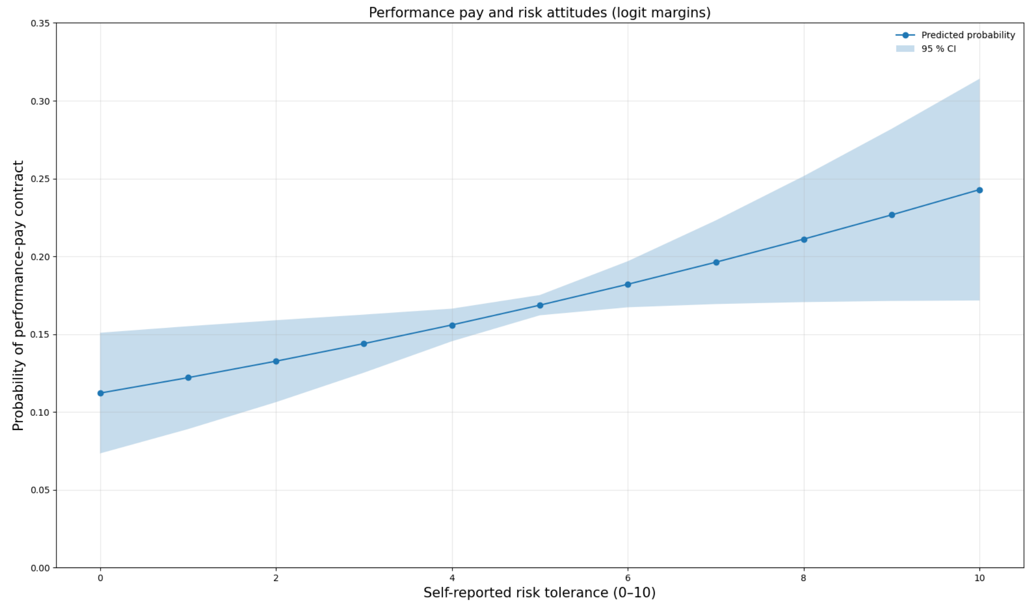

Figure 1: Predicted probability of performance-pay, based on Table 1, by self-reported risk tolerance (95 % confidence band) — *Source:* Author's calculations using SOEP v39.

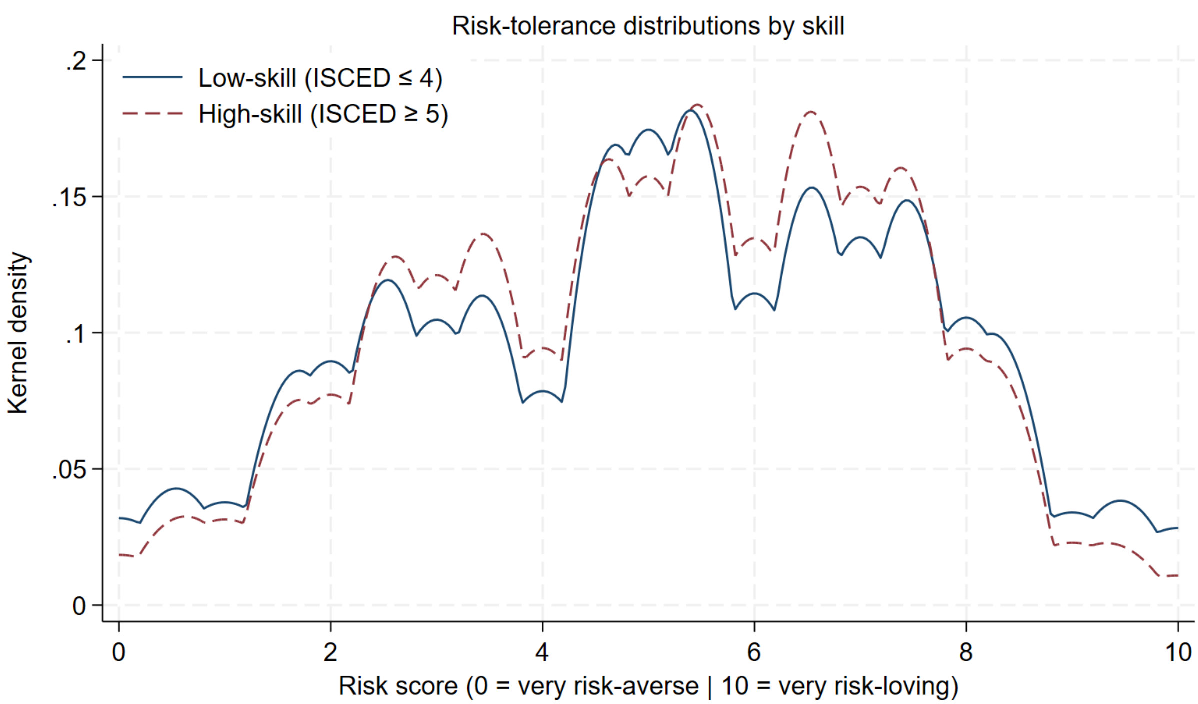

Figure 2: Kernel density of risk-tolerance scores by skill group. — *Source:* Author's calculations using SOEP v39.

	Lower Bound	Upper Bound
β_ρ	0.0	5.0
β_δ	0.0	5.0
β_λ	0.0	4.0
β_θ	0.0	4.0
β_ψ	0.0	4.0
η_b	0.001	0.8
η_r	0.001	0.8
σ_ε	0.05	0.20

κ is omitted because m is set to 0 in the calibration.

Table 2: Bounds of calibrated parameters

Calibration outcome. The global minimum is

$$\theta^* = (4.193,\ 4.375,\ 3.992,\ 2.412,\ 1.652,\ 0.347,\ 0.444,\ 0.070),$$

implying a root mean-squared moment error (RMSE) of 0.051. At θ^* the model reproduces:

- overall take-up of $\hat{p}^{\text{sim}} = 11.36\%$ (vs. 15.77%), and
- a raw education gap of 12.93 pp (vs. 7.32 pp).

Interpretation. Relative to the data, the calibration *under-predicts* aggregate incidence (by $\approx$ 4.4 pp) but *over-predicts* the raw education gap (by $\approx$ 5.6 pp). Two considerations help reconcile the differences. First, the empirical gap quoted here is *unconditional*; once standard covariates (firm size, public sector, tenure, region, part-time) are partialled out, the conditional schooling coefficient drops toward 5 pp in the logit benchmark, narrowing the discrepancy on the gradient. Second, the exercise is deliberately under-identified: eight free parameters are fit to two aggregate moments under broad plausibility bounds. The objective is illustrative rather than inferential. Matching both moments closely would require either (i) additional empirical targets—e.g., bonus slopes, contract-specific effort proxies, higher-order moments—or (ii) informative priors tied to external experimental estimates of risk, time, effort, and weighting parameters. Given my purpose—to show that endogenising preferences can produce realistic incidence and a non-trivial skill gradient—the current fit seams sufficient.

4.3 Implications and Scope

Taken together, the structural calibration and the reduced-form logit deliver three take-aways.

1. **Plausibility.** Introducing education-dependent *preferences*—rather than allowing schooling to affect productivity alone—permits an otherwise standard principal–agent model to generate levels and skill gradients of performance pay that resemble those observed in the SOEP data.

2. **Parsimony.** Although the calibration pins down only two moments (overall incidence and the unconditional skill gap), the model nevertheless produces a schooling differential that is roughly comparable in size (within a few percentage points) to the conditional logit estimate. This approximate alignment—achieved without explicitly fitting that coefficient—suggests that the schooling-driven preference channel, rather than aggressive over-fitting, is doing most of the explanatory work.[11]

3. **Proof of concept.** The purpose of the twin exercises is illustrative rather than definitive. They demonstrate that endogenising risk, time, and effort preferences is quantitatively meaningful and tractable. A fully identified SMM estimation—using richer moment sets and allowing for monitoring and additional contract forms—is left for future work.

5 Conclusion

Preferences are central to contract design, yet most canonical models treat them as fixed primitives that differ only idiosyncratically around a common mean. A growing body of empirical evidence, however, shows that preference parameters co-vary systematically with observable characteristics—most notably education. University-educated workers are, on average, less risk-averse, more patient, and less sensitive to effort costs than their less-educated peers. Ignoring those gradients risks mis-characterising the contracts workers accept.

This paper embeds those insights in a parsimonious principal–agent model in which each preference coefficient is a function of schooling. The exercise yields three broad results:

[11]The numerical match is used solely as a plausibility (sanity) check on the calibration, it is not treated as an identified causal marginal effect.

1. **Theory.** The firm observes each worker's skill index ϕ_i but only the *conditional means* of the preference parameters. It therefore posts a contract menu calibrated to those means—effectively to the "representative" worker at each skill level. Idiosyncratic (unobserved) taste shocks then drive differential take-up: steeper, performance-contingent pay is attractive to high-skill workers because their education-linked preferences make risky, back-loaded compensation appealing, whereas low-skill workers gravitate toward flatter contracts.

2. **Data congruence.** With only two targeted moments, the calibrated model reproduces (i) an aggregate incidence of performance pay within roughly 5 pp of the SOEP benchmark and (ii) a schooling differential within rougly pp of the SOEP estimate. Although not a full structural estimation, the exercise demonstrates that endogenous preferences alone can account for first-order patterns in German labour data.

3. **Reduced-form corroboration.** A logit regression and kernel-density comparison show that higher education is indeed associated with both greater risk tolerance and a higher likelihood of holding a performance-pay contract. These reduced-form facts align with—rather than identify—the structural mechanism.

Taken together, the results suggest that preference heterogeneity is not a second-order nuisance but a first-order driver of contract sorting. Standard models that treat risk, time, and effort parameters as exogenous constants may therefore under-predict the prevalence of incentive pay in skilled segments and over-predict it among the less skilled.

The contribution is conceptual rather than definitive. The calibration is deliberately light, the moment set sparse, and monitoring is normalised to zero; richer data and a fully-identified SMM or Bayesian estimation are left to future work. Nonetheless, the proof-of-concept underscores a broader point: relaxing the exogeneity of preferences can materially change equilibrium predictions, and doing so does not require abandoning the tractability of the canonical principal–agent framework.

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Appendix A: Complete Proofs of First-Order Conditions and Comparative Statics

A.1. Agent's First-Order Conditions

A.1.1 Individual Performance Contract $C_P = (a, b)$. Under C_P, the agent's utility for effort e is

$$U_P(e) \;=\; v\big(a \mid \Gamma\big) \;-\; k\big(e;\lambda_L\big) \;+\; \delta \int v\big(a + b\,(xe + \varepsilon) \mid \Gamma\big)\, w'_\phi\big(\mathcal{F}(\varepsilon)\big)\, f(\varepsilon)\, d\varepsilon,$$

with:

- $\Gamma = w_F + S$ (reference point).

- $v(c \mid \Gamma; \rho, \psi)$ the reference-dependent utility:

$$v(c \mid \Gamma) = \begin{cases} u(c;\rho) - u(\Gamma;\rho), & c \geq \Gamma, \\ -\,\psi\,\big[u(\Gamma;\rho) - u(c;\rho)\big], & c < \Gamma, \end{cases}$$

  where $u(c;\rho) = (c^{1-\rho} - 1)/(1-\rho)$ if $\rho \neq 1$, or $\ln(c)$ if $\rho = 1$.

- $k(e;\lambda_L) = \frac{\lambda_L}{1+\eta}\, e^{1+\eta}$ with $\eta > 0$, so $k_e(e) = \lambda_L\, e^{\eta}$ and $k_{ee}(e) = \eta\,\lambda_L\, e^{\eta-1} > 0$.

- Output $y = x\,e + \varepsilon$, $\varepsilon \sim \mathcal{F}$, density f.

- The Choquet integral uses $w'_\phi(\mathcal{F}(y))\, f(y)$, where

$$w_\phi(p) \;=\; \exp\big\{-(-\ln p)^{\theta(\phi)}\big\}, \quad w'_\phi(p) \;=\; w_\phi(p)\,\theta(\phi)\,\frac{(-\ln p)^{\theta(\phi)-1}}{p}.$$

Differentiate U_P w.r.t. e. Only two terms depend on e: $-\,k(e)$ and the bonus-integral through $y = x\,e + \varepsilon$. Thus

$$\frac{dU_P}{de} \;=\; -\,k_e\big(e;\lambda_L\big) \;+\; \delta \int v'\big(a + b\,(xe+\varepsilon) \mid \Gamma\big)\,\frac{\partial\big(a + b\,(xe+\varepsilon\big)}{\partial e}\,w'_\phi\big(\mathcal{F}(\varepsilon)\big)\,f(\varepsilon)\,d\varepsilon.$$

Since $y = x\,e + \varepsilon$, $\partial(a + b\,y)/\partial e = b\,x$. Hence

$$\frac{dU_P}{de} \;=\; -\,\lambda_L\,e^{\eta} \;+\; \delta\,b\,x \int v'\big(a + b\,(xe+\varepsilon) \mid \Gamma\big)\,w'_\phi\big(\mathcal{F}(\varepsilon)\big)\,f(\varepsilon)\,d\varepsilon.$$

Setting $dU_P/de = 0$ at the interior optimum e_P^* gives

$$\lambda_L\,\big(e_P^*\big)^{\eta} \;=\; \delta\,b\,x \int v'\big(a + b\,(xe_P^*+\varepsilon) \mid \Gamma\big)\,w'_\phi\big(\mathcal{F}(\varepsilon)\big)\,f(\varepsilon)\,d\varepsilon.$$

In the quadratic–cost case $\eta = 1$, this simplifies to

$$\lambda_L\,e_P^* \;=\; \delta\,b\,x \int v'\big(a + b\,(xe_P^*+\varepsilon) \mid \Gamma\big)\,w'_\phi\big(\mathcal{F}(\varepsilon)\big)\,f(\varepsilon)\,d\varepsilon.$$

A.1.2 Team Performance Contract $C_T = (a, r)$. Under C_T, each worker's payment is $a + \frac{r}{n} Y$, with $Y = \sum_{j=1}^{n} y_j$. In the symmetric equilibrium $y_j = x\,e + \varepsilon_j$, so $Y = n\,x\,e + \sum_j \varepsilon_j$. Then

$$U_T(e) \;=\; v\big(a \mid \Gamma\big) \;-\; k\big(e;\lambda_L\big) \;+\; \delta \int v\Big(a + \tfrac{r}{n}\,(nxe + \mathcal{E}) \mid \Gamma\Big)\, w_\phi'\big(\mathcal{F}(\mathcal{E})\big)\, f(\mathcal{E})\, d\mathcal{E}.$$

Differentiate w.r.t. e. With $\eta = 1$,

$$\frac{dU_T}{de} \;=\; -\,\lambda_L\, e \;+\; \delta\,\frac{r}{n}\,x \int v'\Big(a + \tfrac{r}{n}\,(nxe + \mathcal{E}) \mid \Gamma\Big)\, w_\phi'\big(\mathcal{F}(\mathcal{E})\big)\, f(\mathcal{E})\, d\mathcal{E}.$$

The FOC at e_T^* is

$$\lambda_L\, e_T^* \;=\; \delta\,\frac{r}{n}\,x \int v'\Big(a + \tfrac{r}{n}\,(nxe_T^* + \mathcal{E}) \mid \Gamma\Big)\, w_\phi'\big(\mathcal{F}(\mathcal{E})\big)\, f(\mathcal{E})\, d\mathcal{E}.$$

Hence

$$k_e\big(e_T^*;\lambda_L\big) \;=\; \delta\,\frac{r}{n}\,x \int v'\Big(a + \tfrac{r}{n}\,(nxe_T^* + \mathcal{E}) \mid \Gamma\Big)\, w_\phi'\big(\mathcal{F}(\mathcal{E})\big)\, f(\mathcal{E})\, d\mathcal{E}.$$

A.2. Agent-Side Comparative Statics (Cut-off x_P)

Define

$$V_P\big(x,\rho,\delta,\theta,\lambda_L\big) \;=\; U_P\big(e_P^*(x,\rho,\delta,\theta,\lambda_L);\, x,\rho,\delta,\theta,\lambda_L\big),$$

$$V_T\big(x,\rho,\delta,\theta,\lambda_L\big) \;=\; U_T\big(e_T^*(x,\rho,\delta,\theta,\lambda_L);\, x,\rho,\delta,\theta,\lambda_L\big).$$

The deterministic "sorting" cut-off x_P solves

$$\Phi\big(x_P,\rho,\delta,\theta,\lambda_L\big) \;=\; V_P\big(x_P,\rho,\delta,\theta,\lambda_L\big) \;-\; V_T\big(x_P,\rho,\delta,\theta,\lambda_L\big) \;=\; 0.$$

By the Implicit Function Theorem,

$$\frac{\partial x_P}{\partial \rho} \;=\; -\frac{\dfrac{\partial \Phi}{\partial \rho}}{\dfrac{\partial \Phi}{\partial x_P}}, \quad \frac{\partial x_P}{\partial \delta} \;=\; -\frac{\dfrac{\partial \Phi}{\partial \delta}}{\dfrac{\partial \Phi}{\partial x_P}}, \quad \frac{\partial x_P}{\partial \lambda_L} \;=\; -\frac{\dfrac{\partial \Phi}{\partial \lambda_L}}{\dfrac{\partial \Phi}{\partial x_P}}, \quad \frac{\partial x_P}{\partial \theta} \;=\; -\frac{\dfrac{\partial \Phi}{\partial \theta}}{\dfrac{\partial \Phi}{\partial x_P}}.$$

Envelope step. For each contract C, $V_C(x,\cdot) = \max_{e \geq 0} U_C(e;x,\cdot)$ with $U_e(e_C^*(x);x,\cdot) = 0$, so by the envelope theorem

$$\frac{\partial V_C}{\partial x} = \frac{\partial U_C}{\partial x}\Big|_{e=e_C^*(x)}.$$

We use this identity throughout when differentiating V_C.

A.2.1 Why $\partial\Phi/\partial x_P > 0$. By the envelope theorem,

$$\frac{\partial V_C}{\partial x} = \delta\, b_C\, e_C^* \int v'\big(a + b_C(xe_C^* + \varepsilon) \mid \Gamma\big)\, w_\phi'\big(\mathcal{F}_\varepsilon(\varepsilon)\big)\, f_\varepsilon(\varepsilon)\, d\varepsilon, \quad C \in \{P, T\},$$

with $b_P = b$ and $b_T = r/n$. The integral is strictly positive. Moreover, the effort FOC $k_e(e_C^*) = \delta b_C x \int v'(\cdot)w' f$ and convexity of $k(\cdot)$ imply $e_P^* > e_T^*$ when $b > r/n$. Therefore

$$\frac{\partial V_P}{\partial x} > \frac{\partial V_T}{\partial x}, \quad \Rightarrow \quad \frac{\partial \Phi}{\partial x_P} > 0.$$

A.2.2 Sign of $\partial x_P/\partial\rho$.

$$\frac{\partial \Phi}{\partial \rho} = \frac{\partial V_P}{\partial \rho} - \frac{\partial V_T}{\partial \rho}.$$

In both V_P and V_T, ρ enters only via

$$v'(c \mid \Gamma; \rho, \psi) \propto c^{-\rho} \quad \Longrightarrow \quad \frac{\partial v'(c)}{\partial \rho} < 0,$$

and also within the one-period utility in each integral. Because $b > \frac{r}{n}$, the bonus-integral in V_P is more "exposed" to ρ than that in V_T. Hence $\partial V_P/\partial\rho < \partial V_T/\partial\rho < 0$ in magnitude, so

$$\frac{\partial \Phi}{\partial \rho} = \frac{\partial V_P}{\partial \rho} - \frac{\partial V_T}{\partial \rho} < 0 \quad \Longrightarrow \quad \frac{\partial x_P}{\partial \rho} > 0.$$

A.2.3 Sign of $\partial x_P/\partial\delta$.

$$\frac{\partial \Phi}{\partial \delta} = \frac{\partial V_P}{\partial \delta} - \frac{\partial V_T}{\partial \delta}.$$

Since δ multiplies only the deferred bonus component, we have

$$\frac{\partial V_C}{\partial \delta} = \int v\big(a + b_C(xe_C^* + \varepsilon) \mid \Gamma\big)\, w_\phi'\big(\mathcal{F}(\varepsilon)\big)\, f(\varepsilon)\, d\varepsilon, \quad C \in \{P, T\}.$$

At the cutoff, the higher slope $b > b_T = r/n$ and $e_P^* > e_T^*$ together imply that the bonus term in V_P receives a larger marginal weight than in V_T, hence $\partial_\delta V_P > \partial_\delta V_T$. Therefore $\partial_\delta \Phi > 0$ and $\partial x_P/\partial\delta < 0$.

A.2.4 Sign of $\partial x_P/\partial\lambda_L$.

$$\frac{\partial\Phi}{\partial\lambda_L} = \frac{\partial V_P}{\partial\lambda_L} - \frac{\partial V_T}{\partial\lambda_L}.$$

Since $k(e;\lambda_L) = (\lambda_L/(1+\eta))\, e^{1+\eta}$, one obtains $\partial k/\partial\lambda_L = e^{1+\eta}/(1+\eta)$, and $\partial e_C^*/\partial\lambda_L < 0$. Because $e_P^* > e_T^*$ when $x = x_P$, it follows that increasing λ_L reduces V_P more than V_T. Hence $\partial V_P/\partial\lambda_L < \partial V_T/\partial\lambda_L$, so $\partial\Phi/\partial\lambda_L < 0$ and

$$\frac{\partial x_P}{\partial\lambda_L} > 0.$$

A.2.5 Sign of $\partial x_P/\partial\theta$ (Prelec–1, $\theta \in (0,1)$).

$$\frac{\partial\Phi}{\partial\theta} = \frac{\partial V_P}{\partial\theta} - \frac{\partial V_T}{\partial\theta}.$$

For the Prelec–1 weight $w_\theta(p) = \exp\{-(-\ln p)^\theta\}$ with $\theta \in (0,1)$,

$$\partial_\theta w_\theta(p) = -\, w_\theta(p)\,(-\ln p)^\theta\, \ln(-\ln p) \begin{cases} < 0, & p < e^{-1}, \\ > 0, & p > e^{-1}, \end{cases}$$

so increasing θ attenuates the overweighting of small probabilities and moves decision weights toward linearity.[12]

Tail orientation matters. Let the incremental spread of C_P relative to C_T (due to $b > r/n$) load predominantly on:

- **(Rare upside)** small–probability gains ($p < e^{-1}$). Then raising θ reduces the Choquet contribution of those states more under C_P than under C_T, so $\partial_\theta V_P < \partial_\theta V_T$, whence $\partial_\theta\Phi < 0$. Using $\partial_x\Phi > 0$ from A.2.1, the IFT gives

$$\frac{\partial x_P}{\partial\theta} > 0\,.$$

- **(Moderate/high probabilities)** events with $p > e^{-1}$. Then raising θ increases the Choquet mass more under C_P (higher slope) than under C_T, so $\partial_\theta V_P > \partial_\theta V_T$, hence

[12] For the decision–weight density $w'_\theta(p) = w_\theta(p)\,\theta(-\ln p)^{\theta-1}/p$, $\partial_\theta w'_\theta(p) = w'_\theta(p)\big[\theta^{-1} + \ln(-\ln p)\{1 - (-\ln p)^\theta\}\big]$. Hence $\partial_\theta w'_\theta(p)$ is negative near the extremes $p \approx 0, 1$ and positive over a wide middle range; the two sign–change thresholds $p_-(\theta) \in (0, e^{-1})$ and $p_+(\theta) \in (e^{-1}, 1)$ solve $\ln(-\ln p)\big((-\ln p)^\theta - 1\big) = 1/\theta$.

$\partial_\theta \Phi > 0$ and

$$\frac{\partial x_P}{\partial \theta} < 0\ .$$

Without a tail–orientation restriction, the sign of $\partial x_P/\partial\theta$ is ambiguous.

In Summary:

$$\frac{\partial x_P}{\partial \rho} \ >\ 0, \qquad \frac{\partial x_P}{\partial \delta}\ <\ 0, \qquad \frac{\partial x_P}{\partial \lambda_L}\ >\ 0, \qquad \frac{\partial x_P}{\partial \theta}\ \text{has sign depending on tail orientation (see A.2.5).}$$

A.3. Firm's Programme: First-Order Conditions and Comparative Statics

A.3.1 Profit Function $\Pi(\Theta)$. The firm posts $\Theta = (\,w_F,\, w_E,\, a,\, b,\, r,\, m)$. Let

$$\Pr_C(x,\phi,\lambda_L;\,\Theta) \ =\ \frac{\exp\big(V_C(x,\phi,\lambda_L;\,\Theta)\big)}{\sum_{D\in\{F,E,P,T\}} \exp\big(V_D(x,\phi,\lambda_L;\,\Theta)\big)}, \quad C \in \{F,E,P,T\}.$$

Each worker choosing C supplies effort $e^*_C(x,\phi,\lambda_L;\Theta)$. Denote by $\mathbb{E}_{x,\phi,\lambda_L}[\cdot]$ the expectation over the joint distribution of (x,ϕ,λ_L). Then

$$\Pi(\Theta) = \mathbb{E}\Big[\pi_F\,(xe^*_F - w_F) + \pi_E\,(xe^*_E - w_E) + \pi_P\,\big((1-b)\,xe^*_P - a\big) + \pi_T\,\big((1-r)\,xe^*_T - a\big)\Big] - \frac{\kappa}{2}m^2 - \frac{\eta_b}{2}b^2 - \frac{\eta_r}{2}r^2,$$

where the expectation is over the joint distribution of (x,ϕ,λ_L).[13]

A.3.2 First–order condition w.r.t. b. Only the $C = P$ term depends on b (besides the quadratic cost). Differentiating inside the expectation:

$$\frac{\partial}{\partial b}\Big\{\pi_P\big((1-b)\,xe^*_P - a\big)\Big\} = \pi_P\,\underbrace{\Big((1-b)\,x\tfrac{\partial e^*_P}{\partial b} - xe^*_P\Big)}_{\text{net incentive−pass-through}} + \underbrace{\Big((1-b)\,xe^*_P - a\Big)\,\tfrac{\partial \pi_P}{\partial b}}_{\text{sorting}}.$$

[13] We use $\mathbb{E}[\varepsilon] = 0$, so $\mathbb{E}[\text{bonus} \mid C = P] = b\,xe^*_P$ and $\mathbb{E}[\text{bonus} \mid C = T] = r\,xe^*_T$.

Hence

$$\frac{\partial \Pi}{\partial b} = \underbrace{\mathbb{E}\Big[\pi_P\, x\, \tfrac{\partial e_P^*}{\partial b}\Big]}_{\text{(i) marginal output gain}} - \underbrace{\mathbb{E}\Big[\pi_P\, b\, x\, \tfrac{\partial e_P^*}{\partial b}\Big]}_{\text{(ii-a) wage pass-through on } marginal \text{ output}} - \underbrace{\mathbb{E}\big[\pi_P\, x e_P^*\big]}_{\text{(ii-b) wage pass-through on } current \text{ output}}$$
$$+ \underbrace{\mathbb{E}\Big[x e_P^*\, \tfrac{\partial \pi_P}{\partial b}\Big]}_{\text{(iii) sorting effect on output}} - \underbrace{\mathbb{E}\Big[b\, x e_P^*\, \tfrac{\partial \pi_P}{\partial b}\Big]}_{\text{(iv-a) sorting effect on bonus bill}} - \underbrace{\mathbb{E}\Big[a\, \tfrac{\partial \pi_P}{\partial b}\Big]}_{\text{(iv-b) sorting effect on base pay}} - \eta_b\, b = 0.$$

The bracketed components have the usual interpretation: marginal net output gain via effort response, instantaneous wage pass-through on existing output, and the taste–share (sorting) effect.

A.3.3 Sign of $\partial b^*/\partial\rho$. Higher risk aversion lowers the marginal value of the risky bonus, reducing e_P^* and $\partial e_P^*/\partial b$, and it decreases π_P. Thus the first term falls and the last term becomes less positive, while the pass-through term is unchanged in sign. Total differentiation of the FOC yields $\partial b^*/\partial\rho < 0$.

A.3.4 Sign of $\partial b^*/\partial\lambda_L$. A higher disutility of effort λ_L reduces $\partial e_P^*/\partial b$ and π_P, so the net incentive and sorting terms fall. Hence $\partial b^*/\partial\lambda_L < 0$.

A.3.5 Sign of $\partial b^*/\partial\sigma^2$. Greater outcome noise σ^2 weakens the effectiveness of incentives, reducing $\partial e_P^*/\partial b$ and π_P. Therefore $\partial b^*/\partial\sigma^2 < 0$.

A.3.6 Sign of $\partial b^*/\partial\phi$. A higher preference index ϕ entails lower $\rho(\phi)$, higher $\delta(\phi)$, and *more linear* probability weighting (higher $\theta(\phi) \in (0,1)$). Each raises $\partial e_P^*/\partial b$ and π_P, making the incentive and sorting terms larger. Hence $\partial b^*/\partial\phi > 0$.

A.3.7 Team–bonus slope r. The same argument applied to the $C = T$ term gives

$$\frac{\partial r^*}{\partial\rho} < 0, \qquad \frac{\partial r^*}{\partial\lambda_L} < 0, \qquad \frac{\partial r^*}{\partial\sigma^2} < 0, \qquad \frac{\partial r^*}{\partial\phi} > 0,$$

and free-rider dilution implies $r^* < b^*$.

A.3.8 Wage Menu Parameters a, w_E, w_F. Similar first-order conditions and sign arguments hold for:

- a (the base salary in C_P and C_T): raising a increases both V_P and V_T through their bonus integrals, but because P relies more heavily on b, one checks that $\partial a^*/\partial\rho > 0$ etc.

- w_E (efficiency wage): enters V_E via $v(w_E \mid \Gamma)$ and the gift-exchange term $\xi(w_E - w_F)$. One shows $\partial w_E^*/\partial\rho < 0$ because higher ρ lowers the value of w_E relative to C_F.

- w_F (fixed contract): enters the reference point Γ, so one checks $\partial w_F^*/\partial\rho > 0$ and so on.

A.3.9 Monitoring Intensity m. If output variance $\sigma^2(m)$ fell in m, one would derive $\partial\Pi/\partial m = -\kappa\, m +$ (effect via $\sigma^2(m)$). In the simple case where σ^2 is exogenous, $\partial\Pi/\partial m = -\kappa\, m$, so $m^* = 0$.

Overall, the firm's FOCs yield:

$$\frac{\partial b^*}{\partial\rho} < 0, \quad \frac{\partial b^*}{\partial\lambda_L} < 0, \quad \frac{\partial b^*}{\partial\sigma^2} < 0, \quad \frac{\partial b^*}{\partial\phi} > 0,$$

and similarly for r^*. This completes the firm-side FOCs and comparative-static proofs.

Appendix B: Endogenizing Loss Aversion

Specification of $\psi(\phi)$

I extend the loss-aversion parameter to depend on the preference index ϕ:

$$\psi(\phi) \;=\; 1 \;+\; \beta_\psi \,\big(\frac{1}{1+\phi}\big), \quad \beta_\psi \in \mathbb{R}.$$

Here ψ_0 is the average loss-aversion at $\phi = \bar{\phi}$, and β_ψ captures how preferences shift loss aversion.

Comparative Statics on the Participation Cutoff x_P

The deterministic cutoff x_P solves

$$V_P\big(x_P, \phi, \lambda_L, \psi(\phi)\big) \;=\; V_F\big(\phi, \lambda_L, \psi(\phi)\big).$$

Differentiating implicitly with respect to ψ:

$$\frac{\partial x_P}{\partial \psi} = -\frac{\partial\big(V_P - V_F\big)/\partial\psi}{\partial\big(V_P - V_F\big)/\partial x}.$$

Since $\partial_\psi V_P < 0$ (greater ψ lowers the certainty-equivalent of a risky bonus) and $\partial_x(V_P - V_F) > 0$, it follows that

$$\frac{\partial x_P}{\partial \psi} \; > \; 0.$$

Comparative Statics on the Firm's Optimal Slope b^*

The firm's first-order condition for b can be written schematically as

$$\frac{\partial \Pi}{\partial b} = \underbrace{\mathbb{E}\big[x\,\partial_b e_P^*\big]}_{\text{marginal output gain}} \;-\; \underbrace{\Pr_P \,\mathbb{E}[b\,y]}_{\text{risk premium}} \;-\; \underbrace{\mathbb{E}\big[(a+b\,y)\,\partial_b \Pr_P\big]}_{\text{share effect}} - \eta_b b = 0.$$

An increase in ψ raises the risk premium the wage must cover, so

$$\frac{\partial b^*}{\partial \psi} \; < \; 0.$$

Appendix C: Reference Dependence with Decision Weights: Regularity

I assume:

(A1) $c(e,\varepsilon)$ is Borel-measurable with $c(e,\varepsilon) \in [c_{\min}, c_{\max}]$ and $c_{\min} > 0$ for all admissible (e,ε).

(A2) $v(c \mid \Gamma)$ is piecewise C^1 in c, with a single kink at $c = \Gamma$; $|v(c \mid \Gamma)| + |v'(c \mid \Gamma)| \leq K(1+c^\xi)$ for some $K, \xi > 0$.

(A3) Prelec weight $w_\phi : [0,1] \to [0,1]$ is C^1 on $(0,1)$ with $w_\phi'(p) > 0$ and $w_\phi(0) = 0$, $w_\phi(1) = 1$.

(A4) f_ε is continuous with bounded support as in (LL1).

Then the Choquet integral is well-defined and admits the density form

$$\int v(c)\, d\big[w_\phi(F(c))\big] = \int v(c)\, w'_\phi(F(c))\, f(c)\, dc,$$

and differentiation under the integral sign is valid by dominated convergence. Because v is piecewise smooth, all integrals split at $c = \Gamma$; e.g. in C_P,

$$\int v\big(a + b(xe+\varepsilon) \mid \Gamma\big)\, w'_\phi(F)\, f\, d\varepsilon = \int_{\mathcal{A}_+} \cdot\, d\varepsilon \;+\; \int_{\mathcal{A}_-} \cdot\, d\varepsilon,$$

where $\mathcal{A}_+ = \{\varepsilon :\, a + b(xe+\varepsilon) \geq \Gamma\}$ and $\mathcal{A}_- = \mathcal{A}_+^c$.

Temporal structure. I adopt exponential discounting with factor $\delta(\phi) \in (0,1)$, which preserves dynamic consistency. A quasi-hyperbolic $\beta{-}\delta$ extension is possible.

Well-posedness, interiority and uniqueness. Under (LL1)–(LL3) and (A1)–(A4), $U_C(e)$ is finite for all $e \geq 0$ and contracts $C \in \{P, T\}$. With $k(e) = \frac{\lambda_L}{1+\eta} e^{1+\eta}$, $k_e(e) = \lambda_L e^\eta$ is continuous, strictly increasing, and $\lim_{e\downarrow 0} k_e(e) = 0$, $\lim_{e\uparrow\infty} k_e(e) = \infty$.

For $C = P$, the FOC reads

$$\lambda_L e^\eta \;=\; \delta\, b\, x\, \mathbb{E}\big[v'\big(a + b(xe+\varepsilon) \mid \Gamma\big)\, w'_\phi(F(\varepsilon))\big] \equiv R_P(e).$$

Under (A1)–(A4), $R_P(e)$ is continuous and bounded on $[0,\infty)$, strictly decreasing in e whenever v' is decreasing (risk aversion) and $b > 0$. Therefore the equation $k_e(e) = R_P(e)$ has a unique solution $e_P^* \in [0,\infty)$ by the intermediate value theorem. The same argument applies to $C = T$.[14]

Appendix D: Microfoundation for the gift exchange contract

Let the worker's period-0 utility include a reciprocity term that complements intrinsic effort costs:

$$\tilde{U}_E(e) \;=\; v(w_E \mid \Gamma) \;-\; \tfrac{\lambda_L}{1+\eta}\, e^{1+\eta} \;+\; \eta_R\, (w_E - w_F)\, e,$$

[14]If $b = 0$ (or $r = 0$) the unique solution is $e^* = 0$.

where $\eta_R > 0$ captures reciprocal motivation to higher wages relative to the fixed baseline w_F. FOC: $\lambda_L e^{\eta} = \eta_R (w_E - w_F)$, hence

$$e_E^* \ = \ \gamma\,(w_E - w_F), \qquad \gamma \equiv \big(\eta_R/\lambda_L\big)^{1/\eta}.$$

Thus the reduced-form rule used in the main text is the equilibrium effort under a simple reciprocity microfoundation.[15]

Appendix E: IIA in MNL and Two Feasible Remedies

With i.i.d. Gumbel$(0, \sigma_\varepsilon)$ errors, the multinomial logit (MNL) choice probabilities are

$$\Pr_C = \frac{\exp\{V_C/\sigma_\varepsilon\}}{\sum_{D\in\{F,E,P,T\}} \exp\{V_D/\sigma_\varepsilon\}}, \qquad C \in \{F, E, P, T\}.$$

MNL implies *Independence of Irrelevant Alternatives* (IIA): for any i, k,

$$\frac{\Pr_i}{\Pr_k} = \exp\big\{(V_i - V_k)/\sigma_\varepsilon\big\}, \tag{G.1}$$

which is invariant to the presence or attributes of other contracts. Because $\{P, T\}$ (bonus) are economically more similar to each other than to $\{F, E\}$ (non-bonus), IIA may overstate substitution from non-bonus into bonus when bonus attributes change.

E.1 Nested Logit (Bonus vs. Non-Bonus) Partition contracts into two nests:

$$\mathcal{N}_0 = \{F, E\} \quad \text{(no bonus)}, \qquad \mathcal{N}_1 = \{P, T\} \quad \text{(bonus)}.$$

Let $\lambda_k \in (0, 1]$ denote nest dissimilarity. Define inclusive values

$$IV_k = \left(\sum_{C\in\mathcal{N}_k} \exp\left(\frac{V_C}{\lambda_k}\right)\right)^{\lambda_k}, \quad k \in \{0, 1\}. \tag{G.2}$$

[15] See, e.g., gift-exchange and reciprocity models in efficiency-wage settings. Any alternative social-preferences specification yielding a linear-in-wage effort best response is equally compatible.

Choice probabilities factor as

$$\Pr(C) = \Pr\left(C \mid \mathcal{N}_k\right) \cdot \Pr(\mathcal{N}_k), \qquad C \in \mathcal{N}_k, \tag{G.3}$$

$$\Pr\left(C \mid \mathcal{N}_k\right) = \frac{\exp\left(V_C/\lambda_k\right)}{\sum_{D\in\mathcal{N}_k} \exp\left(V_D/\lambda_k\right)}, \tag{G.4}$$

$$\Pr(\mathcal{N}_k) = \frac{IV_k}{IV_0 + IV_1}. \tag{G.5}$$

Setting $\lambda_0 = \lambda_1 = 1$ recovers MNL; $\lambda_k < 1$ allows correlated unobservables within nests and concentrates substitution between P and T.

E.2 Error–Components Logit (Common Bonus Orientation) Introduce a common random effect α_B for the bonus alternatives:

$$\begin{aligned} U_P &= V_P + \alpha_B + \epsilon_P, & U_T &= V_T + \alpha_B + \epsilon_T, \\ U_F &= V_F + \epsilon_F, & U_E &= V_E + \epsilon_E, \end{aligned} \tag{G.6}$$

with ϵ_C i.i.d. Gumbel and α_B mean-zero. Conditional on α_B the model is MNL; unconditional choice averages over α_B:

$$\Pr(C) = \int \frac{\exp\left(V_C + \mathbf{1}\{C \in \{P,T\}\}\alpha_B\right)}{\sum_D \exp\left(V_D + \mathbf{1}\{D \in \{P,T\}\}\alpha_B\right)} \, dF(\alpha_B). \tag{G.7}$$

This nests the baseline (set $\alpha_B \equiv 0$) and induces positive correlation within the bonus nest, again focusing substitution between P and T.

Remark. Both specifications are standard, tractable relaxations that preserve our qualitative comparative statics while avoiding the strongest implications of IIA. We keep the MNL baseline in the main text and note these options for completeness.

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