sociological science

Bending the Heckman Curve: Competing Declines in Learning Capacity and Skill Relevance Over the Life Course

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Abstract: The Heckman curve has powerfully influenced social policy by providing mathematical support for the concentration of human-capital investments early in the life course. The canonical model behind this curve derives a single relationship for aggregate human capital and does not address how return trajectories vary across skill types. We extend the canonical mathematical framework to derive skill-specific return trajectories, incorporating two key parameters governing declines in (a) human capacity to learn and (b) skill relevance over the life course. Our microfoundation model implies that the shape of return trajectories depends on the relative magnitudes of these two declines, indicating a trade-off: although early investments may be more efficient due to declining human learning capacity, they risk misalignment with future labor market needs. Depending on the targeted skill, investments in adult workers might more effectively align with evolving skill content. We illustrate this result with numerical simulations using empirically plausible parameter ranges and selected skill profiles. Our work suggests that optimal investment timing may be skill-dependent, and identifies empirical questions that can better inform human-capital policy in a time of rapid technological change and lengthening lifespans.

Keywords: life course; human capital investments; education and social policy; microlevel modeling; analytical sociology

Data and code availability statement. This paper does not use external data. Full replication code for numerical simulations and figures available at: https://github.com/joaosoutomaior/competing-declines-code.

Citation: Souto-Maior, João M., and Mitchell L. Stevens. 2026. "Bending the Heckman Curve: Competing Declines in Learning Capacity and Skill Relevance Over the Life Course" Sociological Science 13: 915-944.

Received: April 9, 2026

Accepted: June 16, 2026

Published: August 4, 2026

Editor(s): Stephen Vaisey, Herman van de Werfhorst

DOI: 10.15195/v13.a35

At what stage in life do investments in human talent yield the greatest returns? Governments, firms, families, and individuals all face resource constraints that make this question fateful. Public budgets require choices between early childhood programs and adult reskilling initiatives. Firms allocate training resources across workers at different career stages. Families and individuals must decide when their own investments might yield the greatest return. Understanding how returns vary over the life course can inform these decisions.

The "Heckman curve," named after Nobel laureate James Heckman, who developed the framework (Carneiro and Heckman 2003; Heckman 2006), models the relative payoff of investments in human capital over the life course. Informed by evidence documenting that it is relatively easier to learn many skills (Knudsen 2004) early in life, the curve shows that marginal returns to investments decline with the age of beneficiaries. This idea has been highly influential in the human-capital tradition and in policy debates, serving as an argument for the prioritization of early-childhood investment (Camaione and Muchabaiwa 2021; Council of Economic Advisers 2015; Penn 2011). Its influence reflects both theoretical intuition and alignment with enduring cultural presumptions about the life course: the plasticity of the young, and the notion of childhood as a distinct and privileged stage of life (Bandelj 2026; Barnes et al. 2024; Johfre and Saperstein 2023; Stevens 2009; Zelizer 1985). However, as sociologists have long recognized, models of the life course have a strong normative character: they may impose trajectories as much as describe them (Brückner and Mayer 2005; Neugarten et al. 1965; Settersten 2003; Settersten and Mayer 1997). This insight makes it especially important to consider the conditions under which a functional form with life-course implications holds or varies across domains, historical periods, and economic contexts (Gruijters et al. 2023; Shanahan 2000).

Although powerful, the original framework has an important constraint: it treats timing of investment as a single conceptual problem. In its classic form, the Heckman curve addresses the question: "When in the life course do investments yield the highest returns to aggregate human capital?" It then depicts a single relationship—where the outcome of interest is aggregate human capital—and does not explore whether or to what extent its functional form might vary for different types of skills.[1] In the decades since its initial publication, however, social science and policy discourse on human capital investment has advanced substantially. Researchers and policy analysts increasingly emphasize the importance of skill-specific outcomes (Atalay et al. 2020; Deming 2017; Deming et al. 2025; Liu and Grusky 2013), raising a related but distinct question: "When in the life course do investments in a specific skill yield the highest returns to that skill?" Once the question is posed at the level of specific skills, it becomes clear that the canonical curve abstracts from an additional life-course process that is increasingly salient amid rapid technological change (Acemoglu et al. 2022; Deming et al. 2025) and lengthening working lives (Berkman and Truesdale 2022; Ghilarducci 2024; Scott 2024): potential decline in skill relevance over the life course as the task content evolves (Atalay et al. 2020; Deming and Noray 2020; Hudomiet and Willis 2022; Lentini and Gimenez 2019).

Our work here extends the mathematical framework underlying the Heckman curve to derive skill-specific return trajectories, allowing optimal investment timing to depend on two parameters (learning capacity and relevance decline) rather than one (learning capacity only). Mathematical deductions from our proposed model show that optimal investment timing depends on the relative rates of decline in these two competing processes. When learning capacity declines faster than skill relevance, early investments yield the greatest returns. Conversely, when skill relevance declines faster than learning capacity, later investments can be more productive than earlier ones. We emphasize that these are deductive conclusions that follow directly from our modeling assumptions; they are not empirical findings. The value of our framework lies in making explicit the logical implications of relaxing the canonical model's implicit assumption of no skill relevance decay.

We illustrate our mathematical result through simulations using empirically plausible parameter ranges, but do not attempt empirical estimation. Instead our work completes the necessary prior task of building an explicit theoretical motivation and setting hypotheses for future empirical inquiry. In doing so we follow the analytical-sociology tradition of using formal modeling to make theoretical assumptions explicit, derive macrolevel implications of microlevel assumptions, and generate testable propositions that can guide empirical research (Fararo 1992; Hedstrom 2005; Jasso 1988; Manzo 2014, 2025). Our intervention clarifies that debates about "when to invest" are skill-dependent, and surfaces empirical questions whose answers can profitably inform the timing of human capital investments in an era of rapid technological change and lengthening lifespans.

Motivation

Technological change, particularly AI, is reshaping work (Behrend et al. 2024; Brynjolfsson et al. 2025; Capraro et al. 2024; Lei and Kim 2024) and bringing new uncertainty about which skills will remain valuable in the future (Acemoglu et al. 2022; Autor 2022; Sigelman et al. 2022). This is especially important given increases in life expectancy and in length of working lives (Berkman and Truesdale 2022; Ghilarducci 2024; Scott 2024), which further magnify uncertainty about how to prepare for a long career (Stanford Center on Longevity 2025). Preparing for this uncertainty requires complex decisions about career trajectories and training investments.

Amid this uncertainty, researchers and policy analysts increasingly focus on skill-specific investments, debating the kinds of skills that are likely to yield the greatest returns in the future (Krakowski et al. 2023; Mäkelä and Stephany 2024; Raisch and Krakowski 2021). A sizable chorus emphasizes the potential of technological advancements to substitute for many human cognitive and technical abilities, highlighting that investments in soft skills (e.g., communication, teamwork, emotional intelligence, and decision-making) will yield the best future returns as those remain less substitutable by machines and as durable hedges against technological change (Balasubramanian et al. 2022; Belcher 2025; Fitzgerald 2025; Gunther et al. 2025). In contrast, others emphasize the complementarity between technology and human cognitive skills, highlighting that investments in foundational cognitive skills (e.g., literacy, numeracy, and critical thinking) will remain key drivers of worker productivity (Murray et al. 2021; Raisch and Fomina 2025; Reed 2020; Topol 2019). Still others emphasize context-specific technical abilities (e.g., AI literacy, prompt engineering, and other emerging capabilities) alongside building flexible skill portfolios that provide resilience as demands shift (Knoth et al. 2024; Korzynski et al. 2023; Tamayo et al. 2023; Whiting 2023).

These analyses reflect growing recognition that investments in specific skills may be important determinants of resilience for individual careers and entire economies. This skill-differentiated policy discourse motivates the need for theoretical tools that can formalize optimal timing for investments in specific skills rather than aggregate human capital. Existing policy discourse already points to two key skill-specific characteristics that might shape return trajectories. First, skills exhibit different age-acquisition profiles, what we call *rates of decline in human learning capacity* over the life course. Recommendations that current workers should prioritize investing in selected technical abilities (e.g., AI literacy and prompt engineering) implicitly recognize that other skills (e.g., foundational ones such as numeric reasoning and language abilities), although potentially beneficial, are much harder to acquire later in life. Studies in cognitive neuroscience and psychology support this intuition, documenting substantial variation in age-related learning decline across skill types—see Gignac and Zajenkowski (2025) for a recent review. Foundational cognitive skills such as language and verbal abilities exhibit steep age-related decline (Knudsen 2004; Newport 1990; Pinker 2003), whereas the ability to learn socio-emotional skills, cooperate, or gain from experience are more stable over the life course (Charles and Carstensen 2010; Cutler et al. 2021; Lin et al. 2025; Scheibe and Carstensen 2010; Westhoff et al. 2020).

Second, beyond how easily they can be learned at different ages, skills also differ with respect to what we call *rates of decline in skill relevance* over the life course. Specifically, this concept captures that as the task content of a skill evolves, proficiency in tasks relevant in period t contributes less to one's skill level in period $t+1$. As technologies and organizational practices change, labor market demands shift, redefining which task competencies remain relevant and altering what constitutes proficiency within a given skill (Braxton and Taska 2023; Horton and Tambe 2025). When this happens, workers are obliged to acquire new task competencies to maintain proficiency in that skill domain (Deming and Noray 2020; Lentini and Gimenez 2019; Schultheiss and Backes-Gellner 2023).[2]

For example, the skill of software development has shown substantial content evolution: proficiency in this skill was once defined by competencies in platforms like Adobe Flash and languages like ActionScript, but as these became obsolete, workers had to acquire competencies in different platforms and languages (HTML5, CSS, and Java) to maintain their software development proficiency (Deming and Noray 2020; Horton and Tambe 2025). A perhaps closer example for our readers concerns quantitative social science research: in the 1990s, proficiency was largely defined by tasks related to the survey design and regression analyses in SPSS/Stata; today the same skill comprises a wider range of tasks, including R/Python programming and more computationally intensive methods (machine learning, text analysis, and network analysis). In both cases, earlier-acquired task proficiencies contribute less to current skill level than they once did, reducing the complementarity between past and present skill stocks in the production function.

Importantly, skills vary substantially in their rates of task content evolution, and thus also in their rates of relevance decline (Brumberger and Lauer 2015; Deming and Noray 2020; Gallavin et al. 2004; Hudomiet and Willis 2022; Lentini and Gimenez 2019; Todd et al. 1995). Although technical skills such as software development and quantitative research have experienced rapid task content change, socio-emotional skills (e.g., interpersonal communication, cooperation, and leadership) arguably comprise more stable task sets. Core tasks such as active listening, persuasive communication, collaborative teamwork, and relationship-building have remained largely unchanged despite shifting platforms (in-person, phone, email, and video) and application contexts (Deming 2017; Deming and Noray 2020). For these skills, earlier-acquired task proficiencies retain their productive value over longer time horizons.

Although the mathematical foundations of the Heckman curve incorporate a parameter capturing the rate of decline in learning capacity, we still lack a formal

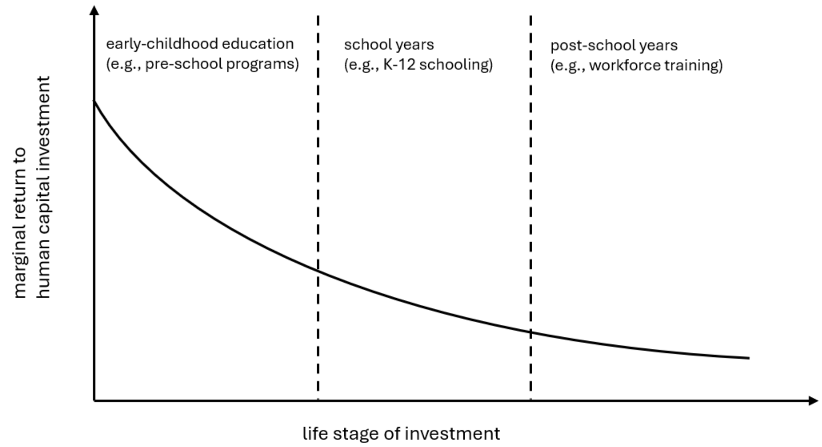

Figure 1: Representation of the Heckman curve—see Heckman (2006) for detailed discussion. The plot describes a conceptual model of how the marginal return to human capital investment (y axis) varies over the life stage of investment (x axis).

framework to systematically consider the decline in skill relevance over time and how these two processes interact to influence optimal investment timing. Our work formalizes both parameters within a unified mathematical model, extending the core logic of the Heckman curve to derive skill-specific return trajectories.

Prior Work

The Heckman curve, Figure 1, is a theoretical construct comparing marginal returns to human capital investments at different stages of the life course (Carneiro and Heckman 2003; Heckman 2006). These investments include efforts and interventions made by individuals, families, and social institutions such as schools. The curve identifies investments in early childhood as having the highest potential returns: "[c]eteris paribus, the rate of return to a dollar of investment made while a person is young is [exponentially] higher than the rate of return to the same dollar made at a later age" (Carneiro and Heckman 2003: p. 90). This result is often interpreted as an axiom for public policy, providing, as Heckman himself puts it, an "eye-opening understanding that society invests too much money in later development when it is often too late to provide great value" (The Heckman Equation website n.d.).

The curve is largely attributed to a theoretical mathematical model[3] of skill formation during childhood (Cunha and Heckman 2007) and subsequent extensions (Cunha and Heckman 2008; Cunha et al. 2010)—henceforth the canonical model. Building on evidence that learning plasticity declines with age for key knowledge domains such as language (Knudsen 2004; Newport 1990; Pinker 2003)—our notion of decline in human learning capacity—the canonical model demonstrates that early investments are difficult to compensate for later on. This complementarity across periods yields higher marginal returns for early investments. When extrapolated over the life course, this result provides the foundation for the Heckman curve.

The Canonical Model

The canonical model provides a formal mathematical framework to describe how investments in skill formation during childhood contribute to an individual's stock of skills as they enter adulthood. This was an important contribution since, at the time of its publication, economic models generally treated childhood as a single period in the life course. Dividing childhood into multiple periods brought novel insight. In the following, we describe the canonical formulation in detail. We largely follow the original notation but make minor adaptations to improve readability and facilitate the extensions we present later.

Let childhood be defined by t periods, where $t \in \{1, \dots, T\}$. Let I_t denote the level of skill investment during period t, and let θ_t denote the agent's stock of skills at the end of period t. At the start of the model, agents are endowed with an exogenous stock of skills acquired at birth, θ_0 (e.g., genetic conditions and innate ability), and are characterized by parental characteristics, h (e.g., parental education, family resources, etc.), both treated as constants. An agent's θ_t can be written as a function (f_t) of their prior stock of skills θ_{t-1}, their level of skill investment in period t, I_t, and the characteristics of their parents, h:

$$\theta_t = f_t(\theta_{t-1}, I_t, h). \tag{1}$$

The canonical model specifies f_t using a constant elasticity of substitution (CES) functional form, emphasizing two key features of skill formation. First, inputs are partial substitutes: each can independently bolster skill formation in period t through its own current-period productivity effect. Second, inputs are partial complements: the contribution of one input depends partly on the level of the other inputs. Although the canonical model leaves the functional form of f_t partially unspecified, we follow its empirical implementation (Cunha et al. 2010) by applying the CES specification to all inputs, writing θ_t as

$$\theta_t = \left(\beta_1 h^{\phi} + \beta_2 \theta_{t-1}^{\phi} + \gamma_t I_t^{\phi}\right)^{\frac{1}{\phi}}, \quad \forall t \in 1, \dots, T. \tag{2}$$

Here, $\beta_1 \geq 0$ captures the productivity of parental characteristics, $\beta_2 \geq 0$ captures the productivity of prior skills, and $\gamma_t \geq 0$ captures the productivity of period-t investments. This parameter captures the notion of learning capacity: higher γ_t indicates that investments at age t yield greater skill formation. The parameter $\phi \in (-\infty, 1]$ determines the elasticity of substitution between all inputs, $\sigma \in (0, \infty)$, where $\sigma = \frac{1}{1-\phi}$. The elasticity of substitution captures the extent to which inputs substitute for (or, conversely, complement) one another. When $\sigma \to 0$ (i.e., $\phi \to -\infty$), the skill production function converges to perfect complementarity across inputs; when $\sigma \to \infty$ (i.e., $\phi \to 1$), the function converges to perfect substitutability across inputs.

In the canonical model, γ_t is the only time-varying parameter. Time variation in γ_t captures age-related decline in learning capacity: as individuals age, the same unit of investment produces less skill formation (Knudsen et al. 2006; Newport 1990). This decline in the productivity of investments over time provides the central theoretical foundation for the Heckman curve.

The objective function of interest is θ_T, the individual's stock of skills at the end of childhood, marking the onset of adulthood and, typically, the period of labor-market entry. To compare the returns of relatively earlier and later investments, let e and l denote two different periods such that e occurs before l ($e < l$). Then, as shown in Online Supplement A, the ratio of marginal productivity of a later investment compared to that of an earlier one ($R_{l,e}$) equals

$$R_{l,e} = \frac{\gamma_l}{\gamma_e}. \tag{3}$$

This mathematical result indicates that relatively earlier investments have higher marginal returns than later ones ($R_{l,e} < 1$) whenever learning capacity in the early period is higher than in the later period (i.e., $\gamma_e > \gamma_l$). As the curve's creators have argued (Cunha and Heckman 2007; Cunha et al. 2006; Heckman 2006, 2008; Knudsen et al. 2006), evidence on the importance of sensitive periods for the development of foundational cognitive skills, such as language and verbal abilities (Knudsen et al. 2006; Newport 1990), supports the notion that learning capacity declines with age ($\gamma_e > \gamma_l$). In this sense, the canonical framework provides a compelling account of why earlier interventions can be especially beneficial (relative to later ones) and, thus, sets out the microfoundations for the Heckman curve.

Prior Efforts to Accommodate Skill Heterogeneity

Work in this tradition has recognized that a person's stock of skills comprises different skill types (Cunha and Heckman 2007; Cunha et al. 2010). Indeed, the seminal empirical application of the canonical model estimates distinct production functions for cognitive and noncognitive skills (Cunha et al. 2010), disaggregating the skill stock into $\vec{\theta}_t = (\theta_{t,c}, \theta_{t,n})$ where the subscript c denotes cognitive and n denotes noncognitive skills. This allows separate production functions for each skill type:

$$\theta_{t,c} = f_t(h, \theta_{t-1,c}, I_{t,c}, \theta_{t-1,n}, I_{t,n}); \tag{4}$$

$$\theta_{t,n} = f_t(h, \theta_{t-1,n}, I_{t,n}, \theta_{t-1,c}, I_{t,c}). \tag{5}$$

Such an extension enabled the estimation of skill-specific parameters and revealed complementarities between skill types in producing aggregate human capital indicators such as educational attainment and reduced criminal activity (Cunha et al. 2010).

However, such extensions differ fundamentally from the goal of this paper. Despite estimating separate production functions for cognitive and noncognitive skills, discussions of Heckman-curve-style return trajectories in prior work have focused on the maximization of aggregate outcomes (e.g., educational attainment and crime reduction) rather than skill-specific returns. The policy objective has remained maximizing aggregate human capital indicators expressed as functions of both skill types (Cunha et al. 2010), $\theta_T = f_g(\theta_{T,c}, \theta_{T,n})$.

Given that focus, investments were operationalized as undifferentiated inputs (I_t) that simultaneously affect multiple skill types. Work to date has not explored whether different skill types might exhibit distinct return trajectories (i.e., whether the Heckman curve's shape itself varies by skill type) or whether investments should be timed differently depending on which skill is being developed.

Deriving skill-specific return trajectories requires explicitly modeling mechanisms that generate temporal differences across skill types over the life course. In the following section, we develop such a framework.

Modeling Skill-Specific Curves

Here, we extend the canonical model to address the question of "When in the life course do investments in a specific skill yield the highest returns to that skill?" Central to our extension is the incorporation of two sources of skill-specific variation: rates of decline in (a) human learning capacity and (b) skill relevance over the life course. We then derive return trajectories for specific skills rather than aggregate human capital.

Skill-Specific Production Function

We begin from the skill-specific production functions in the canonical framework (Eqs. 4 and 5) and generalize the cognitive/noncognitive distinction to allow for any skill profile p. Let $\theta_{t,p}$ denote the stock of a particular skill profile p at time t, and let $\theta_{t,p'}$ denote the stock of complementary skills, p', at time t. Let $I_{t,p}$ denote investments in skill profile p at time t and $I_{t,p'}$ denote investments in complementary skill profile p' at time t. The production function for $\theta_{t,p}$ can be written as

$$\theta_{t,p} = f_t(h, \theta_{t-1,p'}, I_{t,p'}, \theta_{t-1,p}, I_{t,p}). \tag{6}$$

Deriving skill-specific return trajectories implies isolating investments in a focal skill ($I_{t,p}$) from the levels of ($\theta_{t,p'}$) and investments ($I_{t,p'}$) in other skills. Intuitively, the question we examine here is a conditional one: given existing capabilities, when should investment in a specific skill occur? This framing is consistent with policy and practical contexts. A firm deciding when to train workers in a specific technical skill, or an individual choosing when to acquire a particular certification, typically takes existing skill stock as given. We therefore treat $\theta_{t,p'}$ and $I_{t,p'}$ as exogenous to our optimization problem.

We can then simplify the production function by absorbing investments in complementary skills ($I_{t,p'}$) into the evolution of the complementary skill stock ($\theta_{t,p'}$)—i.e., for the maximization of $\theta_{t,p}$, what matters is the realized level of complementary skills at each period, not how those skills were produced.[4] This reduces the production function of skill profile p to

$$\theta_{t,p} = f_t(\theta_{t-1,p'}, h, \theta_{t-1,p}, I_{t,p}). \tag{7}$$

Following the canonical model, we apply the CES specification to all inputs. We write the production function for skill profile p as

$$\theta_{t,p} = \left(\beta_1 h^{\phi_p} + \beta_2 \theta_{t-1,p'}^{\phi_p} + \alpha_p \theta_{t-1,p}^{\phi_p} + \gamma_{t,p} I_{t,p}^{\phi_p}\right)^{\frac{1}{\phi_p}}, \quad \forall t \in 1, \ldots, T. \tag{8}$$

As in the canonical model, $\beta_1 \geq 0$ captures the productivity of parental characteristics and $\beta_2 \geq 0$ captures the productivity of complementary skills, $\gamma_{t,p} \geq 0$ captures learning capacity in period t, and $\phi_p \in (-\infty, 1]$ determines the elasticity of substitution between inputs.

Importantly, to reflect the possibility of skill relevance decline due to task content evolution, our extension introduces a per-period relevance retention rate $\alpha_p \in [0, 1]$, which captures the productive value that prior-period skill stock retains in the current period. In the canonical model, this parameter is implicitly set to 1 (no task content evolution). When $\alpha_p < 1$, the model allows for the skill content to evolve and discounts the contribution of the prior period's skill stock in the production of current skill. Importantly, this does not imply that prior skill stocks cease to matter entirely—proficiency in largely obsolete tasks may still support the acquisition of newly relevant ones. Rather, when the task content changes, earlier-acquired proficiencies contribute less to current skill level than they would if content had remained constant.

Temporal Scope and Objective Function

As reviewed earlier, the canonical framework was originally designed for the analysis of childhood development. The model's temporal scope defines childhood by T periods, where $t \in 1, \ldots, T$, with the stock of skills at the end of childhood, θ_T, as the quantity of interest—typically interpreted as skills at labor-market entry. This constrained temporal scope differs from what the Heckman curve proposes, as it is intended to inform investment decisions throughout the life course and not just childhood.

To derive return trajectories consistent with the Heckman curve's life-course perspective, we extend the canonical model's time horizon, setting the evaluation period T to represent peak earning years rather than the end of childhood. Peak earning years provide a natural benchmark for assessing the productive value of accumulated human capital, as they capture a period of high labor market activity, full skill deployment, and key contributions to lifetime earnings (Guvenen et al. 2021; Haider and Solon 2006). We maintain the period structure $t \in 1, \ldots, T$, where each period represents n years of life.

For all numerical illustrations that follow, we set $n = 5$ years per period and $T = 11$, such that $t = 1$ captures ages 0–4, $t = 2$ captures ages 5–9, and so forth, with $t = T = 11$ representing ages 50–54—consistent with empirical evidence on peak earning years (Guvenen et al. 2021; Haider and Solon 2006). This approach preserves the mathematical structure of the canonical framework while aligning it with the Heckman curve's scope. Importantly, our core mathematical result—the relative productivity of investments across periods—is independent of the specific T chosen (see Online Supplement B). The choice of $T = 11$ therefore provides interpretability without affecting the relationship between earlier and later investments.

As in the canonical model, this approach is designed to focus on one mechanism that leads early and late investments to differ: complementarity across periods. Naturally, for policy decisions, another relevant mechanism is that early investments generate returns over more periods. The extension presented here, like the canonical Heckman curve framework, models the first mechanism only. This fixed-horizon approach is most directly applicable to contexts where skill acquisition requires extended development and where investments prepare for anticipated deployment rather than immediate use. Such forward-looking investments are prominent in practice: policymakers preparing workforces for future needs, firms investing in employees' long-term capabilities, and training decisions during formal schooling or early adulthood that prepare for anticipated deployment rather than immediate application.

Given the foundational production function presented earlier and the revised time horizon, we now specify the rates at which learning capacity $\gamma_{t,p}$ and skill relevance α_p decline over time.

Rate of Decline in Human Learning Capacity over Time

To explicitly model the rate of decline in human learning capacity over time for each skill profile p, we introduce a decline parameter $\delta_{\text{learning},p} \in [0,1]$, which captures the yearly rate at which learning capacity diminishes.

For each period t—representing n years—we define learning capacity $\gamma_{t,p}$ as an exponential function of $\delta_{\text{learning},p}$:

$$\gamma_{t,p} = \left(\frac{1}{1 + \delta_{\text{learning},p}} \right)^{n(t-1)}. \tag{9}$$

This specification normalizes learning capacity in the first period to 1 ($\gamma_{1,p} = 1$) and ensures $\gamma_{t,p} \in (0,1]$ for all t, with learning capacity declining monotonically when $\delta_{\text{learning},p} > 0$.

Although a stylized approximation, this exponential specification reflects the compounding nature of age-related neurobiological decline: each year's reduction in plasticity operates on the remaining capacity, producing multiplicative rather than additive effects over time (Knudsen et al. 2006; Salthouse 2019).

Figure 2a illustrates how learning capacity $\gamma_{t,p}$ declines as a function of the decline parameter $\delta_{\text{learning},p}$. When there is no yearly decline ($\delta_{\text{learning},p} = 0$ percent), $\gamma_{t,p} = 1$ for all t. When $\delta_{\text{learning},p} > 0$ percent, learning capacity declines with time. As the decline parameter $\delta_{\text{learning},p}$ increases, learning capacity declines faster with time. For example, when each period represents a 5-year window, with $\delta_{\text{learning},p} = 1$ percent, learning capacity for skill profile p at period 11 (ages 50–54) equals 61 percent of the learning capacity in period 1. With $\delta_{\text{learning},p} = 5$ percent, this share falls to approximately 9 percent.

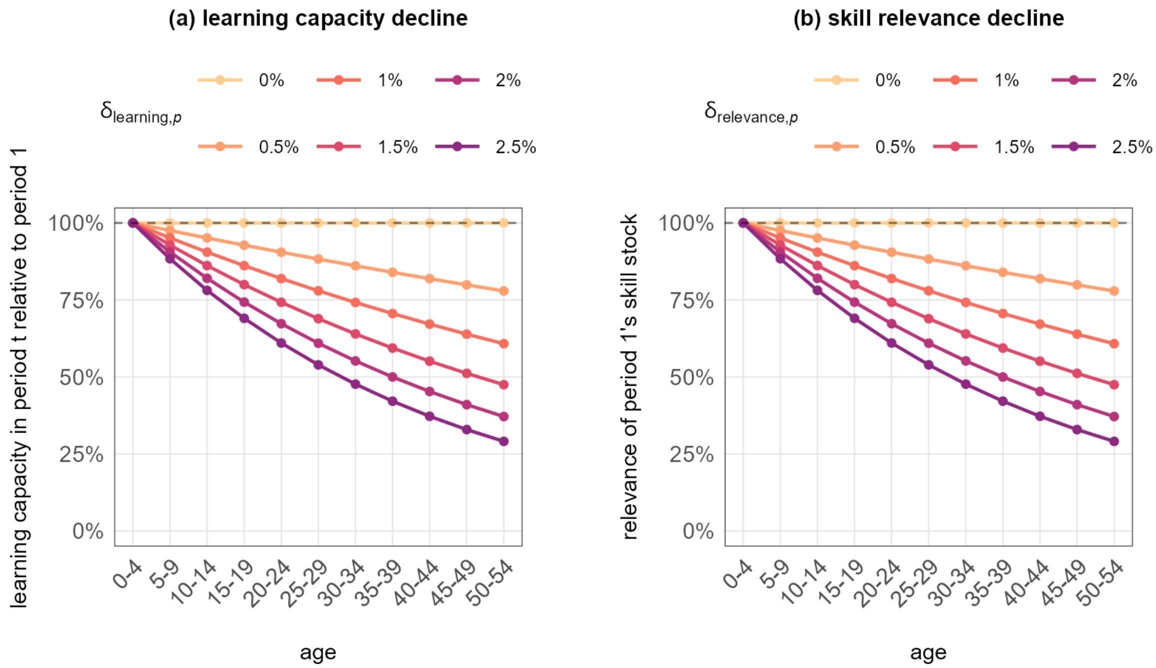

Figure 2: Functional form of declines in learning capacity and skill relevance over the life course. Both panels set $n = 5$ (years per period) and $T = 11$ (latest period capturing ages 50–54). (a) Learning capacity decline over the life course (Eq. 9), plotting $\gamma_{t,p}$ for different yearly decline rates $\delta_{\text{learning},p}$. (b) Skill relevance decline, plotting the productive value of period-1 skill stock over time (α_p^{t-1}) for different yearly skill content change rates $\delta_{\text{relevance},p}$ (Eq. 11).

Rate of Decline in Skill Relevance over Time

As discussed earlier, the relevance of prior skill stocks in the production of current-period skill declines as the skill content evolves. To model the rate of decline in skill relevance over time for each skill profile p, we introduce parameter $\delta_{\text{relevance},p} \in [0,1]$, which captures the yearly rate at which previously acquired task proficiencies lose their productive value within skill domain p.

For each period t—representing n years—we define the per-period skill relevance retention rate α_p as an exponential function of $\delta_{\text{relevance},p}$:

$$\alpha_p = \left(\frac{1}{1+\delta_{\text{relevance},p}}\right)^n. \tag{10}$$

This specification ensures $\alpha_p \in (0,1]$. When $\delta_{\text{relevance},p} = 0$, we have $\alpha_p = 1$ and prior-period skills fully retain their productive value. As $\delta_{\text{relevance},p}$ increases, α_p decreases, reflecting faster decline in the relevance of previously acquired task proficiencies.

To understand how this per-period retention rate (α_p) translates into skill relevance decline over multiple periods, we substitute Eq. 10 into the α_p^{t-j} term that enters the nonrecursive production function (Eq. 19 in Online Supplement A). This yields

$$\alpha_p^{t-j} = \left(\frac{1}{1+\delta_{\text{relevance},p}} \right)^{n(t-j)}. \tag{11}$$

This formulation makes clear that each investment is discounted relative to the time at which it was originally acquired. More distant investments (i.e., those from earlier periods) receive lower weights, and more recent investments receive higher weights, capturing the compounding effects of task content evolution over time.

Further, this shows that the functional form of Eq. 10 implies that skill relevance declines exponentially with temporal distance. Although stylized, this exponential specification reflects empirically observed patterns of skill depreciation over working careers. Deming and Noray (2020) demonstrate that life-cycle wage returns decline exponentially for workers in fields characterized by rapid task content evolution while remaining relatively stable for similar individuals working in fields which have observed slower content evolution. As discussed in more detail in the Numerical Simulations section, these career-specific depreciation patterns directly support our notion of skill relevance decline. When workers continuously deploy skills in domains where the task content changes rapidly, earlier-acquired proficiencies lose relevance for maintaining current skill levels—precisely the mechanism our $\alpha_p < 1$ parameter captures.

Figure 2b illustrates this exponential decline for different values of $\delta_{\text{relevance},p}$. For instance, when $\delta_{\text{relevance},p} = 1$ percent, $\theta_{0,p}$ will retain approximately 58 percent of its productive value by $t = 11$ ($\alpha_p^{11} = (\frac{1}{1+0.01})^{11 \cdot 5} \approx 0.58$). Similarly, $I_{1,p}$ will be weighted by 0.61 ($\alpha_p^{11-1} = (\frac{1}{1+0.01})^{5(11-1)} \approx 0.61$), and $I_{10,p}$ will be weighted by 0.95 ($\alpha_p^{11-10} = (\frac{1}{1+0.01})^{5(11-10)} \approx 0.95$), with other investments weighted by values in between.

Mathematical Result: Competing Declines in Learning Capacity and Skill Relevance over Time

Here, we apply our model to assess the relative productivity of different-period investments. As in our description of the canonical model, to compare the returns of relatively earlier and later investments, let e and l denote two different periods such that e occurs before l ($e < l$). Following the demonstration in Online Supplement A, the ratio of marginal productivity of a later investment compared to that of an earlier one ($R_{l,e,p}$) can be expressed as

$$R_{l,e,p} = \left(\frac{1+\delta_{\text{relevance},p}}{1+\delta_{\text{learning},p}} \right)^{n(l-e)}. \tag{12}$$

By definition, $n > 0$, $e > 0$, $l > 0$, and $l > e$. We then find the conditions under which the marginal productivity of a relatively earlier investment is higher

($R_{l,e,p} < 1$), lower ($R_{l,e,p} > 1$), or equal ($R_{l,e,p} = 1$) to that of a later one:

$$R_{l,e,p} < 1 \iff \delta_{\text{learning},p} > \delta_{\text{relevance},p}, \tag{13}$$
$$R_{l,e,p} = 1 \iff \delta_{\text{learning},p} = \delta_{\text{relevance},p}, \tag{14}$$
$$R_{l,e,p} > 1 \iff \delta_{\text{learning},p} < \delta_{\text{relevance},p}. \tag{15}$$

This mathematical result demonstrates that the relative productivity of investments across periods of the life course depends only on skill-specific decay parameters ($\delta_{\text{learning},p}$ and $\delta_{\text{relevance},p}$), independent of complementary skills and parental characteristics, which affect absolute levels but not relative timing. As discussed in the construction of the model, these decay parameters govern, respectively, the rate of decline in learning capacity and skill relevance over time and, therefore, optimal investment timing depends on the relative magnitude of these two competing processes.

Note that the traditional canonical conclusion that earlier investments yield the greatest returns ($R_{l,e,p} < 1$) holds if and only if $\delta_{\text{learning},p} > \delta_{\text{relevance},p}$—that is, when learning capacity declines faster than skill relevance over the life course. However, if $\delta_{\text{relevance},p} > \delta_{\text{learning},p}$—when skill relevance declines faster than learning capacity—our model reveals that later investments tend to be more productive than earlier ones ($R_{l,e,p} > 1$).

This result adds complexity to the canonical framework, highlighting that neither early nor later investments are inherently superior and that the relative potential of investments over the life course is skill-dependent. Intuitively, this reflects a trade-off: Although early investments may be more efficient due to age-related decline in learning capacity, they may also be more vulnerable to misalignment with future labor market needs. By contrast, later investments, though less efficient from a learning-capacity standpoint, may more accurately align with evolving skill content.

To illustrate how this theoretical result can have important practical applications, in the following we provide numerical simulations grounded in existing empirical estimates. For tractability, we fix the earlier investment period at period 1 ($e = 1$) and allow the later investment period l to vary over the life course: $l = x \in 1, \ldots, T$. This yields a simplified ratio comparing the marginal productivity of investment in period x relative to early childhood (period 1), $R_{l=x,e=1,p} = R_{x,1,p}$. Values of $R_{x,1,p} > 1$ indicate that investments at age x are more productive than early childhood investments; values < 1 indicate lower productivity.

Numerical Simulations for Empirically Plausible Parameter Ranges

We proceed in three steps. First, we specify the parameter space for our simulations using empirically plausible ranges: these ranges are not arbitrarily chosen, they are based on our readings of relevant empirical literature. Importantly, we recognize that precise estimation remains an open empirical challenge. Age-related declines in learning capacity are heterogeneous across tasks and heavily confounded by health and contextual factors (Hertzog et al. 2008; Lindenberger 2014; Salthouse

2010, 2019). Similarly, skill relevance decline presents measurement challenges as it depends on how the task content defining proficiency evolves over time, and how such changes depreciate existing proficiency (Acemoglu and Autor 2011; Deming and Noray 2020; Heckman et al. 2006). Beyond measurement challenges, both parameters are themselves moving targets. Skill-content evolution depends on labor market dynamics that are difficult to forecast in periods of rapid technological change (Deming et al. 2025; National Academies of Sciences, Engineering, and Medicine 2024), while learning capacity trajectories may shift with advances in educational technology, pedagogical practices, and medical interventions that extend cognitive functioning. These challenges notwithstanding, empirical evidence supports classifying yearly decline rates into three categories: slow ($<$ 2 percent), moderate (2–3 percent), and fast ($>$ 3 percent) for $\delta_{\text{learning},p}$; and slow ($<$ 1 percent), moderate (1–2 percent), and fast ($>$ 2 percent) for $\delta_{\text{relevance},p}$.

Second, drawing on research reviewed subsequently, we then map illustrative skill profiles onto this parameter space. We identify well-known skill domains (early-sensitive cognitive, general cognitive, noncognitive, and technical) that can reasonably represent specific combinations of learning capacity and relevance decline. Given relatively thin empirical evidence for some of these parameters, some profile placements are more firmly anchored in existing evidence whereas others require stronger assumptions. We make these distinctions explicit in the sections that follow.

Third, we simulate return trajectories across combinations of the slow, moderate, and fast parameter categories defined earlier, demonstrating how different parameter combinations generate fundamentally distinct optimal investment timing, and place the four illustrative skill profiles within distinct regions of the continuous parameter space.

This parameterization exercise serves two purposes. It demonstrates how even modest variations in decline rates generate qualitatively different optimal investment trajectories, revealing the substantive importance of skill-dependent considerations. Further, it illustrates how future empirical research quantifying these parameters more precisely could inform human capital policy design.

This exercise also makes explicit what is often implicit in policy debates about investment timing. When researchers or policymakers argue that early investment is more efficient, they effectively claim that the benefits of higher learning capacity in childhood outweigh the costs of skill relevance decline over the life course. Conversely, arguments favoring later investment implicitly assume that costs of skill relevance decline are outweighed by efficiency gains from investing when skills are more stable. Our framework reveals that optimal timing depends fundamentally on the relative magnitudes of these two decline processes, and that different assumptions about technological change, labor market evolution, and human neuroplasticity will yield different optimal investment strategies.

Establishing Plausible Parameter Ranges from Available Evidence

Rate of decline in human learning capacity over time ($\delta_{\text{learning},p}$). Empirical studies suggest substantial variation in how learning capacity declines across skill types. At one extreme, certain cognitive skills exhibit sensitive periods in early childhood. For instance, language acquisition (Knudsen 2004; Newport 1990) and phonological awareness (Bradley and Bryant 1983; Werker and Tees 1984) are shaped by narrow windows of high neuroplasticity. Learning capacity declines sharply after these windows close.[5] Although precise estimates remain contested, recent large-scale evidence provides a useful benchmark: by age 18, capacity to acquire grammatical syntax is roughly 50 percent lower than in early childhood (Hartshorne et al. 2018). Under our exponential decline specification (Eq. 9), this pattern implies an annual decline rate of approximately $\delta_{\text{learning},p} \approx 4.5$ percent for language-related skills, motivating our fast decline category (> 3 percent).

Other cognitive skills such as numeracy and reading ability show more gradual decline with age, estimated at approximately 2–3 percent annually (Hanushek et al. 2025; Lubotsky and Kaestner 2016; Salthouse 2010), motivating our moderate decline category (2–3 percent).[6]

Finally, noncognitive and socio-emotional skills including persistence, motivation, cooperation, and ability to gain from experience appear shaped more by environmental conditions and accumulated experience than by age-related biological constraints (Charles and Carstensen 2010; Cutler et al. 2021; Isaacowitz and Blanchard-Fields 2012; Lin et al. 2025; Scheibe and Carstensen 2010; Westhoff et al. 2020), suggesting learning capacity remains relatively stable over the life course, motivating our slow decline category (< 2 percent).

Rate of Decline in Skill Relevance over Time ($\delta_{\textbf{relevance},p}$). In our framework, skill relevance declines because, as the task content of a skill evolves, proficiency in tasks relevant in period t contributes less to one's skill level in period $t + 1$. This process is governed by the relevance decline parameter $\delta_{\text{relevance},p}$ (Eq. 11).

Recent work on skill content evolution and life-course earning cycles provides a helpful empirical basis to bound this parameter (Deming and Noray 2020; Lentini and Gimenez 2019; Shalamova et al. 2019; Todd et al. 1995). Most directly relevant to our framework is Deming and Noray (2020), who document that individuals' life-course earning cycles are associated with the pace of task content evolution in their field. Career-specific wage premiums decline exponentially for workers in rapidly changing fields while remaining relatively stable for similar individuals working in more stable fields. Within our framework, this evidence suggests that as the task content defining proficiency in a skill domain evolves faster, previously acquired skills lose relevance for next-period skill stock at an accelerated rate.

Specifically, Deming and Noray (2020) estimate that college graduates working in occupations with a one standard deviation higher rate of skill content change—approximately the difference between Computer Science and Engineering versus more general fields such as Biology, History, and English—earn 30 percent more at age 24 compared to graduates in slower-changing occupations, but this premium declines to 20 percent by age 50.[7] Under our proposed framework (Eq. 10), this one-third decline in the relative wage premium over 26 years for workers in faster-changing occupations implies $\delta_{\text{relevance},p} \approx 1.6$ percent annually,[8] motivating our moderate decline category (1–2 percent). The baseline occupations with slower skill change rates, which exhibit relatively stable wage premiums over the career, motivate our slow decline category (< 1 percent). Following Deming and Noray (2020), the case for faster depreciation becomes stronger when excluding graduates from education-specific majors, which represent individuals working in occupations with the slowest content evolution in their data. For this restricted sample, the estimated wage premium for workers in faster-changing occupations declines from 52 percent at age 24 to 16 percent by age 50—a two-third decline implying $\delta_{\text{relevance},p} \approx 4.6$ percent annually.[9] This steeper decline motivates our fast relevance decline category (> 2 percent), appropriate for technical skills in rapidly evolving occupational domains.

To provide a foundation for the illustrative cases we offer in the next section, we note that Deming and Noray (2020) provide skill content change rates by college major, allowing us to consider possible skill-specific patterns. Majors emphasizing technical skills—Computer Science, Engineering, and Technology-oriented programs—exhibit the fastest pace of skill content change, suggesting that technical skills such as programming, statistical software, and specialized analytical tools would fall in our fast decline category (> 2 percent). Majors that rely more heavily on general cognitive skills—literacy, numeracy, analytic reasoning—such as Social Sciences, Public Affairs and Policy, Biology and Life Sciences show moderate rates of change, illustrating the types of skills we associate with our moderate relevance decline category (1–2 percent). Finally, majors such as Education, Linguistics and Foreign Languages, Psychology, Liberal Arts, and Humanities, which are largely defined by noncognitive/socio-emotional skill requirements such as interpersonal communication, emotional intelligence, conflict resolution, relationship building, and language abilities, exhibit the slowest skill content evolution, exemplifying skills in our slow decline category (< 1 percent). This pattern aligns with broader evidence on the persistent value and stable definitions of interpersonal skills (Deming 2017; Deming and Noray 2020; Lentini and Gimenez 2019; Shalamova et al. 2019; Todd et al. 1995).

Placing Illustrative Skill Profiles within the Parameter Space

Based on the evidence reviewed earlier, Table 1 identifies four well-known skill domains that can plausibly represent specific combinations of learning capacity and relevance decline. Importantly, as we detail subsequently, some profile placements are more firmly anchored in existing evidence than others.

We offer early-sensitive cognitive skills (including language acquisition and phonological awareness) as a domain that exhibits fast learning capacity decline and slow skill relevance decline. The proposed level of learning capacity decline reflects well-known results in the neuroscience literature (Hartshorne et al. 2018; Knudsen 2004; Newport 1990). In contrast, the proposed level of skill relevance decline is not as well grounded empirically; it reflects a reasonable (but untested) assumption that foundational language and phonological abilities are likely to exhibit slow task content evolution.

We offer general cognitive skills such as literacy, numeracy, and analytic reasoning to exemplify moderate decline in both learning capacity and skill relevance. This placement is well-anchored in recent empirical analyses of within-person variation

Table 1: Placing Illustrative Skill Profiles within the Parameter Space.

Parameter Category	Illustrative Skill Profile(s)
Learning capacity decline rate ($\delta_{\text{learning},p}$)	
Fast (> 3 percent)	Early-sensitive cognitive
Moderate (2–3 percent)	General cognitive and Technical
Slow (< 2 percent)	Noncognitive
Skill relevance decline rate ($\delta_{\text{relevance},p}$)	
Fast (> 2 percent)	Technical
Moderate (1–2 percent)	General cognitive
Slow (< 1 percent)	Early-sensitive cognitive and noncognitive

in skill acquisition across age groups (Hanushek et al. 2025). This placement for skill relevance follows our reading of Deming and Noray (2020)'s estimates for majors emphasizing general cognitive skills.

We use technical skills such as software development and programming to represent a domain of moderate learning capacity decline and fast skill relevance decline. The placement for relevance decline is reasonably well-anchored in Deming and Noray (2020)'s estimates for fast-changing occupational fields. For the learning capacity placement, in the absence of direct estimates, we assume it follows patterns similar to general cognitive skills, reflecting an assumption that technical skill acquisition might draw on similar underlying cognitive capacities.

Finally, noncognitive skills (e.g., persistence, cooperation, and interpersonal communication) illustrate a domain where both parameters decline slowly. The learning capacity placement is anchored in evidence on the stability of socio-emotional functioning across the life course (Charles and Carstensen 2010; Scheibe and Carstensen 2010). The relevance decline placement follows our reading of Deming and Noray (2020)'s estimates for majors with the slowest rates of skill content evolution.

Simulated Return Trajectories across Empirically Plausible Parameter Ranges

Figure 3 shows $R_{x,1,p}$ over the life course for representative parameter combinations within our empirically informed ranges. Panels fix yearly decline in learning capacity ($\delta_{\text{learning},p}$) at representative slow (1 percent), moderate (2.5 percent), and fast (4 percent) values, whereas line colors distinguish rates of skill relevance decline ($\delta_{\text{relevance},p}$) for representative slow (0.5 percent), moderate (1.5 percent), and fast (3 percent) levels. Although these nine combinations fall within empirically plausible bounds, they are chosen to cover the full theoretical range of interaction patterns within those bounds, demonstrating how the relative magnitudes of the two decline rates influence the shape of return trajectories. We then use Figure 4 to locate the four illustrative skill profiles (Table 1) within the continuous parameter space.

Consider first cases defined by fast learning capacity decline ($\delta_{\text{learning},p} =$ 4 percent, right panel). Under this condition, all return trajectories favor early

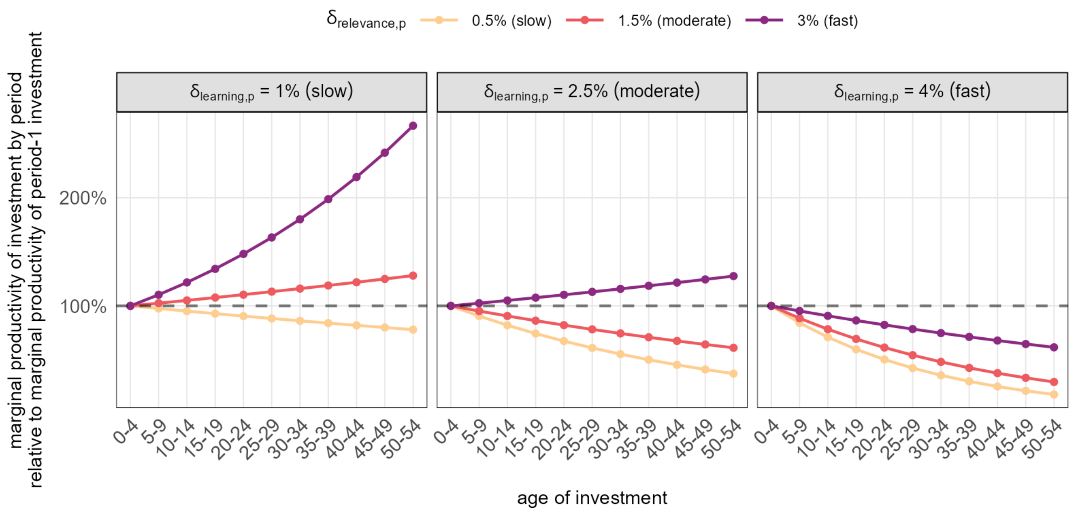

Figure 3: Skill-specific return trajectories over the life course for representative parameter combinations within our empirically informed ranges. The figure depicts the marginal productivity of investments at different ages relative to early childhood (period 1; ages 0–4). Each panel fixes learning capacity decline ($\delta_{\text{learning},p}$) at a representative value (slow, moderate, or fast), whereas line colors distinguish rates of skill relevance decline ($\delta_{\text{relevance},p}$). The horizontal dashed line at 100 percent indicates parity with early childhood investment productivity. Values above this line indicate later-life investments are more productive; values below indicate early childhood investments are more productive.

investment regardless of how rapidly skill relevance declines. Even when skill relevance declines quickly (darkest line), the steep drop in learning capacity dominates, producing steeply declining trajectories that favor early investment. The lightest line (slow skill relevance decline, $\delta_{\text{relevance},p} = 0.5$ percent) displays the steepest decline, generating the negative exponential pattern traditionally associated with the Heckman curve. Note that this combination of fast learning capacity decline and slow skill relevance decline corresponds to the early-sensitive cognitive skill profile in Table 1—exemplified by domains such as language acquisition—which are precisely the skills frequently cited in motivations for the Heckman curve (Cunha and Heckman 2007; Hartshorne et al. 2018; Heckman et al. 2006; Knudsen 2004).

In contrast, consider cases characterized by moderate learning capacity decline ($\delta_{\text{learning},p} = 2.5$ percent, middle panel). Here, optimal investment timing depends on the rate of skill relevance decline. When relevance declines slowly (lightest line, $\delta_{\text{relevance},p} = 0.5$ percent), early investment remains optimal, though returns decline less steeply than under fast learning capacity decline. Most notably, when relevance declines rapidly (darkest line, $\delta_{\text{relevance},p} = 3$ percent), the direction of the curve reverses and marginal returns increase over the life course, favoring later investment.

Finally, when learning capacity declines slowly ($\delta_{\text{learning},p} = 1$ percent, left panel), return trajectories become even more likely to favor later investments. When combined with slow skill relevance decline (lightest line, $\delta_{\text{relevance},p} = 0.5$ percent), the trajectory still exhibits a modest decline, though much less steep than under faster learning capacity decline. As skill relevance decline accelerates (middle and darkest lines), the curve reverses direction, with the most dramatic case (slow

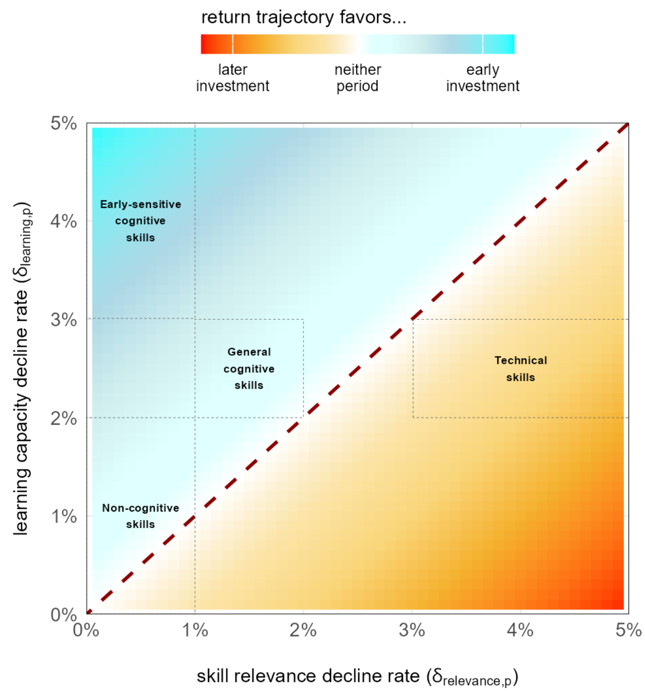

Figure 4: Placing illustrative skill profiles in the parameter space. The heatmap locates our illustrative skill profiles from Table 1 into the parameter space defined by learning capacity decline ($\delta_{\text{learning},p}$, y axis) and skill relevance decline ($\delta_{\text{relevance},p}$, x axis). The color gradient indicates whether early investment (cyan/blue), later investment (orange/red), or neither period (white) generates higher returns. The diagonal dashed line marks where both decline rates are equal. Boxes indicate approximate regions rather than precise placements, reflecting varying degrees of empirical support: for learning capacity decline, placements are more firmly anchored for early-sensitive cognitive and general cognitive skills but more assumed for technical skills, with noncognitive skills falling in between; for skill relevance decline, placements are more firmly anchored for technical skills but more assumed for early-sensitive cognitive skills, with general cognitive and noncognitive skills falling in between. See text for additional details.

learning capacity decline combined with fast skill relevance decline) producing a steep exponential increase in returns over the life course.

Although Figure 3 demonstrates how different parameter combinations can shape optimal investment timing across a wide range of theoretically possible configurations, we now turn to mapping these patterns onto the illustrative skill profiles summarized in Table 1. Figure 4 synthesizes the results. The color gradient illustrates how optimal investment timing shifts continuously across parameter combinations: cyan/blue regions indicate configurations where early investment is optimal (learning capacity declines faster than skill relevance), orange/red regions indicate configurations favoring later investment (skill relevance declines faster than learning capacity), and white regions indicate relatively flat return trajectories. The diagonal dashed line marks parameter combinations where both decline rates are equal ($\delta_{\text{learning},p} = \delta_{\text{relevance},p}$). The four skill profiles from Table 1 occupy distinct regions of this space, illustrating how differences in empirically observed decline rates generate heterogeneous predictions about optimal investment timing.

These heterogeneous trajectories add important nuance to existing frameworks for thinking about human capital investment timing. Whereas the canonical Heckman curve emphasizes early childhood as the optimal period for investment, our skill-specific extension suggests this conclusion depends critically on which skills are being developed. Based on our proposed placements—with the admitted uncertainties discussed earlier—early interventions appear to be most advantageous when prioritizing foundational, early-sensitive cognitive skills whose acquisition windows narrow with age and whose relevance remains stable over time. This pattern is consistent with evidence that substitutability in skill production is roughly constant in childhood for noncognitive skills but not for cognitive ones (Cunha et al. 2010), and with studies documenting that high school education emphasizing general skills tends to provide higher long-term returns than vocational training (Decker et al. 2023; Hampf and Woessmann 2017; Hanushek et al. 2017). In contrast, later interventions may prove more efficient when directed toward technical skills whose relevance declines rapidly due to evolving task content, or toward noncognitive domains whose learning capacity appears to remain more stable into adulthood. These patterns motivate continued empirical work to refine estimates of skill-specific decline rates, which would allow for more precise policy guidance about optimal investment timing across different domains of human capital development.

Discussion

The Heckman curve has had a profound influence on human capital policy, providing theoretical grounding for prioritizing investment early in the life course. As with all of the most consequential social science, its influence has come less from specific empirical findings than from how it has shaped the logic of everyday thinking and public policy (Berman 2022; O'Connor 2001). Together with longstanding cultural notions of childhood as a privileged period of the life course (Bandelj 2026; Stevens 2009; Zelizer 1985), Heckman's canonical conclusions have made early childhood investments approach the level of common sense (Bandelj and Spiegel 2023).

The influence of conceptual models like the Heckman curve extends beyond narrow policy prescriptions. Assumptions about optimal investment timing can shape the institutional and cultural organization of the life course itself. Life-course sociologists have long emphasized how modern societies are age-structured; they distribute roles, resources, and opportunities through both formal institutions and informal cultural timelines that define appropriate duration and sequencing of life transitions (Elder 1994; Settersten 2003; Settersten and Mayer 1997). Policy frameworks that privilege investments at particular ages can legitimize and stabilize a specific developmental rhythm, channeling funding and attention toward some life stages and away from others. Debates over when to invest are therefore also debates about how to allocate opportunity across the life course, and may create, as much as reflect, age-based expectations and inequalities (Barrett 2022; Johfre and Saperstein 2023).

Rapid technological change (Acemoglu et al. 2022; Deming et al. 2025) together with increasing working lives (Berkman and Truesdale 2022; Ghilarducci 2024; Scott 2024), suggest that front-loading human capital investments may no longer be sufficient to allow individuals to navigate longer and less predictable working lives. These changes have motivated growing recognition that investments in specific skill types may be important determinants of resilience for individual careers and entire economies. The shift toward skill-differentiated thinking raises new policy questions about when to invest in which specific domains rather than aggregate human capital. Thus inherited heuristics designed for questions about aggregate human capital may provide insufficient or even inaccurate guidance for skill-specific investment timing.

Our extension of the Heckman curve illustrates how changed conditions can motivate different modeling choices. Here, we have sought to expand analytic and policy imaginations by shifting the guiding question from "when to invest?" to "when to invest in which skills?" We then offered skill-specific parameters: rates of change in (a) human learning capacity and (b) skill content over the life course. Our mathematical results suggest that optimal timing becomes context-specific, depending on characteristics of the skills being developed and the labor market conditions they will face. This framing provides a more nuanced approach to human capital policy than implied by the canonical framework's singular emphasis on early childhood investment.

Extending the Heckman curve in this way also highlights the historically contingent nature of the life course. The sequencing of education, work, and family is shaped by broader political-economic circumstances that alter both the ordering of roles and the returns to investments made at different stages (Brückner and Mayer 2005; Gruijters et al. 2023; Shanahan 2000); what constitutes optimal investment timing may reactively shift in turn. As demographic and technological conditions change, the puzzle of reactivity becomes both more urgent and more complex. Navigating this puzzle might be well served by conceptual tools capable of accommodating contextual or historical variance and enabling modeling of different prospective scenarios. This is the intent of our effort here.

As with any theoretical investigation, our goal is not to provide definitive prescriptions, but rather to shed fresh light on empirical phenomena that are central to policy decisions. Rigorous implementation requires measuring skill-specific rates of learning capacity decline over the life course, and quantifying rates of skill content evolution in evolving labor markets. Both of these tasks are challenging, especially as the objects of measurement themselves evolve with changes in technology and pedagogy. Still, by making explicit the assumptions underlying investment timing debates, we hope that the work presented here motivates a rigorous and ongoing interdisciplinary research agenda. Such an agenda might benefit from several complementary strategies. First, building on longitudinal studies tracking skill acquisition across different age groups (e.g., Hanushek et al. (2025)), future research can help estimate age-related learning capacity decline for specific skill domains. Second, building on recent economic work analyzing occupational task evolution (Deming and Noray 2020), stratification research examining returns to education would benefit from moving beyond cross-sectional wage comparisons to longitudinal analyses of how skill content evolution shapes earning trajectories differentially across fields of study, career stages, as well as social background. Finally, life-course analyses integrating these skill-specific dynamics with broader patterns of stratification could reveal how optimal investment timing varies across social positions and institutional contexts.

Declaration of Conflicting Interest

The authors declare no conflicts of interest.

Funding Statement

This paper is part of the project "Education and Learning for Longer Lives" (2025–2026) funded by the Stanford Center on Longevity and Center for Advanced Study in the Behavioral Sciences.

Notes

1 Throughout the paper, following a task-based approach (Autor et al. 2003; Deming 2017), we use "skills" to denote broad domains of human capability (e.g., language, communication, quantitative research, and software development) rather than narrow proficiencies in specific tasks or platforms (e.g., coding in SPSS, Stata, or Python). In this sense, one's proficiency in a skill is defined here as their ability to successfully perform the set of tasks that collectively define that skill at a given point in time.

2 Importantly, skill relevance decline differs from declining skill demand: a skill domain (e.g., software engineering) may remain highly valued even as the task competencies that define proficiency within it change, so earlier-acquired proficiencies contribute less to current proficiency as the task content evolves.

3 Although empirical applications support the model's childhood predictions (Cunha and Heckman 2008; Cunha et al. 2010), the broader life-course claim remains theoretically derived. Recent direct empirical tests (Hendren and Sprung-Keyser 2020; Rea and Burton 2020; Rosholm et al. 2021) have sparked academic debate, but face fundamental challenges in distinguishing theoretical predictions at optimal program efficiency from program quality variation (Deming 2022; Heckman 2020).

4 Mathematically, this simplification follows without loss of generality because our quantity of interest—the relative returns across periods for a given skill, defined by the ratio $R_{l,e,p}$—depends only on skill-specific parameters, not on the trajectory of $\theta_{t,p'}$ (Eq. 12).

5 The precise timing and whether these constitute sensitive or critical periods remains debated. See Gabard-Durnam and McLaughlin (2020) for a review.

6 Hanushek et al. (2025) is uniquely suited for estimating learning capacity decline in reading and numeracy because it measures within-individual *changes* in skills between assessment waves for individuals of varied ages. We calculate implied annual decline rates from their age coefficients (Hanushek et al. 2025: Table 1). For their literacy model, holding covariates at their means, predicted skill change declines from 0.103 SD at age 20 to 0.043 SD at age 50, implying an annual decline rate of $\delta = (0.103/0.043)^{1/30} - 1 \approx$ 3.0 percent. For their numeracy model, the corresponding decline is from 0.119 to 0.055 SD, implying $\delta \approx 2.6$ percent annually.

7 Skill requirement evolution is measured at the occupation level using vacancy posting data (2007–2019), capturing the absolute change in the share of job postings (within that occupation) requiring each skill over this period.

8 If the relative wage premium declines from 0.30 to 0.20 over 26 years, then $0.20 = 0.30\left(\frac{1}{1+\delta_{\text{relevance},p}}\right)^{26}$, which yields $\delta_{\text{relevance},p} \approx 0.016$.

9 Following the same calculation: $0.16 = 0.52\left(\frac{1}{1+\delta_{\text{relevance},p}}\right)^{26}$ yields $\delta_{\text{relevance},p} \approx 0.046$.

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Acknowledgments: This paper is part of the project "Education and Learning for Longer Lives," sponsored by the Stanford Center on Longevity (SCL) in 2025–2026. We thank the SCL's Futures Fellows and New Map of Life Postdoctoral Fellows for the contexts in which this work germinated. We are especially grateful to Bernardo Mackenna, Chris Heitzig, Leon Marbach, and Arik Lifschitz for written feedback, and to Matt Sigelman for valuable advice. Earlier versions of this work benefited from critical feedback (all in 2025) in Stanford's Pathways Network Seminar and Inequality Workshop, the SCL Fellows Seminar, the Sociological Science Annual Conference, and the International Network of Analytical Sociology Conference. Any errors are our own.

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