# Incentives to Discover Talent

Tobias Brünner[*], Guido Friebel[†], Richard Holden[‡], Suraj Prasad[§]

April 25, 2019

**Abstract**

We study an agent's incentives to discover where her talents lie before putting them to productive use. In our setting, an agent can *specialize* and learn about the same type of talent repeatedly, or *experiment* and learn about different types of talent. When talents are normally and symmetrically distributed we find that experimentation is efficient, regardless of one's initial draw of talent. Competitive labor markets encourage experimentation whereas monopsonistic labor markets induce specialization. Relaxing our assumptions of normality and symmetry in the distribution of talents, and allowing for human capital acquisition, provides a role for specialization in discovering talents.

## 1 Introduction

The idea that people have different talents and can benefit by specializing their efforts is an old one–dating to around 2,400 years ago in Plato's *Republic*. It was, of course, expanded into one of the cornerstones of modern economics by Adam Smith in *The Wealth of Nations* where he emphasized the benefits of the *division of labor* in his hypothetical pin factory.

The gains from the division of labor among people with different talent are no less relevant in the modern economy, and the gains from specialization that it generates remain a fundamental consideration in fields from labor economics to international trade.

But far less attention has been paid to how people come to discover their talents. Sometimes talents are apparent, but more often they must be discovered. The implicit and explicit incentives provided by labor markets and other institutions play a critical role in guiding the discovery of individual talents–and it is these incentives which are the topic of this paper.

Indeed, we suggest that talents needing to be discovered is the rule, not the exception. In a beautiful article about "late bloomers" Malcolm Gladwell[1] reminds us that Pablo Picasso once said

[*]Lincoln Business School, University of Lincoln. tbruenner@lincoln.ac.uk

[†]Department of Management and Microeconomics, Goethe University, Frankfurt. gfriebel@wiwi.uni-frankfurt.de

[‡]UNSW Australia Business School. richard.holden@unsw.edu.au

[§]School of Economics, University of Sydney. suraj.prasad@sydney.edu.au

[1]Malcolm Gladwell, "Late Bloomers", *The New Yorker*, October 20, 2008. Available at https://www.newyorker.com/magazine/2008/10/20/late-bloomers-malcolm-gladwell

"In my opinion, to search means nothing in painting. To find is the thing...The several manners I have used in my art must not be considered as an evolution or as steps toward an unknown ideal of painting...I have never made trials or experiments."

But most of us are not Picassos. Indeed, as Gladwell points out, no lesser artist than Paul Cézanne said "I seek in painting". And Cézanne's paintings done when he was in his mid-sixties are worth fifteen times as much as those he painted early in his career. Cézanne's later work was just better–after he discovered where his true talent lay. A painting done by Picasso in his mid-twenties was worth, he found, an average of four times as much as a painting done in his sixties. For Cézanne, the opposite was true. The paintings he created in his mid-sixties were valued fifteen times as highly as the paintings he created as a young man.

The workhorse model for analyzing the role of talent in economics is the now classic *career concerns* model of Holmstrom (1982) in which the market and a worker symmetrically learn about the worker's innate ability. By now there is a substantial literature that applies aspects of the career concerns framework to issues of institutional and organizational design: public sector management (Dewatripont, Jewitt and Tirole (1999)), team management and compensation (Jeon (1996), Auriol, Friebel and Pechlivanos (2002), and Ortega (2003)), job design (Meyer (1994), Ortega (2001), and Kaarboe and Olsen (2006)), and compensation design (Gibbons and Murphy (1992) and Meyer and Vickers (1997)).

We use this workhorse model to ask a simple question: to what extent can people be expected to be willing to invest optimally in discovering at which activity they are best? In particular, we focus on the role of incentives as provided by the institutional structure of the labor market.

In our model there are two sectors with at least one firm in each sector and an agent who can choose to work in either sector. The agent's sector-specific talent is unknown and production depends on an agent's talent.

There are two phases: *learning* and *working*. Prior to working, the agent can get a signal about her talents by *sampling*, but she can only sample one type of talent per period of learning. In the working phase, the agent shares the surplus generated from the employment relationship via generalized Nash bargaining.

The learning phase is readily interpretable as education. As Schultz (1968) put it, one of the "three major functions of higher education...[is]...the discovery of talent." Thus, our model speaks to the incentives that education systems and labor markets provide for discovering talent.

We show that when the two sectors are symmetric in the sense talents in both sectors have the same mean and the same variance, and are normally distributed, experimentation is efficient.

To understand why consider the choice of the agent after having sampled, say, sector A in the first period. Experimentation involves sampling sector B in period 2, whereas specialization involves sampling sector A again. By symmetry of the sectors, a first signal from sector B is Blackwell more informative than a second signal from sector A. So there is more to learn from experimentation. But there is also nothing to lose. If the agent learns that she has little aptitude for sector B she can always switch to sector A.

Turning to labor-market incentives, we show that competition leads to efficient experimentation. To see this, note that when the labor market is perfectly competitive, the agent is the residual claimant and thus has incentives to choose the efficient sampling strategy.

On the other hand, when labor markets are monopsonistic, the agent has no bargaining power and so her wage is just her reservation wage–which is determined by the the lesser of her two talents. Thus, second period signals are irrelevant, but low signals entail a cost in terms of a lower reservation wage. Specialization, by suppressing learning, limits this cost.

A strength of our model is that we can clearly see how our assumptions of symmetry, normality, and the absence of human capital drive our main result that experimentation is efficient. Relaxing these assumptions highlights circumstances in which there is a role for specialization. When talents are asymmetric, sampling the talent with the higher variance repeatedly can be optimal because there is more to learn from that talent. To understand the role normality plays, we consider a setting where talents have a $t$-distribution. Unlike the case where talents are normally distributed, the posterior variance now depends on the realization of the signal, which once again makes specialization efficient for extreme draws (negative or positive) of the talent sampled. Finally, when sampling a talent is associated with the accumulation of sector-specific human capital, specialization once again has a role to play for high draws of the initial talent sampled.

Our study shares features with the multi-armed bandit literature.[2] As in the multi-armed bandit problem, our setup includes experimentation and exploitation; but whereas in the former an agent can repeatedly switch between experimentation and exploitation over an infinite horizon, in our setup, experimentation can only happen in the learning phase (periods 1 and 2) and exploitation occurs in the working phase (period 3). Modeling the labor market as a multi-armed bandit problem, Miller (1984) shows that, ceteris paribus, an agent chooses the job with the highest information value. Since working in a job reduces uncertainty about the job-specific match value, agents have an incentive to switch between jobs (and occupations). This result is consistent with our finding that agents in competitive labor markets experiment during the learning phase. Following Jovanovic (1979), Miller (1984) considers many firms that compete for a single agent, who is, therefore, able to extract the entire match value. In contrast, Felli and Harris (1996) assumes that there are only two firms, one for each job, such that the agent's wage from its current employer equals the agent's match value with the other firm. In this setting, Felli and Harris (1996) show that the agent experiments efficiently, in the sense that total surplus is maximized. This contrasts with our finding that efficient experimentation occurs only if the labor market is sufficiently competitive.

A key feature of our model is that the talent to be discovered has multiple dimensions. This feature appears in other learning contexts as well: job design (Meyer (1994) and Ortega (2001)) and education systems (Malamud (2010) and Malamud (2011)). But in these models, the decision about which type of talent to learn about is *fixed* upfront and cannot depend on new information.

[2] See Bergemann and Välimäki (2008) for a review of the multi-armed bandit problem and its applications in economics.

By contrast, this decision in our framework is *flexible* and is allowed to vary with new information.

# 2 The model

## 2.1 Environment and Production

There are two sectors: sector A and sector B. Associated with each sector is at least one risk neutral firm. There is a risk neutral agent who chooses to work in either sector A or sector B.

The agent's talent in sector A (B) is given by $\eta^A(\eta^B)$. This talent is unknown and is distributed normally with mean 0 and variance $\sigma_\eta^2 > 0$. Talents across sectors are independent of one another. Production depends on the talent of the agent in the sector. An agent who works in sector A (B) produces an output $\eta^A(\eta^B)$.

## 2.2 Sampling Talents

Prior to working, the agent *samples* (or learns about) her talents in a sector over two periods. An agent who samples sector $i$, $i = A, B$, in period $t$, $t = 1, 2$, draws an informative signal $s_t^i = \eta^i + \epsilon_t^i$ at the end of the period, where $\epsilon_t^i$ is an idiosyncratic error term which is normally distributed with mean 0 and variance $\sigma_\epsilon^2 > 0$. The error terms are independent across periods.

The key constraint that the agent faces is that she can only sample one type of talent per period. If the agent samples the same type of talent over both periods, we say that she *specializes*. On the other hand, if the agent samples different types of talents over both periods, we say that she *experiments*. We assume that the agent must sample a talent in each period.

## 2.3 Labor Market Competition and Incentives

The agent's wage from working for a firm is determined by Nash Bargaining over the expected surplus. Let the parameter $\mu \in [0, 1]$ denote the agent's bargaining weight. We use this parameter to model labor market competition in a reduced form way. In particular, we assume that $\mu = 0$ corresponds to a case of *monopsony* where there is only one firm in each sector. An increase in $\mu$ can then be interpreted as more competition in the labor market with the extreme case of $\mu = 1$ corresponding to a *perfectly competitive labor market*. Alternatively, the case with $\mu = 1$ can also be thought of as entrepreneurship where the agent is the residual claimant of her talent.

## 2.4 Timing and Information Structure

There are three periods in the model: two sampling periods followed by a working period. Given the symmetry in the distribution of both talents, we assume without loss of generality that the agent samples sector A in the first period. Thus for all of our analysis, we treat the realized signal in period 1 for talent A, $s_1^A$, as an exogenous parameter. The timing and information structure of the model then is as follows.

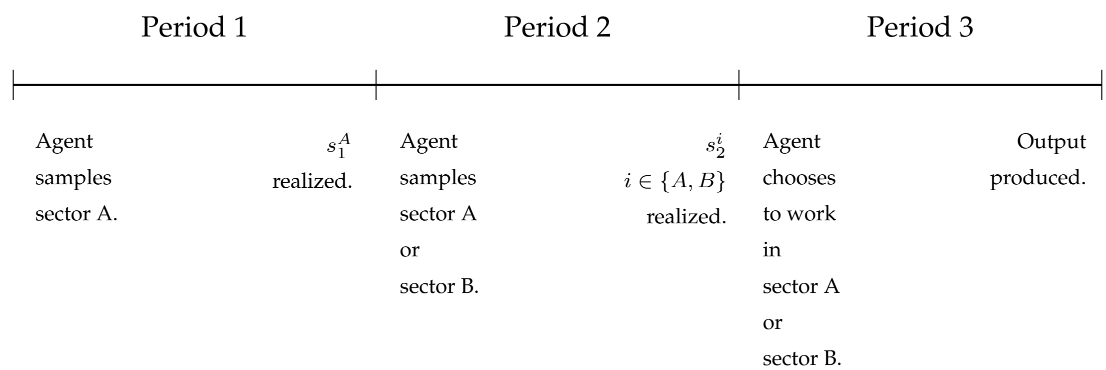



Figure 1: Timeline.

The agent samples sector A at the start of period 1. At the end of this period, she draws a publicly observable signal $s_1^A$. Conditional on this realized signal the agent decides which sector to sample at the start of the second period. And at the end of the second period, the signal $s_2^i$, where $i \in \{A, B\}$, is realized. At the start of period 3, the agent decides which sector to work in. Finally, at the end of period 3, production takes place. Figure 1 depicts the timing of the model.

## 3 Efficiency

Efficiency requires that the agent's sampling choice maximizes expected output. In this section, we compare the expected surplus (output) from specializing versus experimenting, given the realization of the first period signal $s_1^A$. We first sketch the total surplus functions associated with specialization and experimentation. We then compare the expected surplus across these two sampling strategies.

Consider the surplus function associated with specialization first. To convey the intuition for our results clearly, it is useful to work with a transformation of the second period signal in sector A. In particular, define $\hat{s}_2^A = s_2^A - \lambda_1 s_1^A$. This normalized signal $\hat{s}_2^A$ has a mean of 0 and the same variance as the signal $s_2^A$ . Let $F^A$ and $F^B$ be the distribution functions for $\hat{s}_2^A$ and $s_2^B$ respectively.

Because the agent can pick which sector to work in after sampling talents, the surplus from specialization is given by:

$$\begin{aligned} TS_S &= \max\{E(\eta_A | s_1^A, \hat{s}_2^A), E(\eta_B | s_1^A, \hat{s}_2^A)\} \\ &= \max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}, \end{aligned}$$

where $\lambda_1 = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\epsilon^2}$ and where $\lambda_2 = \frac{\sigma_\eta^2}{2\sigma_\eta^2 + \sigma_\epsilon^2}$ .

Similarly, the surplus from experimentation is given by:

$$\begin{aligned} TS_E &= \max\{E(\eta_A | s_1^A, s_2^B), E(\eta_B | s_1^A, s_2^B)\} \\ &= \max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}. \end{aligned}$$

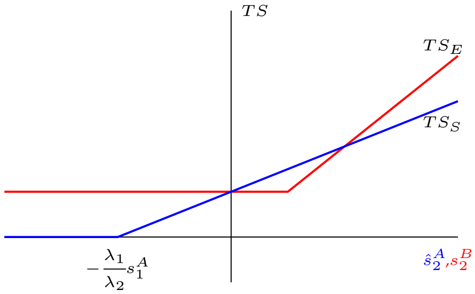



Figure 2: Total Surplus Functions: $s_1^A > 0$.

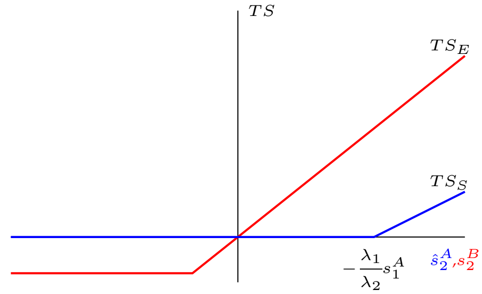



Figure 3: Total Surplus Functions: $s_1^A < 0$.

The expected surplus from specialization, $V_S$, is then given by:

$$V_S = E_{\hat{s}_2^A}[TS_S] = E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}]$$

and the expected surplus from experimentation, $V_E$, is given by:

$$V_E = E_{s_2^B}[TS_E] = E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}]\,.$$

Figures 2 and 3 plot the surplus from experimentation and specialization as a function of the realization of the second period signal. Looking at these figures, it is not clear which of the two sampling strategies yields a higher expected surplus. Notice that the surplus functions overlap. Also expectations are taken with respect to different random variables: $\hat{s}_2^A$ and $s_2^B$. Our main result in this section is that experimentation yields a higher expected surplus relative to specialization regardless of the initial draw of talent.

But first we state a useful Lemma.

**Lemma 1** *Let $x$ be a normally distributed random variable with mean 0. Let $a$ be a positive real number and let $c$ and $d$ be real numbers. Then $E_x[\max\{ax + c, d\}] = E_x[\max\{ax + d, c\}]$.*

**Proof** Let $F$ denote the distribution function of $x$. Since the normal distribution is symmetrical around zero, $F(x) = 1 - F(-x)$. Then

$$\begin{aligned} E_x[\max\{ax + c, d\}] - E_x[\max\{ax + d, c\}] &= F(\tfrac{d-c}{a})\, d + a \int_{\frac{d-c}{a}}^{\infty} x dF + (1 - F(\tfrac{d-c}{a}))\, c \\ &- F(\tfrac{c-d}{a}) c - a \int_{\frac{c-d}{a}}^{\infty} x dF - (1 - F(\tfrac{c-d}{a})) d \\ &= a \int_{\frac{d-c}{a}}^{\infty} x dF - a \int_{\frac{c-d}{a}}^{\infty} x dF \\ &= 0\,, \end{aligned}$$

where the last step again follows from the symmetry of the normal distribution. ■

The above Lemma says that when a random variable is normally distributed with a mean of zero, then interchanging intercepts across components of the max function does not change the expected value of the max function. It is worth pointing out that the lemma above holds not just for a normal distribution but for any symmetric distribution with mean 0.

We now turn to our main result in this section.

**Proposition 1** *Experimentation, where the agent samples different sectors in each period, is efficient.*

**Proof** We split the proof into three claims.
**Claim 1:** $E_{\hat{s}_2^A}[TS_S] = E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}] \leq E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 s_2^B, 0\}]$.

The distribution of signal $\hat{s}_2^A$ given $s_1^A$ is $N(0, (1-\lambda_1^2)(\sigma_\eta^2 + \sigma_\epsilon^2))$. The distribution of signal $s_2^B$ is $N(0, \sigma_\eta^2 + \sigma_\epsilon^2)$. Therefore the two random variables $\hat{s}_2^A$ and $s_2^B$ have the same mean but the former has smaller variance than the latter. Thus $\hat{s}_2^A$ second-order stochastically dominates $s_2^B$. Since the max function is convex, $E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}] \leq E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 s_2^B, 0\}]$.
**Claim 2:** $E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 s_2^B, 0\}] < E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_1 s_2^B, 0\}]$.

Consider two possible cases.

First, suppose $s_1^A \leq 0$. Then $\max\{\lambda_1 s_1^A + \lambda_2 s_2^B, 0\} \leq \max\{\lambda_1 s_1^A + \lambda_1 s_2^B, 0\}$ with the inequality strict for $s_2^B$ sufficiently large. Thus $E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 s_2^B, 0\}] < E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_1 s_2^B, 0\}]$.

Second, suppose $s_1^A > 0$. Then $\max\{\lambda_1 s_1^A, \lambda_2 s_2^B\} \leq \max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}$ with the inequality strict for $s_2^B$ sufficiently large. From Lemma 1, it follows that $E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 s_2^B, 0\}] = E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_2 s_2^B\}] < E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] = E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_1 s_2^B, 0\}]$.
**Claim 3:** $E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_1 s_2^B, 0\}] = E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] = E_{s_2^B}[TS_E]$.

This claim follows from Lemma 1.

Taking all three claims together, the result holds. ■

To understand the intuition for this result it helps to take a closer look at the surplus functions in Figures 2 and 3 above. In particular, notice that there is an *upside* effect: a high signal in the second period increases the posterior mean of the sampled talent and thus increases surplus, whereas a low signal entails no cost because the agent can switch to the non-sampled sector. It turns out that the upside effect is stronger in the case of experimentation for the following two reasons.

First, since the agent's talent in sector B is sampled for the first time in the case of experimentation, the weight placed on this signal is larger relative to the weight placed on the signal in the specialization case ($\lambda_1 > \lambda_2$). This is because a signal drawn for the first time is more informative about talent.

Second, both the signals $\hat{s}_2^A$ and $s_2^B$ have the same mean of 0, but the signal in sector B, which is drawn for the first time, has larger variance.[3] Or put differently, the signal $\hat{s}_2^A$ second-

[3] The signal $\hat{s}_2^A \sim N(0, (1-\lambda_1^2)(\sigma_\eta^2 + \sigma_\epsilon^2))$, whereas the signal $s_2^B \sim N(0, \sigma_\eta^2 + \sigma_\epsilon^2)$.

order stochastically dominates the signal $s_2^B$. This is because less is known about a talent which is sampled for the first time.

To summarize, there is *more to learn* from experimentation: the weight placed on signal B when updating beliefs is stronger ($\lambda_1 > \lambda_2$) and extreme values of signal B are more likely ($\hat{s}_2^A$ second-order stochastically dominates $s_2^B$). As a result, the upside effect is larger for experimentation. This larger upside effect combined with the symmetry of the normal distribution ensures that experimentation yields a higher expected surplus relative to specialization.

Given that experimentation always does better than specialization, we now look at how the difference in the expected surplus across both of these cases varies as we vary parameters in our model.

**Proposition 2** *$V_E - V_S$ is:*

*i strictly increasing in $\sigma_\eta^2$.*

*ii strictly decreasing in $|s_1^A|$ and tends to 0 as $|s_1^A|$ tends to infinity.*

The proof of Proposition 2 is in the appendix. The intuition for the first part of this proposition is clear. As the variance of talents gets larger, there is more to learn from experimentation which makes it more valuable relative to specialization. Part (ii) of the proposition, on the other hand, is less obvious and says that the gains from experimentation are the largest for intermediate draws of talent, and that in the limit (for very good or very bad draws of talent) these gains disappear.

To see why the second part of Proposition 2 holds, notice from Lemma 1 that we can rewrite $E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}] = E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A, \lambda_2 \hat{s}_2^A\}]$. Comparing this expression with the expected surplus from experimentation, which is $E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}]$, we see that two things matter: the floor of the total surplus function $\lambda_1 s_1^A$ which is common across both expressions, and the inferences drawn from the second period signal across sectors ($\lambda_2 \hat{s}_2^A$ versus $\lambda_1 s_2^B$). For a very good first period draw in sector A, the common floor is highly likely to bind and hence both sampling strategies yield close to the same value. For a very low draw in sector A, on the other hand, the common floor rarely binds. Since the mean of $\hat{s}_2^A$ and the mean of $s_2^B$ are both 0, the sampling strategies once again yield a similar value. Thus, it is for intermediate draws of the first period signal – where the floor is partially relevant and where there is more to learn from experimentation – where these sampling strategies differ the most.

## 4 Incentives to Sample

We now turn to incentives that the agent has to specialize or experiment. Given that the agent bargains with a firm over the surplus, the agent's expected utility from specializing and experimenting are given by:

$$EU_S = E_{\hat{s}_2^A}[\mu \max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\} + (1-\mu)\min\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}]$$

and

$$EU_E = E_{s_2^B}[\mu \max\{\lambda_1 s_1^A, \lambda_1 s_2^B\} + (1-\mu)\min\{\lambda_1 s_1^A, \lambda_1 s_2^B\}].$$

The proposition below shows the agent's optimal sampling strategy.

**Proposition 3** *The agent experiments if and only if* $\mu \geq \frac{1}{2}$.

**Proof** Notice that

$$\begin{aligned}
E_{\hat{s}_2^A}[\min\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}] &= \int_{-\infty}^{-\frac{\lambda_1}{\lambda_2}s_1^A} (\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A) dF^A + (1 - F^A(-\frac{\lambda_1}{\lambda_2}s_1^A))\, 0 \\
&= -\int_{-\frac{\lambda_1}{\lambda_2}(-s_1^A)}^{\infty} (\lambda_1(-s_1^A) + \lambda_2 \hat{s}_2^A) dF^A \\
&= -E_{\hat{s}_2^A}[\max\{\lambda_1(-s_1^A) + \lambda_2 \hat{s}_2^A, 0\}] \\
&= -V_S(-s_1^A)\,,
\end{aligned}$$

where the second line follows from the symmetry of the normal distribution.

Also

$$\begin{aligned}
E_{s_2^B}[\min\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] &= \int_{-\infty}^{s_1^A} \lambda_1 s_2^B dF^B + (1 - F^B(s_1^A))\,\lambda_1 s_1^A \\
&= -\int_{(-s_1^A)}^{\infty} \lambda_1 s_2^B dF^B - F^B(-s_1^A)\lambda_1(-s_1^A) \\
&= -E_{s_2^B}[\max\{\lambda_1(-s_1^A), \lambda_1 s_2^B\}] \\
&= -V_E(-s_1^A)\,,
\end{aligned}$$

where the second line follows from the symmetry of the normal distribution.

Thus we have

$$\begin{aligned}
EU_E - EU_S &= \mu(E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] - E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}]) \\
&+ (1-\mu)(E_{s_2^B}[\min\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] - E_{\hat{s}_2^A}[\min\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}]) \\
&= \mu(V_E - V_S) - (1-\mu)(V_E(-s_1^A) - V_S(-s_1^A)) \\
&= (2\mu - 1)(V_E - V_S)\,,
\end{aligned}$$

where the last line follows from the fact that $V_E - V_S$ only depends on the absolute value of the first period signal $|s_1^A|$ (from Proposition 2).

Since $V_E - V_S > 0$ (from Proposition 1), it follows that $EU_E - EU_S \geq 0$, if and only if $\mu \geq \frac{1}{2}$. ■

Proposition 3 says that an agent (efficiently) experiments as long as labor markets are sufficiently competitive. The cutoff that induces experimentation ($\mu = \frac{1}{2}$) lies right in the middle of the two polar cases: $\mu = 1$ (perfectly competitive labor markets) and $\mu = 0$ (monopsony). This is because talents are symmetrically distributed and because the updating rule for normally distributed talents and signals is linear.

To see the intuition for the proposition more clearly, let's go back to the two extreme cases of competition. When $\mu = 1$ so that labor markets are perfectly competitive, the agent is the residual claimant and thus has incentives to choose the efficient sampling strategy. On the other hand, when $\mu = 0$ so that labor markets are monopsonistic, the agent has no bargaining power. She hence receives her reservation wage which is the lesser of her two talents. As a result, her incentives are distorted away from experimentation: sampling the second talent in the hope of receiving a high signal in the second period yields no benefit (as wages are capped above by the non-sampled sector) while low signals entail an additional cost, because they would reduce the reservation wage. Specialization helps limit this cost: because the residual variance of sampling the same talent in the second period is lower than sampling the other talent. Put differently, specialization suppresses learning, which in monopsony only has costs and no benefits.

# 5 A Role for Specialization

Our main result in Proposition 1 is that experimentation is efficient regardless of the initial draw of talent. This result, however, hinges crucially on some assumptions made in our paper: talents are symmetrically and normally distributed, and there is no human capital acquired during the learning phase. In this section, we show that specialization has a role to play from an efficiency viewpoint when these assumptions are relaxed. The proofs of all the propositions that follow are in the appendix.

## 5.1 Human Capital

We now introduce human capital into our analysis. When an agent samples a sector, she does not just get a signal of her talent; she also acquires human capital $H > 0$. Output in each sector is the agent's talent plus her human capital. When human capital is general across sectors, we can rewrite the surplus functions as:

$$TS_S^{General} = \max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A + 2H, 2H\}$$

and

$$TS_E^{General} = \max\{\lambda_1 s_1^A + 2H, \lambda_1 s_2^B + 2H\}.$$

When human capital is specific to a sector, on the other hand, the surplus functions become:

$$TS_S^{Specific} = \max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A + 2H, 0\}$$

and

$$TS_E^{Specific} = \max\{\lambda_1 s_1^A + H, \lambda_1 s_2^B + H\}.$$

The following proposition characterizes the efficient sampling strategy with human capital.

**Proposition 4** *i When human capital is general across sectors, experimentation is efficient.*

*ii When human capital is specific to a sector, specialization is efficient for a sufficiently large first period signal $s_1^A$, and experimentation is efficient for a sufficiently small first period signal $s_1^A$.*

With general human capital, nothing changes in our analysis: experimentation is still efficient regardless of the first period signal. But when human capital is specific to a sector, our main result in Proposition 1 changes. With specific human capital, when an agent gets a really good draw in sector A, then it is efficient for her to sample the same sector again. And when she gets a really bad draw in sector A, efficiency dictates that she should experiment instead. The intuition for the result is the following. Because human capital is sector specific, it is lost if the agent ends up working in a different sector. For a large first period signal in sector A, the agent is more likely to work in sector A which makes it more costly to sample and accumulate human capital in sector B. For a low first period signal on the other hand, the agent is more likely to work in sector B so that experimentation is more valuable.

## 5.2 Asymmetric Model

So far in our model, sectors are symmetric: talents in both sectors have the same mean and the same variance. In this section, we allow for asymmetries across sectors.

Let $\eta^A \sim N(0, \sigma_\eta^2)$ and $\eta^B \sim N(b, v\sigma_\eta^2)$ where $v > 0$ and where $b$ is any real number. Also let $\epsilon_t^A \sim N(0, \sigma_\epsilon^2)$ and $\epsilon_t^B \sim N(0, w\sigma_\epsilon^2)$ for $t = 1, 2$ with $w > 0$. Using this information structure we have that $E(\eta^B | s_2^B) = (1 - \lambda_1^B)b + \lambda_1^B s_2^B$, where $\lambda_1^B = \frac{v\sigma_\eta^2}{v\sigma_\eta^2 + w\sigma_\epsilon^2}$. The unconditional distribution of the signal $s_2^B$ is normal with mean $b$ and variance $v\sigma_\eta^2 + w\sigma_\epsilon^2$.

We break this section into two parts. In the first part, we assume that the agent exogenously samples sector A in period 1. In the second part, the agent's choice of which sector to sample initially is made endogenous.

The following proposition gives sufficient conditions under which experimentation is efficient when the agent exogenously samples sector A in period 1.

**Proposition 5** *Let $1 - \lambda_1^2 < v\lambda_1 + w(1 - \lambda_1) < v(1 + \lambda_1)$. Then, experimentation, where the agent samples different sectors in each period, is efficient.*

Notice first that the parameter $b$ plays no role in the proposition above – the sufficient conditions do not depend on $b$. What the result does depend on is the variances of talents and the variances of the error terms. The first condition in the proposition, $1-\lambda_1^2 < v\lambda_1 + w(1-\lambda_1)$, ensures that signal B has larger variance than signal A. The second condition, $v\lambda_1 + w(1-\lambda_1) < v(1+\lambda_1)$, ensures that the weight placed on signal B while updating the mean is higher. These two conditions, combined with the symmetry of the normal distribution ensure that experimentation, once again, is efficient.

Next, we relax the assumption that the agent exogenously samples sector A in the first period. We restrict our attention to the case where $v > 1$ and $w = 1$. Thus, talent has a larger prior variance in sector B and signals are equally noisy across sectors. For this case we have a very simple condition under which experimentation is efficient.

**Proposition 6** *Let $v > 1$, $w = 1$, and let the agent choose which sector to sample in period 1. Then experimentation is efficient if and only $\frac{\sigma_\eta^2}{\sigma_\epsilon^2} \geq \frac{v-1}{v}$.*

The proposition above offers a simple condition that is both necessary and sufficient for experimentation to be efficient. The left-hand side of the condition $\frac{\sigma_\eta^2}{\sigma_\epsilon^2}$ is simply the signal to noise ratio, whereas the right-hand side of the condition, $\frac{v-1}{v}$ measures the degree to which variances across sectors are asymmetric. The proposition then says that as long as the signal to noise ratio is at least as large as the degree of asymmetry in the variances, then experimentation is efficient.

### 5.3 How Sensitive is the Result to the Normal-Normal Model?

The fact that the result that experimentation is more efficient than specialization is independent of the realization of the signal drawn in the first period is surprising. We conjecture that the independence on the first period signal is specific to the normal-normal model and, more specifically, to the property that the variance of the updated normal distribution is independent of the first period signal.

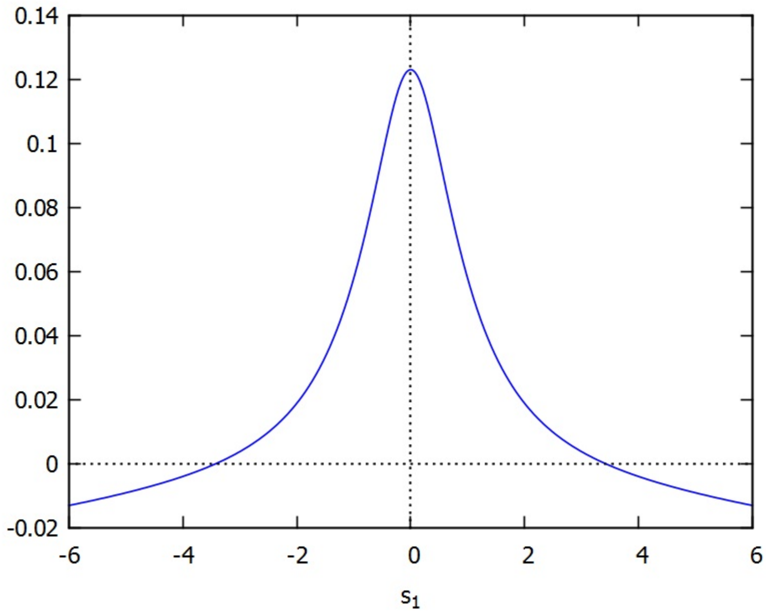
To explore this conjecture we analyze a slightly more general information structure. We assume that the agent's talent, $\eta^i$, in sector $i = \{A, B\}$ follows a Student $t$-distribution with $\nu > 2$ degrees of freedom, a mean of zero and scale parameter of $\frac{\nu-2}{\nu}\sigma_\eta^2$, i.e.,

$$\eta^i \sim t_\nu(0, \tfrac{\nu-2}{\nu}\sigma_\eta^2).$$

As before, conditional on $\eta^i$, signals are normally distributed with mean $\eta^i$ and variance $\sigma_\epsilon^2$. When the prior distributions for the agent's talents follow a $t$-distribution and signals are normally distributed, the posterior distributions for the agent's talents are also $t$-distributions DeGroot (1970). The posterior means of the agent's talents are the same as for the normal-normal model.

Similarly, the unconditional distribution of the first signal and the conditional distribution of

Figure 4: The difference in expected surplus from experimentation over specialization ($V_E - V_S$)




the second signal given the first signal follow Student $t$-distributions. More specifically,

$$
\begin{aligned}
s_2^B &\sim t_\nu(0, \tfrac{\nu-2}{\nu}(\sigma_\eta^2 + \sigma_\epsilon^2)) \\
\text{and} & \\
\hat{s}_2^A | s_1^A &\sim t_{\nu+1}(0, (\tfrac{\nu-2}{\nu} + \tfrac{1}{\nu+1}\tfrac{(s_1^A)^2}{\sigma_\eta^2+\sigma_\epsilon^2})(1-\lambda_1^2)(\sigma_\eta^2 + \sigma_\epsilon^2))
\end{aligned}
$$

These posterior distributions are very similar to the ones obtained in the normal-normal model. Posterior means are identical and, as $\nu \to \infty$, the variances and distributions converge to the normal-normal model.

The crucial difference to the normal-normal model is that the posterior variance of the second signal in sector A depends on the first signal. The greater the magnitude of the first signal, the greater the posterior variance of the second signal. If $s_1^A$ is very high or very low, the posterior variance of the second signal from sector A can get larger than the unconditional variance of the signal from sector B. In this case it can be efficient to sample from sector A again and, thus, specialize.

This is illustrated in Figure 4, which shows the difference in expected surplus from experimentation and specialization. Here, $\sigma_\eta^2 = \sigma_\epsilon^2 = 1, \lambda_1 = 0.5, \lambda = 0.33$ and $\nu = 3$.

Figure 4 confirms our conjecture: The result that experimentation is more efficient than specialization *for all* realizations of the first signal relies on the normal-normal model. In Figure 4 specialization is more efficient when the first signal is below -3.4 or above 3.4. Note that for the parameter values used in Figure 4, the signal $s_1^A$ follows a $t$-distribution with 3 degrees of freedom, mean zero and standard deviation of $\sqrt{2}$. Given this distribution, the probability of choosing a signal below -3.4 or above 3.4 is less than 10%. Thus, for the vast majority of realized signals, experimentation is still efficient.

## 6 Conclusion

People's talents are the driving force for innovation and growth. But in many cases these talents are unknown. Institutions in society thus have to be designed to provide incentives for individuals to learn about their talents in an efficient way. Our paper is a deliberately abstract attempt to make this link between institutions – particularly those governing competition in the labor market – and incentives to discover talents. We develop a tractable model to compare the relative merits of experimentation (where different types of talent are sampled) and specialization (where the same type of talent is sampled repeatedly). We also find that while competitive labor markets induce efficient learning of talents, monopsonistic labor markets move incentives towards specialization.

Our focus has mainly been on incentives provided by labor market institutions. But there are other institutions that matter for discovering talent: education systems, regulations that entrepreneurs are subject to, access to finance, and taxation, are all arguably important. Our tractable model serves as a useful starting point to better understand the role that these institutions play in discovering talent.

## Appendix

**Proof of Proposition 2:** We first prove that:

$$V_E - V_S = \int_{\frac{|s_1^A|}{\sigma_B}}^{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}} (\lambda_1 \sigma_B z - \lambda_1 |s_1^A|) f_z dz + \int_{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}}^{\infty} (\lambda_1 \sigma_B z - \lambda_2 \sigma_A z) f_z dz \,,$$

where $z$ is distributed normally with mean 0 and variance 1, $\sigma_A$ is the standard deviation of the random variable $\hat{s}_2^A$, and $\sigma_B$ is the standard deviation of the random variable $s_2^B$.

Consider two cases. Suppose $s_1^A \geq 0$. Then:

$$\begin{aligned}
V_E - V_S &= E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] - E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}] \\
&= E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] - E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A, \lambda_2 \hat{s}_2^A\}] \\
&= E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\} - \lambda_1 s_1^A] - E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A, \lambda_2 \hat{s}_2^A\} - \lambda_1 s_1^A] \\
&= \int_{\frac{|s_1^A|}{\sigma_B}}^{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}} (\lambda_1 \sigma_B z - \lambda_1 s_1^A) f_z dz + \int_{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}}^{\infty} (\lambda_1 \sigma_B z - \lambda_1 s_1^A) f_z dz - \int_{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}}^{\infty} (\lambda_2 \sigma_A z - \lambda_1 s_1^A) f_z dz \\
&= \int_{\frac{|s_1^A|}{\sigma_B}}^{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}} (\lambda_1 \sigma_B z - \lambda_1 |s_1^A|) f_z dz + \int_{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}}^{\infty} (\lambda_1 \sigma_B z - \lambda_2 \sigma_A z) f_z dz \,,
\end{aligned}$$

where the second line above follows from Lemma 1, and the fourth line makes use of the transformation $s_2^B = \sigma_B z$ and $\hat{s}_2^A = \sigma_A z$.

Next, suppose $s_1^A < 0$. Then:

$$\begin{aligned}
V_E - V_S &= E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 s_2^B\}] - E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}] \\
&= E_{s_2^B}[\max\{\lambda_1 s_1^A + \lambda_1 s_2^B, 0\}] - E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, 0\}] \\
&= \int_{-\frac{s_1^A}{\sigma_B}}^{-\frac{\lambda_1 s_1^A}{\lambda_2 \sigma_A}} (\lambda_1 \sigma_B z + \lambda_1 s_1^A) f_z dz + \int_{-\frac{\lambda_1 s_1^A}{\lambda_2 \sigma_A}}^{\infty} (\lambda_1 \sigma_B z + \lambda_1 s_1^A) f_z dz - \int_{-\frac{\lambda_1 s_1^A}{\lambda_2 \sigma_A}}^{\infty} (\lambda_2 \sigma_A z + \lambda_1 s_1^A) f_z dz \\
&= \int_{\frac{|s_1^A|}{\sigma_B}}^{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}} (\lambda_1 \sigma_B z - \lambda_1 |s_1^A|) f_z dz + \int_{\frac{\lambda_1 |s_1^A|}{\lambda_2 \sigma_A}}^{\infty} (\lambda_1 \sigma_B z - \lambda_2 \sigma_A z) f_z dz \,.
\end{aligned}$$

Now consider the comparative static results with respect to $\sigma_\eta^2$ and $|s_1^A|$ respectively.

i

$$
\begin{aligned}
\frac{\partial(V_E - V_S)}{\partial\sigma_\eta^2} &= \frac{\partial\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}}{\partial\sigma_\eta^2}(\frac{\lambda_1\sigma_B - \lambda_2\sigma_A}{\lambda_2\sigma_A})\lambda_1|s_1^A|f_z(\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}) - \frac{\partial\frac{|s_1^A|}{\sigma_B}}{\partial\sigma_\eta^2}(0) \\
&+ \int_{\frac{|s_1^A|}{\sigma_B}}^{\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}} \lambda_1\frac{\partial\sigma_B}{\partial\sigma_\eta^2}zf_z dz \\
&+ \int_{\frac{|s_1^A|}{\sigma_B}}^{\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}} (\frac{\partial\lambda_1}{\partial\sigma_\eta^2}(\sigma_B z - |s_1^A|))f_z dz \\
&- \frac{\partial\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}}{\partial\sigma_\eta^2}(\frac{\lambda_1\sigma_B - \lambda_2\sigma_A}{\lambda_2\sigma_A})\lambda_1|s_1^A|f_z(\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}) \\
&+ \int_{\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}}^{\infty}(\lambda_1\frac{\partial\sigma_B}{\partial\sigma_\eta^2} + \frac{\partial\lambda_1}{\partial\sigma_\eta^2}\sigma_B - \lambda_2\frac{\partial\sigma_A}{\partial\sigma_\eta^2} - \frac{\partial\lambda_2}{\partial\sigma_\eta^2}\sigma_A)zf_z dz\,.
\end{aligned}
$$

Notice that the first and fourth lines in the expression above cancel each other out. The third line is positive since $z \geq \frac{|s_1^A|}{\sigma_B}$. Also, since $\lambda_1 > \lambda_2$, $\sigma_B > \sigma_A$, $\frac{\partial\lambda_1}{\partial\sigma_\eta^2} > \frac{\partial\lambda_2}{\partial\sigma_\eta^2}$ and $\frac{\partial\sigma_B}{\partial\sigma_\eta^2} > \frac{\partial\sigma_A}{\partial\sigma_\eta^2}$, the last line is positive. Thus $\frac{\partial(V_E - V_S)}{\partial\sigma_\eta^2} > 0$.

ii

$$
\begin{aligned}
\frac{\partial(V_E - V_S)}{\partial|s_1^A|} &= \frac{\lambda_1^2|s_1^A|}{\lambda_2^2\sigma_A^2}(\lambda_1\sigma_B - \lambda_2\sigma_A)f_z(\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}) \\
&- \frac{\lambda_1|s_1^A|}{\sigma_B}(0)f_z(\frac{|s_1^A|}{\sigma_B}) \\
&- \int_{\frac{|s_1^A|}{\sigma_B}}^{\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A}} \lambda_1 f_z dz \\
&- \frac{\lambda_1^2|s_1^A|}{\lambda_2^2\sigma_A^2}(\lambda_1\sigma_B - \lambda_2\sigma_A)f_z(\frac{\lambda_1|s_1^A|}{\lambda_2\sigma_A})\,.
\end{aligned}
$$

Notice that the first and fourth lines cancel each other out. Thus $\dfrac{\partial(V_E - V_S)}{\partial|s_1^A|} < 0$.

**Proof of Proposition 4:**

i Suppose human capital is general. Then

$$E_{s_2^B}[TS_E^{General}] - E_{\hat{s}_2^A}[TS_S^{General}] = V_E - V_S.$$

From Proposition 1, it follows that experimentation is efficient.

ii Suppose human capital is specific to a sector.

We can write $E_{s_2^B}[TS_E^{Specific}] = V_E + H$ . Similarly, we can write

$$E_{\hat{s}_2^A}[TS_S^{Specific}] = V_S + H + g(s_1^A)\,,$$

where $g(s_1^A) = \int_{\frac{-(\lambda_1 s_1^A + 2H)}{\lambda_2}}^{0} 2H dF^A + \int_{\frac{-(\lambda_1 s_1^A + 2H)}{\lambda_2}}^{\frac{-\lambda_1 s_1^A}{\lambda_2}} (\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A) dF^A$.

Thus the expected gain in surplus from experimenting over specializing is given by $V_E - V_S - g(s_1^A)$ . In the limit as $s_1^A$ tends to infinity, $V_E - V_S - g(s_1^A)$ tends to $-H$ and as $s_1^A$ tends to minus infinity, $V_E - V_S - g(s_1^A)$ tends to $H$. Furthermore,

$$g'(s_1^A) = \frac{2H\lambda_1}{\lambda_2} f^A\left(\frac{-(\lambda_1 s_1^A + 2H)}{\lambda_2}\right) + \lambda_1 \int_{\frac{-(\lambda_1 s_1^A + 2H)}{\lambda_2}}^{\frac{-\lambda_1 s_1^A}{\lambda_2}} dF^A - \frac{2H\lambda_1}{\lambda_2} f^A\left(\frac{-(\lambda s_1^A + 2H)}{\lambda_2}\right) > 0\,.$$

Thus there is a threshold level of the first period signal, above which it is efficient to specialize. And since $V_E - V_S > 0$, there is a threshold level of the first period signal below which it is efficient to experiment.

**Proof of Proposition 5:** Let $\hat{s}_2^B = s_2^B - b$ . We split the proof into three claims.

**Claim 1:** $E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, b\}] \leq E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^B, b\}]$.

**Proof** The distribution of signal $\hat{s}_2^A$ given $s_1^A$ is $N(0, (1-\lambda_1^2)(\sigma_\eta^2 + \sigma_\epsilon^2))$. The distribution of signal $\hat{s}_2^B$ is $N(0, v\sigma_\eta^2 + w\sigma_\epsilon^2)$. When $1 - \lambda_1^2 < v\lambda_1 + w(1-\lambda_1)$ the two random variables $\hat{s}_2^A$ and $\hat{s}_2^B$ have the same mean but the former has smaller variance than the latter. Thus $\hat{s}_2^A$ second-order stochastically dominates $\hat{s}_2^B$. Since the max function is convex, $E_{\hat{s}_2^A}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^A, b\}] \leq E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 s_2^B, b\}]$.■

**Claim 2:** $E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^B, b\}] < E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_1^B \hat{s}_2^B, b\}]$.

**Proof** Notice that $\lambda_1^B > \lambda_2$ when $v\lambda_1 + w(1-\lambda_1) < v(1+\lambda_1)$.

Consider two possible cases.

First, suppose $\lambda_1 s_1^A \leq b$. Then $\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^B, b\} \leq \max\{\lambda_1 s_1^A + \lambda_1^B \hat{s}_2^B, b\}$ with the inequality strict for $\hat{s}_2^B$ sufficiently large. Thus $E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^B, b\}] < E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_1^B \hat{s}_2^B, b\}]$.

Second, suppose $\lambda_1 s_1^A \geq b$. Then $\max\{\lambda_1 s_1^A, \lambda_2 \hat{s}_2^B + b\} \leq \max\{\lambda_1 s_1^A, \lambda_1^B \hat{s}_2^B + b\}$ with the inequality strict for $\hat{s}_2^B$ sufficiently large. From Lemma 1 it follows that $E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_2 \hat{s}_2^B, b\}] = E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A, \lambda_2 \hat{s}_2^B + b\}] < E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A, \lambda_1 \hat{s}_2^B + b\}] = E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_1^B \hat{s}_2^B, b\}]$.■

**Claim 3:** $E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_1^B \hat{s}_2^B, b\}] = E_{s_2^B}[\max\{\lambda_1 s_1^A, (1-\lambda_1^B)b + \lambda_1^B s_2^B\}]$.

**Proof**

$$\begin{aligned}
E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A + \lambda_1^B \hat{s}_2^B, b\}] &= E_{\hat{s}_2^B}[\max\{\lambda_1 s_1^A, \lambda_1^B \hat{s}_2^B + b\}] \\
&= E_{s_2^B}[\max\{\lambda_1 s_1^A, \lambda_1^B (s_2^B - b) + b\}] \\
&= E_{s_2^B}[\max\{\lambda_1 s_1^A, (1-\lambda_1^B) b + \lambda_1^B s_2^B\}] \, ,
\end{aligned}$$

where the equality in the first line follows from Lemma 1. ■

Taking all three claims together, the result holds.■

**Proof of Proposition 6:** Since $v > 1$ and $w = 1$ both the inequalities in Proposition 5 hold. Thus specializing in sector A is dominated by sampling sector A in the first period and experimenting with B in the second. Also, since we can switch the order of integration, experimentation yields the same expected surplus regardless of which sector the agent samples first. Thus it is sufficient for us to compare two cases: the case where the agent samples sector B first and then experiments with sector A and the case where the agent specializes in sector B.

Note that:

$$\frac{\sigma_\eta^2}{\sigma_\epsilon^2} \geq \frac{v-1}{v} \iff \frac{v\sigma_\eta^2\sigma_\epsilon^2}{v\sigma_\eta^2 + \sigma_\epsilon^2} \leq \sigma_\eta^2 \iff \lambda_2^B = \frac{v\sigma_\eta^2}{2v\sigma_\eta^2 + \sigma_\epsilon^2} \leq \lambda_1 \, ,$$

where $\frac{v\sigma_\eta^2\sigma_\epsilon^2}{v\sigma_\eta^2 + \sigma_\epsilon^2}$ is the posterior variance of the talent in sector B and where $\lambda_2^B$ is the updating weight that the agent places on the second period signal in sector B if she specializes.

When $\frac{\sigma_\eta^2}{\sigma_\epsilon^2} < \frac{v-1}{v}$, the following three claims (as in the proof of Proposition 5) hold.

Claim 1: $E_{s_2^A}[\max\{\lambda_1 s_2^A, (1-\lambda_1^B)b + \lambda_1^B s_1^B\}] \leq E_{\hat{s}_2^{B'}}[\max\{\lambda_1 \hat{s}_2^{B'}, (1-\lambda_1^B)b + \lambda_1^B s_1^B\}]$, where $\hat{s}_2^{B'} = s_2^B - ((1-\lambda_1^B)b + \lambda_1^B s_1^B)$. This claim holds because the signals $s_2^A$ and $\hat{s}_2^{B'}$ have the same mean, but the former has smaller variance than the latter.

Claim 2: $E_{\hat{s}_2^{B'}}[\max\{\lambda_1 \hat{s}_2^{B'}, (1-\lambda_1^B)b + \lambda_1^B s_1^B\}] < E_{\hat{s}_2^{B'}}[\max\{\lambda_2^B \hat{s}_2^{B'}, (1-\lambda_1^B)b + \lambda_1^B s_1^B\}]$. This claim holds because $\lambda_2^B = \frac{v\sigma_\eta^2}{2v\sigma_\eta^2 + \sigma_\epsilon^2} > \lambda_1$.

Claim 3: $E_{\hat{s}_2^{B'}}[\max\{\lambda_2^B \hat{s}_2^{B'}, (1-\lambda_1^B)b + \lambda_1^B s_1^B\}] = E_{\hat{s}_2^B}[\max\{0, \lambda_2^B s_2^B + (1-\lambda_2^B)((1-\lambda_1^B)b + \lambda_1^B s_1^B)\}]$. This claim follows from Lemma 1.

Thus, specializing in sector B is optimal when $\frac{\sigma_\eta^2}{\sigma_\epsilon^2} < \frac{v-1}{v}$.

On the other hand, when $\frac{\sigma_\eta^2}{\sigma_\epsilon^2} \geq \frac{v-1}{v}$, the following three claims once again hold.

Claim 1: $E_{\hat{s}_2^{B'}}[\max\{0, \lambda_2^B \hat{s}_2^{B'} + (1-\lambda_1^B)b + \lambda_1^B s_1^B\}] \leq E_{s_2^A}[\max\{0, \lambda_2^B s_2^A + (1-\lambda_1^B)b + \lambda_1^B s_1^B\}]$, where $\hat{s}_2^{B'} = s_2^B - ((1-\lambda_1^B)b + \lambda_1^B s_1^B)$. This claim holds because the signals $\hat{s}_2^{B'}$ and $s_2^A$ have the same mean, but the former has smaller variance than the latter.

Claim 2: $E_{s_2^A}[\max\{0, \lambda_2^B s_2^A + (1-\lambda_1^B)b + \lambda_1^B s_1^B\}] < E_{s_2^A}[\max\{0, \lambda_1 s_2^A + (1-\lambda_1^B)b + \lambda_1^B s_1^B\}]$, where $\lambda_2^B = \frac{v\sigma_\eta^2}{2v\sigma_\eta^2+\sigma_\epsilon^2}$. This claim holds because $\lambda_2^B = \frac{v\sigma_\eta^2}{2v\sigma_\eta^2+\sigma_\epsilon^2} \le \lambda_1$.

Claim 3: $E_{s_2^A}[\max\{0, \lambda_1 s_2^A + (1-\lambda_1^B)b + \lambda_1^B s_1^B\} = E_{s_2^A}[\max\{\lambda_1 s_2^A, (1-\lambda_1^B)b + \lambda_1^B s_1^B\}$. This claim follows from Lemma 1.

Thus experimenting is optimal when $\dfrac{\sigma_\eta^2}{\sigma_\epsilon^2} \ge \dfrac{v-1}{v}$. ■

## References


**Auriol, E., G. Friebel, and L. Pechlivanos**, "Career Concerns in Teams," *Journal of Labor Economics*, 2002, *20* (2), 289–307.

**Bergemann, D. and J. Välimäki**, "Bandit Problems," in Steven N. Durlauf and Lawrence E. Blume, eds., *The New Palgrave Dictionary of Economics, 2nd Edition*, Vol. 1 Palgrave Macmillan 2008, pp. 336–340.

**DeGroot, M.H.**, *Optimal Statistical Decisions.*, New Jersey: John Wiley and Sons, 1970.

**Dewatripont, M., I. Jewitt, and J. Tirole**, "The Economics of Career Concerns, Part II: Application to Missions and Accountability of Government Agencies," *Review of Economic Studies*, 1999, *66*, 199–217.

**Felli, L. and C. Harris**, "Learning, Wage Dynamics, and Firm-Specific Human Capital," *Journal of Political Economy*, 1996, *104* (4), 838–868.

**Gibbons, R. and K.J. Murphy**, "Optimal Incentive Contracts in the Presence of Career Concerns: Theory and Evidence," *Journal of Political Economy*, 1992, *100* (3), 468–505.

**Holmstrom, B.**, "Managerial Incentive Problems – A Dynamic Perspective," in "Essays in Economics and Management in Honor of Lars Wahlbeck" Sweedish School of Economics Helsinki 1982.

**Jeon, S.**, "Moral Hazard and Reputational Concerns in Teams: Implications for Organizational Choice," *International Journal of Industrial Organization*, 1996, *14*, 297–315.

**Jovanovic, B.**, "Job Search and the Theory of Turnover," *Journal of Political Economy*, 1979, *87* (5), 972–990.

**Kaarboe, O.M. and T.E. Olsen**, "Career Concerns, Monetary Incentives and Job Design," *The Scandinavian Journal of Economics*, 2006, *108* (2), 299–316.

**Malamud, O.**, "Breadth versus Depth: The Timing of Specialization in Higher Education," *LABOUR*, 2010, *24* (4), 359–390.

——, "Discovering One's Talent: Learning from Academic Specialization," *Industrial and Labor Relations Review*, 2011, *62* (2), 372–405.

**Meyer, M.**, "The Dynamics of Learning with Team Production: Implications for Task Assignment.," *Quarterly Journal of Economics*, 1994, *109* (4), 1157–1184.

**Meyer, M.A. and J. Vickers**, "Performance Comparisons and Dynamic Incentives.," *Journal of Political Economy*, 1997, *105* (3), 547–581.

**Miller, R. A.**, "Job Matching and Occupational Choice," *Journal of Political Economy*, 1984, *92* (6), 1086–1120.

**Ortega, J.**, "Job Rotation as a Learning Mechanism.," *Management Science*, 2001, *47* (10), 1361–1370.

——, "Power in the Firm and Managerial Career Concerns," *Journal of Economics and Management Strategy*, 2003, *12* (1), 1–29.

**Schultz, T.**, "Resources for Higher Education: An Economists View.," *Journal of Political Economy*, 1968, *67* (3), 327–347.