# Economic Decision-Making Skill Predicts Income in Two Countries

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**Abstract**

Jobs increasingly require good decision-making. Workers are valued not only for how much they can do, but also for their ability to decide what to do. In this paper we measure the ability to make good decisions about resource allocation, which we call *economic decision-making skill*. Our assessment requires an intuitive understanding of comparative advantage and is motivated by a model where decision-makers strategically acquire information about factor productivity under time and effort constraints. Economic decision-making skill strongly predicts labor earnings in representative samples of full-time workers in the U.S. and Denmark, conditional on education, IQ, numeracy, and other covariates. Economic decision-making skill is more valuable in management and other decision-intensive occupations.

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# 1 Introduction

Most jobs require decision-making, in part because routine physical and information processing tasks are increasingly automated (e.g. Autor et al. 2003, Deming 2021).[1] Workers are valued not only for *how much* they can do, but also for their ability to *decide what to do*. Human capital theory traditionally emphasizes productive efficiency, in which people with more skill or education produce more output per unit of time (Mincer 1958, Becker 1962, Mincer 1974). Yet firms invest in managerial talent and emphasize problem-solving as the most desirable quality in new hires, suggesting that they also greatly value decision-making skills (Welch 1970, NACE 2020).

Figure 1 shows the rising importance of decision-making across the entire U.S. economy, using job vacancy data to measure employer skill demands.[2] We form a consistent definition of decision-making over time using data from Atalay et al. (2020) and from Burning Glass Technologies (BGT), covering the 1960-2000 and 2007-2019 periods respectively.[3] The share of all jobs requiring decision-making increased from 6 percent in 1960 to 34 percent in 2018, with nearly half of the increase occurring since 2007.[4]

Figure 2 presents a scatterplot of average wage and salary income against decision intensity, with labels attached to selected occupations. We measure decision intensity using data from the Occupational Information Network (ONET), a survey administered by the U.S. Department of Labor to a random sample of U.S. workers in each occupation.[5] Decision

[1]In settings ranging from retail banks to manufacturing plants, firms that automate routine tasks also delegate more decision-making authority to employees (Autor et al. 2002, Bresnahan et al. 2002, Bartel et al. 2007).

[2]Atalay et al. (2020) collect the text of classified ads placed in the *New York Times,* the *Wall Street Journal,* and the *Boston Globe* and map them to work activities from the Occupational Information Network (ONET) data, among other measures. We use their keyword mapping to the three ONET work activities Making Decisions and Solving Problems, Developing Objectives and Strategies, and Planning and Prioritizing Work - see the appendix to Atalay et al. (2020) for details. BGT classify vacancy text into thousands of unique job skills, and we use job skills (and related strings) with the key words and phrases above to create a consistent definition over time.

[3]To ensure representativeness, we weight the job ad data by the actual distribution of occupations in each year. To reduce classification error from narrowly defined occupations (some of which only exist in certain years of the data), we aggregate occupations to the 3 digit SOC level using occupation crosswalks and compute weights using Census and American Community Survey (ACS) data to make the job vacancy data representative of the actual occupation distribution in each year. We then apply a 5-year moving average of the share of ads requiring decision-making, to account for gaps between Census years and to reduce noise.

[4]The grey lines show the same trend but controlling for occupation fixed effects, which diminishes the impact only slightly, implying that most of the shift toward decision-making is occurring within rather than between occupations. Excluding management occupations diminishes the growth only slightly, suggesting that growing demand for decision-making is an economy-wide phenomenon.

[5]Our measure of decision-making intensity is a simple average of the three work activities also used in Figure 1 - making decisions and solving problems, developing objectives and strategies, and planning and prioritizing work. Since the raw ONET values have no cardinal meaning, we transform the decision intensity variable into a 0-10 scale that reflects each occupation's percentile rank in the labor supply-weighted

intensity is strongly correlated with average earnings. Not surprisingly, managers are among the most decision-intensive occupations, as well as scientists, engineers, doctors and lawyers.[6] Personal services and clerical occupations are the least decision-intensive.

This paper develops and tests a theoretically motivated measurement instrument for assessing individual variation in the ability to make good decisions about resource allocation, which we call *economic decision-making skill*. We model a decision-maker assigning factors of production to different roles to maximize total output. This could be a manager assigning workers to jobs, or workers allocating their own effort to job tasks. Factors have heterogeneous productivity schedules, so the decision-maker must compare hypothetical assignments and choose the one with the highest expected output. The decision-maker acquires costly information about payoffs, paying attention strategically to the most important features of a problem (e.g. Sims 2003, Caplin and Dean 2015, Matějka and McKay 2015, Maćkowiak et al. 2023).

We define individual attention costs in the model using an approach that is analogous to the role of input costs in standard production theory. In a competitive labor market, workers with higher earnings per unit of time (e.g. wages) have a higher marginal product of labor. In our model, people with higher levels of economic decision-making skill make better decisions about resource allocation, holding constant information complexity and time constraints. Thus economic decision-making skill measures the *marginal product of attention*.

We measure economic decision-making skill by creating a novel task called the Assignment Game. Participants are managers who assign fictional workers to jobs to maximize output. They observe multiple draws from workers' productivity schedules over tasks and then make an assignment. Participants are scored based on each worker's mean output in the task to which they were assigned. The Assignment Game requires participants to process information and to exploit comparative advantage by assigning workers to their highest value task given the skills of the others. Participants with higher average scores over multiple decision problems make better economic decisions about resource allocation, holding all else constant.

We test the implications of our model in two independent samples of full-time, prime age workers. The first sample includes more than a thousand U.S. workers ages 25-55 who were recruited on the research platform Prolific and were paid for performance on the Assignment Game and several other cognitive assessments. Our second sample includes more than two

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distribution of employment from the 2018-2019 ACS. We use the "level" variable in ONET, and apply separate scalings for each SOC code disaggregation (6 digit, 5 digit, etc).

[6] Appendix Table A1 presents decision intensity, average educational attainment, and earnings for all three digit occupations using the 2018 Standard Occupational Classification (SOC) codes and data from the 2018 and 2019 American Community Survey.

thousand workers drawn from the population registry of Denmark.[7] We sent surveys using an official government email address assigned to each resident and linked the results of the Assignment Game to administrative data from Statistics Denmark. Both samples are more educated than average but otherwise fairly representative, and we reweight them both to match their respective working-age populations.

Economic decision-making skill is strongly associated with income, with similar magnitudes in both samples. The positive correlation between Assignment Game score and income holds even after controlling for IQ, numeracy, education, occupation, and other covariates. Participants with one standard deviation higher economic decision-making skill have 8 percent higher earnings in the U.S. and 6 percent higher earnings in Denmark. The association between economic decision-making skill and income is nearly twice as large as the association with IQ, and is the largest of the four cognitive assessments when all are included in the same model.[8]

The association between economic decision-making skill and income is significantly greater in decision-intensive occupations, which we define using task data from the 2019 Occupational Information Network (ONET) as in Figure 2. For managerial and professional jobs at the 75th percentile of decision intensity and above, a one standard deviation increase in economic decision-making skill is associated with 10 percent higher earnings in the U.S. and 7 percent in Denmark. In contrast, economic decision-making skill is unrelated to income in jobs at the 25th percentile of decision intensity and below in both countries. We also find that participants with higher economic decision-making skill are more likely to work in decision-intensive occupations, with similar amounts of occupational sorting across the two countries.

We provide direct evidence for strategic decision-making by showing that some participants deploy an attention-saving strategy we call the *sequential assignment heuristic*. In the Assignment Game, participants first see worker productivity schedules in sequential order (e.g. all draws for worker 1, then for worker 2, etc.), and then they are shown productivity for all workers simultaneously before making an assignment. We find that participants frequently conserve attention by picking the best assignment for worker 1, then the best remaining assignment for worker 2, and so on.[9] This occurs even though they eventually see

[7]The first draft of this paper (titled "Allocative Skill") only included the U.S. survey results. After releasing that paper, we fielded a parallel survey in Denmark and constrained ourselves to the same tests and empirical specifications across the two countries.

[8]Economic decision-making skill is positively correlated with nonverbal IQ ($\rho = 0.38$), numeracy ($\rho = 0.31$), and cognitive reflection ($\rho = 0.29$). It is positively correlated with having a bachelor's degree ($\rho = 0.11$) and negatively correlated with age ($\rho = -0.13$).

[9]Participants who use the sequential assignment heuristic respond only to the information in front of them and never change their minds, which is similar to a *satisficing* strategy as in Simon (1955).

everything and can change their assignment at any time. Assignment Game scores are much less predictive of income when participants give multiple sequential answers, suggesting a direct connection between the ability to allocate attention strategically and real-world labor market success.

Economic decision-making skill captures total processing bandwidth, but also the ability to strategically pay attention to the most important features of a decision problem and to understand comparative advantage. We use the term *economic* to distinguish our measure from broader notions of decision-making competence. Psychologists have developed assessments like the Adult Decision-Making Competence scale, which measures people's average susceptibility to decision errors like sunk costs, framing, and under- or overconfidence (e.g. Bruine de Bruin et al. 2020).[10] Here we specifically study decisions about resource allocation under time and attention constraints. We emphasize this narrower domain rather than the broader construct of decision-making competence because it allows us to establish a tight link between theory and measurement. However, we recognize that decision-making competence is multi-dimensional, and we leave analysis of broader definitions of decision-making skill for future research.

Our paper contributes to human capital theory by formalizing and testing the value of allocative efficiency in the labor market. Economic decision-making skill matters in the labor market because attention is a scarce resource, and some people deploy it more effectively than others (e.g. DellaVigna 2009, Bordalo et al. 2012, Gabaix 2019). Our empirical measure of economic decision-making skill - the Assignment Game - requires both raw information processing capacity and an ability to seek information strategically and to understand comparative advantage. Unlike IQ, which is a simply a common individual factor estimated across tests, the labor market value of economic decision-making skill is grounded in economic theory (e.g. Spearman 1961).

An older literature in economics studies "allocative ability", with a particular focus on technology adoption and decision-making in agriculture (e.g. Nelson and Phelps 1966, Welch 1970, Huffman 1977).[11] Standard competitive theory rules out allocative ability as an im-

[10]Bruine de Bruin et al. (2020) review the psychological literature on the adult decision-making competence (ADMC) measurement instrument. They find that decision-making competence is distinct from fluid intelligence, that it is negatively correlated with behavioral outcomes like juvenile delinquency, drug use, and bankruptcy, and that there is a strong positive within-person correlation across different sub-tasks of the ADMC.

[11]This paper also contributes to the management literature by focusing on and empirically measuring one aspect of management skill, the ability to assign factors of production their best use (e.g. Bloom and Van Reenen 2010, Bandiera et al. 2020, Bertrand and Schoar 2003, Hoffmann et al. 2020, Minni 2022, Adhvaryu et al. 2022, 2023, Metcalfe et al. 2023). However there are many other aspects of being a good manager, such as social skills, leadership, and other factors that are not captured by our approach (e.g. Deming 2017, Hansen et al. 2021).

portant driver of outcomes through the assumption of perfect information, yet evidence of allocative inefficiency - or "X-inefficiency" - is everywhere (Leibenstein 1966, Stigler 1976). A few other papers study decision-making skill in healthcare, where doctors vary in both procedural skill and diagnostic skill (Currie and MacLeod 2017, Chan Jr et al. 2019). Goldfarb and Xiao (2011) and Hortaçsu et al. (2019) find that education and other proxies for skill improve managerial decision-making. Our results help explain why informational interventions in a variety of settings lead to improved decision-making and better long-run outcomes (e.g. Jensen 2010, Hjort et al. 2021). Our findings are also related to the literature on misallocation as a constraint on economic growth (e.g. Restuccia and Rogerson 2017).

The paper proceeds as follows. Section 2 develops the model. Section 3 describes the survey data and measurement constructs. Section 4 presents the results, and Section 5 concludes.

# 2 Model

The evidence in Figures 1 and 2 shows that good decision-making is increasingly valuable in the labor market. Yet people commonly make mistakes and suffer from behavioral biases even in very high-stakes decisions (e.g. Enke et al. 2023). A large literature in economics and behavioral science documents the nature and prevalence of decision-making biases and heuristics (e.g. Thaler 2016, Gabaix 2019). This literature finds tremendous variation across people in the prevalence of biases and decision errors (Chapman et al. 2023, Stango and Zinman 2023).

Our model of decision-making accounts for two stylized facts from this literature. First, people vary systematically in the quality of their decision-making. Multiple studies have found that people with higher cognitive ability are less "behavioral" (e.g. Frederick 2005, Oechssler et al. 2009, Burks et al. 2009, Benjamin et al. 2013).[12] Cognitive ability appears to reduce decision errors by increasing sensitivity to intermediate outcome probabilities (e.g. Binswanger and Salm 2017, Choi et al. 2022), improving forecasting (D'acunto et al. 2023), and improving strategic responses to risk (Dohmen et al. 2018).[13] Cognitive ability may

[12] Frederick (2005) shows that performance on a three-item "Cognitive Reflection Test (CRT)" predicts better decision-making, and Oechssler et al. (2009) find that people with higher CRT scores have fewer behavioral biases. Burks et al. (2009) find that cognitive skills are positively related to patience, small-stakes risk neutrality, and strategic awareness in prisoner's dilemma games. Benjamin et al. (2013) show that small-stakes risk aversion and short-run discounting are more common in high school students with low measured cognitive ability.

[13] Alternatively, cognitive ability might improve decision-making because it is correlated with risk and/or time preferences (e.g. Dohmen et al. 2010). However, a meta-analysis by Mechera-Ostrovsky et al. (2022) finds that the correlation between cognitive ability and risk preferences is fully mediated by differences in rates of decision error. Jagelka (2020) finds that up to 60 percent of heterogeneity in risk and time preferences

improve decision quality by increasing the mental resources available for rational analysis (e.g. Kahneman et al. 2002, Benjamin et al. 2013).[14]

Second, complexity greatly increases the cost of evaluating information, and people respond rationally to decision complexity with inattention and simple heuristics.[15] Holding the difficulty of a decision constant, people with higher cognitive ability may be more likely to weigh options rationally and less likely to deploy heuristics or "rules of thumb" in decision-making (Enke 2020, Oprea 2020, Mechera-Ostrovsky et al. 2022, **?**).

## 2.1 Model Setup

Consider a risk-neutral decision-maker assigning factors of production to different tasks to maximize total output. This could be a manager assigning workers to jobs, or a worker allocating their own effort over job tasks. The decision-maker chooses the optimal assignment of factors to tasks when productivity varies over tasks and is costly to observe. Our model extends the canonical allocation problem with comparative advantage developed by Koopmans and Beckmann (1957), with the addition of costly attention.

A set of $M$ factors, indexed by $1 \leq m \leq M$, is assigned to $M$ tasks, indexed by $1 \leq n \leq M$. We assume a 1:1 mapping of factors to tasks only for simplicity; this can be relaxed. An *assignment* is a 1:1 onto function $a : \{1, ...., M\} \rightarrow \{1, ...., M\}$, with $a(m)$ denoting the task to which factor $m$ is assigned and $a^{-1}(n) \in \{1, ...., M\}$ denoting the factor assigned to task $n$.

There is a finite set of possible productivity types, where a type specifies the potential output of factor $m$ in all $M$ tasks. The state $\omega \in \Omega$ specifies all factor productivities in all tasks. We denote productivity type of factor $m$ in state $\omega$ as $\omega(m) = (\omega_1(m), ...., \omega_M(m)) \in \mathbb{R}_+^M$, and $\omega_n(m) \in \mathbb{R}_+$ is factor $m$'s productivity type in task $n$. A production function $F(t_1, \cdots, t_M)$ maps task levels $t_n \geq 0$ into output.

Thus the decision-maker's output for any assignment of factors $a \in A$ in any state $\omega \in \Omega$

and in people's propensity to make mistakes can be explained by cognitive ability and personality factors, and that cognitive ability is especially important in avoiding mistakes.

[14] According to the resource-rational paradigm in cognitive psychology, decision-makers prefer heuristics because they conserve mental resources (e.g. Lieder and Griffiths 2020). Resource-rational analysis in psychology endogenizes a decision-maker's choice of mechanism (for example, whether to use a heuristic), while the rational inattention literature in economics assumes a rational approach and endogenizes the extent of information gathering (e.g. Sims 2003, Caplin and Dean 2015, Maćkowiak et al. 2023).

[15] The automata literature in economic theory models decision-making strategies as algorithms and uses formal definitions of complexity from the computer science literature (e.g. Abreu and Rubinstein 1988). This literature generally defines the implementation complexity as the number of possible states in a decision procedure (Oprea 2020). Banovetz and Oprea (2023) show that people use simple decision rules that economize on states when acting alone but switch to maximally complex decision rules when aided by a computer that tracks and organizes past events.

is:

$$f\left(a,\omega\right)\equiv F\left(\omega_1\left(a^{-1}\left(1\right)\right),....,\omega_M\left(a^{-1}\left(M\right)\right)\right) \tag{1}$$

If the decision-maker can perfectly observe worker productivity types at no cost, they simply evaluate all possible assignments and choose the one that maximizes output. However, if information is costly to observe, decision-makers will weigh the expected output from equation (1) against the expected cost of acquiring information about the state of the world $\omega$. When attention is costly, the ability to learn more efficiently about factor productivity has economic value, which connects our work to the the long tradition in economics of studying the relationship between learning and productivity (e.g. Nelson and Phelps 1966, Jovanovic and Nyarko 1996).

Our model treats costly attention as a fundamental source of allocative inefficiency in decision-making. With perfect information, "allocative ability" can never be the source of the return to a factor of production, yet firms behave as though good decision-making matters by paying for information and investing in managerial talent (Welch 1970). The empirical existence of allocative inefficiency spurred a high-profile debate between Leibenstein (1966) and Stigler (1976), summarized in Perelman (2011). Stigler (1976) argued that the existence of waste does not imply that workers and firms aren't maximizing agents. Rather, "waste is error within the framework of modern economic analysis, and it will not become a useful concept until we have a theory of error" (Stigler 1976). This paper develops and tests such a theory of error by measuring individual differences in the cost of paying attention.

## 2.2 The Attention Strategy

The decision-maker begins with a finite amount of attention and some prior beliefs about the state of the world, which we denote as $\mu\left(\omega\right)$. We assume that the decision-maker knows the production function $F$ and the number of factors $M$, but is *ex ante* uncertain about the state of the world $\omega$. Their goal is to use their attention to update their beliefs - i.e. to proceed from priors $\mu\left(\omega\right)$ to posteriors $\gamma\left(\omega\right)$. We formalize this as choosing a set of signals that help them refine their beliefs about $\omega$.

For example, if the decision-maker is a manager, they choose which workers to monitor and for how long, what questions to ask, and how much attention to pay to other important features of the problem. We call the choice of how to proceed from $\mu\left(\omega\right)$ to $\gamma\left(\omega\right)$ an *attention strategy.* In principle, the attention strategy captures a dynamic process in which the decision-maker seeks information, receives feedback, and updates their beliefs. After updating their beliefs, the decision-maker chooses an assignment $a$ that maximizes expected output given

$\gamma(\omega)$.[16]

We first define an attention strategy function $Q$ that assigns probabilities to posterior beliefs. The attention strategy is Bayes consistent, meaning posterior beliefs average back to prior beliefs, e.g. $\sum_Q \gamma Q(\gamma) = \mu$ where $Q(\gamma)$ is the unconditional probability of posterior belief $\gamma$ (Kamenica and Gentzkow 2011). Further define the optimal value of a posterior belief as:

$$\hat{f}(\gamma) = \max_{a \in A} \sum_{\omega} f(a, \omega) \gamma(\omega) \tag{2}$$

which makes the optimal value of attention strategies $\hat{f}(Q) = \sum_\gamma Q(\gamma) \hat{f}(\gamma)$. We can think of $\hat{f}(Q)$ as capturing the benefits of paying attention in any particular decision problem.

## 2.3 Attention as a Production Input

When attention is costly, the decision-maker will weigh the benefits of paying attention against the costs. Just as production theory requires functional form assumptions to deliver smooth comparative statics, we consider an attention cost function $K(Q)$ that can be scaled up or down linearly by some multiple $c > 0$. In that case, they choose an attention strategy that maximizes:

$$V(c, Q) = \hat{f}(Q) - cK(Q) \tag{3}$$

Equation (3) is effectively a production function with costly attention as the only input. Including $Q$ as an argument in the cost function formalizes the idea that paying attention is costly. The decision-maker chooses an attention strategy that maximizes the value of their attention strategy $\hat{f}(Q)$, subject to $K(Q)$. It implies, for example, that decision-makers will optimally pay greater attention to the elements of a decision that most affect payoffs.

To develop the analogy to production theory, we define an *attention production possibility set* of outputs that are jointly feasible given prior beliefs:

$$\mathcal{Y} \equiv \left\{ (x, y) \in \mathbb{R}^2 | \exists Q \in Q(\mu) \ s.t. \ \hat{f}(Q) \geq y, K(Q) \leq x \right\} \tag{4}$$

where $y$ is the output level, $x$ is an attention input, and $K(Q)$ is an attention cost function that depends on the distribution of beliefs associated with the attention strategy.

The set $\mathcal{Y}$ includes all outputs achievable for any given amount of attention $x$. We also define an *attention production function* $g(x)$ which is the supremum of $\mathcal{Y}$ for attention inputs

[16] A rational decision-maker will allocate their attention strategically to maximize output. This implies that they will not waste costly attention on acquiring redundant signals, such as asking the same question twice. Since rationality requires that no two signals ever lead to the same action, there is a one-to-one mapping between attention strategies and actions and we can model the two step process as the optimal choice of a joint strategy-action distribution (Kamenica and Gentzkow 2011, Maćkowiak et al. 2023).

of $x$ or below, e.g. $g(x) \equiv \sup\{y \in \mathbb{R} | (x, y) \in \mathcal{Y}\}$.

Two further assumptions are required to treat attention as a scarce input in classic production theory. The first assumption concerns the structure of attention costs. Inattention must have zero cost, learning more must require more attention, and it must be possible to mix learning strategies and average costs across them. Axiom 1 states these assumptions formally.[17]

**Axiom 1** *The cost function assigns zero cost to inattention, is weakly increasing in the Blackwell order, and satisfies Mixture Feasibility: given any two attention strategies $Q_0, Q_1$ and a share parameter $\lambda \in (0, 1)$, define the corresponding mixture strategy $Q_\lambda$ by taking the appropriate weighted average of the probabilities of the posteriors,*

$$Q_\lambda(\gamma) = \lambda Q_0(\gamma) + (1 - \lambda) Q_1(\gamma). \tag{5}$$

*Then it must be true that:*

$$K(Q_\lambda) \leq \lambda K(Q_0) + (1 - \lambda) K(Q_1). \tag{6}$$

For the second axiom, define $Q_P$ as the least Blackwell informative form of learning that delivers the empirical probability-weighted choice function $P(a, \omega)$ as in Matějka and McKay (2015), and define the induced cost function on $P$ as $\hat{K}(P) \equiv K(Q_P)$.

**Axiom 2** *The induced cost function $\hat{K}(P)$ is continuous in $P$.*

If these two assumptions hold, we can derive standard comparative statics for the cost parameter $c$:

**Theorem 1** *With Axioms 1 and 2, $\mathcal{Y}$ is a closed convex set, optimal strategies exist for all $c > 0$, and the attention production function $g(x)$ is non-decreasing in $x$, concave,bounded below and above by the values of inattentive and fully attentive strategies $Q_I$ and $Q_F$ respectively,*

$$\begin{aligned} g(0) \quad &\geq \quad \max_{a \in A} \sum_{\omega} f(a, \omega) \mu(\omega); \\ \lim_{x \longrightarrow \infty} g(x) \quad &\leq \quad \sum_{\omega} \max_{a \in A} f(a, \omega) \mu(\omega). \end{aligned}$$

[17] Caplin and Dean (2015) show that this axiom holds without loss of generality in behavioral data. Moreover inequality (6) is satisfied strictly for the broad class of posterior separable cost functions introduced in Caplin et al. (2022).

Theorem 1 establishes that $\mathcal{Y}$ is a convex set, that the production function $g(x)$ is concave, and that optimal output is diminishing in $c$. See the Theory Appendix for a proof. Conceptually, $c$ indexes the marginal cost of attention and its reciprocal can be interpreted as a technology term that augments attention inputs (e.g. the marginal product of attention).

Figure 3 presents a visual illustration of how the production function $g(x)$ translates attention into output. The lefthand panel shows the concavity of the production function, with the lowest output arising from an inattentive strategy (e.g. random guessing) and output asymptoting as attention increases. The righthand panel shows the impact of a decrease in the marginal cost of attention $c$. When $c$ declines from 1 to 0.5, the slope of the tangent line becomes flatter, and the decision-maker optimally pays more attention and produces higher expected output. Intuitively, the slope of $g(x)$ captures the marginal benefit of attention, with a flatter slope indicating a more complex decision.

We treat the decision-maker like a firm, which maximizes profits by choosing inputs to equate marginal benefits and marginal costs. While the firm's inputs are labor and capital, the decision-maker's input is costly attention. Since attention is more difficult to measure empirically than physical inputs, we develop an empirical approach to isolating individual differences in attention costs based on revealed behavior.

## 2.4 Economic Decision-Making Skill

We develop the empirical analog of the decision-maker's problem by expressing equation (3) as a set of contingent assignment probabilities $P(a \mid \omega) \geq 0$ which must sum to one in each state:

$$V(a,\omega) = \max_{P \in P(A)} \sum_a \sum_\omega y(a,\omega) P(a \mid \omega) \mu(\omega) - cK(P) \tag{7}$$

subject to the constraints that $P(a \mid \omega) \geq 0$ and $\sum_a P(a \mid \omega) = 1$.

Equation (7) shows that the decision-maker develops a joint attention-action strategy $P(a \mid \omega) \mu(\omega)$ that maximizes expected output in any possible state, taking into account the cost of acquiring information.

We study variation in attention costs by adding individual-specific subscripts $j$ to the decision-maker's problem:

$$V_j(a,\omega) = \max_{P_j \in P(A)} \sum_a \sum_\omega y_j(a,\omega) P_j(a \mid \omega) \mu_j(\omega) - c_j K(P_j) \tag{8}$$

where $c_j > 0$ is the marginal cost of attention.[18] We refer to the inverse of $c_j$ as *economic*

[18] And where the cost of $P_j$ can be computed from $K(Q)$ as the least Blackwell informative distribution

*decision-making skill,* $\alpha_j = \frac{1}{c_j}$, which is equivalent to the marginal product of attention.

We hypothesize that economic decision-making skill is an individual trait. For example, the righthand panel of Figure 3 could represent optimal output for two individuals with different amounts of economic decision-making skill. All else equal, decision-makers with higher economic decision-making skill will process information more efficiently, flattening the slope of the tangency with $\mathcal{Y}$ and achieving higher optimal output.[19]

Measuring economic decision-making skill requires us to hold fixed several key aspects of the decision problem. First, we must clearly define the set $A$ of possible assignments. Second, output should map directly to utility so we can compare performance differences across individuals. Third, we must account for decision-makers' prior beliefs $\mu(\omega)$, so that we can attribute performance to differences in $c_j$ rather than differences in preexisting knowledge about the setting.

After accounting for the action set, the mapping between output and utility, and prior beliefs, the only remaining variation across individuals in equation (8) is the assignment probabilities $P_j(a \mid \omega)$ and the marginal cost of attention $c_j$ (and its inverse $\alpha_j$). Thus we measure economic decision-making skill by observing individual differences in $P_j(a \mid \omega)$ and the associated output $V_j(a, \omega)$.

Our empirical setting closely matches the theory above. We administer an assessment to survey participants which asks them to play the role of managers assigning $M$ fictional workers to $M$ tasks, so there are exactly $M!$ possible assignments. Participants first acquire signals by observing workers' productivity schedules and then choose what they believe to be an output-maximizing assignment. We also fix the information received by participants, the amount of time available to make assignments, and the overall difficulty of the problems. When participants are paid for performance, payments are small enough that risk aversion is unlikely to be a concern. Finally, workers and tasks are given generic labels (e.g. workers 1 and 2, tasks A and B) to ensure that workers and job tasks are seen as *ex ante* equivalent.

With these restrictions, individual heterogeneity in performance arises only from variation in economic decision-making skill, and we can identify ordinal differences between people given the assumptions outlined in Theorem 1. However, we can also solve the model analytically using individual performance data on a series of problems like equation (8). In the Theory Appendix we develop a maximum likelihood estimator that derives an individual's marginal cost of information by comparing their actual assignment to all possible assignments for each decision problem.[20]

of posteriors that can produce $P_j$.

[19]More generally, given $c_1 > c_2 \geq 0$, let $x_1$ be an optimal input choice for $c_1$ and $x_2$ for $c_2$, $x_1 \leq x_2 \implies g(x_1) \leq g(x_2)$.

[20]Matějka and McKay (2015) show that how to solve a model similar to ours above, using the assumption

# 3 Data

## 3.1 U.S. Survey

We measure economic decision-making skill in two independent samples. Our first sample was recruited from the online research website Prolific, a platform that is specifically designed for academic research.[21] We restrict the Prolific sample to U.S. residents age 25 to 55 who spoke fluent English and were employed at least 35 hours per week. We conducted the study on weekends so that people with full-time jobs could participate. We also asked respondents what share of their total income is derived from Prolific and other research sites, and we excluded from our analysis sample the 8.6 percent of respondents who reported a share greater or equal to 10 percent. However, our results are not sensitive to this sample restriction.

We recruited a total of 1,250 survey participants. 9 participants failed to complete the experiment, 79 failed one of the attention or effort checks during the survey, 108 reported earning 10 percent or more of their income through Prolific, 40 did not report income data, and 6 did not report some other demographic variable. This left us with a core analysis sample of 1,008 respondents, all of whom were full-time employed U.S. residents between the ages of 25 and 55 with valid income and demographic data.

The Prolific survey had three parts. First, we administered a 16-item version of our main assessment (the Assignment Game), described in more detail in Section 3.3. Second, we administered several widely-used and psychometrically validated skills assessments, including an IQ test and a numeracy test, described in Section 3.4. Third, we collected survey data on income, occupation, and demographics, described in Section 3.5.

All participants who passed the attention checks were paid \$12 for their time. To ensure a fair comparison across assessments, participants were paid for their performance on each cognitive assesment, including the Assignment Game. Participants spent an average of 44 minutes on the study. They were informed that their performance directly influenced their pay, and that outstanding performance would more than double their pay (bonuses were between \$0 and \$14). Ultimately, the maximum bonus was \$13.85, and the minimum was \$0.01. The mean bonus payment was \$4.45.

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that attention costs take on the Shannon mutual information form. Moreover, Bucher and Caplin (2021) show that if the decision-maker's problem is symmetric, meaning all workers are seen as *ex ante* equivalent, then $P_j(a \mid \omega) = \frac{\exp(\alpha_j y_j(a,\omega))}{\sum_{b \in a} \exp(\alpha_j y_j(b,\omega))}$ is the unique solution and individual attention costs can be estimated directly from the decision-maker's observed state-dependent choice probabilities. Appendix Table A2 presents results using a marginal cost of attention measure derived from the analytic solution to the model described above, which yields very similar results. See the Model Appendix for details, including a formal definition of symmetry.

[21] Douglas et al. (2023) compares sample participation, representativeness, and other measures of data quality across research website and find that Prolific outperforms MTurk, Qualtrics and other competitors.

## 3.2 Danish Registry Data

The second sample is drawn from the population registry of Denmark. Invitations to participate in a survey were sent through an official government email account (called *e-boks*) given to anyone born or ever had an address in Denmark. The survey included a few basic demographic questions to verify identity and a short, 5-item version of the Assignment Game. Due to concerns about survey attrition in the registry sample, we opted for a shortened version of our main assessment and did not administer additional cognitive assessments. Survey invitations were sent to 50,500 randomly selected people between the ages of 25 and 55 as of September 2023. Participants who finished the survey were entered into a lottery to receive one of 50 gift cards worth 1,000 Danish Kroner (about $150 USD) and one gift card worth 10,000 Danish Kroner.

Survey data were merged by Statistics Denmark to administrative records using the unique personal identifier that was also used for sending out the invitations in *e-boks*, anonymized, and made available to our research team on servers located at Statistics Denmark. The data contain records of employment, earnings, hours worked, occupation, education and demographic information. We use administrative data from 2022, the latest year currently available. We were able to match 96.4 percent (N=48,681) of the survey invitations to the Danish registry data.

The survey response rate was 6.5 percent (N=3,151), consistent with several other surveys in the Danish registry data (e.g. Epper et al. 2020). 89.6 percent of the respondents who began the survey completed it (N=2,822). The employment rate among survey completers was 81.4 percent, and there was no significant relationship between employment and our measure of economic decision-making skill (see Appendix Table A3 for details). Therefore, our final analysis sample in the Danish registry data consists of the 2,297 survey completers who are employed and have valid earnings and demographic data as of 2022.

Table 1 lists summary statistics for both analysis samples. Panel A compares our sample of U.S. full-time workers (N=1,008) to the average characteristics of the US full-time employed population age 25 to 55, calculated from the 2018-2019 ACS. The U.S. sample is 76 percent white compared to 72 percent nationally, with slightly fewer Black respondents (8 percent vs. 13 percent) but otherwise fairly representative. The sample is also slightly more male (64 percent vs. 56 percent). However, the Prolific sample is much more educated than the U.S. average, with 67 percent having obtained a bachelor's degree versus 41 percent nationally. The occupations held by sample participants are at the 65th percentile nationally in terms of decision intensity, compared to the 55th percentile in the full-time employed ACS sample. Wage and salary income are nearly identical across the two samples ($71,784 versus $71,528, both in 2022 dollars).

Panel B of Table 1 compares survey completers in Denmark to the rest of the sample based on administrative data. Completers are slightly older, less likely to be immigrants (10 percent vs. 19 percent), and much more likely to have a college degree (48 percent vs. 33 percent). They also have slightly higher earnings. Because the Danish data include contractual work hours, we are able to separate earnings from wages. Appendix Table A4 shows no significant relationship between Assignment Game score and hours worked, suggesting that any relationshiop between economic decision-making skill and earnings arises from higher wages rather than more hours worked.

Overall, both samples are more educated than average but otherwise fairly similar to the prime age, full-time employed population in each country. In both datasets we construct weights to make our results representative of the working-age population.[22]

### 3.3 The Assignment Game

Before starting the Assignment Game, participants completed a tutorial that explains how the game works and includes a practice problem.[23] In the Assignment Game, participants play the role of a manager who assigns a set of tasks to a set of fictional workers. In each assignment problem there are 3 or 4 tasks and a matching number of workers. Each worker must be assigned to only 1 task, and all tasks must be assigned. The manager's goal is to assign workers to the right tasks to maximize the total output of the team. Conceptually, the Assignment Game requires participants to find patterns in complex, non-verbal information stored in working memory, which makes it similar in some respects to an IQ test (e.g. Kyllonen and Christal 1990). However, it also requires the ability to allocate attention strategically and to understand comparative advantage, which IQ tests and other measures of reasoning ability do not capture.

In the first phase of the Assignment Game, participants observe worker output. Each worker has a productivity schedule over the tasks, and participants are shown multiple draws of workers' output for each task. Participants are told that "workers have good days and bad days" and that as manager their job is to figure out "how good workers are at different tasks ON AVERAGE". Figure 4 presents screenshots of the information provided

[22]In the Prolific sample, we reweight observations to make them representative of the 2018-2019 American Community Survey by matching observations on the average sample weights for respondents with the same demographic characteristics. In the Danish registry data we estimate a probit model of survey participation on demographic characteristics, use the estimates to predict the probability of participating in the survey, and then reweight observations using the inverse of the estimated propensity scores.

[23]The tutorial in the Danish registry was translated into Danish but otherwise identical to the U.S. tutorial. A shortened version of the Assignment Game is available for public use at `https://www.skillslab.dev/assignment-game`. The site asks visitors to enter an ID, which can be any combination of letters and numbers.

to participants. Participants are initially shown multiple draws of each worker's output by worker (the outputs worker 1, then worker 2 etc; see top panel of Figure 4). A worker's output for all tasks on a given day is displayed for 2 seconds. Next, there is a review period in which information about all workers is presented simultaneously (see bottom panel of Figure 4; note that the review repeats information that participants have already seen). Each review table is presented for 3 seconds.

Participants must assign exactly one worker to exactly one task. They can assign workers at any point during the game, including during the observation period - see the top panel of Figure 5, which shows a screenshot of a participant making an initial assignment for all three workers on day 4 of worker 3's observation period. Participants can change their assignments at any time. After the observation period ends, participants have 10 seconds to finalize their assignments. They lose access to worker productivity information during this period - see the bottom panel of Figure 5 for a screenshot.

Scores are based on the average productivity of workers. For example, suppose the left panel of Figure 6 gives the average worker productivity across the observation period. If a participant chooses the assignment on the right panel of the figure (Task A to worker 3, Task B to worker 1, and Task C to worker 2) the raw score would be 16=4+10+2. Participant scores have both a ceiling a floor, calculated as the highest and lowest possible scores among all possible assignments.

Assignment Game items can vary in complexity, from trivially easy to extremely difficult. In our version, easier items have 3 tasks and 3 workers while harder items have 4 tasks and 4 workers. There are $m!$ possible assignments for an $mxm$ item (e.g. 6 for a 3x3 item and 24 for a 4x4 item). To make the 3x3 and 4x4 items as comparable as possible, each 4x4 item has a 3x3 embedded within it.[24] The full Assignment Game assessment in the U.S. survey consisted of 16 items - 8 were 3x3, and 8 were 4x4. The mean score was 68, the standard deviation was 9.4, and the maximum score of 84 was achieved by less than one percent of participants. There were 3 3x3 and 2 4x4 items in the shorter Assignment Game administered in the Danish registry. The mean score in this version was 18.6, the standard deviation was 8.2, and the maximum score of 27 was achieved by 9 percent of participants.

## 3.4 Other Assessments

We administered three other widely-used assessments of cognitive skills in the U.S sample - the Raven's Advanced Progressive Matrices (Ravens), the Cognitive Reflection Test (CRT),

[24]To disguise this fact, we jumbled task labels and changed the levels of various worker outputs by adding or subtracting a constant. However, we left relative productivities untouched, thus retaining the structure of the 3x3 item when increasing it to 4x4.

and the Berlin Numeracy Test (BNT).

The Ravens test measures participants' pattern recognition and spatial reasoning, and is widely interpreted as a measure of IQ (e.g. Ravens 2003). Participants observe a pattern and determine what comes next - see Appendix Figure A.1 for an example item. Our Ravens test included 14 items. The maximum score of 14 was achieved by only 1 participant. 11 participants scored 0 out of 14. The mean score on the Ravens IQ test was 5.7, and the standard deviation was 2.7.

The CRT is a simple test designed to assess a participant's ability to 'reflect on a question and resist reporting the first response that comes to mind' (Frederick 2005). The original test has 3 questions, and some researchers have suggested that the items might have become too well known and are now subject to floor effects (Toplak et al. 2014). We add 3 new items reported in Toplak et al. (2014) to the original version, which gives us a total of 6 items (listed in Appendix Figure A.2). 194 participants answered all 6 CRT items correctly, and 107 scored 0 out of 6. The mean score on the CRT was 3.47, and the standard deviation was 1.96.

We use the original version of the BNT from Cokely et al. (2012), which contains 4 questions (listed in Appendix Figure A.3). The BNT is a validated test of statistical numeracy that has been taken by over 100,000 participants across a large number of countries and professions (Cokely et al. 2018). The BNT helps us account directly for numerical fluency, which is an important sub-component of economic decision-making skill. Moreover, existing research finds that performance on the Berlin Numeracy Test predicts decision-making quality independent of fluid intelligence, working memory and cognitive reflection (Cokely et al. 2018). The mean score on the BNT was 1.75, and the standard deviation was 1.32.[25]

## 3.5 Demographics and Other Characteristics

We collected basic demographic information from participants in the U.S. sample, including gender, race and ethnicity, age, and educational attainment. Participants reported their income in ranges of $20k USD up to $200k (0-$20k,$20k-$40k,...,$180k-$200k). We code income as the midpoint in the range. There were two categories for high earners: $200k-$250k (coded as $225k) and "Over $250k" (coded as $300k; only 9 participants reported income over $250k). We also elicited information about participant's current occupation, which we

[25]To assess the reliability of the Assignment Game score in the U.S. sample, we randomly split the items into two samples 5,000 times, calculated a Spearman-Brown adjusted correlation between each half, and took the mean of the 5,000 estimates. The split sample reliability is 0.75. The split sample reliabilities of the Ravens test (a measure of nonverbal IQ), the Cognitive Reflection Test, and the Berlin Numeracy test are 0.72, 0.76, and 0.65 respectively. As a result, adjusting for differential measurement error across assessments has no substantive impact on our main results.

mapped to Standard Occupation Classification (SOC) codes.[26] We link participants' reported occupations to ONET and ACS data using the most detailed level available, up to six digits whenever possible. This allows us to link participants' Assignment Game scores to the decision intensity of their occupation, as measured in Figure 2.

In the Danish sample we obtained administrative data on earnings, work hours, occupation, and demographics from Statistics Denmark. This includes monthly records of earned income from all employers, contractual hours worked and occupation codes. The occupation codes are from the Danish International Standard Classification of Occupations 2008 coding structure (DISCO-08), which we merge to the European ISCO-08 codes and then to U.S. SOC codes at the 3-digit level.[27] This allows us to measure heterogeneity in economic decision-making skill across occupations in both the U.S. and Denmark. Demographic data come from the population and education registries and include age, gender, family structure, and highest level of completed education.

Table 2 presents correlations between the Assignment Game score and other assessments, as well as selected demographics in the U.S. sample. Assignment Game score is positively correlated with nonverbal IQ ($\rho = 0.38$) and with the CRT and the BNT ($\rho = 0.31$ and $\rho = 0.29$ respectively). All the cognitive assessments are modestly positively associated with each other. Having a bachelor's degree is also modestly positively correlated with Assignment Game score ($\rho = 0.11$) and with other cognitive assessments. Age is negatively correlated with performance on the Assignment Game ($\rho = -0.13$), and men score slightly higher ($\rho = 0.06$). The correlation between Assignment Game score and having a tertiary degree is 0.13 in the Danish registry sample, while the correlations with age and being male are similar to the U.S. sample as well ($\rho = -0.16$ and 0.08 respectively).

[26]This was a three step process. First, participants provided their current job title and a 1-sentence description of their role. Second, they were asked to select the job category that most closely matched their current job from a dropdown list that was based on the ONET-SOC taxonomy of major and minor occupation groups. Participants were then presented with the top 5 options generated from their selections by the ONET online tool Autocoder and asked to make a selection (or they could see more options if they requested). See Appendix Figure A.4 for a screenshot. Finally, participants were shown a brief description of the job category they chose and were asked to confirm whether or not this adequately described their current job. If not, they were asked to repeat steps 2 and 3 using a modified job description. This process yielded a valid SOC code for all but three survey participants.

[27]We are unable to link SOC codes to ISCO or DISCO codes at a level more detailed than 3 digits because of inconsistencies across countries in the coding of occupations.

# 4 Results

## 4.1 Economic Decision-Making Skill Predicts Income in the U.S. and Denmark

Our first main hypothesis is that economic decision-making skill - as measured by the Assignment Game - is positively associated with income. To facilitate comparison we normalize scores on the Assignment Game and all the cognitive assessments to have a mean of zero and a standard deviation of one.

Panel A of Table 3 presents regressions of income on Assignment Game score in the U.S. survey, controlling for demographics, other cognitive assessments, and other variables. Column 1 shows the bivariate association. A one standard deviation increase in economic decision-making skill is associated with a \$6,006 increase in annual income in the U.S. survey, which is statistically significant at the less than one percent level and equivalent to about 8 percent of the sample mean. Panel B presents analogous results in the Danish registry sample, with all figures converted to U.S. dollar equivalents (1 Danish Kroner = 0.15 USD) for ease of comparison.

A one standard deviation increase in economic decision-making skill is associated with a \$3,694 increase in annual income in Denmark ($p < 0.01$), about 6 percent of the sample mean. Column 2 adds controls for gender, race/ethnicity, age and age squared, and educational attainment. The coefficient in Panel A drops to \$4,480 but still remains significant at the less than one percent level. The coefficient in the Danish registry sample in Panel B increases slightly to \$4,050 and is also significant at the less than one percent level. Column 3 adds population weights to both samples. The coefficient on economic decision-making skill increases to \$5,881 in the U.S. sample and falls to \$3,243 in the Danish registry sample. Both estimates are statistically significant at the less than 1 percent level. Overall, there is a strong positive association between Assignment Game score and income in both the U.S. and Denmark, albeit slighlty larger in the U.S. sample.

Column 4 estimates the population-weighted association between IQ and income in the U.S. sample, controlling for demographics. A one standard deviation increase in IQ is associated with a \$3,099 increase in income ($p = 0.051$), which is a little more than half the size of the association with economic decision-making skill. Column 5 estimates the same regression, but with economic decision-making skill and IQ together in a horse race specification. The coefficient on economic decision-making skill is \$5,012 ($p < 0.01$), whereas the coefficient on IQ drops to \$1,601 and is no longer statistically significant.[28]

[28] A recent study in Finland, where nearly all men are conscripted into the army and given an IQ test, finds that a one standard deviation increase in nonverbal IQ increases earnings at ages 30-34 by \$1,390,

Column 6 adds controls for the CRT and the BNT, the other two cognitive assessments. This increases the coefficient on economic decision-making skill slightly to \$5,227 ($p < 0.01$). Notably, the coefficients on the other assessments are all smaller in magnitude, and none are statistically distinguishable from zero.[29]

The relationship between economic decision-making skill and income is positive, highly statistically significant, and robust to controlling for multiple other cognitive assessments. Economic decision-making skill is a stronger predictor of income than nonverbal IQ, the Cognitive Reflection test, or the Berlin Numeracy test. However, it is important to note that AG score and IQ are strongly related, and in many specifications we cannot reject the hypothesis that they have the same magnitude. We do not argue that IQ is irrelevant, only that AG score is on average a stronger predictor of labor market success and that it is more firmly grounded in economic theory.

## 4.2 Occupational Sorting

Table 4 studies occupational sorting in both the U.S. and Denmark. We regress the decision intensity of a participant's current occupation on economic decision-making skill, controlling for other cognitive assessments and demographics. Column 1 shows the bivariate association, which suggests that a one standard deviation increase in economic decision-making skill is associated with an increase in decision intensity of about 3.1 percentile ranks in the U.S. and 3.4 percentile ranks in Denmark. Both estimates are statistically significant at the less than one percent level. The association falls to 2.2 and 2.1 percentile ranks in the U.S. and Denmark respectively when adding controls for demographics in Column 2. Column 3 adds population weights, which increases the magnitudes to 2.6 and 2.8 percentile ranks respectively.

Column 4 estimates an association between decision intensity and IQ in the U.S. sample only. We find that a one standard deviation increase in IQ is associated with a 2.2 percentile rank increase in decision intensity. Column 5 includes both economic decision-making skill and IQ in the same regression. Both independently predict occupation decision intensity, with magnitudes of 2.1 and 1.6 percentile ranks for economic decision-making skill and IQ respectively. Finally, Column 6 includes all four cognitive assessments. The coefficients on economic decision-making skill remains positive but drops to 1.6 ranks and is not quite significant at the ten percent level ($p = 0.133$). The assocation with numeracy is larger (2.9

about 6 percent of the sample mean (Jokela et al. 2017).

[29]The negative coefficient on the Berlin Numeracy Test in Table 3 is an artifact of the high degree of collinearity between tests. To show this directly, Appendix Table A5 presents separate regressions of income on each cognitive assessment plus demographic covariates. Economic decision-making skill is most strongly related to income, but all the coefficients are positive.

ranks) and statistically significant, but the other two assessments are not.

Overall, we find a statistically significant positive relationships between economic decision-making skill and the decision intensity of a participant's current occupation, with remarkably similar magnitudes in the U.S. and Denmark.

## 4.3 Economic Decision-Making Skill Predicts Income More Strongly in Decision-Intensive Jobs

The equilibrium relationship between economic decision-making skill and occupation decision intensity is ambiguous, and depends on the value of other skills in the labor market. For example, workers who are good decision-makers may also have strong technical skills, and thus may sort into less decision-intensive jobs that nonetheless pay higher wages (e.g. Borjas 1987, Heckman and Honore 1990, Hsieh et al. 2019). However, conditional on Roy-type occupational sorting, the return will unambiguously be higher in decision-intensive occupations. Thus in an earnings regression we should expect to see a positive coefficient on the interaction between economic decision-making skill and decision intensity.

Table 5A tests this prediction in the U.S. sample by regressing income on economic decision-making skill, decision intensity of current occupation, and the interaction between the two.[30] Table 5B presents the same set of analyses in the Danish registry sample.

We find strong evidence that economic decision-making skill is more important in decision intensive occupations. Column 1 shows results without any controls. The coefficient on the interaction term is large and statistically significant, and suggests that the impact of a one standard deviation increase in economic decision-making skill increases by $1,115 for every 10 percentile rank increase in occupation decision intensity in the U.S. ($p = 0.025$) and $679 in Denmark ($p = 0.022$).[31] For occupations at the 75th percentile of decision intensity, this translates to an increase in annual earnings of about 10 percent in the U.S. and 7 percent in Denmark. Column 2 adds demographic controls, which slightly increases the coefficient on the interaction term in the U.S. and slightly decreases it in Denmark. Adding population weights has little impact on the results, and both remain statistically significant at the five percent level or less.

Column 4 of Table 5A shows analogous results for nonverbal IQ. Unlike the results for economic decision-making skill, the interaction between IQ and decision intensity is not

[30] We de-mean the decision intensity variable when interacting it with each cognitive assessment, so that the main effect captures the average impact of a one standard deviation increase in each skill measure for workers in jobs of average decision intensity. This makes the direct effect easier to interpret, but has no effect on the magnitude or the precision of the interaction terms themselves.

[31] The results are also robust to splitting respondents by terciles or quartiles of occupation decision intensity and interacting the Assignment Game score separately with each quantile.

statistically significant. Column 5 includes all four cognitive assessments and their interaction with decision intensity. The interaction between economic decision-making skill and decision intensity remains highly statistically significant (\$1,126, $p = 0.027$) and has a very similar magnitude to Column 1, despite additional controls that more than double the R-squared (from 0.121 in Column 1 to 0.248 in Column 5). However, we find no evidence that the economic returns to IQ, cognitive reflection, or numeracy are increasing in decision intensity. All of the coefficients are smaller in magnitude than the coefficient on economic decision-making skill, and none are statistically significant. This strongly suggests that economic decision-making skill is particularly important in occupations that require more decision-making.

Appendix Table A6 presents heterogeneous impacts of economic decision-making skill by gender, age, and educational attainment. In Denmark, the association between economic decision-making skill and income is positive and statistically significant at the less than 5 percent level for all subgroups except young workers. In the U.S., it is statistically significant for all subgroups except women. While the magnitudes vary, we can never reject the null hypothesis of equal effects by subgroup, and there are no clear patterns that hold equally across both countries.

# 5 Attention Costs and Heuristic Decision-Making

Assignment Game scores are positively correlated with IQ, and good performance requires some amount of fluid intelligence, pattern recognition skills, and working memory. Is economic decision-making skill just another measure of IQ, or is it something different? While intelligence clearly matters, we argue that good decision-making also requires a *strategy* for how to allocate attention and an intuitive understanding of comparative advantage. Economic decision-making skill predicts income even after conditioning on incentivized assessments of IQ, numeracy, and cognitive reflection, which suggests indirectly that it is conceptually distinct from IQ and other cognitive assessments.

However, we also test the attention mechanism directly by studying participants' choices. Our model implies that people with high attention costs will seek cognitive shortcuts, or *heuristics*. Shah and Oppenheimer (2008) define a heuristic as any decision-making strategy that reduces effort, including ignoring potential alternatives, simplifying assessment of probabilities, seeking less information, and other approaches.[32] In the context of our model,

[32] Common examples include the availability heuristic, where the decision-maker relies on information that comes more easily to mind, and satisficing, where the decision-maker pre-commits to picking the first action that meets their own standard of acceptability (Simon 1955, Kahneman et al. 2002).

a heuristic is a strategy that yields a "good enough" output while conserving costly attention.[33] An alternative hypothesis is that decision errors are driven primarily by bandwidth constraints. For example, decision-makers making the wrong selection because of numerical errors or mixing up workers.

We use the structure of our experiment to test for heuristic decision-making. Recall from Figure 4 that participants first see all the days for each worker in order, and then are shown the entire productivity schedule (e.g. all workers in all tasks) for each day. This helps prevent them from forgetting early information, so working memory limitations should not be a constraint.

However, participants can conserve attention and reduce complexity by adopting a sequential assignment heuristic. Recall from Figure 5 that participants are allowed to make or change their assignment at any time. After seeing all the days of worker 1 (but not any of the subsequent workers), they can check the box to assign worker 1 to her most productive task. This effectively reduces complexity, turning a 4x4 matrix into a 3x3 or a 3x3 into a 2x2. Participants can do the same thing for each worker, eliminating possible choices at each step by assuming that the information they have already observed is the only thing that matters, or "what you see is all there is" as in Enke (2020).

Figure 7 provides an illustration of the sequential assignment heuristic. The participant observes 5 days, deduces that worker 1's most productive task is task A, and selects that task. This eliminates the top row and the leftmost column from consideration. The same analysis of worker 2 concludes that their best remaining task is task B. This leaves task C for worker 3, for a total score of 16 (6+5+5). However, notice that the optimal score is actually 19 (5+4+10). Task A has the highest output for all three workers, with the greatest value of 10 for worker C. Even though worker 1 is best at Task A, their biggest comparative advantage is in task B, and the optimal assignment is B-C-A.

Optimal performance requires participants to notice that the best assignment changes each time new information is revealed. This is easy to execute in principle, because task assignments can be changed at any time. However it requires a lot of attention because participants cannot give up on any possibility until the end. The average participant makes 1.9 sequential assignments out of the 16 decision problems, and 17 percent of the sample never chooses the sequential assignment. The correlation between the number of sequential

[33]One approach is to explicitly model the decision-maker's choice between a "system 1" heuristic strategy and a "system 2" rational strategy. For example, we could assume that choosing a heuristic is equivalent to choosing a strategy with constant information costs, e.g. $K = \overline{\mathcal{K}}$ rather than the cost function $K(Q)$ in Section 2.2 that depends on posterior beliefs. Intuitively, people with higher attention costs will be more likely to choose the heuristic strategy because they find the rational approach of refining beliefs through information acquisition relatively more costly.

assignments and IQ is $-0.18$, while the correlation with income is $-0.06$.

The relative frequency of the sequential assignment heuristic is a key test of whether mistakes are strategic responses to limited attention. If decision mistakes are driven primarily by bandwidth constraints such as numerical errors or forgetting, the sequential assignment heuristic should not be more common than other errors.

However, we find that the sequential assignment heuristic is by far the most common mistake. In each of the 16 decision problems in the U.S. sample, there is a unique optimal assignment of workers to tasks (e.g. the assignment with the highest score). There are 6 possible assignments for a problem with 3 workers and 3 tasks, and participants select the optimal assignment in 52 percent of these 3x3 problems.[34] The remaining 49 percent of answers are mistakes in the sense that participants could have achieved a higher score. If mistakes were random, we would expect them to be divided evenly among the remaining 5 answers. Yet we find that participants select the one sequential assignment 18 percent of the time, compared to 30 percent total for the other 4 mistakes (an average of 7.5 percent for each). Similarly in the 4x4 problems, participants select the optimal assignment 43 percent of the time, the sequential assignment 23 percent of the time, and the other 22 mistakes comprise the remaining 34 percent. Mistakes from adopting a sequential assignment heuristic are much more common than other mistakes.

Table 6 studies this formally by estimating a regression at the item-by-assignment level of the percent of participants selecting that assignment on the score that assignment yields, interacted with an indicator for whether it was the sequential assignment. Intuitively, we are testing whether the sequential assignment was more likely than other mistakes of the same magnitude. The sample size has 210 observations because there are 42 possible responses to the 7 3x3 items and 168 possible responses to the 7 4x4 items. Column 1 shows, not surprisingly, that participants are 3.3 percentage points more likely to select an assignment for every 1 point value increase in output. Column 2 adds an interaction for whether the assignment was sequential. The coefficient of 0.034 relative to the main effect of 0.30 shows that participants are more than twice as likely to select the sequential assignment at any given score. Column 3 adds item fixed effects, which nearly doubles the coefficient and implies that for an item of any given difficulty respondents are nearly three times more likely to select a sequential answer than any other answer. Overall, these results show that participants respond to complexity by choosing assignments sequentially, which reduces the dimensionality of the decision problem.

Heuristics are valuable because they sometimes deliver a "good enough" score while re-

[34] For 2 of the 16 decision problems, the sequential assignment is also the optimal assignment. We exclude those problems from this calculation, so that all sequential assignments are mistakes.

quiring minimal attention. Empirically, participants using the sequential assignment heuristic will sometimes get lucky and receive a high score. Thus participants who frequently rely on the sequential assignment heuristic will have lower true economic decision-making skill, conditional on their Assignment Game score. If this is true, we should expect a weaker relationship with income for scores obtained through the sequential assignment heuristic. We test this hypothesis by estimating a regression of income on Assignment Game score interacted with the number of times each participant chose the sequential assignment. In the 2 of 16 cases where the sequential assignment is also the optimal assignment, we code those as non-sequential for ease of interpretation, so that all sequential assignments are mistakes.

The results are in Table 7. Column 1 presents estimates with no other controls. The main effect on economic decision-making skill is \$10,457 ($p < 0.01$) and the interaction term is \$-1,944 ($p = 0.016$). The main effect implies that a one standard deviation increase in economic decision-making skill is associated with nearly 15 percent higher income when the score is obtained without any sequential assignments. In contrast, a one standard deviation increase in economic decision-making skill has no significant relationship to income when it is obtained with 4 or more sequential assignments. The interaction term increases very slightly with the addition of demographic controls and population weights in Column 2. Columns 3 and 4 show that adding IQ controls make little difference and that there is no significant relationship between IQ and the number of sequential assignments. Column 5 shows no significant relationship with cognitive reflection or numeracy. The number of sequential assignments is not related to income overall except through its relationship to economic decision-making skill, nor is it correlated with the other cognitive assessments. Overall, Table 7 provides strong evidence that our results are consistent with the strategic attention mechanism.

# 6 Conclusion

This paper develops a theory and measurement paradigm for assessing individual differences in *economic decision-making skill*. We first show that modern work increasingly requires decision-making. We then develop a simple model where decision-makers assign factors of production to different tasks to maximize total output. This could be a manager assigning workers to jobs, or a worker assigning her own effort over job tasks. Factors have heterogeneous productivity over tasks, and productivity information is costly to observe. People with more economic decision-making skill achieve higher total output in a decision problem, holding constant complexity and time constraints.

We measure economic decision-making skill with a novel task we call the Assignment

Game, where participants are managers who assign fictional workers to jobs to maximize output. We administer the Assignment Game in two independent samples of prime-age workers in the U.S. and in Denmark. In both cases we find that economic decision-making skill is strongly associated with income even after controlling for many different covariates, including education, IQ, and numeracy. The association between earnings and economic decision-making skill is twice as large as the association with IQ. We also find that economic decision-making skill predicts income much better for workers in decision-intensive occupations such as management. Strikingly, the direction and magnitude of our empirical results is very similar across the two countries. Moreover, we exploit the choice data directly to show that workers with lower levels of economic decision-making skill use attention-saving heuristics, and that greater use of these heuristics is negatively related to income.

Our paper contributes to human capital theory by formalizing and testing the idea that good decision-making is rewarded in the labor market. Measuring individual differences in economic decision-making skill requires us to take seriously the idea that attention is a scarce resource. People with greater economic decision-making skill put the same information to better use when making complex decisions. Put another way, to understand labor productivity in the information age, we must use the tools of information theory. Good decision-making is likely to be increasingly important in the labor market as routine information processing tasks are increasingly automated.

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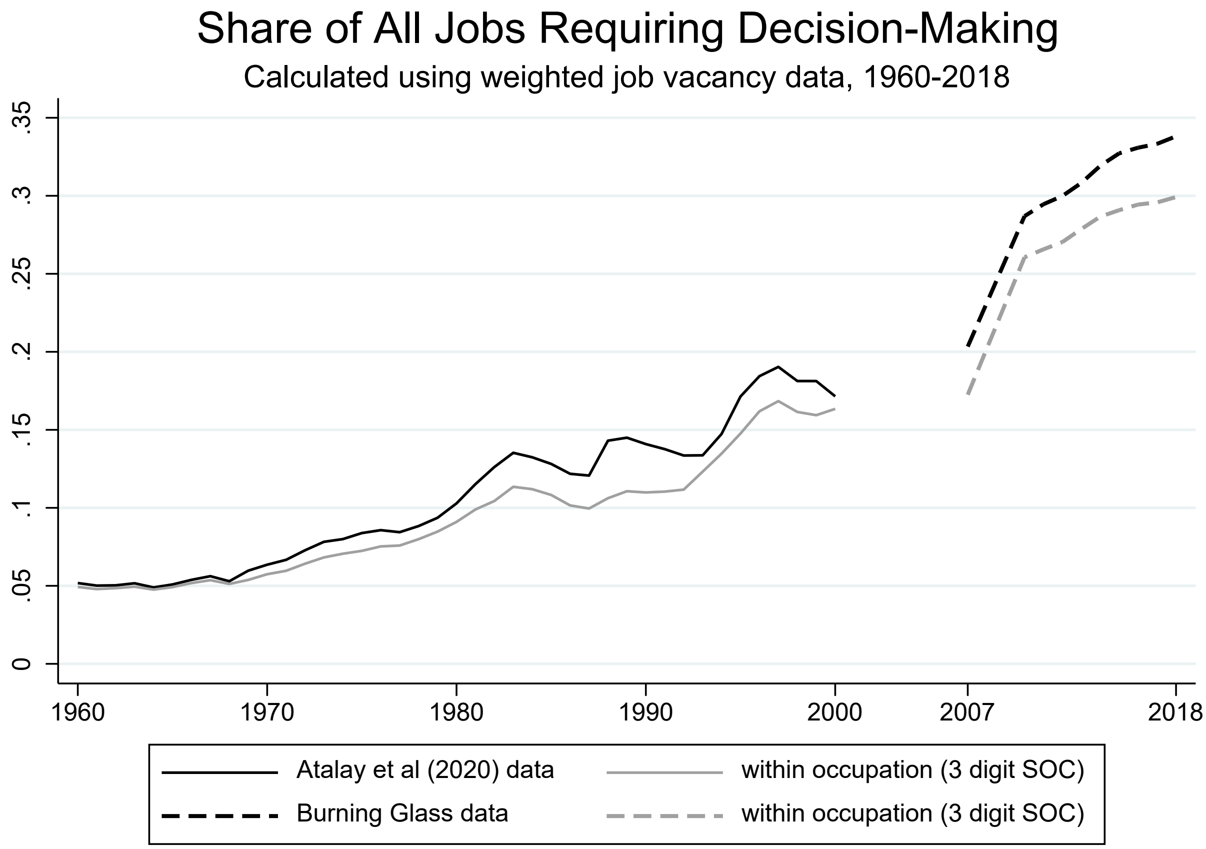
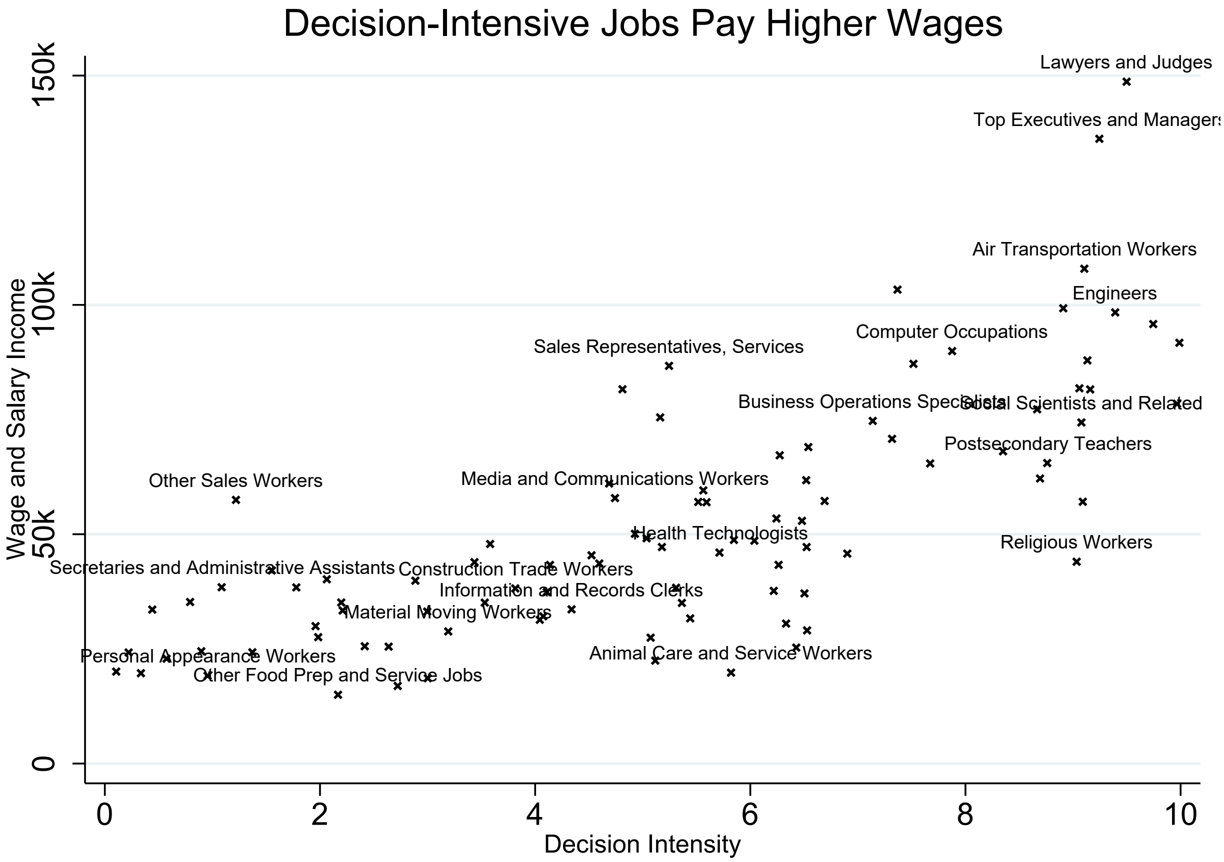
**Figure 1**



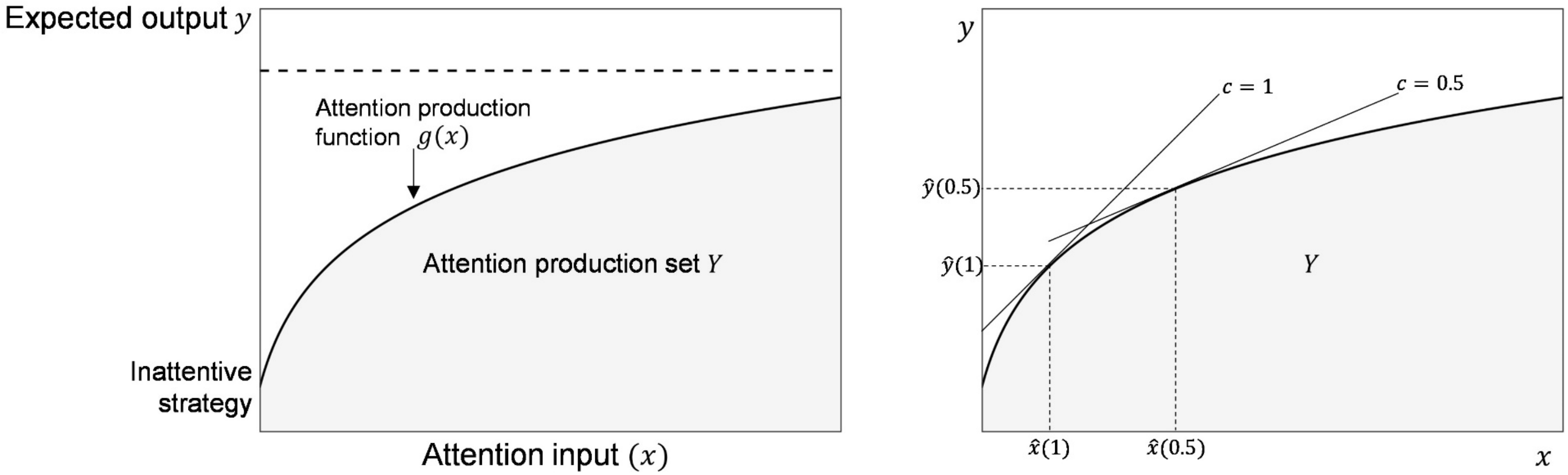

*Notes:* This figure computes the labor supply-weighted share of all job vacancies that include key words and phrases signaling a demand for worker decision-making – see the text for detailed definitions. The solid line uses classified ad data collected by Atalay et al (2020) over the 1960-1999 period, while the dashed line uses Burning Glass Technologies data from 2007 and 2010-2018. The data are weighted by the actual occupation distribution in the nearest Census and ACS years and are smoothed using a five-year moving average. The grey lines below present the same series except controlling for occupation fixed effects at the three-digit Standard Occupation Classification (SOC) level. We convert Census occupation codes to SOC codes using a crosswalk developed by Atalay et al (2020).

**Figure 2**



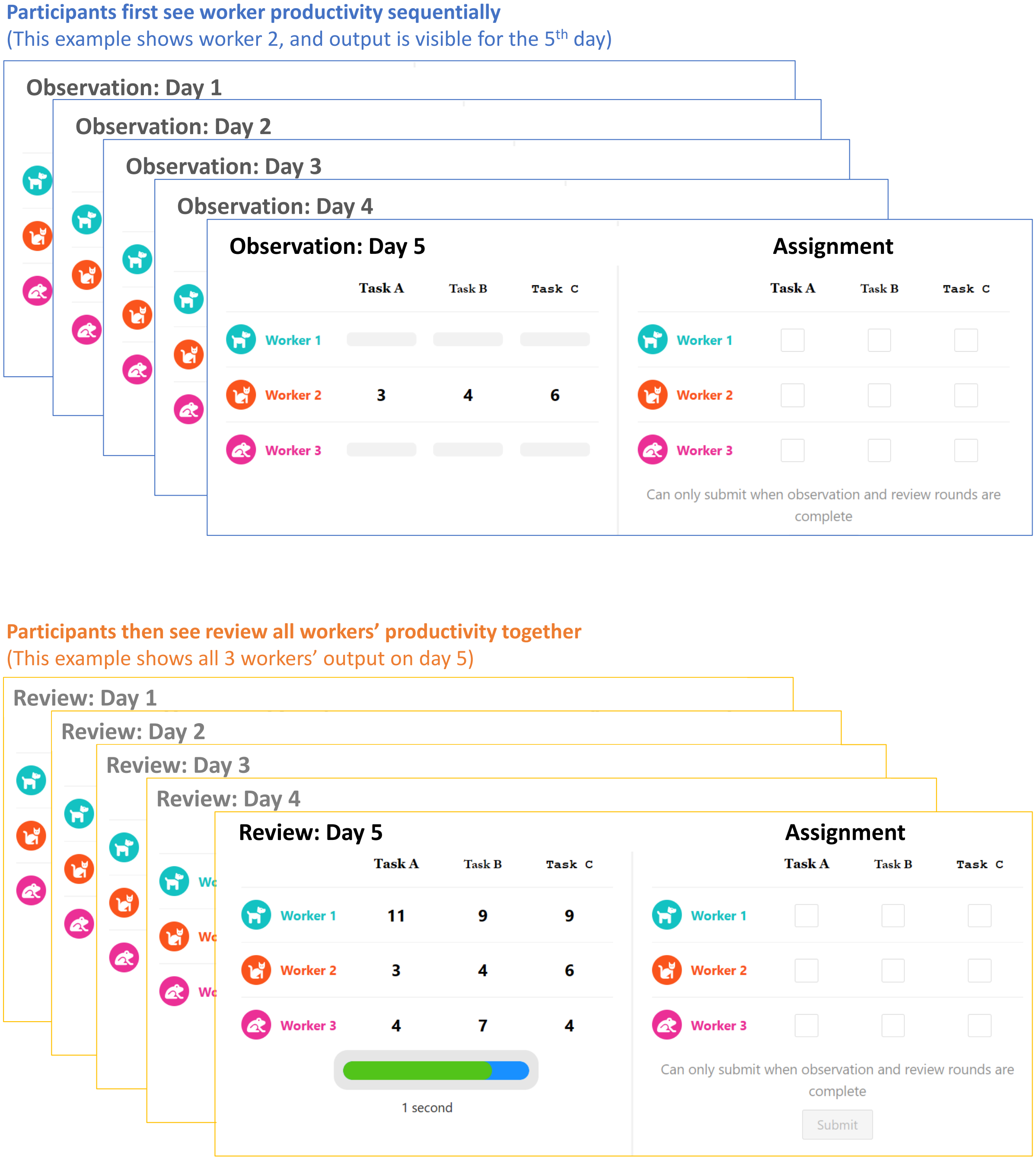

*Notes:* This figure plots average wage and salary income in the 2018 and 2019 American Community Survey against the average decision intensity of occupations at the 3-digit Standard Occupation Classification (SOC) code level, with selected occupations labeled. Occupation decision intensity is represented on a 0 to 10 percentile scale, where 5 represents occupations at the 50th percentile of decision intensity according to the full 2018-2019 ACS sample. Income is reported in 2022 dollars. We construct the decision intensity variable as the unweighted average of three task measures in the 2019 O*NET - Making Decisions and Solving Problems, Developing Objectives and Strategies, and Planning and Prioritizing Work. See the text for further details.

**Figure 3**



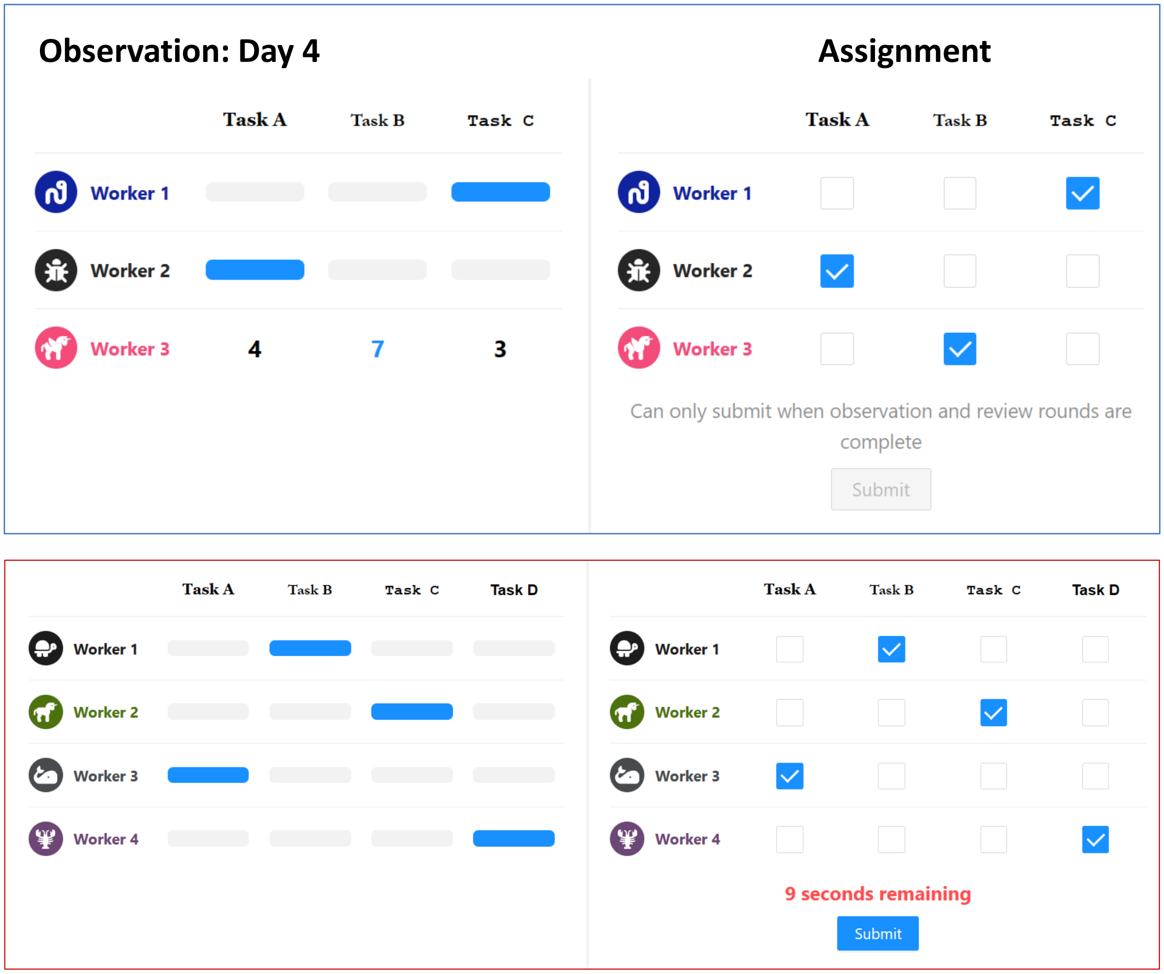

*Notes:* This figure presents a graphical illustration of the attention production set $Y$ from equation (4), which maps the space of possible outputs the decision-maker can achieve for any fixed amount of attention $x$. The vertical axis intercept corresponds to output under a fully inattentive strategy (e.g. random guessing.) The production function $g(x)$ maps the frontier of expected output for any given input. The righthand panel depicts the impact of a decrease in the marginal cost of attention from $c = 1$ to $c = 0.5$, which flattens the slope of the tangency line and causes the agent to optimally pay more attention and produce higher expected output. See Sections 2.1-2.3 of the paper for details.

## Figure 4




*Notes:* This figure shows screenshots from the Assignment Game. The top panel illustrates how participants initially see each worker's productivity individually and sequentially. The bottom panel illustrates how participants are then shown a review where all workers productivity schedules are shown simultaneously.

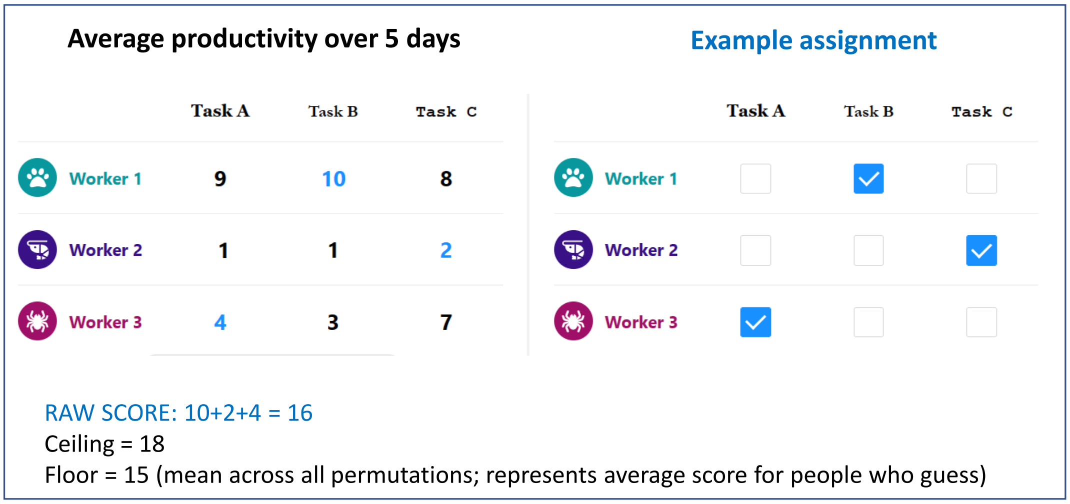
**Figure 5**




*Notes:* This figure shows another screenshot from the Assignment Game. The top panel shows a 3x3 puzzle and demonstrates how participants are able to make assignments at any point in the game (i.e. they can start assigning from the observation period onwards). The bottom panel shows a 4x4 puzzle and illustrates the final 10 second 'submission period'. This is an important part of the design, as it substantially reduces the burden on working memory. During this time participants lose access to productivity information and need to make their final assignments before hitting 'Submit'. If participants fail to hit submit, we still record any assignments that have been made and give people partial credit.[1]

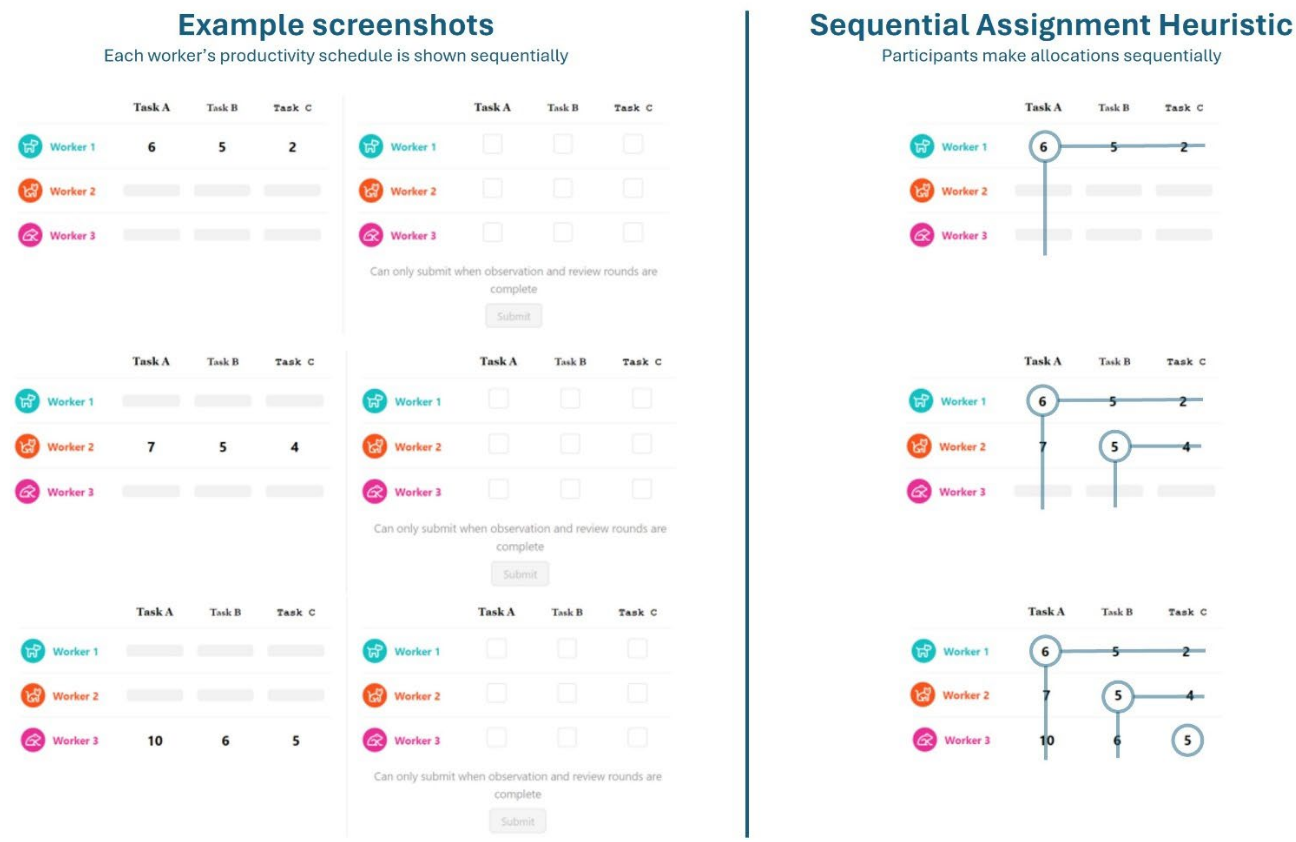
[1] In this scenario, unassigned workers receive a score of 0.

**Figure 6**




*Notes:* This figure demonstrates how the raw scores for the assignment game are calculated. The table on the left represents the average productivity schedule across all 5 days of a puzzle. Note that this **would not** be shown to participants. Combining the productivity schedules on the left with the assignment on the right, we see that the participants score is 16 (10+2+4). The optimal solution on this problem would score 18 (worker 1 -> task B; worker 2 -> task A; worker 3 -> task C).

**Figure 7 – The Sequential Assignment Heuristic**




*Notes:* The lefthand panel of this figure shows screenshots from the Assignment Game where productivity schedules are presented in order (worker 1, then worker 2, then worker 3). The righthand panel shows how participants might assign workers according to a *sequential assignment heuristic*, first selecting the optimal assignment for worker 1 given the information presented (the top panel), then condensing the problem to a 2x2 and selecting the optimal assignment for worker 2 (the middle panel), then selecting the last remaining option for worker 3. For ease of presentation, we show average productivity over days rather than showing all days at once. In this example the participants obtains a score of 16 (6+6+5), even though the optimal score is 19 (5+4+10). Achieving the optimal score requires participants to update their beliefs continuously as more information is presented.

**Table 1 - Summary Statistics**

*Panel A - U.S. Survey Data*

| | Prolific | 2018-2019 ACS |
|---|---|---|
| | (1) | (2) |
| Male | 0.64 | 0.56 |
| White | 0.76 | 0.72 |
| Black | 0.08 | 0.13 |
| Asian | 0.08 | 0.07 |
| Other Race / Not Reported | 0.08 | 0.09 |
| Age | 37.8 | 39.3 |
| Bachelor's Degree | 0.67 | 0.41 |
| Occupation Decision Intensity | 6.54 | 5.54 |
| Wage and Salary Income ($USD) | 71,784 | 71,528 |
| Sample Size | 1,014 | 1,446,680 |

*Panel B - Danish Registry Data*

| | Completed Survey | Did Not Complete Survey |
|---|---|---|
| Male | 0.51 | 0.50 |
| Immigrant | 0.10 | 0.19 |
| Married | 0.76 | 0.76 |
| Number of Children | 1.07 | 1.07 |
| Age | 41.7 | 40.3 |
| Vocational Degree | 0.32 | 0.34 |
| Tertiary Degree | 0.48 | 0.33 |
| Occupation Decision Intensity | X | X |
| Wage and Salary Income ($USD) | 61,803 | 66,135 |
| Sample Size | 2,297 | 48,681 |

*Notes*: Panel A of Table 1 present summary statistics for our U.S. survey sample (collected on Prolific) and compares them to the combined 2018 and 2019 American Community Survey. Column 2 is weighted to be nationally representative of the full-time working population age 25 to 54. Panel B presents summary statistics for the Danish registry sample. Column 1 shows characteristics of the respondents who completed the survey, and Column 2 shows the same for people who did not respond to the survey invitation, which was sent to a random sample of everyone between the ages of 25 and 55 who was either born in Denmark or had an address in Denmark as of 2022. Occupation decision intensity is represented on a 0 to 10 percentile scale, where 5 represents occupations at the 50th percentile of decision intensity according to the full 2018-2019 ACS sample. Income is reported in 2022 dollars, We construct the decision intensity variable as the unweighted average of three task measures in the 2019 O*NET - Making Decisions and Solving Problems, Developing Objectives and Strategies, and Planning and Prioritizing Work. See the text for further details.

**Table 2 - Correlations between Economic Decision-Making Skill and Other Variables**

| | ED Skill (AG Score) | Nonverbal IQ (Ravens) | Cognitive Reflection Test | Berlin Numeracy Test | Male | Age |
|---|---|---|---|---|---|---|
| ED Skill (AG Score) | 1 | | | | | |
| Nonverbal IQ (Ravens) | 0.381 | 1 | | | | |
| Cognitive Reflection Test | 0.313 | 0.430 | 1 | | | |
| Berlin Numeracy Test | 0.293 | 0.355 | 0.598 | 1 | | |
| Male | 0.064 | 0.108 | 0.126 | 0.108 | 1 | |
| Age | -0.132 | -0.162 | -0.026 | -0.098 | -0.047 | 1 |
| Bachelor's Degree | 0.109 | 0.119 | 0.149 | 0.099 | -0.011 | -0.003 |

*Notes*: Table 2 presents correlations between our measure of economic decision-making skill (the Assignment Game) and other cognitive assessments and demographics. All tests are normalized to have mean zero and standard deviation one. The data come from our Prolific survey sample, N=1,008. See the text for a more detailed description of the cognitive assessments.

**Table 3 - Economic Decision-Making Skill Predicts Higher Wage and Salary Income**

*Panel A - U.S. Survey Sample*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ED Skill (AG Score) | 6,006 | 4,480 | 5,881 | | 5,012 | 5,227 |
| | [1,423] | [1,312] | [1,520] | | [1,516] | [1,538] |
| Nonverbal IQ (Ravens) | | | | 3,099 | 1,601 | 1,811 |
| | | | | [1,588] | [1,611] | [1,653] |
| Cognitive Reflection Test | | | | | | 978 |
| | | | | | | [1,916] |
| Berlin Numeracy Test | | | | | | -2,183 |
| | | | | | | [1,756] |
| Demographic Controls | | X | X | X | X | X |
| Population Weights | | | X | X | X | X |
| R-Squared | 0.018 | 0.182 | 0.193 | 0.186 | 0.195 | 0.197 |
| Sample Size | 1,008 | 1,008 | 1,008 | 1,008 | 1,008 | 1,008 |

*Panel B - Danish Registry Sample*

| | (1) | (2) | (3) |
|---|---|---|---|
| ED Skill (AG Score) | 3,694 | 4,050 | 3,243 |
| | [709] | [665] | [676] |
| Demographic Controls | | X | X |
| Population Weights | | | X |
| R-Squared | 0.010 | 0.252 | 0.262 |
| Sample Size | 2,297 | 2,297 | 2,297 |

*Notes*: Table 3 presents estimates from a regression of wage and salary income on economic decision-making skill and the additional covariates indicated in each column. Robust standard errors are shown in brackets. The regression is estimated in our U.S. survey sample in Panel A and the Danish Registry sample in Panel B, with Danish kroner converted to U.S. dollars for ease of comparison. The Assignment Game score and all other cognitive assessments are normalized to have mean zero and standard deviation one. Demographic controls in Panel A include indicators for gender, race and ethnicity, and whether the participant has a bachelor's degree, as well as age and age squared. Demographic controls in Panel B include gender, indicators for vocational and tertiary degrees, age and age squared, and whether the respondent is married and their number of children. Columns 3 through 6 weight the data to be nationally representative according to the 2018-2019 ACS sample in Panel A and the Danish registry sample in Panel B, see Table 1 for details.

**Table 4 - Occupational Sorting on Economic Decision-Making Skill**

*Panel A - U.S. Survey Sample*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ED Skill (AG Score) | 0.311 | 0.220 | 0.258 | | 0.209 | 0.157 |
| | [0.077] | [0.076] | [0.096] | | [0.102] | [0.105] |
| Nonverbal IQ (Ravens) | | | | 0.218 | 0.155 | 0.079 |
| | | | | [0.086] | [0.092] | [0.098] |
| Cognitive Reflection Test | | | | | | 0.016 |
| | | | | | | [0.122] |
| Berlin Numeracy Test | | | | | | 0.286 |
| | | | | | | [0.114] |
| Demographic Controls | | X | X | X | X | X |
| Population Weights | | | X | X | X | X |
| R-Squared | 0.015 | 0.136 | 0.149 | 0.147 | 0.152 | 0.163 |
| Sample Size | 1,033 | 1,033 | 1,033 | 1,033 | 1,033 | 1,033 |

*Panel B - Danish Registry Sample*

| | (1) | (2) | (3) |
|---|---|---|---|
| ED Skill (AG Score) | 0.343 | 0.211 | 0.275 |
| | [0.051] | [0.046] | [0.051] |
| Demographic Controls | | X | X |
| Population Weights | | | X |
| R-Squared | 0.019 | 0.253 | 0.232 |
| Sample Size | 2,297 | 2,297 | 2,297 |

*Notes*: Table 4 presents estimates from a regression of occupation decision intensity on economic decision-making skill and the additional covariates indicated in each column. Robust standard errors are shown in brackets. The regression is estimated in our U.S. survey sample in Panel A and the Danish Registry sample in Panel B. Occupation decision intensity is represented on a 0 to 10 percentile scale, where 5 represents occupations at the 50th percentile of decision intensity according to the full 2018-2019 ACS sample. We construct the decision intensity variable as the unweighted average of three task measures in the 2019 O*NET - Making Decisions and Solving Problems, Developing Objectives and Strategies, and Planning and Prioritizing Work. See the text for further details. The Assignment Game score and all other cognitive assessments are normalized to have mean zero and standard deviation one. Demographic controls in Panel A include indicators for gender, race and ethnicity, and whether the participant has a bachelor's degree, as well as age and age squared. Demographic controls in Panel B include gender, indicators for vocational and tertiary degrees, age and age squared, and whether the respondent is married and their number of children. Columns 3 through 6 weight the data to be nationally representative according to the 2018-2019 ACS sample in Panel A and the Danish registry sample in Panel B, see Table 1 for details.

**Table 5A - Economic Decision-Making Skill in Decision-Intensive Occupations**

*Panel A - U.S. Survey Sample*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ED Skill (AG Score) | 4,200 | 3,758 | 4,701 | | 5,059 |
| | [1,381] | [1,318] | [1,536] | | [1,622] |
| * Decision Intensity | 1,115 | 1,177 | 1,064 | | 1,126 |
| | [497] | [467] | [506] | | [507] |
| Decision Intensity (O*NET) | 5,793 | 4,031 | 3,907 | 3,963 | 3,984 |
| | [468] | [456] | [474] | [477] | [483] |
| Nonverbal IQ (Ravens) | | | | 2,215 | 1,760 |
| | | | | [1,540] | [1,610] |
| * Decision Intensity | | | | 602 | 416 |
| | | | | [579] | [593] |
| Cognitive Reflection Test | | | | | 927 |
| | | | | | [1,999] |
| * Decision Intensity | | | | | 631 |
| | | | | | [624] |
| Berlin Numeracy Test | | | | | -3,921 |
| | | | | | [1,825] |
| * Decision Intensity | | | | | -1,015 |
| | | | | | [558] |
| Demographic Controls | | X | X | X | X |
| Population Weights | | | X | X | X |
| R-Squared | 0.121 | 0.229 | 0.240 | 0.231 | 0.248 |
| Sample Size | 1,003 | 1,003 | 1,003 | 1,003 | 1,003 |

*Notes*: Table 5A presents estimates from a regression of wage and salary income on economic decision-making skill interacted with decision intensity. Robust standard errors are shown in brackets. The regression is estimated in our U.S. survey sample. Average income in the sample is $71,728. Occupation decision intensity is represented on a 0 to 10 percentile scale, where 5 represents occupations at the 50th percentile of decision intensity according to the full 2018-2019 ACS sample. Income is reported in 2022 dollars. We construct the decision intensity variable as the unweighted average of three task measures in the 2019 O*NET - Making Decisions and Solving Problems, Developing Objectives and Strategies, and Planning and Prioritizing Work. See the text for further details. The Assignment Game score and all other cognitive assessments are normalized to have mean zero and standard deviation one. The interaction terms multiply each cognitive assessment times a demeaned version of the decision intensity variable for ease of comparison. Demographic controls include indicators for gender, race and ethnicity, and whether the participant has a bachelor's degree, as well as age and age squared. Columns 3 through 5 weight the data to be nationally representative according to the 2018-2019 ACS sample, see Table 1 for details.

**Table 5B - Economic Decision-Making Skill in Decision-Intensive Occupations**

*Panel B - Danish Registry Sample*

| | (1) | (2) | (3) |
|---|---|---|---|
| ED Skill (AG Score) | 2,144 | 3,387 | 2,558 |
| | [682] | [658] | [611] |
| * Decision Intensity | 679 | 563 | 630 |
| | [272] | [245] | [253] |
| Decision Intensity (O*NET) | 4,879 | 3,706 | 3,826 |
| | [278] | [298] | [314] |
| Demographic Controls | | X | X |
| Population Weights | | | X |
| R-Squared | 0.131 | 0.306 | 0.321 |
| Sample Size | 2,297 | 2,297 | 2,297 |

*Notes*: Table 5B presents estimates from a regression of wage and salary income on economic decision-making skill interacted with occupation decision intensity. Robust standard errors are shown in brackets. The regression is estimated in the Danish Registry sample. Average income in the sample is $61,803. Occupation decision intensity is represented on a 0 to 10 percentile scale, where 5 represents occupations at the 50th percentile of decision intensity according to the full 2018-2019 ACS sample. Income is reported in 2022 dollars, We construct the decision intensity variable as the unweighted average of three task measures in the 2019 O*NET - Making Decisions and Solving Problems, Developing Objectives and Strategies, and Planning and Prioritizing Work. See the text for further details. The Assignment Game score is normalized to have mean zero and standard deviation one. The decision intensity variable is demeaned for ease of comparison. Demographic controls include gender, indicators for vocational and tertiary degrees, age and age squared, and whether the respondent is married and their number of children. Column 3 weights the data to be nationally representative, see Table 1 for details.

**Table 6 - Sequential Assignment Heuristic is the Most Common Mistake**

*Outcome is the Percentage of Responses*

| | (1) | (2) | (3) |
|---|---|---|---|
| ED Skill (AG Score) | 0.033 | 0.030 | 0.033 |
| | [0.004] | [0.005] | [0.005] |
| * Sequential | | 0.034 | 0.060 |
| | | [0.012] | [0.013] |
| Assignment was Sequential | | 0.014 | -0.088 |
| | | [0.026] | [0.040] |
| Item Fixed Effects | | | X |
| R-Squared | 0.306 | 0.353 | 0.473 |
| Sample Size (Possible Answers * Items) | 210 | 210 | 210 |

*Notes*: Table 6 presents estimates from an item-by-assignment level regression of the percent of respondents selecting that assignment on the economic decision-making skill score interacted with whether that choice resulted from a sequential assignment heuristic. Robust standard errors are shown in brackets. The regression is estimated in the U.S. survey sample and has a sample size of 210 because there are 24 possible responses to the 7 4x4 items and 6 possible responses to the 7 3x3 items ((24*7)+(6*7)=210). The Assignment Game score is on an absolute scale, with the range varying for each item. Column 3 also includes fixed effect for each of the 16 items.

**Table 7 - AG Score is Less Predictive of Income when Answers are Heuristic**

| | (1) | (2) | (3) | (4) | (6) |
|---|---|---|---|---|---|
| ED Skill (AG Score) | 10,457 | 10,109 | 9,617 | 9,387 | 9,450 |
| | [2,420] | [2,460] | [2,445] | [2,427] | [2,663] |
| AG * # Sequential | -1,944 | -2,205 | -2,177 | -2,060 | -2,008 |
| | [804] | [809] | [806] | [825] | [886] |
| # of Sequential Answers | -242 | -826 | -790 | -779 | -908 |
| | [1,098] | [997] | [995] | [997] | [995] |
| Nonverbal IQ (Ravens) | | | 1,438 | 1,997 | 2,158 |
| | | | [1,594] | [2,614] | [2,687] |
| IQ * # Sequential | | | | -314 | -261 |
| | | | | [955] | [975] |
| Cognitive Reflection Test | | | | | 955 |
| | | | | | [3,253] |
| CRT * # Sequential | | | | | 32 |
| | | | | | [1137] |
| Berlin Numeracy Test | | | | | -1,643 |
| | | | | | [2,969] |
| BNT * # Sequential | | | | | -512 |
| | | | | | [1,155] |
| Demographic Controls | | X | X | X | X |
| Population Weights | | X | X | X | X |
| R-Squared | 0.024 | 0.202 | 0.203 | 0.203 | 0.205 |
| Sample Size | 1,003 | 1,003 | 1,003 | 1,003 | 1,003 |

*Notes*: Table 7 presents estimates from a regression of wage and salary income on the interaction between economic decision-making skill and the number of problems participants answer with a sequential information heuristic, plus the additional covariates indicated in each column. Robust standard errors are shown in brackets. The regression is estimated in our U.S. survey sample. The Assignment Game score and all other cognitive assessments are normalized to have mean zero and standard deviation one. Demographic controls include indicators for gender, race and ethnicity, and whether the participant has a bachelor's degree, as well as age and age squared. Columns 3 through 5 weight the data to be nationally representative according to the 2018-2019 ACS sample, see Table 1 for details.