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THE GROWING IMPORTANCE OF DECISION-MAKING ON THE JOB

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ABSTRACT

Machines increasingly replace people in routine job tasks. The remaining tasks require workers to make open-ended decisions and to have "soft" skills such as problem-solving, critical thinking and adaptability. This paper documents growing demand for decision-making and explores the consequences for life-cycle earnings. Career earnings growth in the U.S. more than doubled between 1960 and 2017, and the age of peak earnings increased from the late 30s to the mid-50s. I show that a substantial share of this shift is explained by increased employment in decision-intensive occupations, which have longer and more gradual periods of earnings growth. To understand these patterns, I develop a model that nests decision-making in a standard human capital framework. Workers predict the output of uncertain, context-dependent actions. Experience reduces prediction error, improving a worker's ability to adapt using data from similar decisions they have made in the past. Experience takes longer to accumulate in high variance, non-routine jobs. I test the predictions of the model using data from the three waves of the NLS. Life-cycle wage growth in decision-intensive occupations has increased over time, and it has increased relatively more for highly-skilled workers.

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A data appendix is available at http://www.nber.org/data-appendix/w28733

1 Introduction

A growing body of work in economics studies the impact of automation on jobs, with an emphasis on the technological replacement of *routine* job tasks (Autor et al. 2003, Acemoglu and Restrepo 2019). Machines increasingly substitute for humans in physical, mechanical, and information processing tasks that are predictable enough to be scripted ahead of time (Autor et al. 2002, Chin et al. 2006, Bartel et al. 2007, Autor 2015).[1] The remaining job tasks are increasingly open-ended and require workers to make decisions and adapt to unforeseen circumstances, which explains why employers consistently rate problem-solving and critical thinking as the most essential needs among new hires (e.g. Dessein and Santos 2006, NACE 2020).

The rising importance of decision-making can be seen in the rapid growth of management jobs in the U.S. over the last half-century. Figure 1 shows that the total wage bill paid to management and management-related occupations in the U.S. has more than doubled since 1960, from 15 percent to 32 percent.[2] This trend incorporates both increasing employment growth and rising relative wages, is more pronounced in the private sector and in high-growth industries, and is not driven by growth in top-end executive pay.[3]

Figure 2 shows the rising importance of decision-making across the entire U.S. economy, using job vacancy data to directly measure employer skill demands. I combine data from Atalay et al. (2020) and from Burning Glass Technologies (BGT), covering the 1960-2000

[1]Autor et al. (2003) define routine tasks as those requiring "methodical repetition of an unwavering procedure" that "can be exhaustively specified with programmed instructions and performed by machines."

[2]Figure 1 computes the product of labor supply-weighted employment shares and inflation-adjusted annual wage and salary incomes by occupation and year using data from the 1960-2000 U.S. Census, the 2006-2018 American Community Survey, and the 1968-2020 Annual Social and Economic Supplement (ASEC) of the Current Population Survey. I define management and management-related occupations using the "occ1990dd" crosswalk developed by Autor and Dorn (2013) and extended by Deming (2017). The definition includes management, management support (occ1990dd codes 4 through 37), and supervisors of frontline workers in other fields. The results are similar with stricter definitions of management jobs, but less consistent over time due to differences in occupation coding over time.

[3]The private sector management wage bill increased from 16 percent in 1960 to 35 percent in 2017 across all industries, and from 19 percent to 43 percent for business services and finance, insurance and real estate. The results in Figure 1 are almost identical when I exclude the occupation code for CEOs and other executives, and when I use median rather than mean wages.

and 2007-2019 periods respectively, and I use the actual text of job ads to form a consistent definition of decision-making over time.[4] To ensure representativeness, I weight the job ad data by the actual distribution of occupations in each year.[5]

Figure 2 shows that 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 occuring just since 2007. 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 in Figure 2 only slightly, suggesting that growing demand for worker decision-making is an economy-wide phenomenon.

This paper documents growing demand for decision-making and explores the consequences for returns to skills and life-cycle wage growth. I develop a model that nests worker decision-making into a standard human capital framework. In the model, task output is uncertain and depends on a set of background variables (or "context"), which the worker observes imperfectly. Workers decide what to do by predicting the outcome of an action using data from their past experiences. Experience is valuable because data quantity and quality reduce prediction error, which allows workers to better *adapt* their actions to context. Firms endogenously choose the level of worker autonomy to balance the gains from adaptation against the losses from prediction error, as in Dessein and Santos (2006) and Bartling et al.

[4] 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 (O*NET) data, among other measures. I use their mapping to the three O*NET work activities Making Decisions and Solving Problems, Developing Objectives and Strategies, and Planning and Prioritizing Work, which includes key words and phrases such as "decision-making', "problem-solving", "diagnosing", "judgment", "strategize", "planning", "prioritizing", "goals", and others. See the appendix to Atalay et al. (2020) for a complete list. BGT classify vacancy text into thousands of unique job skills, and I use job skills (and related strings) with the key words and phrases above to create a consistent definition over time.

[5] Atalay et al. (2020) map their data to both Standard Occupation Classification (SOC) codes and Census occupation codes, and they provide a crosswalk between them. To reduce classification error from narrowly defined occupations (some of which only exist in certain years of the data), I 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 represenative of the actual occupation distribution in each year. I then apply a moving average to the weights so that classified ad data from 1965 is weighted 50/50 between the 1960 and 1970 Censuses (for example), and finally I compute a 5-year moving average of the share of ads requiring decision-making in order to reduce yearly noise.

(2012).

The model delivers several testable predictions. Firms relying more on worker decision-making will have higher experience requirements and demand higher levels of worker skill. I verify this prediction using detailed job vacancy data from BGT, which includes firm identifiers and detailed measures of skill demands.

In the model, a worker's decision-making skill has three important components. The first is data *quantity.* More data reduces prediction error, but at a decreasing rate, and so the return to work experience should be positive and concave. The second component is *variance*, or the difficulty of the prediction problem. If the output of an action is invariant to context, then there is nothing to predict and the model collapses to a standard human capital framework. Low prediction variance formalizes the concept of a routine task. The model implies that learning occurs faster in routine occupations, because higher task variance makes prediction more difficult. Empirically, life-cycle wage growth should persist longer and be more gradual in non-routine, decision-intensive occupations.

Using data from the Census and ACS and multiple waves of the National Longitudinal Surveys (NLS), I show that relative employment growth of decision-intensive occupations has shifted U.S. age-earnings profiles outward substantially over the last half-century. In 1960, earnings of full-time workers peaked in the late 30s, compared to the mid-50s today, and the magnitude of life-cycle earnings growth has more than doubled over this period. Comparing this to the cross-country variation documented by Lagakos et al. (2018) reveals that life-cycle earnings growth in the U.S. in 1960 was similar to less developed countries such as Mexico today.

I find that wage growth after age 35 is substantially greater for workers in decision-intensive occupations. I then perform a decomposition which shows that rapid relative employment growth in these occupations can explain nearly half of the outward shift in age-earnings profiles since 1980 and nearly all since 2000, net of other demographic changes. Importantly, this pattern of growing relative returns to decision-intensive jobs holds within gender, race and education groups, and does not replicate when I use other measures of job tasks such as the "nonroutine analytic" task intensity measure used by Autor et al. (2003). Taken together, this evidence shows that an economy-wide shift toward decision-intensive occupations has had substantial impacts on patterns of life-cycle wage growth in the U.S.

The third component of decision-making skill is *data quality*. In the model, the worker must use data from their own experiences to make inferences about a larger population of potential outcomes. Their ability to make good decisions will suffer if their own experiences are not representative of the current context, or if they exhibit behavioral biases such as excessive risk aversion or inference on winners (Tversky and Kahneman 1973, Thaler 1988, Rabin and Thaler 2001, Andrews et al. 2019).

Since a large body of evidence shows that cognitive ability improves learning in new environments and reduces behavioral biases and decision errors, the model predicts that ability, decision intensity and work experience will be complements (e.g. Nelson and Phelps 1966, Dohmen et al. 2010, Rustichini 2015, Gill and Prowse 2016). I find strong support for this prediction using individual data on cognitive ability and occupation and earnings trajectories from multiple waves of the NLSY. I also show that excessive risk aversion is penalized relatively more in decision-intensive jobs. Finally, I find that the returns to working in decision-intensive occupations have grown over time, and have grown more for high ability workers.

This paper makes three main contributions. First, I add to the large literature on technological replacement of routine work by focusing on the growing importance of decision-making in unstructured work environments. Autor et al. (2003), Acemoglu and Restrepo (2018) and others show how automation increasingly replaces people in predictable tasks, but also that automated systems are "brittle" and lack flexibility (Autor 2015). This paper develops a framework for understanding how the shift away from routine work has affected returns to skills and life-cycle earnings growth. The finding that returns to experience are greater in decision-intensive occupations connects to a literature on firm structure and knowledge hierarchies, where human capital is occupation-specific and worker autonomy is important for wage determination (e.g. Garicano and Rossi-Hansberg 2006, Kambourov and Manovskii 2009, Gathmann and Schönberg 2010, Bartling et al. 2012, Bayer and Kuhn 2019). It is also consistent with Lise and Postel-Vinay (2020) and Stinebrickner et al. (2019), who find much flatter wage growth for workers performing manual tasks compared to cognitive tasks.

The model yields insights about the likely impact of machine learning and artificial intelligence, which are fundamentally prediction technologies (Agrawal et al. 2018). These technologies will be more effective substitutes for human labor as data quality increases, and their impact is potentially larger in occupations where work experience has previously been more important. This paper connects to a growing literature on the economics of data, which emphasizes the value of data as an input into prediction that reduces firm uncertainty but has diminishing returns (Veldkamp and Chung 2019, Farboodi and Veldkamp 2021).

This paper also contributes to our understanding of how human capital increases earnings. Going back to Mincer (1958) and Becker (1962), a standard approach assumes that human capital augments effective units of labor in a production function, so that workers with more schooling or higher ability can produce more output per hour. This paper is related to an older literature showing that human capital can increase allocative efficiency, especially in agriculture, where educated farmers are more likely to adopt new technologies (e.g. Welch 1970, Huffman 1974, 1977, Ram 1980, Foster and Rosenzweig 1995, Yang 2004). The model nests the standard productive human capital model as a special case, and integrates productive and allocative human capital together into a unified framework. Finally, it explains how behavioral decision-making errors affect worker productivity and connects to the idea of Nelson and Phelps (1966) that human capital improves one's ability to adapt to change.

I am aware of only a few economics papers that focus on decision-making as a skill. Currie and MacLeod (2017) show that doctors vary not only in procedural skill but also in their ability to correctly diagnose individual patients' suitability for different medical procedures. Chan Jr et al. (2019) and Chandra and Staiger (2020) develop frameworks where expert decisions incorporate diagnostic skill, beliefs about treatment effectiveness, and preferences. Goldfarb and Xiao (2011) and Hortaçsu et al. (2019) find that education and other proxies for skill improve managerial decision-making. There is a large literature in psychology on the determinants of effective decision-making, including some evidence that general intelligence and numeracy in particular predict effective decision-making among those who are not domain experts (e.g. Baron 2000, Stanovich and West 2000, Cokely et al. 2018)

The third contribution of this paper is to the macroeconomics literature on educational investment and life-cycle wage growth. It is well-known that educated workers have steeper age-earnings profiles, yet the role of occupations is less well understood (Murphy and Welch 1990, Lemieux 2006, Guvenen et al. 2015)[6] The model provides a microfoundation for the learning-by-doing (LBD) model in macroeconomics and helps explain why on-the-job learning and thus wage growth might differ across occupations and countries (Chang et al. 2002, Hendricks 2013, Manuelli and Seshadri 2014, Blandin 2018, Lagakos et al. 2018). Jobs that allow for more worker decision-making facilitate human capital accumulation on the job, which has important implications for wage subsidy policies and for optimal taxation over the life-cycle (Heckman et al. 2002, Stantcheva 2015, Blandin and Peterman 2019).

The rest of the paper proceeds as follows. Section 2 develops a model of worker decision-making on the job and generates testable predictions. Section 3 presents the main empirical results. Section 4 discusses implications of the model for technological change and automation, educational investment and economic growth. Section 5 concludes.

[6]Lagakos et al. (2018) find that educational attainment explains about one-third of cross-country differences in age-earnings profiles, and that manual occupations have flatter age-earnings profiles than cognitive occupations. These results complement a series of papers showing that fluctuations in the growth of the supply of college graduates can explain cohort differences in age-earnings profiles (e.g. Freeman 1979, Welch 1979, Katz and Murphy 1992).

2 Model

In the classic formulation of Becker (1962), schooling, training and other forms of human capital increase labor productivity, which translates into higher wages when workers are factors in a production function that takes capital and labor as inputs. But unlike machines, individual workers have autonomy and can decide what to do. In fact, the ability to adapt to unforeseen circumstances is one reason a firm might choose to employ labor rather than capital. Machines can increasingly be programmed to do any one thing better than a person, but people are more flexible. Highly paid workers are valuable not only because they know *how* to do, but also because they know *what* to do.

What is the value of human capital for decision-making? Decisions are choices over a set of potential actions. Workers make choices by predicting the likely outcome of each action and choosing the one with the highest expected output. In this sense, predictions are inputs into decision-making, and predictions require data (Agrawal et al. 2019b). When workers make predictions, they use data from past experiences on the job, schooling, peer influences, and other sources. Thus experience is a form of human capital when it helps workers make better decisions. I formalize these insights with a simple model of worker decision-making.

In a standard human capital model, worker skill takes a simple factor-augmenting form, with the output of a worker from task j increasing in some measure of skill α (such as cognitive ability or education) times l_j, the quantity of labor supplied. Skills are then applied to job tasks to produce output.[7] In this setup, the optimal choice of tasks is determined by workers' skills and by the production technology. Human capital is *productive* in the sense that it augments effective units of labor.

Consider a simple extension of the standard model, where the output of task j is uncertain and depends on a vector of background variables X_j:

[7] In Acemoglu and Autor (2011), output for task j is $y_j = \alpha_j l_j$, where y_j specifies the production level or *output* of task j, and total output arises from a production function that maps tasks into a final good, such as $Y = \exp\left[\int_0^1 \ln y_j dj\right]$.

$$\alpha_j = \alpha(X_j), j = 1, ..., N \tag{1}$$

The function $\alpha(X_j)$ contains all N possible mappings between the vector of background variables X_j and output for task j. A doctor deciding whether to perform surgery must consider not only the success of her past surgeries, but also a particular patient's risk factors, the quality of the surgical equipment, the skill of her coworkers, and other data. Equation (1) could be modified so that productivity varies across workers by some constant term (e.g. $A_i\alpha_{ij}$), but I omit any consideration of individual differences and focus on a representative worker.

2.1 Decision-making as a prediction problem

Facing this uncertainty, workers must decide what to do by predicting the output of each potential action. I draw a distinction between *tasks* and *actions.* In models such as Acemoglu and Autor (2011), tasks are units of work that can be specified *ex ante*. For example, the tasks associated with the job "machinist" include calculating dimensions or tolerances using instruments, measuring and examining completed units to check for defects and ensure conformance to specifications, and machining parts to specifications using tools such as lathes, milling machines, shapers, and grinders.[8]

Actions, on the other hand, are responsive to the local environment. In the course of performing a task, unforeseen things can happen, and workers adjust on the fly. Machinists must make judgments about exactly why a mechanical instrument is malfunctioning and what should be done. The job of nurse includes answering patients' calls and determining how to assist them, which cannot easily be specified in advance. For managers, entire categories of job tasks are highly open-ended and rely on worker adaptation (e.g. "Direct and coordinate activities of businesses and departments", "Direct administrative activities related to making

[8]See O*NET data for a complete listing. As discussed in Acemoglu and Autor (2011), tasks are in some sense infinitely divisible and indeed their model assumes a continuum of tasks are combined to produce output. The key distinction is that they can be specified *ex ante*.

products or providing services").

More formally, assume that there are many possible actions for each workplace task. Each of the actions has the same *average* output for any particular worker, but the exact ordering depends on X_j. For example, sales workers may differ predictably in their ability to close deals, but their choices about how to convince any particular customer to buy a product depend on the local context X_j in ways that the firm does not observe and that cannot be specified in advance. This is similar in spirit to Dessein and Santos (2006), where actions must be adapted to a local information shock that is observed by the worker but not foreseeable ahead of time.[9]

Workers choose an action by observing the background variables, predicting the ordering of actions, and selecting the one with the highest output in that context. This could be a sales worker deciding how to pitch a particular buyer, or a health worker deciding which treatment will work best given a patient's symptoms and underlying risk factors. A worker who has observed all N cases and the resulting mapping between X_j and α_j can choose the best action in any situation. Denote this "population" average value of α_j over all N as α_j^N.

Workers have limited experience and information, and never observe all N cases. Instead they possess a sample of data that is drawn from their own experience. Define the worker's sample as $\{X_j, j \in D_n\}$, where D_n is a size subset of N. The worker predicts their output as the average value of α_j over the sample, which I call α_j^n:[10]

$$\alpha_j^n = \frac{1}{n} \sum_{j \in D_n} \alpha_j = \frac{\sum_{j=1}^N S_j \alpha_j}{\sum_{j=1}^N S_j} \tag{2}$$

where S_j is an indicator function that is equal to one for data that is part of the worker's sample, e.g. $S_j = 1$ for $j \in D_n$ and $S_j = 0$ otherwise. S_j captures the idea that workers bring different experiences to the job. These experiences are inputs into decision-making,

[9] In Dessein and Santos (2006), the payoff to an action is determined by a quadratic loss function $\left(\alpha_j^N - \theta\right)^2$ where θ is a common variance shock that only the worker can observe. Here, the worker's ability to adapt to the local information shock is determined by the quality of their prediction α_j^n.

[10] Meng et al. (2018) develops a similar approach to understanding the role of sample selection in problems requiring "big data", with an application to the 2016 presidential election.

and so workers with the same productive human capital could make different predictions about their own output in any particular context. For example, two attorneys representing the same client might have different views about the likelihood of success at trial based on their experiences with the judge, past cases with similar characteristics, or their training in law school.

Workers improve their output by successfully adapting their actions to the local context. I assume that output from task j is equal to the worker's productive human capital - the "population" average output α_j^N - minus a quadratic loss function $\left(\alpha_j^n - \alpha_j^N\right)^2$ which represents prediction error, or the losses from imperfect adaptation to X_j. The marginal product for workers performing J tasks is:

$$\sum_{j=1}^{J} \left[\alpha_j^N - \left(\alpha_j^n - \alpha_j^N\right)^2\right] l_j \tag{3}$$

where l_j is labor supplied to action j and $\sum_{j=1}^{J} l_j = 1$ for each worker.

Note that the task-based version of the standard human capital model is just equation (3) when there is no prediction error (e.g. $\alpha_j^n = \alpha_j^N$). Thus the model nests productive and allocative human capital together in a single framework (e.g. Nelson and Phelps 1966, Welch 1970). The worker's output depends on their productive human capital α_j, but also how well they can minimize prediction error by adapting their actions to X_j using data from past experiences.

2.2 The firm's problem

Workers vary in their productive capacity for each task and also in their decision-making skill. Knowing this, firms will choose how much to rely on worker decision-making. I assume that each firm chooses an organizational form that grants workers more or less autonomy, following Dessein and Santos (2006). For simplicity, I further assume that there are only two types of tasks - $\alpha\left(X_j\right)$, and α_0, where the latter are constants that do not depend on X_j and thus have no prediction error $\left(\alpha_j^n = \alpha_j^N\right)$.

In a competitive labor market, the marginal profit from employing a worker is:

$$\left[\theta\alpha_j^N + (1-\theta)\,\alpha_0\right] - \theta\left(\alpha_j^n - \alpha_j^N\right)^2 \tag{4}$$

where the parameter $\theta \in [0,1]$ measures the labor supply-weighted share of all tasks that depend on worker decision-making. Firms choose θ to maximize profits, which amounts to trading off the relative gains from each task type against the costs of imperfect worker adaptation. As $\theta \to 1$, workers have more autonomy on the job but also make more errors. When $\theta = 0$, equation (3) collapses to the standard model where actions and output are fully deterministic.[11] Firms will not rely on worker decision-making unless there is a gain from doing so, e.g. $\alpha_j^N > \alpha_0$. Thus in equilibrium job tasks that require worker discretion will have higher productive value than job tasks where output is deterministic.

Equation (4) considers labor as the only factor of production, but in Section 4 I consider a simple extension where α_0 type tasks can be performed by machines.

2.3 The components of prediction error

From equation (2) above, the worker's prediction error can be rewritten as:[12]

$$\alpha_j^n - \alpha_j^N = \frac{E_J\left(S_J\alpha_J\right)}{E_J\left(S_J\right)} - E_J\left(\alpha_J\right) = \frac{Cov_J\left(S_J\alpha_J\right)}{E_J\left(S_J\right)} \tag{5}$$

Because S_J is just an indicator variable defined over the sample subset n, $E_J\left(S_J\right) = \frac{n}{N}$ and $Var_J\left(S_J\right) = \frac{n}{N}\left(1 - \frac{n}{N}\right)$, and we can rewrite equation (5) as:

[11] An important question is whether the firm also possesses information about local context. In principle, firms can possess more information than workers, but in that case they will choose $\theta = 0$ and just tell workers what to do. Formally, we can define the firm's information sample as $\{X_j, j \in d_n\}$, where d_n is a size subset of D_n, which itself is a subset of N.

[12] The set of potential outputs $\{\alpha_1, ..., \alpha_N\}$ can be viewed as the support of a random variable α_J, with random index J defined over $\{1, ..., N\}$. If J is uniformly distributed, $E_J\left(\alpha_J\right) = \alpha_j^N$. Likewise for the subset n, $\frac{E_J(S_J\alpha_J)}{E_J(S_J)} = \alpha_j^n$. Equation (5) follows because $Cov_J\left(S_J\alpha_J\right) = E_J(S_J\alpha_J) - E_J(S_J)E_J(\alpha_J)$ for a Bernoulli random variable, and E_J and Cov_J are taken over a uniform distribution on $J \in \{1, ..., N\}$. '

$$\alpha_j^n - \alpha_j^N = \left(\sqrt{\frac{N-n}{n}}\right) * \sigma_\alpha * corr\left(S, \alpha\right) \tag{6}$$

Taking the squared expectation of equation (6) yields:

$$E_S\left[\alpha_j^n - \alpha_j^N\right]^2 = \left(\frac{N-n}{n}\right) * \sigma_\alpha^2 * E_S\left[\rho_{S,\alpha}^2\right] \tag{7}$$

Equations (6) and (7) show that prediction error has three components.[13] The first term is *data quantity*, reflected by the term $\left(\frac{N-n}{n}\right)$. As $n \to N$, prediction error decreases, although with diminishing returns. Empirically, we can think of n as increasing with work experience. Workers make decisions by considering the outcomes of similar decisions they made in the past.

The second term σ_α^2 is *variance*, which captures the difficulty of the prediction problem. If α_j is invariant to background variables X_j, the worker's prediction problem resolves instantly. When the output of an action is always the same we have $\sigma_\alpha^2 = 0$, which reduces prediction error to zero and collapses equation (3) to the standard human capital model.

Jobs have different values of σ_α^2. In some occupations, the work environment is highly regulated and predictable. These are *routine* jobs, following the task literature in labor economics (Autor et al. 2003, Acemoglu and Autor 2011). In other jobs, tasks are open-ended and workers are given the freedom to adapt their actions to background variables X_j. Empirically, I treat σ_α^2 as the occupation-level variance associated with a bundle of job tasks, while θ is a firm-level parameter that identifies the amount of decision-making autonomy granted to workers both within and across occupations.

We might also expect to see variation in σ_α^2 within jobs over time. The economics literature shows that skill-biased technological change alters job tasks in ways that grant workers more autonomy, perhaps because humans are more flexible than machines (Caroli and

[13] I focus on a static decision problem and abstract away from dynamic learning considerations such as experimentation and explore/exploit dynamics over time (e.g. Bolton and Faure-Grimaud 2009, Caplin and Dean 2015, Gopnik 2020).

Van Reenen 2001, Autor et al. 2002, **?**, Bartel et al. 2007, Bloom and Van Reenen 2011).

The third term of equation (7) is *data quality,* which is determined by the sample selection mechanism S_j. Recall that S_j defines the worker's past experiences, in the sense that it is an indicator variable equal to one for the size n subset of the α_j's that are in their sample. If the worker's sample is representative of the population mapping between context and output, then $corr\left(S, \alpha\right) = 0$ and α_j^n will be an unbiased predictor of α_j^N In that case, prediction error quickly approaches zero as sample size increases.[14]

Yet poor data quality reduces the gains from work experience. As shown by the third term of equation (7), prediction error is increasing in $E_S\left[\rho^2_{S,\alpha}\right]$, the squared correlation between the worker's sample selection mechanism S and the α's and associated X_j's they use for prediction.

There are at least two explanations for poor data quality. The first is non-representativeness. For example, suppose N indexes the set of tasks undertaken in the job of "economist", and we have samples n representing economists who work in university positions, or in banks, or in private sector firms. Past experiences (or "data") from one context X_j might be an imperfect guide to decision-making in other contexts, which would limit the gains from experience. This is consistent with evidence that human capital only partly transfers across jobs and employers (e.g. Kambourov and Manovskii 2009, Gathmann and Schönberg 2010, Pavan 2011, Robinson 2018). Experience might also include differences in education, social networks, and family background.

The second determinant of data quality is behavioral biases. Workers might overemphasize the outcomes of successful decisions, a form of inference on winners that would induce a positive correlation between S and α (e.g. Thaler 1988, Andrews et al. 2019). Excessive risk aversion would lead workers to repeatedly choose the "safe" action over time, inducing

[14]Random sampling ensures representativeness. If the worker's sample is drawn randomly, then prediction error from equation (6) is equal to the standard error of the estimate $\frac{\sigma_\alpha}{\sqrt{n}}$ times $\sqrt{\frac{N-n}{N-1}}$, a finite population correction factor that accounts for the fact that the sample is drawn without replacement. Plugging this into equation (7) yields $\left(\frac{\sigma_\alpha}{\sqrt{n}} * \sqrt{\frac{N-n}{N-1}}\right)^2 = \left(\frac{N-n}{n}\right) * \sigma^2_\alpha * \frac{1}{N-1}$, which is approximately equal to $\frac{\sigma^2_\alpha}{n}$ as N becomes large.

a negative correlation between S and α (Rabin and Thaler 2001). More broadly, behavioral biases such as anchoring, availability, base rate neglect, correlation neglect and others can all be thought as methods of data selection that introduce sample selection bias and hinder decision-making (e.g. Tversky and Kahneman 1973, Benjamin et al. 2019, Enke and Zimmermann 2019, Enke 2020).

Cognitive skill, or intelligence, can be interpreted broadly as the ability to acquire and interpret higher quality data for decision-making. Psychologists, economists, and computer scientists all define intelligence similarly as the ability to learn and adapt to change, or as the efficiency of skill acquisition (Nelson and Phelps 1966, Sternberg 2013, Chollet 2019, Sternberg 2021). Interpreted through the lens of the model, the ability to learn more from the past would be captured by the data quality term $E_S\left[\rho^2_{S,\alpha}\right]$.

Many studies also highlight the role of cognitive ability in reducing biases and decision errors. Intelligence is positively correlated with patience, willingness to take calculated risks, and social awareness, all attributes that should improve decision-making (Burks et al. 2009, Oechssler et al. 2009, Rustichini 2015). People with higher measured cognitive skills learn games of strategy faster and make better decisions over time (Burnham et al. 2009, Bayer and Renou 2016, Gill and Prowse 2016). Dohmen et al. (2010) find that low cognitive ability is associated with higher risk aversion and increased impatience in a large, representative sample of German adults. Similarly, Benjamin et al. (2013) find a positive correlation between academic achievement and both risk neutrality and patience. Frederick (2005) shows that "cognitive reflection" – the ability to resist an intuitive answer and activate conscious cognition – is correlated with cognitive ability and risk preferences and predicts avoidance of behavioral decision errors.

2.4 Empirical Predictions

The model yields four testable predictions:

1. *Jobs with more experience requirements will also require more decision-making, and*

firms that rely more on decision-making will seek to hire more experienced, higher-skilled workers. Equation (4) shows that firms will rely more on worker decision-making as prediction error decreases, which predicts a firm-level relationship between the autonomy granted to workers and experience and skill requirements.[15] We should also expect to see a positive correlation between decision-making and work experience requirements at the job level. I test this prediction using job vacancy data that contain firm identifiers, occupation codes and job titles, and direct measures of education, experience and skill requirements.

2. *The return to work experience is positive and concave.* Equation (7) shows that prediction error always decreases as workers acquire more data, but at a decreasing rate.[16] This is consistent with the well-known empirical finding that age-earnings profiles are concave across many different countries and periods of time (e.g. Murphy and Welch 1990, Heckman et al. 2003, Lagakos et al. 2018). In the classic Ben-Porath (1967) model, concave age-earnings profiles are due to depreciation of human capital investments made earlier in life. In macroeconomic models of learning-by-doing (LBD), learning and earning are complements rather than substitutes, and so the concavity of age-earnings profiles derives from an assumption that human capital accumulation declines with experience (e.g. Shaw 1989, Imai and Keane 2004, Hendricks 2013, Blandin 2018). This model provides a different explanation for why earnings continue to increase throughout the life-cycle, which is that accumulated experience increases human capital in decision-making.[17]

[15]Plugging equation (7) into equation (4) and taking the derivative of the firm's marginal profit with respect to θ yields $\left[\left(\alpha_j^N - \alpha_0\right) - \left(\left(\frac{N-n}{n}\right) * \sigma_\alpha^2 * E_S\left[\rho_{S,\alpha}^2\right]\right)\right]$, which suggests that the three terms in equation (7) decrease as θ increases.

[16]Plugging in equation (7), the derivative of equation (4) with respect to n is $\frac{N}{n^2}\left(\theta\sigma_\alpha^2 E_S\left[\rho_{S,\alpha}^2\right]\right)$, which is always positive and decreasing in n. The second derivative of equation (4) with respect to n is $-\frac{2N}{n^3}\left(\theta\sigma_\alpha^2 E_S\left[\rho_{S,\alpha}^2\right]\right)$, which is always negative and increasing in n.

[17]Most calibrations of the Ben-Porath model find almost no depreciation and a human capital accumulation function that is close to linear, which implies that learning-by-doing must be important (Heckman et al. 1998, Hendricks 2013, Manuelli and Seshadri 2014). The finding of no human capital depreciation is inconsistent with Deming and Noray (2020), which shows evidence of skill obsolescence in technology-intensive careers.

3. *The return to work experience is less concave in decision-intensive occupations.* Plugging equation (7) into equation (4) shows that as σ_α^2 increases, the return to work experience n becomes less concave.[18] This is because higher-variance environments are harder to predict, which has the same effect as data reduction. Empirically, occupations that require more decision-making should have longer and more gradual periods of earnings growth, reflecting the fact that each year of work experience effectively provides less data for prediction. I test this using cross-sectional and panel data on job characteristics and the age-earnings profiles of individual workers as they gain experience and move in and out of different occupations.

4. *Cognitive skill, work experience, and decision intensity are complements.* The evidence on cognitive skill, learning and decision errors suggests that the selection bias term $E_S\left[\rho_{S,\alpha}^2\right]$ in equation (7) will be smaller for more skilled workers. The functional form of equation (7) thus implies that the labor market return to cognitive skill will be increasing in experience, and will increase faster in decision-intensive occupations. I test this using panel data from the NLS surveys where I can observe cognitive skill directly, and I estimate models of earnings growth that allow for within-worker complementarity between cognitive skill, decision intensity and work experience. I also show direct evidence that excessive risk aversion generates an earnings penalty that increases with work experience and is greater in decision-intensive occupations.

3 Results

3.1 Decision-making and work experience

The first prediction of the model is that firms requring more decision-making will seek to hire more experienced and more highly skilled workers. I test this prediction using job vacancy

[18]As shown in the previous footnote, the second derivative of equation (4) with respect to n is always negative, and is increasing in σ_α^2 as well as n. This implies that the age-earnings profile becomes less concave as the variance of task output increases.

data from Burning Glass Technologies (BGT), an employment analytics and labor market information firm that scrapes job vacancy data from more than 40,000 online job boards and company websites. BGT applies an algorithm to the raw scraped data that removes duplicate postings and parses the data into a number of fields, including job title and six digit Standard Occupational Classification (SOC) code, industry, employer name, location, and education and work experience. BG translates key words and phrases from job ads into a large number of unique skill requirements. I use an extract of BG data that cover the 2007-2019 period. Following Deming and Noray (2020), I exclude vacancies with missing employers and employ a pruning algorithm to create unique employer IDs.[19]

I construct a vacancy-level measure of decision-making intensity by creating an indicator variable that is equal to one if the vacancy includes one of several key words or phrases that relate to decision-making.[20] The results are not sensitive to other reasonable choices such as using only the word "decision" itself.

Figure 3 presents scatterplots of the establishment (firm-by-MSA) level correlation between the share of vacancies requiring decision-making and experience (Panel A) and education (Panel B) requirements. I restrict the sample to establishments with 500 or more vacancies over the entire period for ease of presentation. Panel A shows a strong positive correlation ($\rho = 0.59$) between decision-making and average years of experience required. Panel B shows a similarly strong relationship ($\rho = 0.65$) between decision-making and requiring at least a bachelor's degree. Figure 3 shows that firms require higher levels of education and experience in jobs that also require decision-making and problem solving.[21]

[19]Several existing studies discuss the coverage of BG data and comparisons to other sources such as the Job Openings and Labor Force Turnover (JOLTS) survey (Hershbein and Kahn 2018, Deming and Kahn 2018, Deming and Noray 2020). The algorithm eliminates common words and word fragments such as "Inc", "LLC", and "Corp" from the firm name field.

[20]BGT classify vacancy text into thousand of unique job skills, and I create the decision-making variable using the key words and phrases "decision-making', "problem-solving", "diagnosing", "judgment", "strategize", "planning", "prioritizing", "goals", and "project management" plus closely relate word stems. As mentioned earlier, these closely map to three O*NET work activities associated with decision-making.

[21]I also find positive correlations of around 0.35 between decision-making and education and experience requirements when collapsing the data to occupation-by-establishment cells, where occupation is measured by six digit SOC codes, suggesting that these relationships hold even with narrowly defined job categories.

I also estimate a vacancy-level regression of the decision-making variable on indicators for experience requirements, controlling for metropolitan statistical area (MSA), employer, and occupation fixed effects. The results are in Figure 4. Jobs that require more work experience are much more likely to also require decision-making. The decision-making share increases from 22 percent at zero years of experience to 50 percent at five years of experience, and then levels off. This finding holds even when controlling for establishment fixed effects (the dashed line) and for six digit SOC-by-establishment fixed effects (the dotted line).[22]

Bayer and Kuhn (2019) show that increases in complexity, autonomy and responsibility - what they call *job levels* - explain a substantial share of within-occupation wage dispersion as workers gain experience.[23] Job levels are not directly measured in commonly used U.S. data sources, but the results in Figure 4 are consistent with a job levels interpretation and suggest that we should expect to find increases in decision intensity *within* occupations as workers gain experience.

I compare the decision-making variable from BGT data to publicly available data from the Occupational Information Network (O*NET), a survey administered by the U.S. Department of Labor to a random sample of U.S. workers in each occupation. I create a measure of decision-making intensity in the O*NET data using a simple average of the three work activities also used in Figure 2 - making decisions and solving problems, developing objectives and strategies, and planning and prioritizing work. The labor supply-weighted occupation-level correlation between the BGT and O*NET measures of decision-making intensity is 0.83.

Appendix Figure A1 shows a scatterplot of the relationship between BG and O*NET measures of decision intensity for each three digit SOC code. The three digit SOC codes

[22] The results in Figure 4 also hold when substituting the actual job title for 6 digit SOC code and controlling for job title-firm-MSA fixed effects.

[23] Pierce (1999) and the appendix material in Bayer and Kuhn (2019) explore data on job levels collected by the U.S. Department of Labor's National Compensation Survey (NCS). The NCS assigns job levels by evaluating jobs in terms of required knowledge, job controls and complexity, personal contacts, and physical environment. They find that wages rise with job level, even within occupation categories, and that variation in average job level *across* occupations explains a substantial share of occupation wage premia.

with the highest decision intensity are all managerial occupations. Other than management, the most decision-intensive occupation categories are business operations and financial specialists, and the lowest are entertainment attendants, food and beverage workers, and personal service workers. Non-retail sales, health technologists, and pilots are examples of jobs that pay above-median wages but have relatively low decision intensity. Because the BGT and O*NET data yield such similar results, I use the publicly available O*NET measures of decision intensity in the analyses below to increase transparency and replicability.[24]

Appendix Table A1 shows averages by 3 digit SOC code of decision intensity, the share of workers with a bachelors degree, and mean wage and salary income, all measured as of the 2018 ACS. While education, earnings and decision intensity are strongly correlated across occupations, substantial variation remains. Occupations with below-average or average decision-intensity but high levels of education and earnings include Business Operations Specialists, Financial Specialists, Healthcare Practitioners (include doctors and dentists) and Sales Representatives.

3.2 The outward shift in U.S. age-earnings profiles since 1960

I estimate age-earnings profiles using data from the 1960 to 2000 U.S. Census and the 2007–2018 American Community Surveys (ACS), extracted from the Integrated Public Use Microdata Series (IPUMS) 1 percent samples (Ruggles et al. 2017). To maximize consistency across years, I restrict the sample to workers age 20 to 59 who are not living in group quarters and not enrolled in school. I harmonize occupation codes across sample years using the "occ1990dd" classification system developed in Autor and Dorn (2013) and extended by Deming (2017). The main outcome is the natural log of inflation-adjusted annual wage

[24] An alternative approach would be to use an occupation-level measure of routineness, following the task literature (e.g. Autor et al. 2003). The occupation-level correlation between decision-intensity and a direct measure of routineness is -0.69, and the main results are similar if I substitute routineness for decision intensity as a way of classifying occupations. I prefer decision intensity because it maps directly to the conceptual framework above, and because manual and cognitive routineness are not easy to separate in O*NET data. For example, the most relevant O*NET job characteristic for capturing routineness is "How important is repeating the same physical activities or mental activities over and over, without stopping to performing this job?", which mixes both concepts together.

and salary income, and all results use Census/ACS weights multiplied by the share of weeks worked the previous year to make them nationally representative of the working population.

The second prediction of the model is that the return to work experience is positive and concave. This is consistent with a large body of evidence showing rapid early-career wage growth (Topel 1991, Topel and Ward 1992, Neal 1999, Dustmann and Meghir 2005, Jeong et al. 2015).

Figure 5 shows how life-cycle earnings growth in the U.S. has changed over the past sixty years. Following Lagakos et al. (2018), I group respondents in the 1960, 1980 and 2000 Censuses and the 2007-2009 and 2016-2018 ACS into five-year age bins and estimate log earnings differences relative to the age 20-24 group, controlling for year fixed effects.

Age-earnings profiles in the U.S. in 1960 are similar to what Lagakos et al. (2018) find for Mexico over the 1990-2010 period. Earnings growth peaks at about 40 percent when workers are in their late thirties and early forties. This peak is followed by a gradual decline of about 10 percentage points over the next twenty years of age. The 1980 profile is shifted upward, with a peak around 50 percent, but is otherwise similar to 1960.

By 2000, U.S. age earnings profiles had shifted outward dramatically, with a higher peak that occurs much later in the life-cycle. In 2000, full-time workers age 50-54 earned about 90 percent more than full-time workers age 20-24. In 2017, earnings growth peaked at nearly 100 percent and workers age 55-59 were earning substantially more than workers in their 30s.

The demographics of the U.S. workforce have changed substantially over the last half-century, with higher rates of female labor force participation and pronounced growth in educational attainment (e.g. Goldin et al. 2006, Blau and Kahn 2017). Appendix Figure A2 shows age-earnings profiles by decade, separately for high school graduates (Panel A) and for workers with at least some college education (Panel B).

Life-cycle wage growth is much greater overall for college-educated workers. Yet there have been substantial increases in life-cycle wage growth since 1960 for both education groups, as well as a shift in the peak age of earnings from the early 40s to the mid-50s. Appendix Figures A3 and A4 show splits by gender and race respectively. While the outward shift in age-earnings profiles is more pronounced for men and for whites, the basic pattern holds for all demographic groups.

I adjust for demographic change more systematically with a non-parametric decomposition exercise that shifts only the occupation distribution across decades, holding other factors constant. I collapse mean earnings in Census and ACS data into age-race-sex-education-occupation cells and compute labor supply shares for each year. I then hold earnings constant for each demographic group and year, but adjust the occupation weights to reflect the composition of jobs in each decade.

The results are in Figure 6. The solid lines show age-earnings profiles in 1960 and 2017, using the true occupation distribution for each year. The dashed line shows how age-earnings profiles would look if earnings by age, race, sex and education were held at their 1960 levels, but occupations shifted to their 2017 frequencies for each cell. Life-cycle earnings look very similar through age 35, but then start to diverge noticeably, with counterfactual earnings about 15 to 20 percent higher after age 45. The dotted line shows the impact of holding earnings by demographic group at their 1980 levels, and the dashed-dotted line shows the same thing for 2000. Figure 6 shows that the shifting occupation distribution explains about half of the outward shift in U.S. age earnings profiles between 1980 and 2017, and nearly all of the change since 2000.[25]

3.3 Greater wage growth in decision-intensive occupations

Which occupations are responsible for the outward shift in U.S. age-earnings profiles? Figure 7 shows that life-cycle earnings growth after age 35 is much greater in decision-intensive occupations. I regress log earnings on five-year age group by census year bins, controlling also

[25] The inflation-adjusted earnings peak in 1960 was \$40,338 and \$65,641 in 2017, compared to \$54,815 for the 1980 simulated distribution and \$65,370 for 2000. (54,815-40,338)/(65,641-40,338) = 57.2 percent and (65,370-40,338)/(65,641-40,338) = 98.9 percent.

for year-sex-race-education interactions. I then estimate separate regressions for occupations that are in the bottom and top quartiles of the O*NET decision intensity variable described in Section 3.1. Panels A through D present results for 1960, 1980, 2000 and 2017 respectively.

Across all decades, mid-career earnings growth is substantially higher in decision-intensive occupations even after controlling for demographics. In 1960, workers in decision-intensive occupations experienced more than 15 percentage points of cumulative wage growth after age 35, compared to small declines in occupations where decision-making is less important. This basic pattern holds all the way through 2017, where wage growth after age 35 is twice as fast in decision-intensive occupations.

Cross-sectional comparisons of age-earnings profiles have at least two potential sources of bias. First, workers with higher potential earnings growth might sort into decision-intensive occupations over the life-cycle. The second concern is that there might be differences by cohort in potential earnings growth. For example, some of the outward shift in age-earnings profiles since 1960 might be explained by improvements in childhood and adult health which enable workers to remain more productive as they age.

I address both of these sources of potential bias by studying individual age-earnings profiles using longitudinal data from the 1966/67, 1979 and 1997 waves of the National Longitudinal Surveys (NLS). The oldest NLS cohort follows men and women age 14-24 in 1966 and 1967 respectively. The NLSY-79 starts with a sample of youth ages 14 to 22 in 1979, while the NLSY-97 starts with youth age 12–16 in 1997. The NLS surveyed women through 2003 but men only through 1981, at either annual or biannual intervals. The NLSY-79 was collected annually from 1979 to 1993 and biannually through 2017, whereas the NLSY-97 was always biannual.

Each survey collects detailed measures of pre-market skills, schooling experiences, occupations and wages. The oldest NLS cohort combines information from a variety of different aptitude and achievement tests into a standardized composite score.[26] The NLSY-79 and

[26]https://www.nlsinfo.org/content/cohorts/older-and-young-men/topical-guide/education/aptitude-achievement-and-intelligence

NLSY-97 measure aptitude using the Armed Forces Qualifying Test (AFQT), and I adopt the crosswalk developed by Altonji et al. (2012) to make the AFQT scores comparable across surveys. I normalize the aptitude measures within each NLS survey, and I map occupation codes from each survey to the "occ1990dd" crosswalk so that they are consistent across waves.[27] The main outcome is the real log hourly wage (in constant 2017 dollars), and I trim values that are below 3 and above 200, following Altonji et al. (2012).

Workers originally surveyed in the NLSY-79 are now in their mid to late 50s, making this by far the longest panel of the three. Both the original NLS and the NLSY-97 only allow me to track earnings through age 40, so I use the NLSY-79 as the main sample for these analyses and compare differences across cohorts in Section 4.

I first produce a parallel analysis to Figure 7, which estimates age-earnings profiles for occupations in the bottom vs top quartile of decision intensity. I regress log wages on interactions between age and the decision intensity of a worker's occupation, controlling for year, occupation and *individual* fixed effects. This shows how an individual worker's earnings shift when they switch into and out of decision-intensive occupations. The baseline model is:

$$\ln\left(wage_{ijt}\right) = \beta_0 + \sum_{a}^{A}\left[\beta_a a_{ijt} + \gamma_a \left(a_{ijt} * d_{ijt}\right)\right] + \phi_i + \lambda_j + \Gamma_t + \epsilon_{ijt} \quad (8)$$

where a indexes four-year age bins, i indexes individuals, j indexes occupations and t indexes year. The decision intensity of an occupation (d_{ijt}) is measured on a 0-10 scale with 5 being the decision intensity of the median (50th percentile) occupation in 2017.

The results are in Figure 8. The figure plots implied values for occupations at the 25th (solid line) and 75th (dashed line) percentiles of decision intensity, while the table below shows the actual regression coefficients on age and age-by-decision intensity interactions. Consistent with Figure 7, I find that no wage growth after age 40 for workers in 25th percentile decision-intensive occupations. The coefficients imply that a 10 percentile increase

[27] Altonji et al. (2012)construct a mapping of the AFQT score across NLSY waves that is designed to account for differences in age-at-test, test format and other idiosyncracies. I take the raw scores from Altonji et al. (2012) and normalize them to have mean zero and standard deviation one.

in occupation decision intensity increases wage growth by about 4 percentage points between the ages of 35 and 55. All of the coefficients on the age-by-decision intensity interactions are statistically significant at the less than one percent level, and they grow substantially with time.

Appendix Table A2 presents the age-by-decision intensity interactions for various subsamples of the NLSY79, including race, gender and education. Wage growth is substantially greater in decision-intensive jobs for all of these demographic groups. Appendix Table A2 also presents results that divide the sample into professional, managerial and technical occupations versus all other occupations. The same pattern broadly holds in both subsamples, although the absolute value of wage growth is substantially greater in higher-skilled occupations. The table also shows that the main results are robust to controlling for employer tenure in addition to the other terms in equation (8). Finally, I also presents results that include interactions between age and nonroutine analytical (math) intensity, following Autor et al. (2003) and Deming (2017). Including both sets of interactions does not change the results in Figure 8 at all, and the interactions between age and mathematical intensity are negative and not statistically significant. This suggests that decision-making, rather than general analytical skills, is the key predictor of life-cycle wage growth.

3.4 Complementarity between cognitive skill, decision intensity, and work experience

The fourth prediction of the model is that cognitive skill, decision intensity, and work experience are complements. I test this using panel data from the NLSY-79, in a model similar to equation (8) but adding interactions with cognitive skills:

$$\ln\left(wage_{ijt}\right) = \beta_0 + \sum_{a}^{A}\left[\beta_a a_{ijt} + \gamma_a\left(a_{ijt} * d_{ijt}\right) + \delta_a\left(a_{ijt} * cog_i\right) + \zeta_a\left(a_{ijt} * d_{ijt} * cog_i\right)\right] + \phi_i + \lambda_j + \Gamma_t + \epsilon_{ijt} \tag{9}$$

where cog_i indexes the cognitive skill of worker i as measured by AFQT scores, and the other terms are defined similarly to equation (8). Figure 9 plots the implied coefficients for workers with low (-1σ) vs. high ($+1\sigma$) AFQT scores and in low (25th percentile) vs. high (75th percentile) decision-intensity occupations. The solid and dashed lines show age-earnings profiles for low and high decision-intensity jobs respectively, and the circles and squares show results for workers with low vs. high AFQT scores respectively.

There are three important takeaways from Figure 9. First, higher cognitive skill increases earnings, with relatively greater impacts as workers age. A one standard deviation increase in cognitive skill increases earnings by 5.3 percent at ages 24-27 and 8.2 percent at ages 56 to 59, and I can reject equality of the δ_a coefficients at the less than one percent level. Second, the relative returns to working in a decision-intensive occupation are small initially but grow substantially over the life cycle, with greater convexity for high ability workers. A ten percentile point increase in decision intensity increases earnings by 0.7 percent at ages 24-27 and 6.3 percent at ages 56-59, and again we can reject equality of the γ_a coefficients at the less than one percent level.

Third, Figure 9 shows strong evidence of complementarity between cognitive skill, decision intensity and work experience, confirming the fourth prediction of the model. High ability workers in decision-intensive jobs pull farther away from other workers as they age. All of the ζ_a coefficients on the three-way interaction term are statistically significant at the less than one percent level, and we can reject that they are equal to each other at the less than one percent level.

Appendix Figures A5 through A8 present results that plot estimates of equation (9) by gender and educational attainment. The patterns are stronger for men and for college attendees, but I find evidence of complementarity in all four subgroups. The results in Figure 9 are also robust to controlling for interactions with the mathematical intensity of occupations.

Appendix Figure A9 presents results of models similar to equation (9), except replacing cognitive abiilty with a self-reported measure of risk tolerance.[28] I find that higher risk tolerance has little or no payoff in low decision jobs, but has a statistically significant return in high decision jobs that grows with age.

To construct formal statistical tests of the patterns shown in Figure 9, I estimate versions of equation (9) using data from the NLSY79, but with linear interactions between age, decision intensity, and cognitive ability. The results are in Table 1. Column 1 presents the simplest model, with age and age interacted with AFQT score. Earnings grow 0.54 percent faster per year for workers with one standard deviation higher cognitive ability. Column 2 includes two-way interactions between age, cognitive ability and the decision intensity of a worker's occupation. The return to decision-intensive occupations increases by 0.14 percent per year, and workers with higher cognitive ability earn relatively greater returns in these jobs.

Column 3 adds the three-way interaction between age, cognitive ability and decision-intensity, and the interaction term is positive and statistically significant at the less than one percent level. Column 4 repeats Column 3 but replaces cognitive ability with risk tolerance. The three-way interaction is statistically significant at the less than one percent level. Column 5 shows that both measures have independent predictive power for earnings in ways that are consistent with the predictions of the model. The three-way interaction terms for cognitive ability and risk tolerance are both statistically significant at the less than one percent level, and interestingly the individual correlation between the two measures is almost exactly zero.

[28]The question asks NLSY respondents to "Rate yourself from 0 to 10, where 0 means 'unwilling to take any risks' and 10 means 'fully prepared to take risks'." I estimate equation (9)replacing cognitive ability with a categorical variable that is equal to 1 if respondents answer 0-3 (unwilling), 1 if they answer 4-6 (middle), and 2 if they answer 7-10 (fully prepared),. Results are not sensitive to other groupings.

4 Implications

4.1 Technological Replacement of Routine Tasks

Figure 2 shows that the demand for decision-making began to increase rapidly in the 1990s, right around the time that computers and information and communication technology (ICT) made their way into the workplace. Several studies show that ICT increases the demand for worker autonomy by producing large amounts of data and depending on workers to analyze it and react, which decentralizes firm-level decision-making and increases the breadth of workers' responsibilities (e.g. Lindbeck and Snower 2000, Bresnahan et al. 2002, Dessein and Santos 2006). Autor et al. (2002) find that the use of automated check imaging in a retail bank reorganized work, eliminating the routine job of check processing but increasing the complexity and autonomy of jobs dealing with nonroutine exceptions such as repeated customer overdrafts. Bartel et al. (2007) find that the introduction of computer numerically controlled (CNC) machines in a valve manufacturing plant automated manual tasks related to valve cutting and machining but increased firms' demand for workers who can problem-solve and troubleshoot unforeseen issues.

Recall that in the model in Section 2, firms choose the level of worker autonomy θ that maximizes profits, which suggests that they will hire workers to perform non-routine tasks $\alpha\left(X_j\right)$ only when the benefits relative to routine tasks α_0 exceed the costs of worker prediction error.

Assume now that firms can choose to employ capital rather than labor, but that capital can only perform α_0 type tasks, where everything is scripted in advance and no adaptation is necessary. Following Autor et al. (2003), assume further that the price of routine-replacing computer capital is declining exogenously over time, which increases the productivity per unit cost of capital in type α_0 tasks. Under these assumptions, firms will optimally shift production toward routine tasks overall, and these tasks will increasingly be done by machines. However, a higher share of the total work performed by humans will be nonroutine, which will increase the relative returns to cognitive skills and work experience.[29]

I test this implication of the model by comparing the returns to work experience, decision intensity and cognitive skill across all three waves of the NLS. I estimate models like equation (9) above, but in the pooled NLS data and adding interactions between the variables above and indicators for each sample wave. To maintain consistency acros NLS waves I restrict the sample to ages 20 to 40 only.

The results are in Table 2. Column 1 shows that the economic return to working in decision-intensive occupations has grown over time. A 10 percentile point increase in decision intensity increased earnings by 2.2 percent for respondents in the 1966 NLS cohort, 3.1 percent in the NLSY79 cohort, and 5.7 percent in the NLSY97. Column 2 adds interactions between decision intensity and age. The complementarity between age and decision intensity is substantially greater in later waves, and we can reject equality of these coefficients at the less than one percent level. Column 3 includes three-way interactions between age, cognitive ability and NLS wave. The complementarity between age and cognitive ability is much greater in later years, and again we can reject equality of these coefficients at the less than one percent level.

Column 4 adds four-way interactions between age, decision intensity, cognitive ability and cohort. The three-way complementarity between age, decision intensity and cognitive ability grows stronger with each wave. Although the difference between the NLSY79 and NLSY97 is not statistically significant, we can reject the difference between the NLS 66 and the other two at the 10 percent level ($p = 0.083$ and $p = 0.063$ for the NLSY79 and NLSY97 respectively). The coefficients imply that the difference in economic returns to decision-

[29] Suppose there is a continuous distribution of labor productivity in type $\alpha(X_j)$ tasks and of both labor and capital productivity in type α_0 tasks, which we can denote as α_0^L and α_0^K respectively. Firms will employ capital for any particular task when $\alpha_0^K > \alpha_0^L$, which occurs for a growing share of tasks over time. In aggregate, machines will perform a larger share of total tasks. However, any production function with imperfect substitution across routine and non-routine task types will still include some type $\alpha(X_j)$ tasks, which can only be done by people. Thus a higher share of human tasks will be non-routine. This places a greater premium on workers with higher levels of experience and cognitive ability, for the reasons outlined in Section 2, and suggests that the magnitudes of the relationships predicted by the model will increase over time.

intensive work are substantially greater in later cohorts, especially for workers with high cognitive ability. The coefficients imply that the economic return to decision intensity for high ability workers at age 40 increased from 22 percent for the 1966 cohort to 38 percent for the 1997 cohort. Appendix Table A3 presents evidence that workers with high cognitive ability are more likely to self-select into decision-intensive occupations over time.

As pointed out by Autor (2015), machine learning and artificial intelligence differ from other automation technologies because they “apply statistics and inductive reasoning to supply best-guess answers where formal procedural rules are unknown (Autor 2015). Agrawal et al. (2018) model artificial intelligence as substituting for human prediction while complementing human judgment. Business processes such as resume screening and demand forecasting are prediction problems, and machines might make more accurate forecasts than their human counterparts, although the net effect of machine prediction on jobs is theoretically ambiguous (Agrawal et al. 2019a).

The model provides some insights about how artificial intelligence could replace or alter job tasks previously performed by people. For example, humans have capacity constraints on the amount of data they can use to make predictions, which we could think of as a cap on sample size n. Machine learning technologies, on the other hand, do not face the same data processing constraints, and so all else equal they will make more accurate predictions.

However, humans may have an advantage when not all of the relevant data are formally codified. If people observe important decision-making context (X_j) that is not formally collected as data, they may outperform machines even after accounting for capacity constraints. Since the magnitude of sample selection bias increases with data size, big data will still yield poor predictions if it is non-representative or missing important features (Meng et al. 2018). Overall, the increasing availability of big data and the falling cost of prediction suggests that the value of work experience may decline relative to the ability to make good decisions by minimizing sample selection bias.

4.2 Education and Human Capital Development

Does education improve decision-making? Beginning with the Mincer equation, economists mostly abstract away from decision-making and assume that education increases earnings by improving job or task productivity directly (Mincer 1958, Becker 1962, Acemoglu and Autor 2011). An older literature discusses the impact of education on allocative efficiency. Welch (1970) argues that the return to education consists of two effects - the "worker effect", which encompasses the impact of education on factor productivity, and an "allocative effect", where education improves the "ability to acquire and decode information about costs and productive characteristics of other inputs" (Welch 1970).

Several studies have found that educated farmers are more likely to adopt productivity-enhancing new technologies (Huffman 1974, 1977, Ram 1980, Yang 2004). Nelson and Phelps (1966) hypothesize that education improves one's ability to adapt to change, and they distinguish between the impact of education on "the completely routinized job" compared to jobs where more autonomy and innovation is required. This idea is closely related to the model's conception of sample selection bias, where skilled workers are better able to learn the right lessons from past experiences. There is also a large literature suggesting that more educated managers are more strategically adept and make better decisions (Bloom and Van Reenen 2010, Goldfarb and Xiao 2011, Hortaçsu et al. 2019).

To investigate the role of education, I estimate versions of equation (9) that replace cognitive ability with years of completed education, as well as models that include both sets of interactions. Appendix Table A4 presents results in the format of Table 1, replacing cognitive ability with education. while Appendix Table A5 looks at changes in the return to education by NLS wave following the format of Table 2. Finally, Appendix Table A6 examines the trend across cohorts in selection into decision-intensive occupations among more educated workers. The bottom line is that almost all of the results I find for cognitive ability also extend to years of completed education, suggesting that education may also improve decision-making skill.

The relationship between education and decision-making has important implications for skill development and curriculum design. Deming and Noray (2020) find that the earnings premium for college graduates majoring in technology-intensive subjects diminishes with experience, mostly because other majors catch up rapidly. One possible explanation is that a general liberal arts college curriculum teaches "soft" skills like problem-solving and critical thinking that improve graduates' ability to make decisions and adapt to unfamiliar environments (NACE 2020). More generally, styles of teaching management such as the case method are consistent with education improving the ability to make accurate predictions about the future from data about the past.

5 Conclusion

This paper presents evidence of the growing importance of worker decision-making. Modern jobs increasingly require workers to adapt to unforeseen circumstances and to solve abstract, unscripted problems without employer oversight. As automation technology progresses, machines can increasingly perform any pre-scripted task better than a person, which leaves non-routine, open-ended tasks as the domain of human labor.

I formalize this insight with a simple model of decision-making on the job. The output of a job task depends on a set of background variables, or "context", which are only imperfectly observed. Workers predict the likely output of an action using a sample of data from their past experiences. As workers gain experience, their predictions become more accurate, which improves productivity as they are better able to adapt their actions to local context.

The model predicts that the return to work experience will depend on the variability of task output. In routine jobs, the mapping between context and output is easily predictable, and thus work experience accumulates quickly and has limited value. Work experience takes longer to accumulate in high-variance contexts, which implies a longer and more gradual period of earnings growth in non-routine, decision-intensive occupations.

Using repeated cross-sections from the Census and ACS and panel data from three waves of the NLS, I show that wage growth after age 35 is substantially greater in decision-intensive occupations. Moreover, rapid relative employment growth in these occupations has shifted the U.S. age-earnings profile noticeably outward over the last half-century. Life-cycle earnings growth has more doubled since 1960, and the peak age of earnings has shifted from the late 30s to the mid-50s. A simple decomposition exercise that accounts for demographic change and rising educational attainment shows that the shift toward decision-intensive occupations explains half of the outward shift in age-earnings profiles since 1980 and nearly all since 2000.

The model also reveals a connection between cognitive ability, behavioral biases, and the quality of worker decision-making. I formalize decision quality as the ability to make unbiased inferences from data samples based on past experiences. Since a large body of evidence shows that cognitive ability improves decision-making by reducing behavioral biases, the model predicts that cognitive ability, work experience, and the decision intensity of an occupation will be complements. I find strong supporting evidence for this prediction using individual data on ability and earnings trajectories from the NLSY.

Finally, I show that the economic return to working in decision-intensive jobs and the complementarity between cognitive ability and decision-making is increasing over time. This can be explained by technological change. Machines replace humans in a growing variety of job tasks, but only when the environment is perfectly predictable. Advancements in automation technology crowd humans out of routine tasks, and the remaining tasks are open-ended and increasingly dependent on worker adaptation (Autor et al. 2003, Autor 2015, Acemoglu and Restrepo 2018).

The growing value of decision-making on the job has important implications for education, skill development and economic growth. In a world where most predictable, routine job tasks are performed by machines, the remaining work is increasingly open-ended. Education and training for open-ended work will naturally be more abstract and will focus on teaching people how to process information and make decisions. Workers who know what to do without being directly managed are valuable because they can adapt their actions to local context (Dessein and Santos 2006). This micro-level increase in allocative efficiency may help explain variation in the returns to education and life-cycle patterns of wage growth across countries at different stages of economic development (Manuelli and Seshadri 2014, Lagakos et al. 2018).

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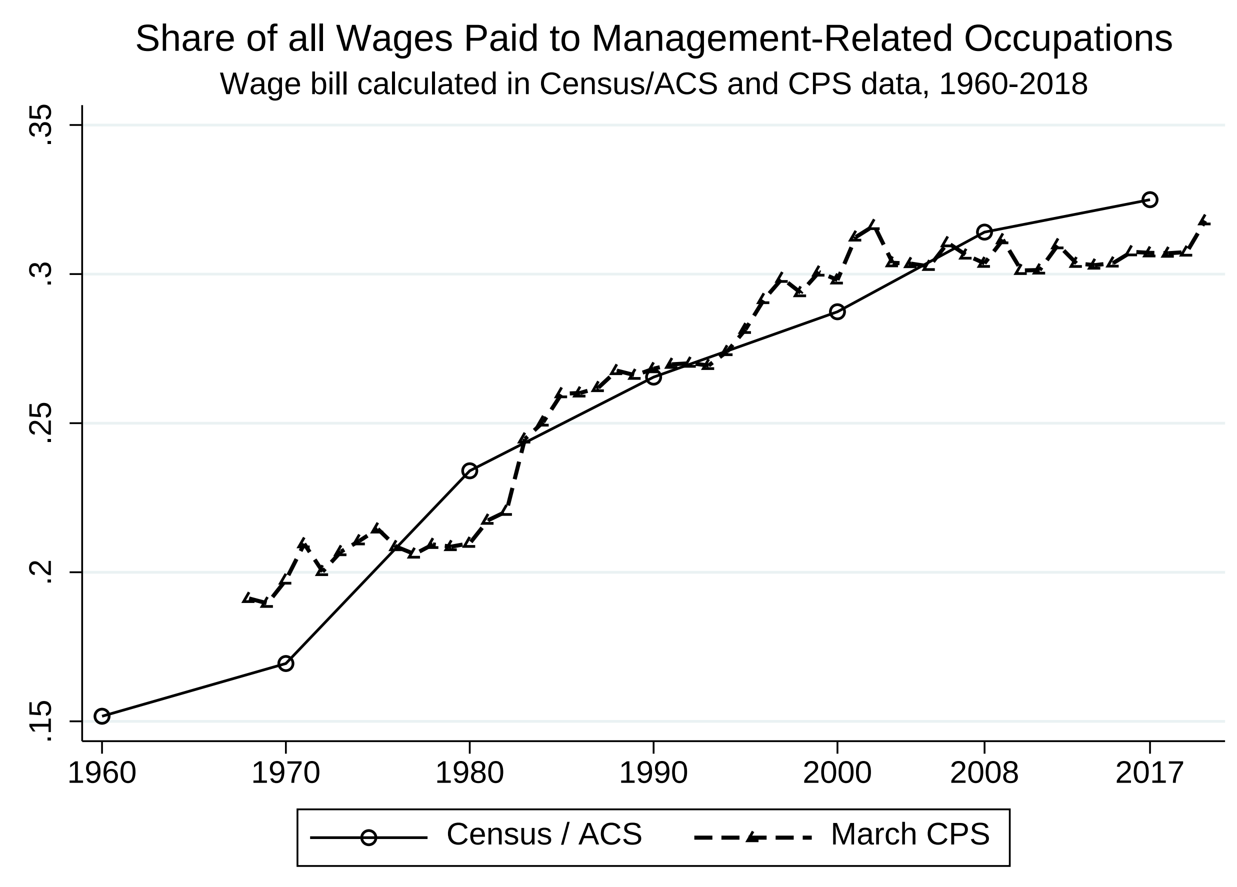
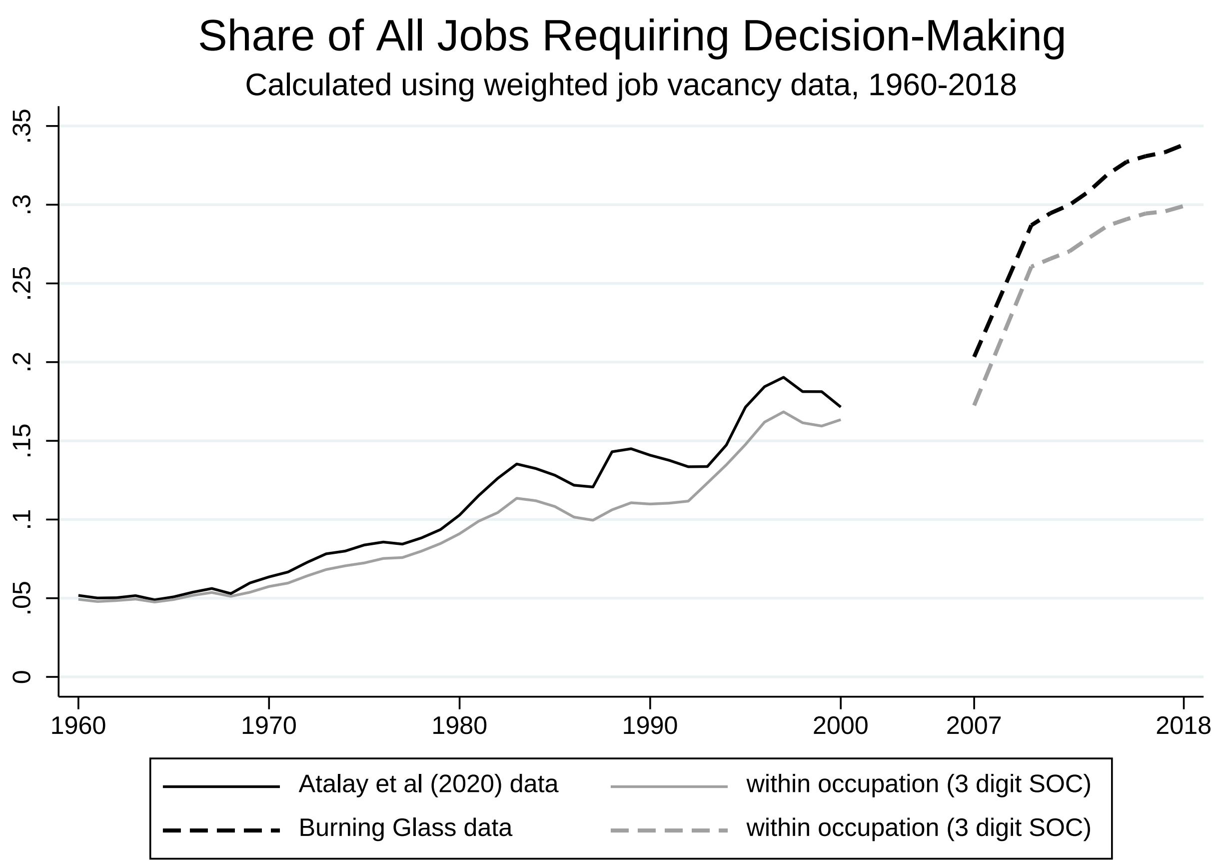
Figure 1



Notes: This figure shows the labor supply-weighted share of all wage and salary income paid to managerial occupations between 1960 and 2020. The solid line shows data from the 1960-2000 U.S. Census and pooled 3-year samples of the 2007-2009 and 2016-2018 American Community Surveys. The dashed line shows data from the 1968-2020 Annual Social and Economic Supplement of the March CPS (ASEC). Occupations are coded consistently using the "occ1990dd" crosswalk developed by Autor and Dorn (2013) and extended by Deming (2017). To maximize consistency over time, the definition pools management (codes 4 to 22) management support (codes 23 to 37) and all first-line supervisors together. See text for details.

Figure 2

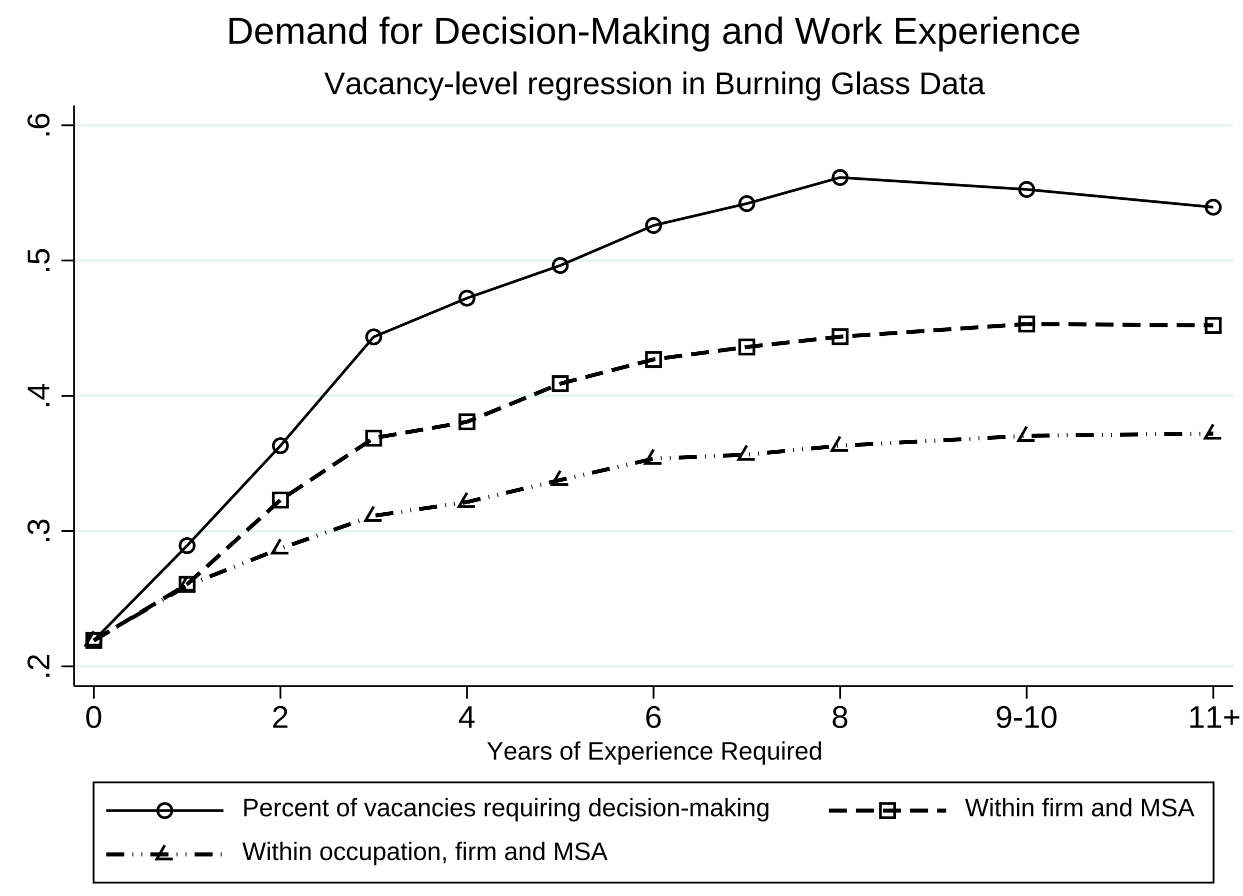


Notes: This figure computes the labor supply-weighted share of all job vacancies that include key words and phrases signaling a demand for worker decision-making – see the text for detailed definitions. The solid line uses classified ad data collected by Atalay et al (2020) over the 1960-1999 period, 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. I convert Census occupation codes to SOC codes using a crosswalk developed by Atalay et al (2020).

Figure 3

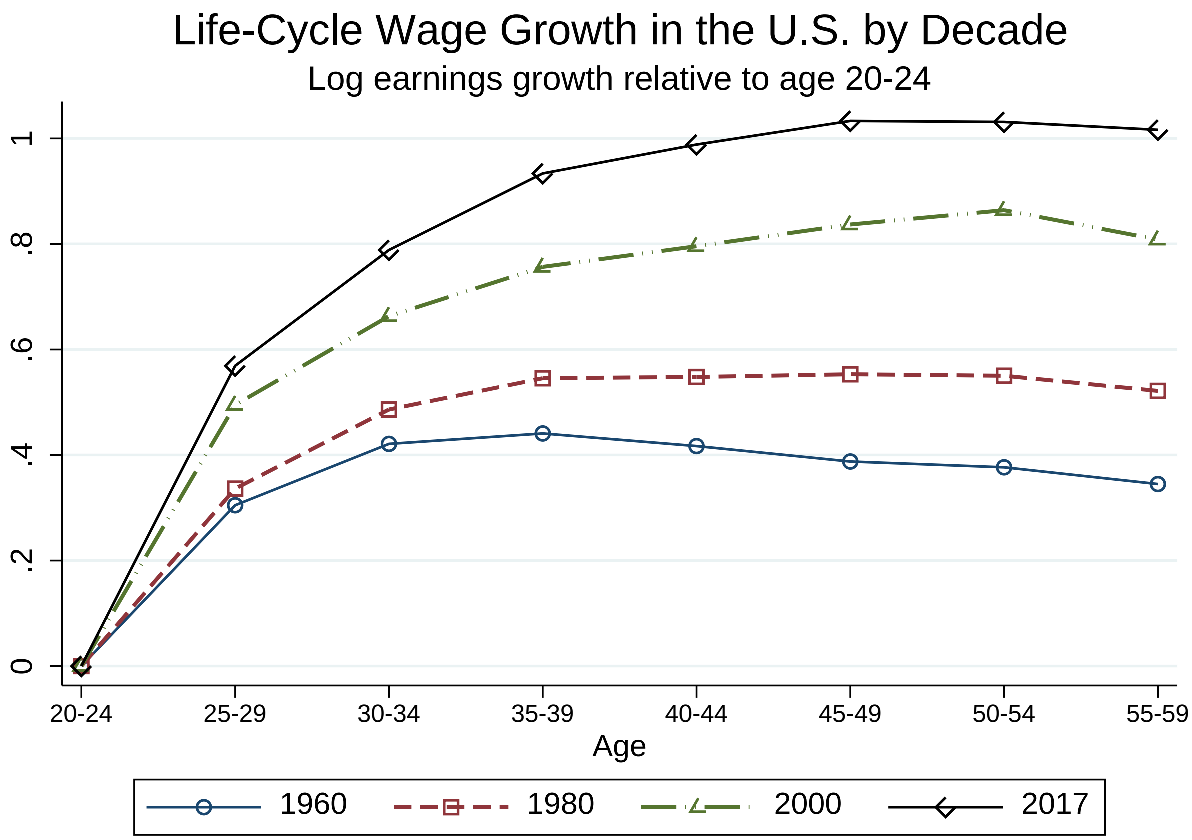
Notes: This figure presents scatterplots of the establishment-level correlation between the share of vacancies requiring decision-making and experience (Panel A, ρ=0.59) and education (Panel B, ρ=0.65) requirements. The data come from job vacancy postings collected by Burning Glass Technologies over the 2007-2018 period. An establishment is a firm name by metropolitan statistical area (MSA) pair. The sample restricted to establishments with at least 500 total vacancies.

Figure 4



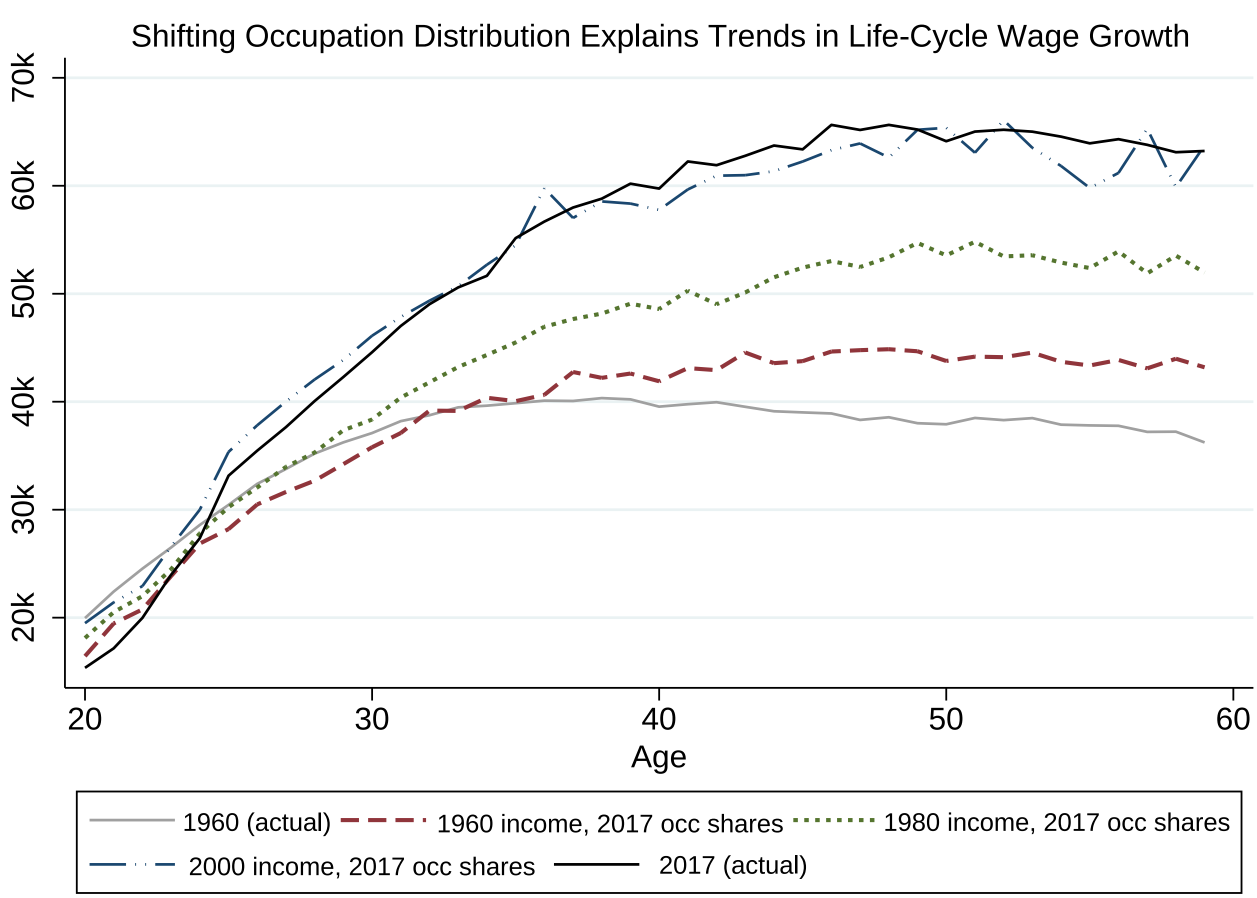
Notes: This figure plots coefficients from a vacancy-level regression of an indicator for whether the job requires decision-making on years of experience indicators, controlling for establishment (firm by metropolitan statistical area (MSA)) or establishment by six-digit Standard Occupation Classification (SOC) codes, as indicated. The data come from job vacancy postings collected by Burning Glass Technologies over the 2007-2018 period.

Figure 5



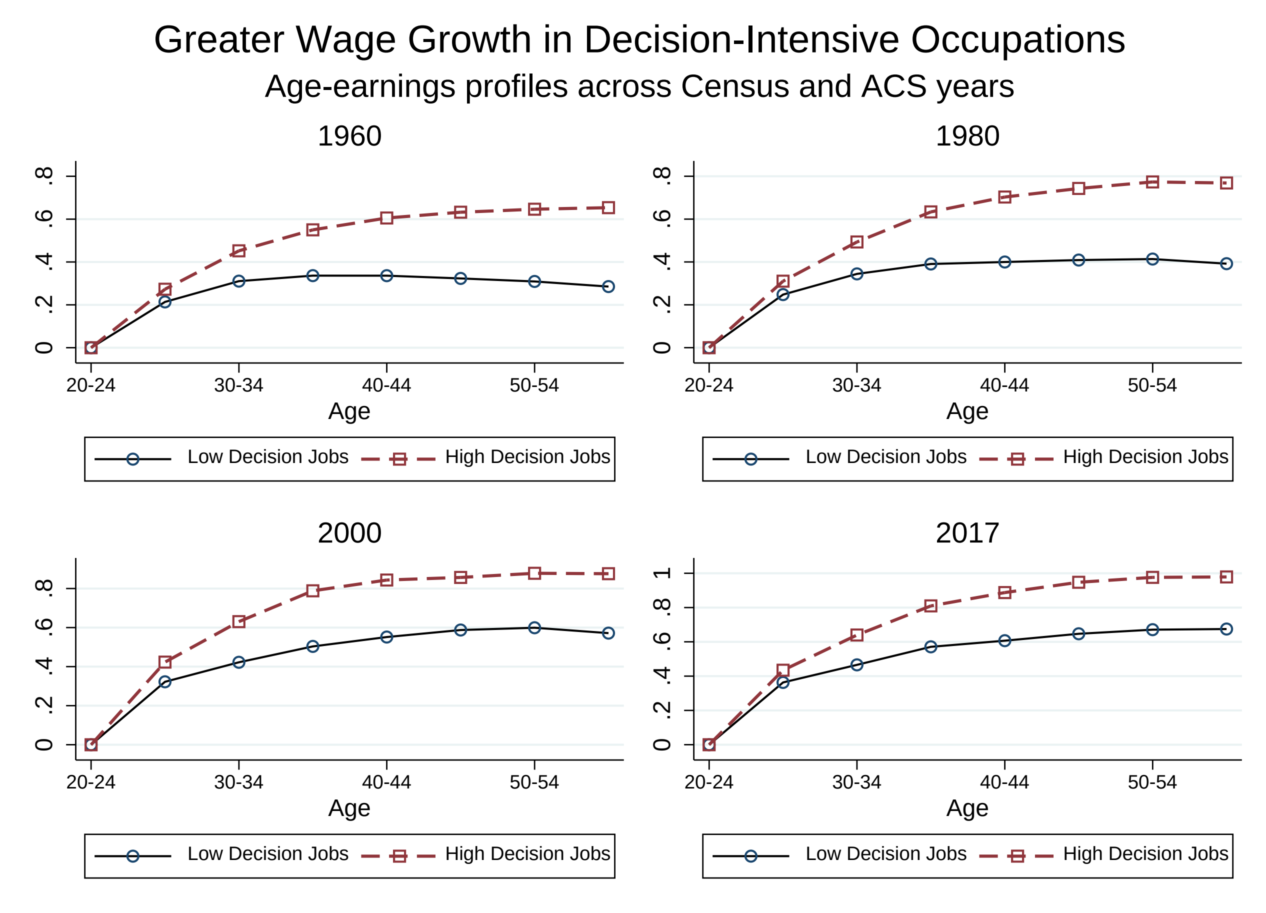
Notes: This figure presents results from a labor supply-weighted regression of log annual wage and salary income on indicators for five-year age bins, controlling for year fixed effects. The sample is all full-time workers ages 20-59 in the 1960-2000 U.S. Census and pooled 3-year samples of the 2016-2018 American Community Surveys.

Figure 6



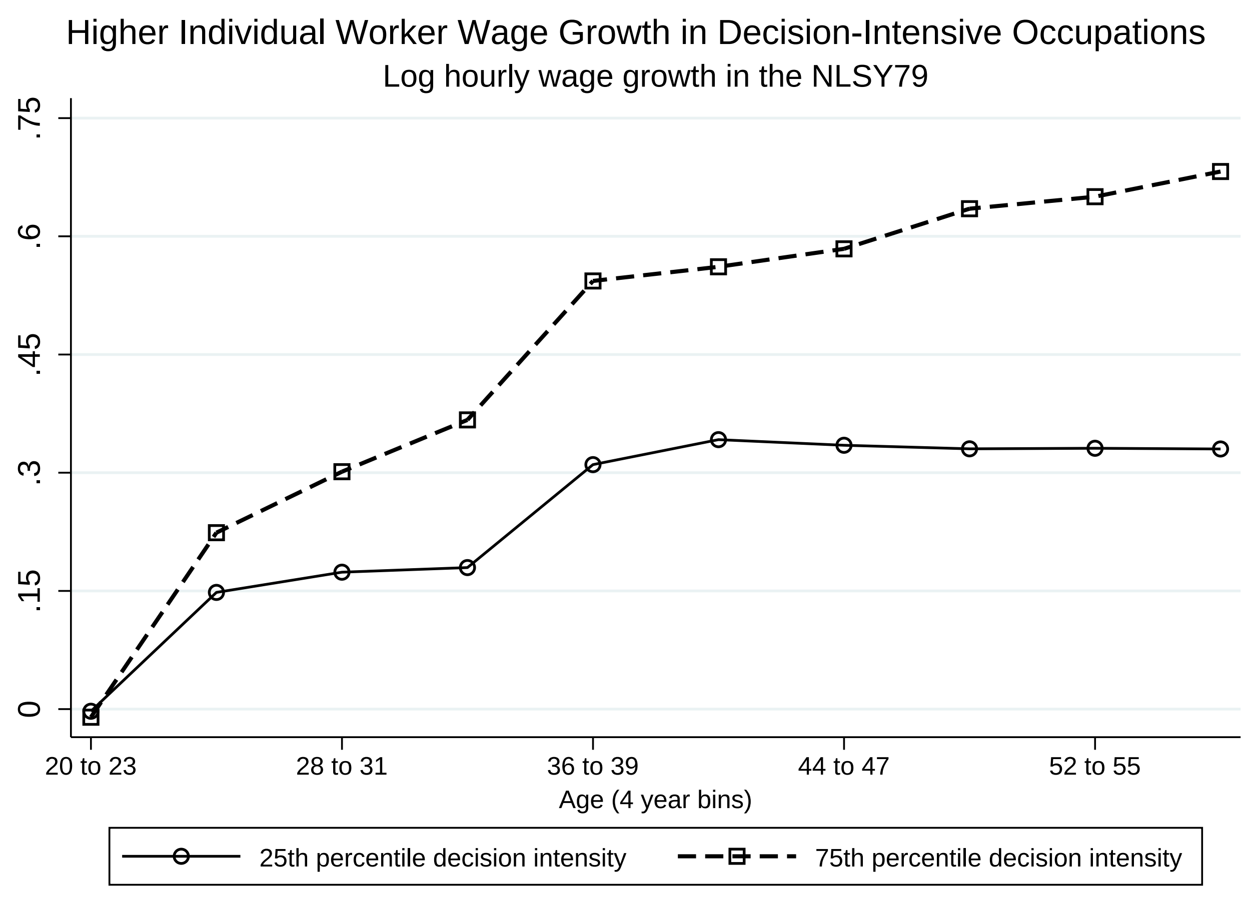
Notes: This figure presents results of a decomposition that holds inflation-adjusted wage and salary income constant within age-race-sex-education-occupation cells, while adjusting employment shares to match the occupation distribution in different years. The sample is all full-time workers ages 20-59 in the 1960-2000 U.S. Census and pooled 3-year samples of the 2016-2018 American Community Surveys. Occupations are coded consistently using the “occ1990dd” crosswalk developed by Autor and Dorn (2013) and extended by Deming (2017).

Figure 7



Notes: This figure presents results from two separate regressions of log annual wage and salary income on indicators for five-year age bins and year fixed effects, restricting the sample to occupations in the 25th percentile or below (the solid line) and the 75th percentile or above (the dashed line of decision intensity. Decision intensity is the average of three task variables related to decision-making from the Occupational Information Network (O*NET) survey – see the text for details. The sample is all full-time workers ages 20-59 in the 1960-2000 U.S. Census and pooled 3-year samples of the 2016-2018 American Community Surveys (ACS). Each panel presents the coefficients from the indicated Census or ACS year.

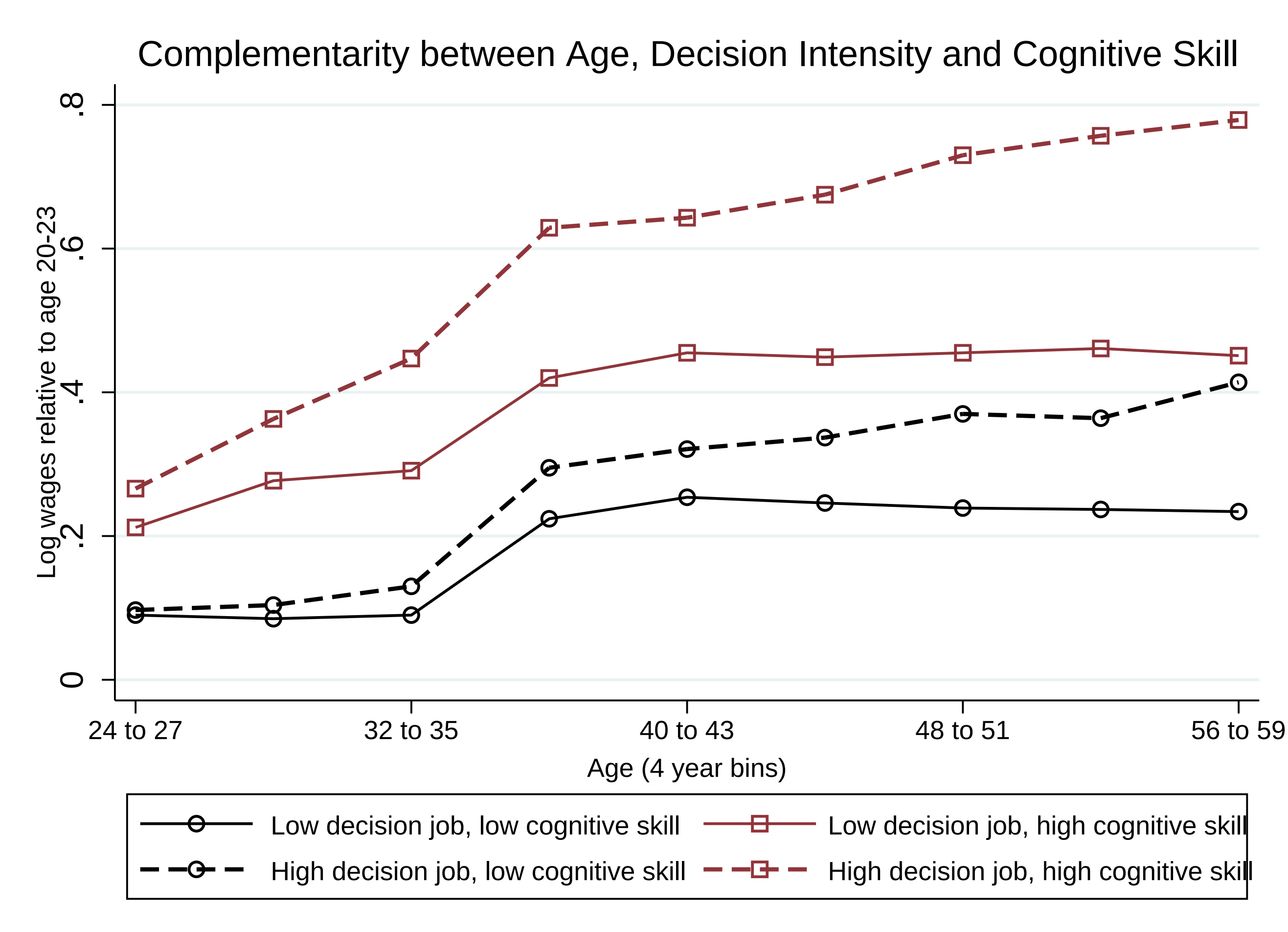
Figure 8



	20 to 23	24 to 27	28 to 31	32 to 35	36 to 39	40 to 43	44 to 47	48 to 51	52 to 55	56 to 59
Age	0	0.121	0.129	0.113	0.228	0.264	0.247	0.222	0.218	0.205
		[0.006]	[0.007]	[0.008]	[0.008]	[0.009]	[0.010]	[0.010]	[0.012]	[0.018]
Decision * Age	-0.002	0.019	0.032	0.046	0.058	0.054	0.062	0.076	0.079	0.087
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]

Notes: The table presents estimates of a version of equation (9) in the paper, where the natural log of real hourly wages is regressed on interactions with age and the decision intensity of a worker's occupation, plus individual and occupation fixed effects. The figure presents the implied value of the coefficients for occupations at the 25th and 75th percentile of decision intensity. The sample is comprised of youth ages 14-22 in 1979 and follows them through 2017. Decision intensity is the average of three O*NET task variables related to decision-making - see the text for details. Standard errors are in brackets and are clustered at the individual level.

Figure 9



Notes: This figure presents implied values from the coefficients of an estimate of equation (9) in the paper, with log hourly wages regressed on interactions between age, decision intensity and cognitive skill, plus occupation, individual and year fixed effects. The figure plots implied wage growth in jobs at the 25th percentile (solid line) and 75th percentile (dashed line) of decision intensity, and for workers with cognitive skill one standard deviation below average (circles) and one standard deviation above average (squares). The sample is youth ages 14-22 in the National Longitudinal Survey of Youth 1979 cohort. Occupations are coded consistently using the "occ1990dd" crosswalk developed by Autor and Dorn (2013) and extended by Deming (2017). Decision intensity is the average of three O*NET task variables related to decision-making – see the text for details. All the regression coefficients - including the three-way interaction between age, decision intensity, and cognitive skill – are statistically significant at the less than one percent level.

Table 1: Returns to Cognitive Skill and Risk Tolerance in Decision-Intensive Occupations

	(1)	(2)	(3)	(4)	(5)
Age	0.0140	0.0100	0.0100	0.0087	0.0104
	[0.0002]	[0.0003]	[0.0003]	[0.0005]	[0.0005]
Age * AFQT	0.0054	0.0038	0.0031		0.0029
	[0.0002]	[0.0002]	[0.0003]		[0.0003]
Age * Decision		0.0014	0.0013	0.0014	0.0007
		[0.0001]	[0.0001]	[0.0002]	[0.0002]
Decision		-0.0141	-0.0121	-0.0147	0.0030
		[0.0059]	[0.0058]	[0.0075]	[0.0075]
Decision * AFQT		0.0143	0.0053		0.0052
		[0.0011]	[0.0033]		[0.0036]
Age * Decision * AFQT			0.0003		0.0003
			[0.0001]		[0.0001]
Age * Risk Tolerance				-0.0007	-0.0007
				[0.0004]	[0.0004]
Decision * Risk Tolerance				-0.0148	-0.0159
				[0.0043]	[0.0043]
Age * Decision * Risk				0.0005	0.0005
				[0.0001]	[0.0001]

Notes: Each column presents estimates of a version of equation (9) in the paper, where the natural log of real hourly wages is regressed on interactions with age, the decision intensity of a worker's occupation, normalized AFQT scores, and/or self-reported risk tolerance, plus individual and occupation fixed effects. See the text for details. The sample is comprised of youth ages 14-22 in 1979, and follows them through 2017. Decision intensity is the average of three O*NET task variables related to decision-making, and risk tolerance is a categorical variable where 0/1/2 are low/medium/high - see the text for details. Standard errors are in brackets and are clustered at the individual level.

Table 2: Returns to Cognitive Skill and Decision Intensity by NLS Cohort

	(1)	(2)	(3)	(4)
Decision * NLS 66	0.0222	-0.0317		-0.0083
	[0.0015]	[0.0059]		[0.0071]
Decision * NLSY79	0.0311	-0.0640		-0.0276
	[0.0010]	[0.0043]		[0.0045]
Decision * NLSY97	0.0571	-0.0528		0.0007
	[0.0017]	[0.0068]		[0.0079]
Age * Decision * NLS 66		0.0019		0.0010
		[0.0002]		[0.0002]
Age * Decision * NLSY79		0.0033		0.0018
		[0.0001]		[0.0002]
Age * Decision * NLSY97		0.0041		0.0018
		[0.0002]		[0.0003]
Age * Cog * NLS 66			0.0063	0.0030
			[0.0006]	[0.0007]
Age * Cog * NLSY79			0.0110	0.0066
			[0.0004]	[0.0004]
Age * Cog * NLSY97			0.0159	0.0093
			[0.0006]	[0.0007]
Age * Decision * Cog * NLS 66				0.00036
				[0.00010]
Age * Decision * Cog * NLSY79				0.00048
				[0.00008]
Age * Decision * Cog * NLSY97				0.00053
				[0.00011]
F (decision * age) terms		0.0000		0.0184
F (cog * age) terms			0.0000	0.0000
F (decision * cog * age) terms				0.1260

Notes: Each column presents estimates of a version of equation (9) in the paper, where the natural log of real hourly wages is regressed on interactions with age, the decision intensity of a worker's occupation, normalized IQ (NLS 66) or AFQT (NLSY79 and NLSY97) scores, and an indicator for survey cohort, plus individual and occupation fixed effects. The coefficients on age interactions are suppressed to conserve space. The sample is comprised of three different cohorts of youth ages 14-22 in 1966, 1979 and 1997. I restrict the age range to 20-40 to keep the sample consistent across survey waves. Decision intensity is the average of three O*NET task variables related to decision-making - see the text for details. Standard errors are in brackets and are clustered at the individual level.