Heterogeneity in Talent or in Tastes? Implications for Redistributive Taxation

Ian Fillmore
Trevor Gallen

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Abstract

Do differences in tastes for leisure play an important role in determining income inequality? Using NLSY79 data on the joint distribution of lifecycle earnings and work hours, we fit a simple lifecycle model in which workers are heterogeneous in (i) their ability to accumulate human capital (talent), (ii) their preferences over consumption vs. leisure (taste), and (iii) their initial human capital. We find that tastes play a large role: 71% of earnings variation at age 44 is due to tastes, rather than talent or initial human capital. These findings are driven by the high standard deviation in "permanent" work hours and a large positive correlation between work hours and earnings. Intuitively, tastes matter because they affect the path of wages via their effect on human capital investment. Finally, we show that exchanging the sources of income variation between talent and tastes changes redistributive tax rates significantly, particularly when heterogeneity is due to differences in the marginal utility of consumption, rather than leisure.

1 Introduction

Do differences in tastes for leisure play an important role in determining income inequality? Following Mirrlees (1971), the literature on optimal tax design has traditionally assumed that individuals possess the same preferences and that their skills (i.e. wages) are exogenously fixed rather than an endogenous product of human capital investment. In this paper, we provide evidence that tastes for leisure differ across individuals and that they can and do have a substantial effect, not just on static labor supply, but on wages themselves by affecting the incentives to invest in human capital earlier in life.

We use data on the joint distribution of lifecycle earnings and work hours (paid work time plus human capital investment) to estimate a simple model that incorporates heterogeneity in both tastes for leisure and talent for accumulating human capital. We find that tastes are an important determinant of income inequality—71 percent of earnings variation at age 44 is due to tastes, rather than talent or initial human capital. Our results are driven by the fact that work hours display a large and relatively constant standard deviation throughout ages 30–44, while the correlation of hours and earnings is also positive, relatively high, and does not decline with age. Finally, we quantify the importance of this taste heterogeneity for optimal redistributive taxation. We find that taste heterogeneity reduces optimal tax rates substantially, although the magnitude of the effect depends crucially on whether taste heterogeneity is a manifestation of heterogeneity in the marginal utility of consumption or the marginal utility of leisure. We are not the first to consider the tax consequences of human capital investment (Stantcheva, 2015), nor are we the first to worry about the effects of taste heterogeneity for optimal taxation (Fleurbaey and Maniquet, 2006; Lockwood and Weinzierl, 2015; Fleurbaey and Maniquet, 2018; Bergstrom and Dodds, 2018). However, we follow Neal and Rosen (2005) in pointing out that incorporating taste heterogeneity into a model of human capital investment introduces a dynamic channel by which relatively small taste differences can compound into large wage and earnings differences later in life.

To understand the dynamic channel by which tastes for leisure can affect wages and earnings, consider the classic lifecycle model of Ben-Porath (1967). In this model, individuals differ in their ability to acquire new human capital, which we call talent. More talented individuals find it easier to acquire new skills and optimally choose to spend more time investing in their own human capital. Their initial earnings are low both because their initial human capital is low and because they devote more of their time to investment (either formal schooling or on-the-job training) rather than paid work. As they accumulate human capital over time, their wages rise and they substitute away from human capital investment and toward paid work. Their low initial earnings are more than compensated for by high earnings later in life. In this manner, highly talented children become highly productive, and thus highly compensated, adults. Even relatively small differences in talent can compound into large differences in earnings later in life.

Neal and Rosen (2005) demonstrate a similar phenomenon regarding tastes for leisure by extending the model of Ben-Porath (1967) to include a labor/leisure choice. They emphasize that workers with low tastes for leisure not only sacrifice little by giving up leisure time to invest in human capital, but, because they tend to work more later in life, they stand to gain more from the additional human capital. Consequently, individuals with low tastes for leisure will tend to have higher wages when older. Low tastes for leisure thereby increase both wages and hours. The model of Neal and Rosen (2005) makes clear how tastes function similarly to talent in driving human capital investment. And just like talent, small differences in a person's taste for leisure can compound into large differences in human capital and wages later in life.

Casual empiricism suggests that at least some of the differences in people's life outcomes are driven by differences in their life goals and preferences. Consistent with this observation, Kahneman (2011, p. 401) reports results from a study of students at elite colleges in 1976. At ages 17 or 18, the researchers asked students about the value they placed on becoming well off financially. The researchers followed these students over time and found that, among those who had placed a high value on financial well-being, adult earnings was an important predictor of happiness. But for those who had placed a low value on financial well being, adult earnings was far less predictive of happiness. These results suggest the possibility that one's preferences may be important drivers of one's earnings. People who care a lot about money and the things it can buy will be more inclined to make choices that lead to high incomes. Those who care more about non-monetary goods will tend to pursue different paths.

In Figure 1, we present some simple reduced form evidence that tastes for leisure are correlated with human capital investment. Consider a classical model of labor supply with homogenous preferences, and contrast the labor supply decisions of college graduates and non-graduates. By assumption there are no differences in taste, so work hours for college graduates may be higher because their wages are higher (substitution effect) or lower because their lifetime income is higher (income effect). However, if we condition on the current wage then only the income effect remains, and we should expect college graduates to work fewer hours than non-graduates who have the same wage at age t, particularly at older ages when human capital investment is minimal. The left graph of Figure 1 shows the opposite is true. Using data on highly-attached, prime-age males from the National Longitudinal Survey of Youth 1979 (NLSY79), we regress weekly hours worked at age t on a dummy for whether the respondent was a college graduate, controlling for the log wage at age t.[1] We find that college graduates actually work *more* hours than non-graduates with the same wage, and that this difference rises over the lifecycle. Although this evidence is inconsistent with a labor supply model with identical preferences, the evidence is perfectly consistent with a model of human capital investment wherein individuals

[1] The regression specification also includes a cubic polynomial in age interacted with the dummy for being a college grad.

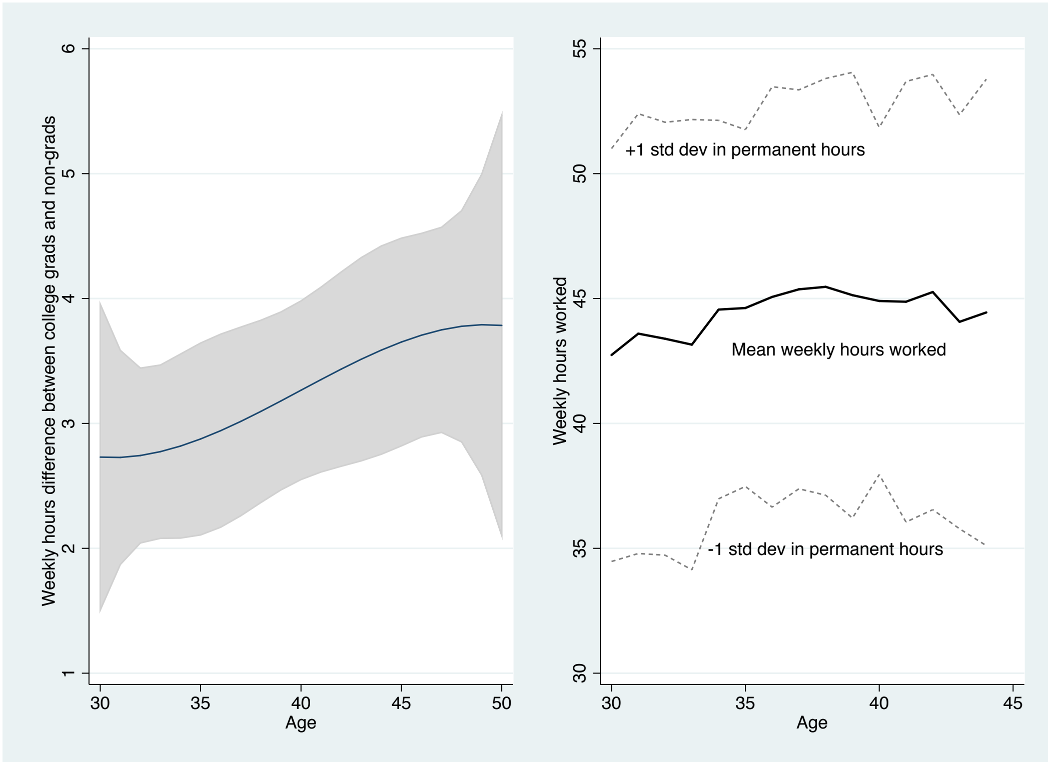

Figure 1: The left graph plots the estimated difference in weekly hours worked between college graduates and non-graduates. The gray bands indicate 95% confidence intervals. The graph is based on a regression of weekly hours at age t on a dummy for being a college graduate interacted with a cubic polynomial in age as well as a control for log wage at age t. The right graph plots the mean weekly work hours for ages 30 through 44. The dotted lines indicate one standard deviation in "permanent" hours where the variation due to transitory shocks has been removed (see Appendix B for details).

with a lower taste for leisure optimally choose to invest more in human capital (i.e. graduating from college).[2]

In a simple lifecycle model with human capital investment and homogenous preferences, early-life work hours may differ for a variety of reasons, such as differences in wages, differences in the marginal utility of lifetime income, and differences in human capital investment. Later in life, when human capital investment is minimal, work hours will only differ across individuals due to differences in wages and the marginal utility of lifetime income. However, an extensive literature in labor economics has established that substitution and income effects in labor supply mostly cancel out, especially for highly-attached prime-age men.[3] Thus, as workers age we would

[2]While preference heterogeneity is not the focus of their study, Imai and Keane (2004) estimate a lifecycle model of labor supply and find significant differences in the disutility of labor parameter by education level (see Table 4 of their paper).

[3]The observation that long-run wages have not affected long-run hours in post-war U.S. data is a persistent one in macroeconomics, and is (re)documented in Aguiar and Hurst (2007). More recently, some attention has

expect the variance of work hours to shrink.

Returning to our sample of highly-attached, prime-age males from the NLSY79, the right graph of Figure 1 provides a second piece of evidence for the existence of taste heterogeneity. This solid line plots mean weekly hours worked from ages 30 to 44, and the dashed lines plot one standard deviation bands in weekly hours across individuals. In calculating these bands, we filter out "transitory" variation in hours and focus on the variance of "permanent" hours worked (see Appendix B for details). Even among highly-attached, prime-age males, "permanent" work hours vary enormously across individuals, and this variance does not decline with age. Both of these facts are difficult to reconcile in a model without taste heterogeneity, but they arise naturally in a model with taste differences.

Finally, Table 1 provides a third piece of evidence that is consistent with heterogeneity in tastes for leisure. In most models of labor supply with separable leisure and consumption preferences, the first order condition for leisure implies that in the absence of taste heterogeneity, leisure depends on (i) the current wage and (ii) the marginal utility of lifetime income. Therefore, after controlling for wages and lifetime income, leisure today should not predict leisure in the future—that is, there should be no third "omitted variable" that connects past and present leisure hours. On the other hand, if individuals differ in their tastes for leisure, then these tastes will function as an omitted variable that will introduce a positive correlation between past and future leisure. In Table 1, we report estimates of the following regression

$$\log\left(\ell_{i,54}\right) = \beta \log\left(\ell_{i,34}\right) + \delta_1 \log\left(w_{i,54}\right) + \delta_2 \log\left(LifeInc_i\right) + u_{i,54}$$

where $\log(\ell_{i,34})$ and $\log(\ell_{i,54})$ are (log) annual hours of leisure during ages 30–34 and 50–54, $\log(w_{i,54})$ is the (log) wage during ages 50–54, and $\log(LifeInc_i)$ is an estimate of (log) lifetime income.[4] In Table 1, β, the coefficient of interest, is positive and highly significant.[5] The estimates imply that, if you compared two workers with the same wage at age 54 and the same lifetime income but the first worker took 10 percent more leisure at age 34, then that worker will take 2.5 percent more leisure at age 54. Although at odds with a model of homogeneous preferences, this result fits naturally within a model that includes differences in tastes for leisure.

In light of these facts, we fit a stylized version of the model of Neal and Rosen (2005) to

been paid to the idea that income effects may be slightly stronger than substitution effects (see, for instance, Boppart and Krusell (2016)) which would strengthen the puzzle illustrated in Figure 1.

[4]Lifetime income was calculated by taking the present value of all labor income reported between ages 18–54 using a discount rate of 5 percent. Wages at 50–54 were calculated by dividing total labor income reported between ages 50–54 by total hours worked between ages 50–54. We choose the age ranges 30–34 and 50–54 to avoid concerns about formal schooling when young and on-the-job training contaminating our measure of wages when older.

[5]The estimated coefficient on the (log) wage is positive due to a well-known data issue called division bias. This bias can be corrected with an instrument, but we do not worry about that here since we are not directly interested in this coefficient.

Table 1: Regressing Leisure Hours at 50–54 on Leisure Hours at 30–34

	Log leisure hours at 50–54
Log leisure hours at 30–34	0.25**
	(0.076)
Log wage at 50–54	0.16***
	(0.035)
Log lifetime income	-0.26***
	(0.045)
Observations	778

* $p < .05$, ** $p < .01$, *** $p < .001$

Table 1: This table reports estimates from regressing (log) leisure hours at ages 50–54 on (log) leisure hours at ages 30–34, controlling for wages at ages 50–54 and lifetime income. Standard errors are reported in parentheses. Data are from the NLSY79. Sample weights were used.

data from the NLSY79. The model allows for differences in the ability to accumulate human capital, which we call "talent," and preferences for leisure rather than consumption, which we call "taste."[6] Allowing for idiosyncratic variation in the taste parameter distinguishes us from a variety of other papers examining the distribution of earnings.[7] Using data from the NLSY79 on the joint distribution of earnings and work hours over the lifecycle, we estimate the distribution of taste and talent for strongly-attached, prime-age males. In our estimated model, tastes play a large role in explaining the variance of earnings even in advanced stages of work-life. For instance, at age 44, we find that tastes alone explain 71% of earnings variation, even for strongly-attached, prime-age male workers.

Based on our estimated model, we compute the welfare maximizing flat income tax policy. We then construct a counterfactual wherein we reduce the variance in talent so as to decrease the standard deviation in (log) earnings by one percent. We simultaneously increase the variance in tastes so as the increase the standard deviation of (log) earnings by one percent, thereby leaving the standard deviation of (log) earnings unchanged. In effect, we are simply exchanging the variation in talent and tastes, holding constant the standard deviation in earnings. We estimate a value of 0.63 for the semi-elasticity of tax rates with respect to such an exchanging of the variation in talent for variation in tastes. In other words, an increase in the variance of tastes that raises earnings inequality by one percent, coupled with an offsetting decrease in the variance of talent, lowers the optimal tax rate by 0.63 percent or 0.3 percentage points.[8] Finally, we find that the magnitude of this result depends on the form of taste heterogeneity: if taste

[6]We also allow individuals to vary by the level of initial human capital.

[7]See, for instance, Blandin (2018), Guvenen et al. (2014), Huggett et al. (2011).

[8]Saez (2001) identifies three "sufficient statistics" for determining the optimal income tax. Within his framework, exchanging the sources of income variation primarily alters the redistributive tastes of government by changing how much different households value consumption.

heterogeneity lies in the marginal utility of consumption, optimal taxes are very sensitive to the source of income variation, while if it lies in the marginal utility of leisure, optimal taxes are less sensitive.

2 Lifecycle Model of Human Capital Investment

In this section, we present a simple model of human capital investment. We do so in three parts. First, in section 2.1 we follow Neal and Rosen (2005) and extend the classic Ben-Porath model of human capital investment to include a labor/leisure tradeoff. In section 2.2 we discuss the strengths and limitations of the model. Finally, in section 2.3 we discuss identification of the model and the moments in the data that drive our results.

2.1 Review of Neal and Rosen (2005) Model

The Ben-Porath model of human capital investment is a canonical model for understanding earnings over the lifecycle. In the model, agents maximize the net present value of earnings over their lifetime, trading off between paid work time and human capital investment, which does not earn wages but increases future wages. Neal and Rosen (2005) extend the Ben-Porath model of human capital investment to include a leisure choice. Agents are characterized by the triple $(A, \phi, \overline{k})$. A captures talent, or the agent's ability to acquire new human capital, ϕ captures his relative taste for leisure, and $\overline{k}$ is his initial level of human capital. In each period, the agent allocates his time between labor n_t, leisure ℓ_t, and human capital investment s_t. Human capital grows according to the law of motion

$$k_{t+1} = (1-\delta)k_t + A(s_t k_t)^\gamma \tag{1}$$

where $\gamma \in (0, 1)$. Talent (A) reflects the agent's efficiency at acquiring new human capital. The agent's wage in period t is $w_t = Rk_t$ and depends solely on his human capital. Note that talent does not directly raise wages. Rather, talented individuals find it easier to increase their human capital over time.

The standard Ben-Porath model does not include a leisure choice and abstracts from consumption by assuming that the agent has access to complete markets. The result is that the agent trades off labor and human capital investment over the lifecycle so as to maximize the net present value of lifetime income. As Neal and Rosen show, one can incorporate a leisure decision into the Ben-Porath model. Period utility depends on consumption c_t, leisure ℓ_t, and the taste parameter ϕ which determines the agent's relative taste for consumption vs leisure. The agent maximizes lifetime utility subject to a period time constraint and a lifetime budget constraint.

In particular, the agent solves

$$\max_{\{c_t s_t \ell_t n_t\}} \quad \sum_{t=1}^{T} \beta^{t-1} U(c_t, \ell_t; \phi) \tag{2}$$

$$s.t. \quad s_t + \ell_t + n_t = 1 \tag{3}$$

$$s_t,\ \ell_t,\ n_t \geq 0 \tag{4}$$

$$\sum_{t=1}^{T} \left(\frac{1}{1+r}\right)^{t-1} c_t = \sum_{t=1}^{T} \left(\frac{1}{1+r}\right)^{t-1} w_t n_t \tag{5}$$

$$w_t = R k_t \tag{6}$$

$$k_{t+1} = (1-\delta) k_t + A (s_t k_t)^{\gamma} \tag{7}$$

$$k_1 = \overline{k} \tag{8}$$

The Kuhn-Tucker conditions for this problem are

$$[c_t]: \quad \beta^{t-1} U_c(c_t, \ell_t; \phi) = \left(\frac{1}{1+r}\right)^{t-1} \lambda \tag{9}$$

$$[\ell_t]: \quad U_\ell(c_t, \ell_t; \phi) = \mu_t \tag{10}$$

$$[n_t]: \quad \left(\frac{1}{1+r}\right)^{t-1} \lambda w_t = \beta^{t-1} (\mu_t + \mu_t^n) \tag{11}$$

$$[n_t]: \quad \mu_t^n n_t = 0;\ \mu_t^n \geq 0;\ n_t \geq 0 \tag{12}$$

$$[s_t]: \quad A\gamma (s_t k_t)^{\gamma-1} k_t \lambda \sum_{\tau=t+1}^{T} \left(\frac{1}{1+r}\right)^{\tau-t} (1-\delta)^{\tau-t-1} R n_\tau = \mu_t \tag{13}$$

where λ is the Lagrange multiplier on the lifetime budget constraint, μ_t is the Lagrange multiplier on the period time constraint, and μ_t^n is the multiplier on the non-negativity constraint for labor. Note that leisure ℓ_t and human capital investment s_t will always be positive because the marginal utility of leisure and the marginal product of human capital investment are both infinite at zero. In the case where $n_t > 0$, so that we are at an interior solution ($\mu_t^n = 0$), the first order conditions for ℓ_t and s_t become

$$[\ell_t]: \quad \beta^{t-1} U_\ell(c_t, \ell_t; \phi) = \left(\frac{1}{1+r}\right)^{t-1} \lambda w_t \tag{14}$$

$$[s_t]: \quad \left(\frac{1}{\beta(1+r)}\right)^{t-1} \frac{R (s_t k_t)^{1-\gamma}}{A\gamma} = \sum_{\tau=t+1}^{T} \left(\frac{1}{1+r}\right)^{\tau-t} (1-\delta)^{\tau-t-1} R n_\tau. \tag{15}$$

To interpret these conditions, consider the case where $\beta = \frac{1}{1+r}$ and the utility function is separable in consumption and leisure. In this case, consumption will be constant over the lifecycle. The agent will also set the marginal utility of leisure proportional to the wage in each period. The wage will rise over the lifecycle as the agent accumulates human capital, causing leisure to decline. The right hand side of (15) captures the benefits of an additional unit of human capital today, in terms of increased future earnings. The left hand side captures the costs of investing in one more unit of human capital today, in terms of earnings in the current period. Equation (15) makes it clear that the agent's human capital investment today depends on his future labor supply. If the agent anticipates working a lot in the future, then he has a stronger incentive to invest in human capital today.

2.2 Strengths and Limitations of the Model

We adopt the simplest possible model of lifecycle human capital investment and labor supply. Much more complex models have been developed and estimated in the labor literature. Unlike these more sophisticated models, we omit many dimensions of labor supply and human capital investment. For instance, we ignore household decisions, health shocks (Hokayem and Ziliak, 2014), fertility (Rosenzweig and Wolpin, 1980), the presence of children (Blundell et al., 2005; Cherchye et al., 2012) involuntary unemployment and search frictions (Low et al., 2010), and credit constraints (Rossi and Trucchi, 2016) while the cited papers do not.

Rather than attempt to explicitly model these factors, we take a similar approach to Kaplan (2012) and mitigate their impact through our choice of subject, age span, and data treatment. We abstract from transitory health shocks, involuntary unemployment, and search frictions by extracting the "permanent" level of hours and earnings from the NLSY data, similar to how researchers interested in secular trends filter out high-frequency noise. Although credit constraints could be important, we note that in the context of our model, credit constraints drive work hours to decline over the lifecycle because credit constrained individuals aren't able to effectively finance consumption when young. In the data, however, hours rise slightly as a function of age. Finally, we minimize the importance of fertility shocks by focusing on prime-age males, whose labor supply is less affected by fertility shocks (Angrist and Evans, 1998).

Our goal is to fit a model that is both canonical and transparent, while still allowing both talent and taste to determine earnings. The model's transparency allows us to identify which empirical moments are key to determining the extent to which earnings are affected by tastes vs talent. Moreover, our choice of sample biases us against finding heterogeneity in tastes. First of all, our sample criteria push the variance in work hours toward zero. Second, in terms of labor supply, we would expect highly-attached, prime-age males to be the most homogeneous group in the population. Given these built-in biases in the construction of the sample, our findings of a prominent role for taste heterogeneity stand out all the more.

2.3 Identification

In this section we illustrate how, within our model, the lifecycle paths of earnings and work hours allow us to disentangle tastes and talent. In Figure 2 we plot the paths of earnings and work hours for an agent with triple $\{A, \phi, \overline{k}\}$. We also plot paths for two alternative triples. In the first, we lower the disutility of work ϕ; in the second, we choose talent A and initial human capital $\overline{k}$ to match the earnings path of the low-disutility triple. Now, imagine two agents: one which follows the baseline earnings path in Figure 2 and another which follows the alternative earnings path. From observations on lifecycle earnings alone, we cannot tell whether these agents differ in tastes or in talent. But if we also observe lifecycle work hours, we can distinguish between tastes and talent. If the second agent is earning more over the lifecycle because he has a lower disutility of work, then we should see him working more hours. On the other hand, if the second agent is earning more because he is more talented, then we should see him working less than the first agent when young (due to an income effect).[9] Thus, despite producing the same lifecycle earnings paths, the low-disutility and high-talent triples display different paths for work hours. Lowering the distaste for labor shifts work hours up. In contrast, increasing talent actually lowers work hours early in life due to an income effect.

3 Estimation

3.1 Data

We use data from the NLSY79 and restrict our sample to strongly attached males. We define strongly attached males to be those with complete or nearly complete data between ages 30 and 44 who never report working zero hours in a year. For each respondent, we observe total labor income across all jobs as well as total hours worked across all jobs in the previous year.[10]

3.2 Model Specification for Estimation

In this section we adapt the model of 2.1 for empirical estimation by specifying a functional form for the agent's period utility function, using the common preferences of MaCurdy (1981):

$$U_i(c, \ell; \phi_i) = \frac{c_t^{1-\sigma}}{1-\sigma} - \phi_i \frac{(1-\ell_t)^{1+\eta}}{1+\eta} \tag{16}$$

and we assume that $\beta = \frac{1}{1+r}$. With this specification, agent i's first order conditions become

$$[c_{it}]: \quad c_{it}^{-\sigma} = \lambda_i \tag{17}$$

$$[\ell_{it}]: \quad \phi_i(1-\ell_{it})^{\eta} = \lambda_i w_{it} \tag{18}$$

$$[s_{it}]: \quad \frac{R(s_{it}k_{it})^{1-\gamma}}{A_i\gamma} = \sum_{\tau=t+1}^{T} \left(\frac{1}{1+r}\right)^{\tau-t} (1-\delta)^{\tau-t-1} R n_{i\tau}. \tag{19}$$

[9] Although it is not shown in Figure 2, high-talent work hours may exceed baseline work hours later in life as wages continue to rise.

[10] Reported work hours include both paid work time as well as human capital investment.

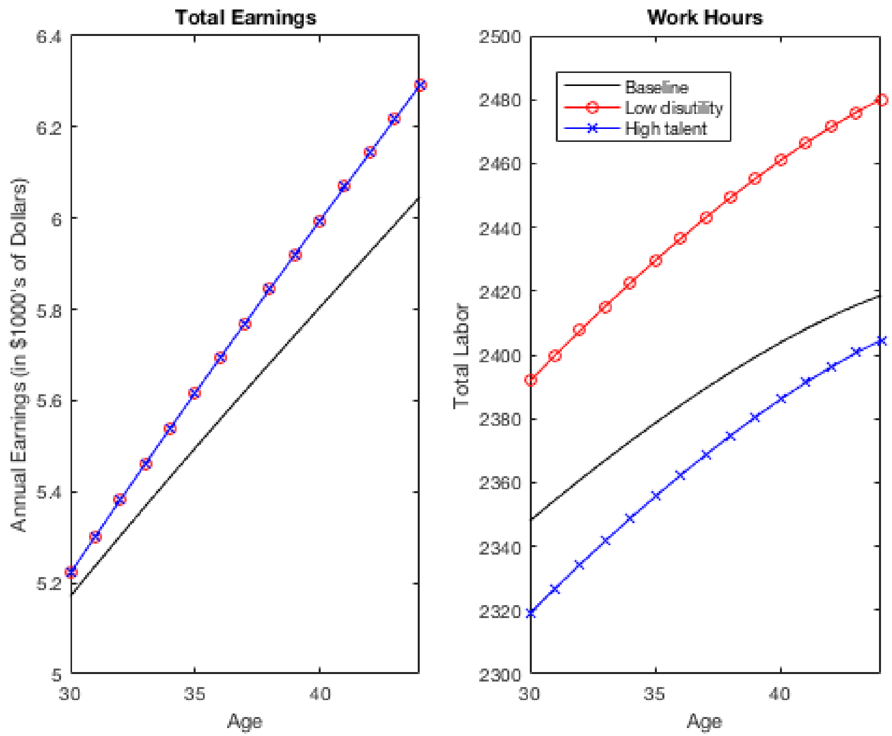

Figure 2: This figure solves the model for three separate triples $(A, \phi, \overline{k})$: a baseline triple (black lines), a low-disutility-of-work triple (red lines) wherein ϕ is lower than in baseline, and a high-talent triple (blue lines). The high-talent triple was set by choosing talent A and initial human capital $\overline{k}$ to match the earnings path of the low-disutility triple. Importantly, although the low-disutility and high-talent triples are observationally equivalent when looking at earnings alone, they can be distinguished by including data on work hours.

3.3 Estimating the Frisch Elasticity of Labor Supply

We estimate the Frisch elasticity of labor supply for men in our sample as follows. First, we follow Heckman et al. (1998) and focus on ages 48 to 55 so that $s_t \approx 0$ at these ages. Then, equation (18) becomes

$$\begin{aligned} n_{it}^{\eta} &= \left(\frac{1}{\beta(1+r)}\right)^{t-1} \frac{\lambda_i}{\phi_i} w_{it} \\ \Rightarrow \qquad n_{it}^{\eta+1} &= \left(\frac{1}{\beta(1+r)}\right)^{t-1} \frac{\lambda_i}{\phi_i} y_{it} \end{aligned}$$

where y_{it} is annual earnings. Writing this in logs gives us a simple fixed effects specification

$$\log n_{it} = \delta t + \alpha_i + \frac{1}{\eta+1} \log y_{it}$$

where δt is a common time trend and the α_i are fixed effects. Running this regression gives us an estimate for $\eta = 3.05$ with a standard error of 0.36, implying a Frisch elasticity of 0.33.[11]

3.4 Calibration

Although we estimate the joint distribution of talent A_i, taste ϕ_i, and initial human capital $\overline{k}_i$ to match lifecycle moments on work hours and earnings, we calibrate several other parameters directly. As described above, we calibrate the Frisch elasticity of labor supply to be 0.33. In our baseline calibration, we choose $\gamma = 0.62$ and $\delta = 0.057$, consistent with Hendricks (2013).[12] The

Table 2: Directly-Calibrated Parameters

Parameter	Symbol	Value	Notes
Frisch elasticity of labor supply	η	-3.05	Frisch labor supply =0.33 (Estimated from NLSY)
Ben-Porath diminishing returns	γ	0.62	(Hendricks, 2013)
Human Capital depreciation	δ	0.057	(Hendricks, 2013)
Elas. of intertemporal subst.	σ	2	EIS=0.5 (Basu and Kimball, 2002)
Discount rate	β	0.945	(Gomme and Rupert, 2007)
Human capital wage	R	1200	Normalization

Table 2: This table depicts our directly-calibrated parameter values.

elasticity of intertemporal substitution is relatively unimportant in our calibration because (i) conditional on σ, differences in ϕ govern the static tradeoff between consumption and leisure, (ii) there are no shocks, and (iii) there are constant interest rates in our model.[13] We set σ so that the elasticity of inter temporal substitution is 0.5, consistent with both long-run labor supply (Basu and Kimball, 2002) and micro-studies on the parameter (Havranek et al., 2015). The discount rate β is chosen to be 0.945, consistent with Gomme and Rupert (2007), while the net-of-tax interest rate r is $1/\beta - 1$, so that absent any financial frictions, households would choose equal consumption in every period. We also set R, a normalization constant in our model, to be 1200. Thus, individual i's potential earnings in year t is given by $Rk_{it} = 1200k_{it}$.[14]

[11] In Appendix A, we take an alternative approach and estimate our model by calibrating η along with the joint distribution of $(A, \phi, \overline{k})$ to match our moments.

[12] While some of the literature suggests a Ben-Porath technology that's nearly linear with near-zero depreciation to match changes in the wage distribution under skill-biased technological change (see, for instance, Guvenen and Kuruscu (2012)), Hendricks (2013) models schooling choice closely and finds that, because near-linear models with zero depreciation see no human capital accumulation after age 45, they (incorrectly) predict near-perfect comovements of the wage profiles of older cohorts.

[13] In our model, the elasticity of intertemporal substitution will, ceteris paribus, help determine optimal tax rates by controlling utility function curvature.

[14] For convenience when interpreting results, we convert fraction of annual hours worked into annual hours worked. Doing so changes the scaling of human capital so that Rk_{it} can now by interpreted as an hourly wage. Consequently, in our results we will report hourly wage Rk_{it}, rather than raw human capital.

3.5 Estimation With Aggregate Moments

3.5.1 Main Estimation

We estimate the joint distribution of A_i, ϕ_i, and $\overline{k}_i$ to match the model to aggregate moments. We do this by choosing a population of triples so that their simulated aggregate moments match aggregate empirical moments from the joint distribution of earnings and work hours in the NLSY79. Specifically, we choose a population of triples $(A_i, \phi_i, \overline{k}_i)$ so that, given the solution to their individual problems, the simulated population matches the NLSY79 data on the following six sets of moments between ages 30 and 44: (i) mean work hours (inclusive of both human capital investment and paid work hours), (ii) the standard deviation of work hours, (iii) mean (log) earnings, (iv) the standard deviation of (log) earnings, (v) the 90/10 ratio of earnings, and (vi) the correlation of (log) earnings and work hours.

3.5.2 Empirical Moments

Our data consist of a panel of individuals from ages 30 to 44 with annual measures of total labor earnings and total work hours. Our first group of aggregate moments are simply the mean number of work hours and the mean of (log) annual income. We calculate these moments separately at each age. Our second group of aggregate moments measure the dispersion in work hours and annual income. We estimate the standard deviations of work hours and of (log) annual income as well as the 90/10 ratio of annual income. Since both annual income and work hours are subject to transitory shocks (as well as measurement error), the raw variances will be inflated. To deal with this, for each individual in the NLSY79 we regress both work hours and (log) earnings on age and store the fitted values and residuals. We use the variance of the residuals, at a given age, to estimate the variance of the transitory shocks. We then subtract the estimated variance of the transitory shocks from the total variance of observed work hours and (log) earnings. The goal is to isolate the variance in hours and earnings that is *not* due to year-to-year transitory shocks or measurement error. When we calculate the 90/10 ratio of annual income, we calculate the ratio of the 90th percentile of fitted annual income (from the individual-specific regressions) to the 10th percentile of fitted annual income. For our final group of moments, we calculate the correlation between work hours and (log) earnings, again adjusting for the additional covariance introduced by the transitory shocks to annual earnings and work hours. All moments were calculated using the NLSY79 sampling weights. In the end, we are left with 90 moments to target. We plot these empirical moments and the model fits in Figure 3.

Because our results depend directly on the moments in Figure 3, we also conduct a series of robustness exercises by modifying our sample selection criteria and censoring extreme observations for work hours. We discuss these exercises, which largely do not change our results, in

Figure 3: This figure depicts the six sets of empirical moments from the NLSY79 (red line) and model fits (black line) that describe the joint distribution of work hours and earnings by age. Bootstrapped 95% confidence intervals for data are depicted as red dotted lines. All moments were calculated using sample weights.

Appendix C.

3.5.3 Fits

Given the calibrated parameter values in Table 2, we find the the joint distribution of talent, taste, and human capital that best fits our 90 empirical moments. Following Kennan (2006), we choose a population of 10 equally weighted, representative agents to fit the six sets of moments. The moments and fits are depicted in Figure 3. While most of our simulated moments closely match their empirical counterparts, one failure stands out: the slope of our yearly work hours "overshoots" the data, rising by nearly 151 annual hours by age 44 whereas the data only rises by 89 annual hours by age 44. This is primarily being driven by our calibrated Frisch elasticity. In Appendix A, we consider fitting the Frisch elasticity along with the distribution of talent, taste, and initial human capital. This improves the fit somewhat, but does not substantially alter our main results.

We numerically solve for ten triples of talent, taste, and initial human capital that minimize the sum of squared errors between the simulated moments and the six sets of empirical moments in the NLSY79. Figure 4 plots these ten triples with talent A_i on the horizontal axis, taste ϕ_i on the vertical axis, and the initial hourly wage $R\bar{k}_i$ beside each of the ten points. Figure 4 illustrates that all three characteristics vary considerably across the then triples. One triple, in the top left, has a low beginning wage, low talent, and a high distaste for work. As a result, an agent with this triple will have a low and flat lifecycle earnings profile. Interestingly, however, the triple with the highest talent also has the third highest distaste of work. This high distaste for work will depress human capital investment so that some of the other triples with lower talent but also lower distaste of work may end up with higher earnings later in life.

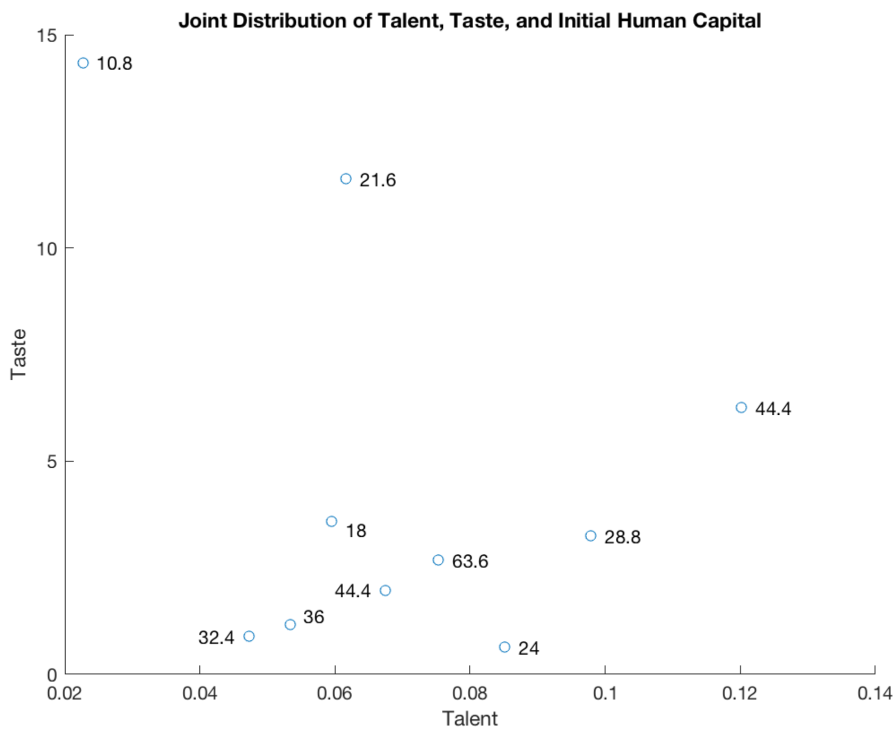

Figure 4: This figure depicts point estimates for the joint distribution of talent A_i, taste ϕ_i, and initial human capital at age 30 (as an hourly wage) $R\bar{k}_i$. Talent is on the x-axis, taste is on the y-axis, and the number next to each point is the initial human capital. Importantly for our results, our model moments put our fit to include people who work many hours (have a low distaste for labor) but are relatively untalented (have a reactively low wage), while there are people with high talent and high initial wage who work relatively little.

To illustrate the importance of allowing for taste heterogeneity, we re-estimate our model without allowing for heterogeneity in tastes (all agents have the same estimated value of ϕ). We estimate the model in two ways. First, we target only the paths for the mean, standard deviation and 90-10 ratio of (log) earnings and the path for mean work hours. In other words, we omit the standard deviation of work hours and the correlation between (log) earnings and work hours.

Second, we estimate the model by targeting all six sets of moments. Figure 5 plots the targeted and simulated moments for these two model fits. The black dashed line depicts the simulated

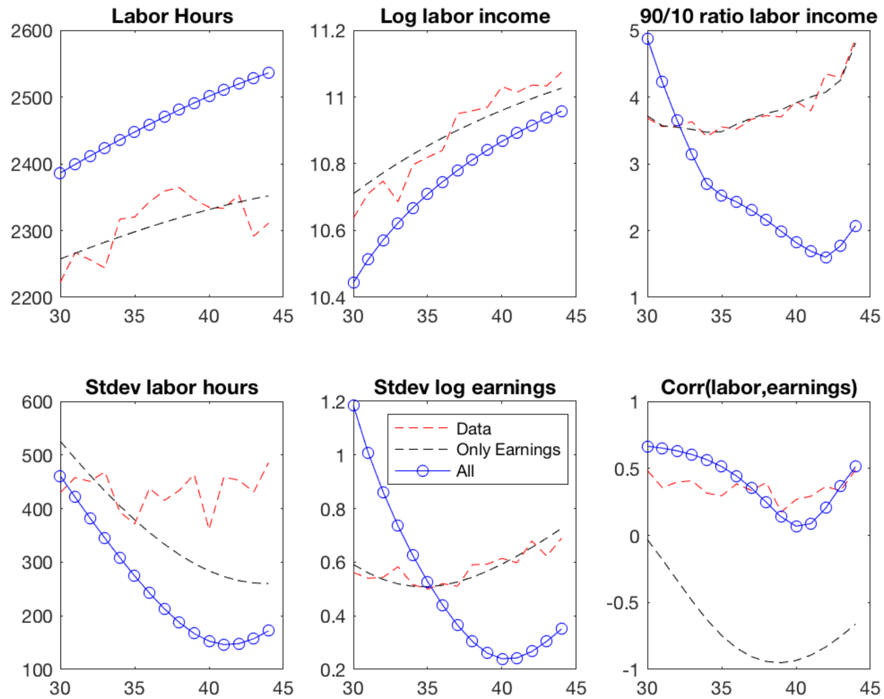

Figure 5: This figure depicts fits for our six sets of moments under the counterfactual assumption that disutility of labor parameter ϕ is constant for all ten representative individuals. The black dashed line depicts the results of fitting all moments but the standard deviation of labor hours and the correlation of hours and earnings. The blue circle-marked line depicts the resulting paths when attempting to fit all six sets of moments without heterogeneity in ϕ.

moments when targeting only earnings and the path of mean work hours. It fits the targeted moments well, mostly replicating the paths of mean (log) labor income, the standard deviation of (log) earnings, the 90/10 ratio of earnings, and mean work hours. However, the fitted model generates a strongly declining path for the standard deviation of work hours and a negative U-shaped path for the correlation of (log) earnings and work hours. In the second estimation when we include these two moments (blue circle-marked line), the fit on the correlation between (log) earnings and work hours improves dramatically, but the fit on remaining five moments worsen relative to the first fit.[15] The reason for this is that the correlation of (log) earnings and

[15]While it may not seem that the blue line is dramatically better than the black line, the weighted sum of square errors is immensely lower. For comparison, our weighted sum of squared errors is ≈ 0.8 when we allow for taste heterogeneity, ≈ 14 with no taste heterogeneity and targeting all moments (blue line), and ≈ 144 when not targeting the standard deviation of work hours and the correlation between (log) earnings and work hours (black line).

work hours is very difficult for the model to fit without taste heterogeneity. Attempting to fit this moment, as the blue line does, comes at the cost of worsening all other fits.

4 Results

In order to decompose how much income variation is due to talent, taste, and initial human capital, we compare the effect of mean-preserving reductions in the standard deviation of each parameter of interest on the standard deviation of earnings. Denoting standard deviation of earnings at age t as $S_{E,t}$, and the standard deviation of each element of the triple as S_x, $x \in \{A, \phi, \bar{k}\}$, we approximate the standard deviation of earnings by using a first-order Taylor approximation with respect to each parameter:

$$S_{E,t} = \overline{S_{E,t}} + \left.\frac{\partial S_{E,t}}{\partial S_A}\right|_{S_A=\overline{S_A}} \left(S_A - \overline{S_A}\right) + \left.\frac{\partial S_{E,t}}{\partial S_\phi}\right|_{S_\phi=\overline{S_\phi}} \left(S_\phi - \overline{S_\phi}\right) + \left.\frac{\partial S_{E,t}}{\partial S_k}\right|_{S_k=\overline{S_k}} \left(S_k - \overline{S_k}\right) + O(x^2)$$

Or, denoting the percentage change in each variable by Δ, this becomes:

$$\Delta S_{E,t} = \epsilon_{A,t}\Delta S_A + \epsilon_{\phi,t}\Delta S_\phi + \epsilon_{k,t}\Delta S_k + \kappa \tag{20}$$

Where $\epsilon_{x,t} = \frac{S_x}{S_{E,t}} \left.\frac{\partial S_{E,t}}{\partial S_x}\right|_{S_x}$ denotes the elasticity of the standard deviation of earnings with respect to the standard deviation of parameter $x \in \{A, \phi, \overline{k}\}$, and κ is the residual category, representing the residual higher-order terms. The relative importance of variation in each of talent, taste, and initial human capital is summarized in their corresponding elasticities. For example, the contribution of taste is given by $\frac{\epsilon_{\phi,t}}{\epsilon_{A,t}+\epsilon_{\phi,t}+\epsilon_{k,t}+\kappa}$. We numerically calculate the relative contribution of each element at each age and depict them graphically in Figure 6.[16]

At age 30, initial human capital is the dominant driver of earnings inequality, but its importance naturally declines over time as both taste and talent become more important.[17] Talent contributes little to earnings inequality at early ages because high-talent individuals spend much of their non-leisure time investing in human capital. Finally, by age 44 talent explains approximately 22% of income variation while taste explains 69%. In the next section, we discuss how this breakdown is driven by the empirical correlation of earnings and hours, and differences in "permanent" hours choices that do not decrease by age. Finally, the near-absence of the residual $O(x^2)$ category (the difference between actual change in variance of income and change predicted

[16]There are many ways to decompose these elasticities. For instance, to calculate $\epsilon_{A,t}$, we could hold S_ϕ and $S_{\overline{k}}$ constant at the baseline level, change S_A by 1% and calculate the change in income variance. Or we could do the same thing but holding S_ϕ and $S_{\overline{k}}$ constant at 1% above baseline for the entire exercise. Numerically, these make little difference (we take the average of all possible decompositions). This reference-dependence parallels the Oaxaca decomposition in labor economics.

[17]Note that human capital at age 30 is a mix of both ability and taste in earlier, unmodelled periods.

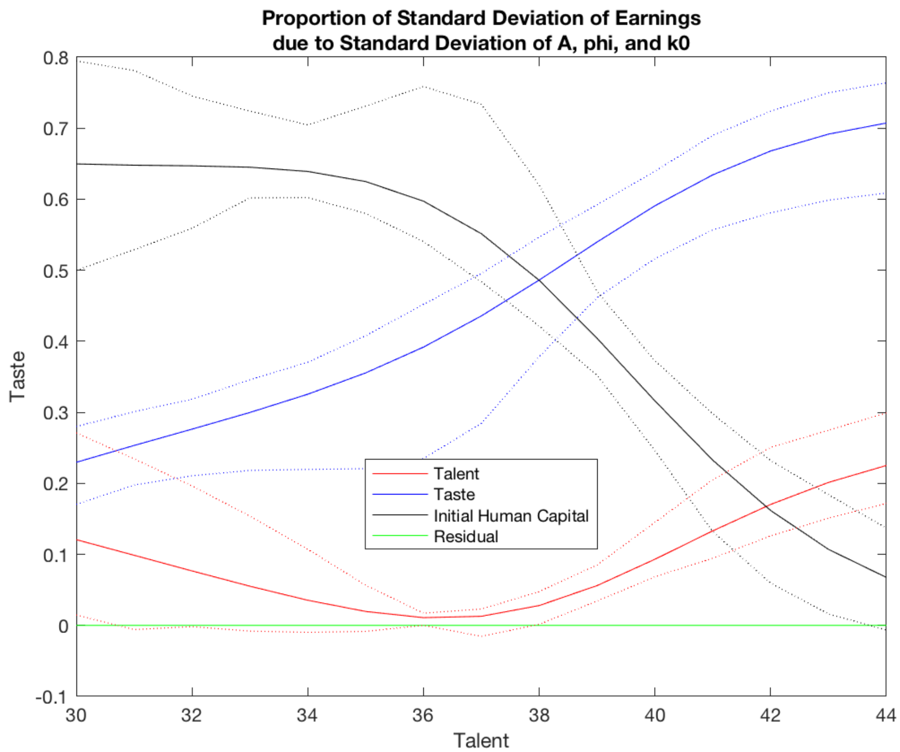

Figure 6: This figure summarizes our main decomposition results, depicting the three elasticities from equation 20. Each of the three visible lines (the residual category, a measure of how bad our linear approximation is, is not visible) indicates how much earnings variance at each age falls if variance in the corresponding parameter falls by 1%. These values are normalized by the total fall in earnings variance at each age.

by the talent, taste, and human capital terms in equation 20) suggests our linear approximation is good.

4.1 Why is taste so important?

It turns out that the correlation between (log) earnings and work hours is an important driver of our finding that tastes dominate talent in explaining earnings inequality. To illustrate this dependence, Figure 7 depicts the components of our decomposition in Figure 6 if we had fitted our moments to a correlation that was 0.2 lower (or higher) than the actual empirical correlation. If the empirical correlation had been 0.2 lower, then the gap in the proportion of variation attributable to taste rather than talent would fall to 36% (from 49%), while if it had been 0.2 higher, the gap would rise to 65%. This exercise makes clear that the path of the correlation between hours and earnings is an extremely important target for a model describing preference heterogeneity.

While the correlation between hours and earnings is an important driver of how much earn-

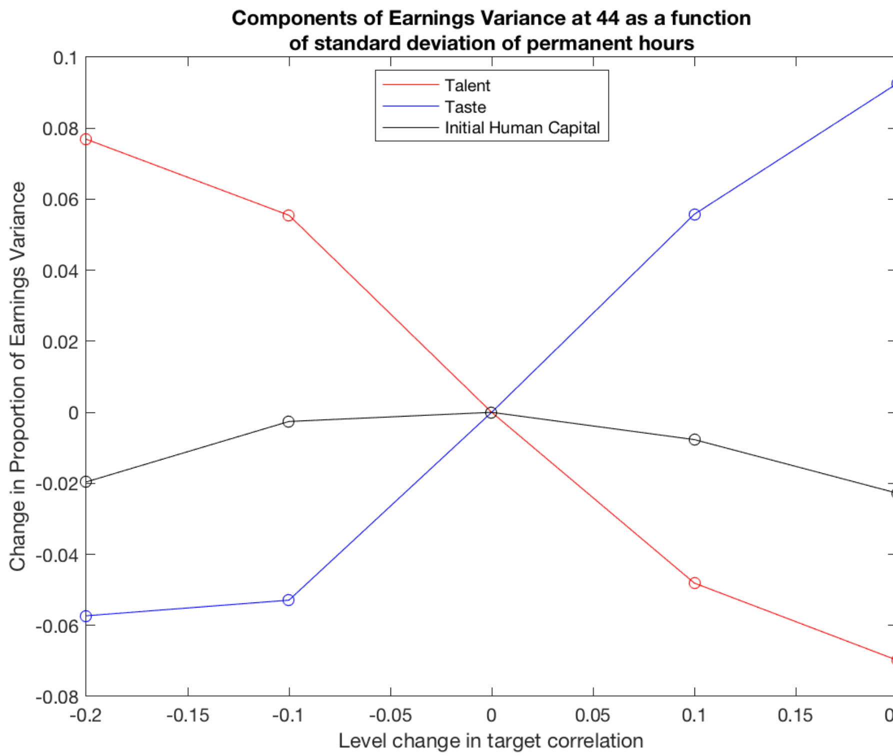

Figure 7: This figure depicts the change in the proportion of earnings variation at age 44 attributable to talent, taste and initial human capital for various level changes in the correlation between earnings and work hours. Each elasticity is calculated using the elasticities of equation 20. As we increase the level of the correlation between hours and earnings throughout agents lifetimes, so that people who earn more typically work more, our model puts more emphasis on taste as the driving force behind earnings variation.

ings variation our model attributes to taste vs. talent, so too is the standard deviation of work hours. Intuitively, a large and persistent standard deviation in "permanent" hours can only be driven by taste, rather than talent. High levels of talent increase the slope of work hours, but do not greatly change their level, particularly for ages 30-44. Figure 8 depicts a similar exercise as Figure 7, but it changes the target standard deviation in hours. The gap between taste and talent increases to as much as 62% (from 49%) when we increase the target level of the standard deviation in hours per year by 100, or falls to 35% when we decrease the target by 100 hours per year.

One hypothesis is that taste and talent primarily express themselves through occupational choice. For example, it could be that high talent or low-distaste-for-work individuals choose occupations with high levels of on-the-job training at first and therefore with lower initial earnings but steeper earnings paths. To investigate this hypothesis, we re-estimate the empirical moments in the NLSY79, but rather than allowing for individual-specific intercepts and slopes in earnings

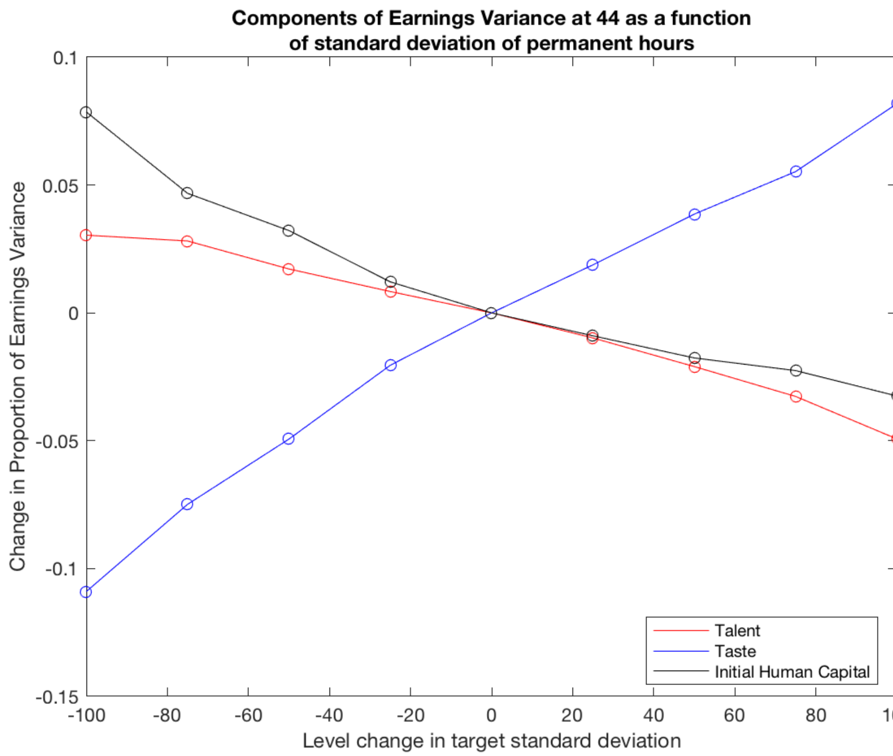

Figure 8: This figure depicts the change in the proportion of earnings variation at age 44 attributable to talent, taste and initial human capital for various level changes in the standard deviation of work hours. Each elasticity is calculated using the elasticities of equation 20. As we increase the "permanent" variation in hours worked, so that there exist some people working many hours and some working few, our model puts more emphasis on taste as the driving force behind earnings variation.

or hours paths, we collapse these to occupation-specific intercepts and slopes (based on initial occupation). With far fewer independent variables, this approach assigns more of the earnings and hours variation to the residual, thereby causing the standard deviation of work hours to fall (a yearly mean across ages 30–44 of 66 hours/year, rather than 434), which tends to reduce our estimates of the importance of taste heterogeneity. However, the estimated correlation of (log) earnings and work hours increases to 0.74, from 0.30, which tends to increase our estimates of the importance of tastes. The two effects largely offset, resulting in a slightly lower estimate of the importance of taste—68% rather than 71%.

4.2 How does varying the importance of taste shift optimal tax rates?

Thus far, we have assumed that taste differences reflected the disutility of work. But we could just as easily have placed the taste heterogeneity on the marginal utility of consumption. Although this ambiguity cannot be settled empirically, it turns out to matter for the optimal tax.

We therefore create a monotonic transformation, $\zeta_i(\alpha)$ that allows us to control the degree to which heterogeneity is on consumption rather than labor preferences. We now rewrite utility as

$$U_i(c, \ell, \phi_i) = \zeta_i(\alpha)\frac{c_t^{1-\sigma}}{1-\sigma} - \zeta_i(\alpha)\phi_i\frac{(1-\ell_t)^{1+\eta}}{1+\eta} \tag{21}$$

where $\zeta_i(\alpha)$ is connected to our ϕ_i's by the monotonic transformation: $\zeta_i = \alpha + (1-\alpha)\frac{1}{\phi_i}$. When $\alpha = 0$, $\zeta_i = \frac{1}{\phi_i}$, and all heterogeneity is in the marginal utility of consumption, while when $\alpha = 1$, all heterogeneity is in the disutility of work. We choose $\alpha = 0.5$ in our baseline optimal tax calculations to "split the difference," but we also explore other values for α as well. To illustrate how optimal tax rates (denoted τ^*) can change when taste is made more or less important, we introduce a simple tax scheme in which the government levies a flat tax τ on labor income and returns the revenue as a uniform lump-sum transfer $\mathscr{T}$. An agent's lifetime budget constraint now becomes:

$$\sum_{t=1}^{T}\left(\frac{1}{1+r}\right)^{t-1} c_t = \sum_{t=1}^{T}\left(\frac{1}{1+r}\right)^{t-1}((1-\tau)w_t n_t + \mathscr{T})$$

Where, in equilibrium, $\mathscr{T}$ is the average tax payment received by the government across all N individuals and all T ages:

$$\mathscr{T} = \frac{1}{N \cdot T}\sum_{t=1}^{T}\sum_{i=1}^{N}\tau w_{it} n_{it} \tag{22}$$

The government chooses τ to maximize utilitarian welfare with equal Pareto weights. Denoting the utility of individual i at age t as $U_{i,t}$, and assuming a population uniform across ages, the government's problem simplifies to:

$$\max_{\tau, \mathscr{T}} \sum_{i=1}^{N}\sum_{t=1}^{T} U_{i,t}$$

subject to (22). The government's problem is a function of the joint distribution of A_i, ϕ_i, and $\overline{k}_i$. By shifting the variation in income due to ϕ_i and replacing it with variation in income due to A_i, we are able to answer the question "how much does the optimal tax rate vary as a function of the proportion of variation due to taste vs. talent?" Table 3 depicts our results.

We quantify the sensitivity of the optimal tax rate to the source (taste vs talent) of income variation. We do this by considering a counterfactual in which we decrease the standard deviation of (log) earnings at age 44 by 1% by reducing the heterogeneity in tastes. However, we simultaneously increase the standard deviation of (log) earnings by 1% by increasing the heterogeneity in talent. Thus, counterfactual earnings at age 44 have the same standard deviation but with less of those earnings differences driven by taste and more driven by talent. Table 3 reports, for various values of α, the optimal tax rate in baseline and in the counterfactual. We measure the sensitivity of taxes to tastes by the percentage difference between the baseline

Table 3: Response of Optimal Tax Rates to Sources of Earnings Heterogeneity

α	Baseline τ	Counterfactual τ^*	Sensitivity of taxes to tastes
0.0	0.252	0.241	-4.11
0.2	0.396	0.389	-1.57
0.4	0.457	0.453	-0.85
0.5	**0.477**	**0.474**	**-0.63**
0.6	0.493	0.491	-0.46
0.8	0.518	0.516	-0.21
1.0	0.535	0.535	-0.03

Table 3: This table displays the optimal flat-tax rate for various levels of α. $\alpha = 0$ refers to heterogeneity lying on consumption utility, while $\alpha = 1$ refers to heterogeneity lying on disutility of labor. Our baseline source of heterogeneity, $\alpha = 0.5$, is bolded. The counterfactual τ refers to the optimal flat tax on a population that has had talent variation reduced while taste variation is increased to hold income heterogeneity at age 44 constant. The counterfactual's reduction in taste variation is set so that income variation at age 44 would be reduced by 1%, if not for the corresponding increase in taste variation. For interpretation, the semi-elasticity's sign is included in this table.

and counterfactual optimal tax rates (column 4 of Table 3). Table 3 shows that in our baseline calibration ($\alpha = 0.5$) the sensitivity of taxes to tastes is -0.63. In other words, the counterfactual tax rate is 0.63 percent lower than in baseline. With a baseline optimal tax rate of 48%, this represents a 0.3 percentage point decrease in the optimal tax rate: the optimal tax rate is highly sensitive to the taste heterogeneity we estimate.

We emphasize that the taste heterogeneity we find may or may not have a substantial impact on optimal tax rates. If all taste heterogeneity came from utility of consumption ($\alpha = 0$), the sensitivity of taxes to tastes would be -4.11, while if all taste heterogeneity came from the disutility of labor, the sensitivity of taxes to tastes would be -0.03. Table 3 illustrates that when α is near zero and we attribute all heterogeneity in taste to the marginal utility of consumption, the optimal tax is low and the sensitivity of taxes to tastes is (extremely) high. At the extreme of $\alpha = 0$, a 1% change in the sources of income heterogeneity causes the optimal tax rate to fall by 4%. However, as α increases and heterogeneity is placed on the disutility of work the optimal tax rate rises, and the sensitivity of taxes to tastes falls. At the extreme of $\alpha = 1$, the sensitivity is only -0.03. The sensitivity of taxes to tastes depends critically on how one apportions taste heterogeneity between the marginal utility of consumption and the marginal disutility of work.

5 Conclusion

Our paper makes four related points. First, tastes for leisure will affect human capital investment early in life, and therefore wages later in life. Thus, even if wages depend only on human capital, they will still reflect both talent *and* tastes. Second, the optimal level of redistribution depends not just on talent, but also on the extent to which individuals differ in their tastes. Third, we find substantial evidence for taste heterogeneity. Finally, the optimal tax policy depends crucially on whether the variation in tastes is due to variation in the marginal utility of consumption or in the marginal utility of leisure.

Our results are driven by two sets of empirical moments. First, earnings and work hours are highly correlated and this correlation does not decline over the lifecycle. Second, even highly-attached prime-age males display significant variation in permanent work hours that does not decline with age. When these two facts are viewed through the lens of our model, we find that tastes are an important driver of income inequality. Moreover, in a simple flat-tax-constant-transfer regime the optimal tax rate is highly sensitive to the relative importance of tastes versus talent, although that sensitivity depends on whether taste differences arise from differences in tastes for consumption or leisure.

Expanding on the last point, the optimal tax depends on the scaling of individuals' utility functions. Since differently scaled utility functions lead to observationally equivalent behavior, we cannot know how to apportion variation in relative tastes between the marginal utility of consumption and the marginal utility of leisure. Therefore, even if we are able to estimate relative tastes, optimal tax policy still depends crucially on untestable assumptions about whether heterogeneous tastes arise from difference in the marginal utility of consumption or of leisure. None of this is a concern if preferences do not vary across individuals, but we find evidence suggesting that they do vary, perhaps substantially.

We restrict ourselves to a simple model and mitigate unmodeled factors by our choices of sample and age range. We acknowledge the possibility that alternative models may exist which find a smaller role for tastes in determining earnings inequality. But any such model must be able to generate persistent variation in permanent work hours using talent alone. This might be done, perhaps, with persistent shocks that reduce lifecycle work hours on the intensive margin. Moreover, any alternative model must be able to generate a high and persistent correlation between hours worked and earnings. One possibility might be to incorporate capital imperfections which force otherwise identical households into occupational paths with different Mincerian tradeoffs. However, these types of models would themselves have important implications for optimal tax policies, reinforcing our view that the standard deviation of work hours and the correlation of work hours and earnings over the lifecycle are crucial moments to target for any model of optimal taxation.

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Appendices

Appendix A Frisch Elasticity of Labor Supply

In this Appendix, rather than directly calibrating the Frisch elasticity, we fit it to the empirical moments of the NLSY79, along with the joint distribution of talent, taste, and inital human capital. Because the Frisch elasticity controls the responsiveness of work hours to wages, it plays a role in determining the slope of hours over the lifecycle, which is the set of moments that our model is least able to fit. While our model fits most of the empirical moments well, mean work hours rise “too much” over the lifecycle, rising 154 annual hours rather than 89 annual hours from ages 30 to 44.

One way of better fitting the lifecycle path of labor conditional on earnings is to reduce the Frisch elasticity, making labor’s path flatter (ceteris paribus). In the context of our preferences, doing so would reduce both the substitution and income effect of a wage change. Because talent affects the lifetime level (as opposed to the slope) of work hours is through the income effect, the model implies a wider variance in talent in order to match the standard deviation in work hours.

Consistent with this intuition, when we jointly fit the Frisch elasticity along with the joint distribution of $\{A_i, \phi_i, \overline{k}_i\}$, the Frisch elasticity falls from 0.33 to 0.22, better fitting the hours data (simulated hours rise by 83 by the age of 44, similar to the empirical moments). Our fitted moments and paths are depicted in Figure A.2 below. While the estimated variance in talent increases, a lower Frisch elasticity means that work hours are less responsive to talent, even as changes in taste have the same effect on work hours. Consequently, talent’s contribution to earnings variation declines slightly, so that tastes explain 74% of earnings variation at age 44, rather than 71%.

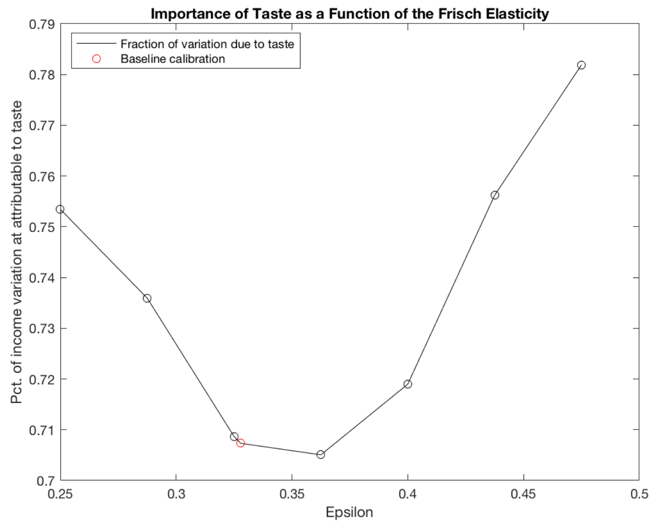

Figure A.1: This figure depicts the

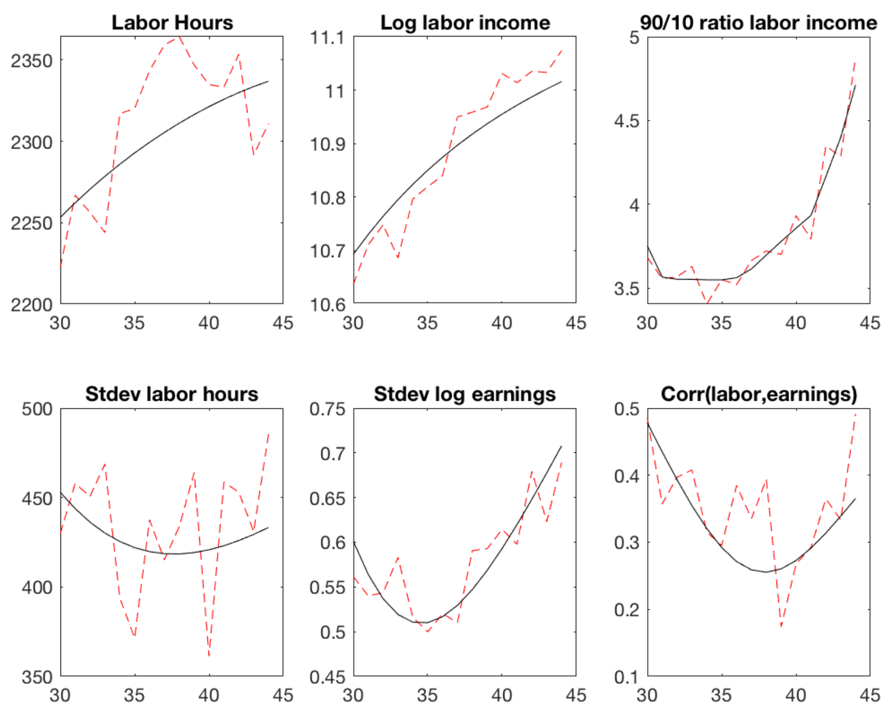

Figure A.2: This figure depicts the six sets of empirical moments from the NLSY79 (red line) and model fits with a flexible Frisch. It may be compared to figure 3, which directly calibrates the Frisch elasticity to 0.33, rather than using it to fit our moments, which results in an elasticity of 0.22.

Appendix B Calculation of Moments

In this Appendix, we describe the method we use to calculate moments using the NLSY79. As is common in the structural labor literature, we interpreted deviations from the model at the individual level as coming from either measurement error or unforeseen, transitory shocks. That is, individuals are subject to possibly correlated shocks to both their (log) annual earnings and their annual work hours (which include both paid work time and human capital investment). Following the literature, we assume that individuals have access to complete markets so that they can insure against these shocks and their optimization problem reverts to the perfect foresight model in the paper. The presence of these shocks does not affect the estimates of mean (log) earnings or work hours, but it does affect estimates of their variances and covariance.

We estimate the variances and covariance of (log) annual earnings and annual work hours as follows.[18] First, we estimate the following regression

$$y_{it} = \beta_{0i} + \beta_{1i}\text{age}_{it} + \delta_t + u_{it}.$$

where i indexes people and t indexes time in years. y_{it} represents either (log) earnings or work hours while age_{it} denotes person i's age in year t and δ_t denotes a set of year dummies. This specification allows for a person-specific intercept and slope along with an overall time trend. After fitting this regression, we calculate the variance of the residuals at each age. This gives us an estimate of the variance of the transitory shocks to (log) earnings and work hours at each age. To estimate the variances of *permanent* log annual earnings and annual hours, we simply calculate the raw variances at each age and subtract the estimated variances of the corresponding transitory shocks. To calculate the covariance of log earnings work hours, we calculate the raw covariance at each age and subtract the estimated covariance of the corresponding transitory shocks.

We estimate the 90-10 ratio of annual earnings in a slightly different way. For all men in our sample, we store the fitted values from the regression above. Then we calculate the 90-10 ratio of the (exponentiated) fitted values of log earnings at each age.

[18] In calculating all moments, we use the sampling weights provided in the NLSY79.

Appendix C   Moment Robustness

In this Appendix, we explore alternative approaches to calculating the empirical moments using the NLSY79. Specifically, we try all permutations of the following:

1. Calculate the moments using either a linear slope model (as described in Appendix B) or a random slope model with Bayes shrinkage.
2. Restrict the sample to observations with a minimum number of hours equal to either 1 or 100.
3. Censor work hours from below at 0 (no censoring) or 200.
4. Censor work hours from above at 4000 hours or no censoring.

Together, these four potential binary choices yields sixteen alternative treatments of the data. The main estimates in the paper correspond to (i) linear slope model, (ii) minimum work hours equal to 1, (iii) no truncation from below, and (iv) no truncation from above (see the first row of Table A.1).

Table A.1 below summarizes the effect of each of these sixteen possible data treatments on the standard deviation of work hours and the correlation between work hours and log earnings. Rather than plot the moments, we simply report the average standard deviation across ages 30–44, and the correlation of log earnings and work hours at age 37 along with its first two derivatives at age 37. In the final column of table A.1, we report the percentage of the standard deviation in log earnings at age 44 that our model attributes to tastes. As table A.1 illustrates, our results are relatively consistent across all 16 data treatments; for instance, the percentage of variation in earnings that is attributed to tastes fluctuates between 0.666 and 0.693.

Table A.1: Data Robustness

Rand. slope	Min. hours	Left cens	Right cens	SD hours	Corr level	Corr slope	Corr quad.	% variation due to taste at age 44
0	0	0	0	434.14	0.30	-0.0039	0.0029	0.707
0	0	0	1	415.92	0.32	-0.0032	0.0026	0.695
0	0	1	0	433.86	0.30	-0.0039	0.0029	0.709
0	0	1	1	415.62	0.32	-0.0032	0.0027	0.695
0	1	0	0	430.87	0.30	-0.0044	0.0027	0.692
0	1	0	1	412.54	0.32	-0.0036	0.0024	0.684
0	1	1	0	430.78	0.30	-0.0044	0.0027	0.692
0	1	1	1	412.45	0.32	-0.0036	0.0024	0.686
1	0	0	0	417.13	0.31	-0.0039	0.0027	0.691
1	0	0	1	400.26	0.32	-0.0031	0.0025	0.691
1	0	1	0	416.92	0.30	-0.0039	0.0028	0.691
1	0	1	1	400.03	0.32	-0.0032	0.0025	0.696
1	1	0	0	414.39	0.31	-0.0043	0.0025	0.682
1	1	0	1	397.43	0.33	-0.0035	0.0023	0.684
1	1	1	0	414.31	0.31	-0.0043	0.0025	0.674
1	1	1	1	397.34	0.32	-0.0035	0.0023	0.681

Table A.1: This table summarizes how the standard deviation of work hours and the correlation between log earning and work hours vary across all sixteen permutations of the data treatment. “Rand slope” indicates whether the data were filtered using a linear slope model (=0) or a random slope model with Bayesian shrinkage (=1). “Min hours” indicates whether workers were required to work at least 1 hour per year (=0) or 100 hours per year (=1) to be in the sample. “Left cens.” indicates whether work hours were censored from below at 200 (=1) or not (=0). “Right cens.” indicates whether work hours were censored from above at 4000 (=1) or not (=0). “SD hours” reports the average standard deviation of work hours across ages 30 to 44. “Corr Level” reports the correlation between log earnings and work hours at age 37, while “Corr slope” and “Corr quad.” report the slope and second derivative at age 37. Finally, the last column reports the proportion of (log) earnings variation at age 44 that is attributed to taste.