# Essays on the Economics and Psychology of Correlated Multidimensional Heterogeneity in Agents' Preferences and Abilities

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# Dedication

*To my parents, Farideh and Reza.*

# Abstract

Research in economics and psychology has shown that individuals are heterogeneous in their (economically relevant) innate preferences and abilities, and also that heterogeneity along different dimensions is correlated in systematic ways. In the present thesis, I focus on various aspects of a concept in multi-dimensional heterogeneity that may be called the 'Positive Manifold': The fact that many of the different factors contributing to earnings inequality between individuals (e.g. cognitive ability, risk tolerance, industriousness, patience, etc.) are observed to be positively correlated in the population. In Chapter 1, I attempt to build a bridge between the sometimes-disconnected economics and psychology literatures and conclude by arguing that some dimensions of the Positive Manifold have not received sufficient attention in economic models. In Chapter 2, I explore the implications of the Positive Manifold for one important class of those models in more detail: I show that the positive correlation between cognitive ability and risk tolerance limits the capacity of the labor income tax to mitigate inequality/raise revenue in a Mirrleesian framework, even in deterministic settings. I conclude the thesis by proposing, in Chapter 3, a novel evolutionary-economic model that can explain how the aforementioned correlation might have evolved as a result of natural selection in our ancestral environment.

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# Chapter 1

# Correlated Multi-Dimensional Heterogeneity: Evidence and Significance

## 1.1. Introduction

Many models in economics assume that all agents have identical preferences and abilities (which would allow for the 'representative household' approach to be valid under the add assumption of equal endowments or homothetic preferences with endowments that can be unequal), or if they allow for heterogeneity, they typically limit it to a single dimension. For example, the optimal taxation literature in the tradition of Sir James Mirrlees [1] has mostly assumed that individuals differ only in one dimension, which is typically interpreted as representing their innate earning ability, a characteristic assumed to be closely connected to an individual's cognitive ability (as measured by IQ or similar tests [1]; more on this later). As a result, potential heterogeneity in individual preferences has often been ignored. While being advantageous in terms of analytical tractability, this simplifying assumption was recognized from the outset as one of the main shortcomings of his approach [1]. A small subset of the existing literature (to be reviewed in depth in the next chapter) has attempted to introduce at least (and for the most part, only) *one* additional dimension of heterogeneity into the standard Mirrleesian framework [2–13]. However, most of these papers have at least one of the following characteristics: They introduce the added heterogeneity through one particular preference parameter (henceforth referred to as 'preference for leisure'), which, as I will argue, cannot be measured independently from the other parameters, or they impose arbitrary assumptions on the nature of the correlation between the new dimension of heterogeneity and intrinsic ability (including that there is no systematic correlation). Furthermore, all of the theoretical and most of the computational papers apply the so-called 'first-order approach' without providing a justification for why its use is appropriate, and only verify the necessary conditions such as monotonicity and incentive compatibility ex-post. While extensively used in unidimensional models, the first-order approach is in general not valid in multidimensional settings (more on these points in the next chapter).

One area where correlated multidimensional heterogeneity reveals itself is the degree of individuals' aversion to risk and how it relates to their cognitive ability. A number of studies have reported a negative correlation between cognitive ability and risk aversion, at least in the domain of gains (see, for example, [14–22]; see Dohmen, et al. (2018) [23], Lilleholt (2019) [24], and Amador, et al. (2019) [25] for comprehensive reviews of the literature; see also [130] and [134] for more recent results and reviews). The findings in the losses and mixed domains are inconclusive [24], likely due to the fact reaction to losses is further complicated by factors such as reference dependence, reflection and loss aversion (more on this in the next section). For this reason, I focus only on studies that have established the existence of the aforementioned correlation in the gains domain. The correlation has been observed for many different measures of cognitive ability including Raven's Progressive Matrices (RPM), Wechsler Adult Intelligence Scale (WAIS), the Cognitive Reflection Test (CRT), the Armed Forces Qualification Test (AFQT), numeracy tests (NUM), working memory capacity tests (WMC), SAT and ACT scores, and educational attainment, among others. Lilleholt (2019) reports that none of the moderator variables studied had any influence on the correlation in the domain of gains when looking at the full sample or at males only [24], which increases the likelihood that this correlation is innate (more on this in Chapter 3).

As I will argue in this as well as the next chapter, the aforementioned correlation can have important implications for Mirrleesian taxation even in static and deterministic settings. Another place where it might prove useful is in explaining, at least partially, the highly skewed distribution of wealth in the United States. Traditional macroeconomic models have well-known difficulties in generating the high levels of wealth inequality observed in the U.S. while also matching the observed earnings distribution. However, if higher-earning individuals are, on average, also more risk-tolerant (in the relative risk aversion sense), they will tend to invest a greater fraction of their wealth in risky assets such as stocks that generate higher long-term returns; this, in turn, will amplify the dispersion of the underlying earnings distribution and lead to even higher levels of wealth inequality. This explanation can supplement or replace alternative explanations of differential portfolio choice such as non-CRRA (Constant Relative Risk Aversion) preferences [135], cognitive barriers to stock-market participation, and access to superior investment advice. I will not explore this idea further in the present thesis and plan to tackle it in future work.

Another important case of correlated multidimensional heterogeneity is the negative correlation between IQ and the rate of time preference (or impatience) [14, 136]. I will not investigate this topic in the present thesis as it has been dealt with before (see the next chapter for an overview of the literature). Such a correlation can result in a positive optimal rate for capital income taxation in settings where the optimal rate would be zero otherwise.

## 1.2. Related Literature

The most common framework in the Mirrleesian taxation literature is one in which the social planner maximizes a social welfare function (SWF) subject to all the relevant incentive constraints (IC) and a resource constraint (RC) [1]:

$$\max_{c(\theta),y(\theta)} \int G(U(c(\theta),y(\theta);\theta),\theta)f(\theta)d\theta \tag{1}$$

$$s.t. \int y(\theta)f(\theta)d\theta \geq \int c(\theta)f(\theta)d\theta + E \tag{RC}$$

$$U(c(\theta),y(\theta);\theta) \geq U(c(\theta'),y(\theta');\theta) \quad \forall\theta,\theta' \tag{IC}$$

where $c$ is consumption, $y$ is (real) individual output (income), $\theta$ is a vector of individual characteristics distributed according to some $f(\theta)$, $U(.)$ is an individual's utility function, $E$ is an exogenous revenue requirement, and $G(.)$ is a generalized SWF which includes weighted summation of individual utilities as a special case. The most commonly used SWFs are (equal-weight) utilitarian or *Benthamite* (in which case $G(U(.),\theta) = U(.)$) and maximin or *Rawlsian* (which, under certain conditions, is equivalent to assigning all the weight to the 'lowest-type individual' and zero weight to everybody else). I will assume for the rest of this thesis that $E$ is zero. Each individual maximizes their utility subject to a linear income-ability constraint and a tax function that can be any nonlinear function of income but cannot be conditioned on any component of $\theta$ (either because they are unobservable to the planner or due to political/social constraints). The most commonly used utility function is isoelastic:

$$\max_{c,l} U(c,l;\theta) = u(c) - v(l) = \frac{c^{1-\sigma}}{1-\sigma} - \alpha \frac{l^{1+\gamma}}{1+\gamma} \tag{2}$$

$$s.t. \;\; c \le y - T(y) = wl - T(wl) \tag{BC}$$

$$0 \le l \le \bar{l}\,, c \ge 0 \tag{NN}$$

where $\theta = (w, \sigma, \alpha, \gamma)$, $l$ is labor supply (or 'work effort' in the more general sense), *w* is the individual's wage rate that reflects their innate productivity/ability, $\sigma$ is the coefficient of relative risk aversion, $\gamma$ is the inverse of the Frisch (intertemporal) elasticity of labor supply, and $\alpha$ is the preference for leisure parameter referred to earlier. The utility from consumption exhibits constant relative risk aversion (CRRA). $\sigma$ is also the inverse of the elasticity of intertemporal substitution (EIS) for consumption, and as we will see later, it affects the individual's labor supply behavior too.

The traditional optimal taxation literature assumes that individuals are only different in their *w*'s. I will argue, based on several lines of evidence, that the observed correlation between IQ and risk aversion is indeed rooted in latent interpersonal differences in preference and ability parameters and has important implications for optimal taxation even in deterministic settings. The paper I will follow most closely in my numerical evaluations is Burks, et al. (2009) [14], since it is the only one that directly reports the subjects' risk aversion in terms of their CRRA parameter as a function of their IQ quartile. They study a sample of about 1,000 U.S. truck drivers and observe that the RRA coefficient for higher-IQ half of the sample is smaller than that of the other half by 0.5, with the respective numbers being 0.29 and 0.79 [*NOTE*: These numbers are based on the regression coefficients reported in the first column of Table 4 in their appendix. Unlike the numbers in the second column, they are not adjusted for any control variables. The control variables used (education, age, income, etc.) are themselves correlated with IQ, which can lead to multicollinearity issues. However, the underlying pattern of significant reductions in risk aversion with increasing IQ still holds after controlling for those variables, as can be seen in Fig. 3(C) in the paper]. The correlation coefficient they report is –0.16. Consistent with the correlation being negative but weak, Dohmen, et al. (2010) [15] report a Spearman rank correlation of –0.23 between IQ and their own measure of risk aversion in a representative sample of 1,000 German adults. Beauchamp, et al. (2017) report a similar correlation (using an IQ measure taken *four decades before*) in a representative sample of 11,000 Swedish twins using various measures of risk aversion and attempt to correct for measurement error [20]. They report that measurement-error adjustment leads to substantially larger estimates of the predictive power of risk attitudes (with respect to investment decisions, entrepreneurship, and drinking and smoking behaviors), of the size of the gender gap, and of its genetic heritability. In the case of genetic heritability in particular, their estimates (35–55%) [20] are larger than those previously reported in the literature and closer to the heritability estimates for various personality traits reported by psychologists [137–138]. Falk, et al. (2018) report a negative correlation between math skills and risk aversion in a sample covering 76 countries, but both of their measures are based on self-evaluation [21]. Chapman, et al. (2018a) [22] also try to dynamically adjust for individual choice inconsistency and the resultant measurement error in a representative sample of 2,000 US adults. They claim that their method is more than twice as accurate as traditional methods for eliciting risk aversion and report a correlation coefficient of –0.21 between a composite measure of cognitive ability and the RRA coefficient.

On the dissenting side of this debate, [25–29] are among those that are worth mentioning. Some authors have argued [26–28] that the correlation of interest does hold for hypothetical gambles but not for real ones. However. Lilleholt (2019) does not find support for this conclusion in his large meta-analysis [24]. A different line of attack is that the observed correlation might be an artifact of the difficulties associated with making expected-value calculations and the resulting choice inconsistency. For example, if the elicitation task involves a choice between a lottery and a certain option, individuals of lower cognitive ability may find it easier to go with the certain option (since it does not require them to make any calculations), hence creating a false appearance of risk version. However, this issue can be addressed through the use of tasks that involve choice between different lotteries, and Lilleholt (2019) reports that the presence of a certain option did not influence the relationship between cognitive ability and risk aversion in the gains domain (whether one was looking at the full sample or males/females only) [24]. It has also been argued that people with low cognitive ability tend to make more random errors [16, 28], leading risk aversion to be overestimated for this group when the percentage of alternatives permitting a choice indicating risk aversion is high, while underestimated when the opposite is the case [28]. A number of points can be raised with regard to this criticism. First, it is important to note that, while [28] illustrate an important way in which noise can affect our measures of latent risk preference, their results *do not disprove* the existence of a negative correlation between risk aversion and cognitive ability. As Dohmen, et al. (2018) point out, this is because they do not identify whether cognitive ability affects lottery choices solely through other channels other than risk preference (for example, through mistakes in decision-making) or whether cognitive ability impacts latent risk preference

[23]. Newer studies that have tried to correct for choice inconsistency (such as [20] and [22]) have found a correlation of the same sign. Furthermore, Lilleholt (2019) reports that the number of possible risk-averse choices did not moderate the relationship between risk aversion and cognitive ability in his meta-analysis, except in the domain of losses for females only [24]. Second, studies that use self-reported willingness to take risks as one of their measures of risk tolerance (such as [15], [20], and [21]) report a positive correlation between this measure and cognitive ability. The advantage of this measure is that it is not impacted by decision errors or noise [23], while its validity has been established by studies such as [30]. Finally, using principal components analysis on a representative sample of the U.S. population, Chapman, et al. (2018b) [139] report that risk aversion groups together with *inequality aversion*, and, consistent with previous findings, the principal component associated with the cluster containing those two traits is itself weakly and negatively correlated with IQ. A final possible objection might be that individuals of lower cognitive ability are less likely to purchase products such as health and life insurance while being more likely to engage in risky behaviors such as drinking, smoking, and criminal activity, which seems to go against the posited correlation. However, it should be noted that such behaviors are also greatly impacted by an individual's rate of time preference [25], which is found to be higher in individuals of lower cognitive ability [14]. It can also be the case that failure to purchase health or life insurance is (at least partly) explained by the cognitive difficulty of dealing with complex products, as argued by Angrisani & Casanova (2011) [31]. Overall, the weight of the evidence seems to favor the proposition that cognitive ability is indeed correlated with latent risk preference. I will argue, in Chapter 3, that there are biological and evolutionary reasons for such a correlation to exist.

Another area of behavior where the aforementioned correlation demonstrates itself is intertemporal substitution. Kimball, et al. (2015) [32] report that more educated individuals tend to have a higher EIS of consumption, which implies a lower $\sigma$. If education is taken to be a proxy for IQ, this result is, again, an indication that IQ and $\sigma$ are negatively correlated. Furthermore, unlike the previous results, this correlation holds in deterministic settings, and, hence, is unaffected by factors such as the perception of risk and probability.

### 1.3. Relationship to Labor-Supply Behavior

It is important to note that, while there is no risk or time element in my model, heterogeneity in $\sigma$ still shows its impact in such deterministic and static environments through its effect on labor supply [33]. The marginal rate of substitution (MRS) between leisure and consumption is:

$$MRS_{l,c} = \frac{v'(l)}{u'(c)} = \alpha l^{\gamma} c^{\sigma} \tag{3}$$

which means that, other things being equal, individuals with a lower $\sigma$ will have a lower disutility from effort relative to utility from consumption (for $c > 1$), and therefore, be more willing to supply labor. In this case, the negative correlation between IQ and $\sigma$ can potentially explain the observation that high-wage individuals in developed countries tend to work more than the low-wage (see, for example, [13] and [34–36]) despite the fact income effects appear to dominate substitution effects in the aggregate [36–38] (more on this point in the next paragraph).

We also have:

$$\varepsilon^c = \frac{\partial l}{\partial(1-T'(y))}\frac{(1-T'(y))}{l} = \frac{v'/l}{v'' - (v'/u')^2 u''} = \frac{1}{\gamma + \alpha\sigma c^{\sigma-1} l^{1+\gamma}} \tag{4}$$

$$\eta = w[1-T'(y)]\frac{\partial l}{\partial R} = \frac{(v'/u')^2 u''}{v'' - (v'/u')^2 u''} = -\frac{\alpha\sigma c^{\sigma-1} l^{1+\gamma}}{\gamma + \alpha\sigma c^{\sigma-1} l^{1+\gamma}} \tag{5}$$

$$\varepsilon^u = \varepsilon^c + \eta = \frac{v'/l + (v'/u')^2 u''}{v'' - (v'/u')^2 u''} = \frac{1 - \alpha\sigma c^{\sigma-1} l^{1+\gamma}}{\gamma + \alpha\sigma c^{\sigma-1} l^{1+\gamma}} \tag{6}$$

with $\varepsilon^c$ being the compensated elasticity of labor supply with respect to the after-tax wage rate, $\varepsilon^u$ being the uncompensated elasticity thereof, and $\eta$ being the income effect. $R$ is virtual income. As long as leisure is a normal good, which is the case in my framework, $\eta$ is a negative number. Henceforth, whenever a 'stronger' income effect is mentioned, what is meant is a more negative number. It can be verified that $\frac{\partial|\eta|}{\partial\sigma} > 0$, implying that $\sigma$ captures the strength of the income effect; $\sigma = 0$ (quasi-linear utility) corresponds to there being no income effect, $0 < \sigma < 1$ corresponding to the case where the substitution effect dominates the income effect, $\sigma = 1$ (log utility) corresponding to the income and substitution effects cancelling out, and $\sigma > 1$ corresponding to the case where the income effect dominates the substitution effect. Many studies in the optimal taxation literature have used quasilinear utility for the sake of its analytical tractability, and further argued that quasilinearity in consumption in conjunction with a low Frisch elasticity is a good assumption since it is consistent with the low responsivity of labor supply to permanent changes in wages [39]. However, there is evidence that income and substitution effects are actually both large, with the income effect slightly dominating the substitution effect in the aggregate such that average hours per worker have been falling at about 0.4% per year [37–

39]. The aggregation process, however, hides significant heterogeneity in the responses of different groups to increases in their wages over time, namely, that people with the highest educational attainment/wages have somewhat *increased* their labor supply over the past couple of decades, while everybody else has done the opposite (see Figure 1; see also [34–35]). This is also consistent with the fact that, while cross-county and temporal comparisons of average hours worked in the aggregate tend to establish a negative relationship between wages and hours, the cross-sectional within-country comparisons seem to imply the opposite (see [36] and [39]). While Boppart & Ngai (2017) [35] attempt to explain the differential patterns in Figure 1 through intertemporal substitution and differential expectations about future wage trends, I believe that a simpler explanation can be offered by allowing heterogeneity in income effects, such that higher-IQ individuals will have lower $\sigma$'s and exhibit weaker income effects. Note that Boppart & Ngai (2017) [35] still have to assign a lower value to their equivalent of my $\alpha$ parameter for the higher-ability individuals in order to match the cross-sectional distribution of hours in 1965 (the start of their model), since those individuals worked more hours in 1965 as well. Hence, if preference heterogeneity has to be introduced into the model regardless, then it can be argued that realizing it through assigning a lower $\sigma$ to higher-ability individuals is a more parsimonious way of doing so since it can explain *both* the initial cross-sectional distribution of hours worked *and* their differential evolution over time for different groups.

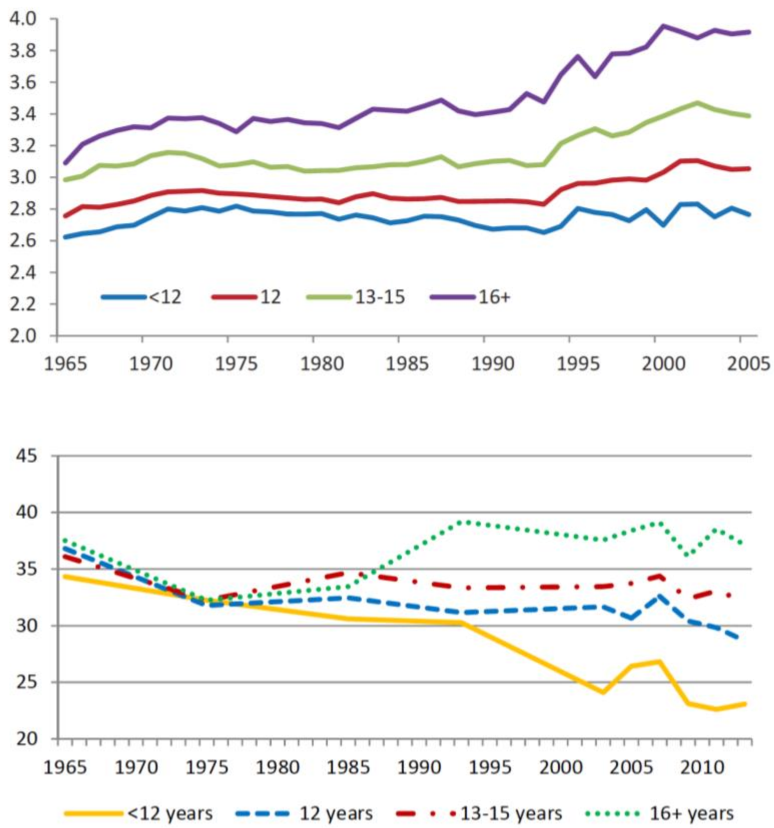


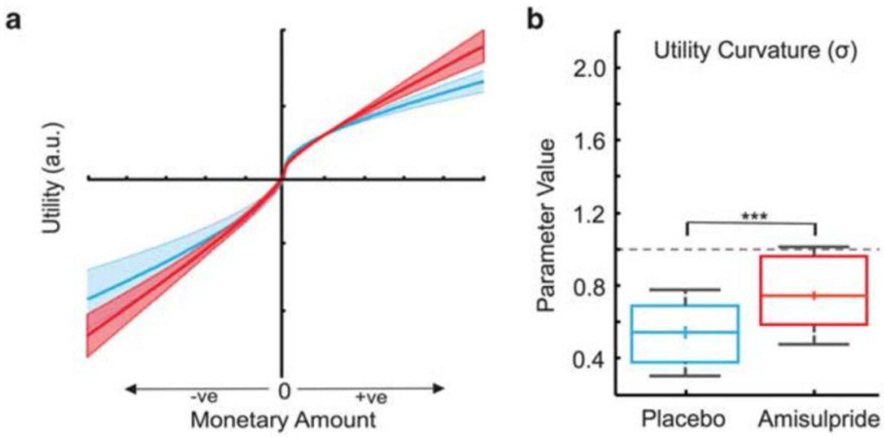

Figure 1. Trends in real wages (top) and working hours (down) by years of education (adopted from Boppart & Ngai (2017) [35]). Nominal wages are deflated by the personal consumption expenditures (PCE) index. Non-farm working individuals aged 21-65 who are not students are included. Source of the data is the CPS March samples.

It can also be verified that $\frac{\partial \varepsilon^c}{\partial \sigma} < 0$, which, along with higher-IQ individuals having a lower $\sigma$ and also weaker income effects, implies an even higher $\varepsilon^u$ for these individuals. While there is abundant evidence that high-earners have a higher elasticity of taxable income (ETI) than the low-earners [40–44], there is disagreement over whether this higher elasticity is due mainly to greater opportunities for tax avoidance/evasion at the top [40] or to decreases in real economic activity [44]. In this context, the present work can be seen as providing at least partial support for the latter view (see Figure 18 and the related commentary for more details). Note that in the models used in most of these papers, ETI is simply equal to one of the labor-supply elasticities ($\varepsilon^u$, $\varepsilon^c$, or the Frisch elasticity $1/\gamma$) depending on what type of tax reform is being considered. Also note that $\varepsilon^u \leq \varepsilon^c \leq 1/\gamma$, with equality holding in the absence of income effects (i.e. quasilinearity of utility in consumption).

Finally, it is worth mentioning that heterogeneity in elasticities of labor supply and taxable income can also be generated by introducing heterogeneity in $\alpha$ or the Frisch elasticity $1/\gamma$. However, direct empirical evidence on heterogeneity in these parameters is either rare or impossible to obtain. For example, the value of $\alpha$ is typically chosen such that the labor supply generated by the model matches some empirically obtained value under certain circumstances, and is therefore dependent on the assumptions made about the values of other parameters (e.g. [13, 45]). There also doesn't seem to be an extensive empirical literature documenting differences in the Frisch elasticity by education or IQ; if anything, the only such paper that I am aware of reports that the Frisch elasticity *declines* with educational attainment [46] (going from a high of 0.49 to a low of 0.30; males only), which, on its own, would generate *lower* ETIs at the top. In view of the consideration that every additional dimension of heterogeneity makes the analysis more difficult, it is preferable to start with the most parsimonious model. As argued earlier, I believe that this goal is achieved best by introducing preference heterogeneity through the $\sigma$ parameter.

## 1.4. Other Evidence

Evidence from psychology and neuroeconomics also points us in the same direction. A number of studies in psychology have reported a positive correlation between IQ and the trait 'Industriousness' [47–49]. Industriousness is an aspect of the broader personality factor Conscientiousness and is related to how hard-working and motivated individuals are [50]. This is despite the fact that broader Conscientiousness is uncorrelated (or even weakly negatively correlated) with IQ [49]. Interestingly, Boyce & Wood (2011) [51] find, using panel data, that more Industrious individuals report higher increases to their subjective well-being (SWB) from increases to their income (while they discuss the relationship between changes in SWB and general Conscientiousness, a closer examination of their personality questionnaire reveals that the questionnaire items load more heavily on the Industriousness aspect of Conscientiousness). They argue that Conscientiousness people might be better planners, enabling them to make wiser purchases with their income and raising their marginal utility of consumption. If Industriousness is, at least in part, due to having a higher marginal utility of consumption (rather than a high preference for leisure), and higher-IQ individuals tend to be more Industrious, then this would be consistent with higher-IQ individuals having a lower $\sigma$. Studies in neuroeconomics also suggest that risk aversion and labor supply might be governed by common factors in the brain. Risk and effort 'costs' seem to be coded in separate areas in the brain (e.g. the insula for risk and the striatum for effort) before being integrated (if necessary) in the frontopolar cortex (FPC) [52]. However, both the insula and the striatum receive dopamine inputs from other parts of the brain, a neurotransmitter known to play a key role in reward sensitivity and motivation. Increasing the activation of the dopamine system has been reported in separate studies to increase *both* the individuals' willingness to take risks [53] *and* their willingness to exert physical effort for a reward [54] (see Figure 2).




(c)

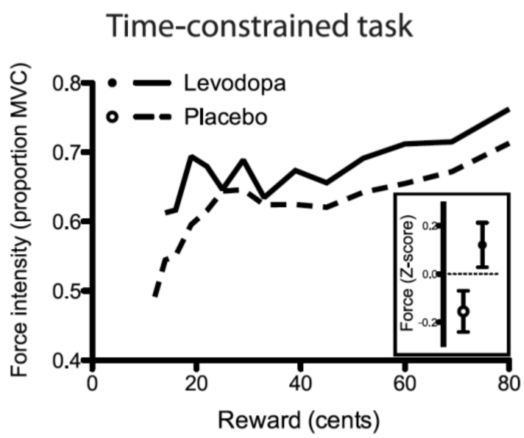



Figure 2. (a) and (b) are adopted from Burke, et al. (2018) [53]. Note that utility curvature here is defined as 1 minus the RRA coefficient ($\sigma$ in out notation). Hence, the administration of amisulpride makes an individual more sensitive to reward (i.e. more risk-taking). (c) is adopted from Zénon, et al. (2016) [54]. The administration of levodopa makes an individual more willing to exert physical effort to obtain a reward. Amisulpride is a D2R antagonist, while levodopa is a D1R agonist. Since D2R receptors are inhibitory and D1R receptors are excitatory, both of these interventions lead to increased activation of the dopamine system.

On a deeper biological level, Strawbridge, et al. recently reported the results of a genome-wide association study (GWAS) of self-reported risk-taking behavior in a sample of 116,255 UK Biobank participants [55]. One of their top hits was a single-nucleotide polymorphism (SNP) within the CADM2 gene on chromosome 3, which had previously been found to be associated with executive functioning, information processing speed, and educational attainment (see Figure 20 in Chapter 3). CADM2 encodes the synaptic cell adhesion molecule 2, which is important in maintaining the synaptic circuitry of the brain. Interesting, the allele associated with increased self-reported risk-taking behavior was also associated with increased CADM2 expression. This is consistent with cognitive ability *causing* more risk taking [18, 127–130] but also with the "correlational selection" [56] of higher cognitive ability and increased risk taking over the course of human evolution, maintained through either pleiotropy (i.e. the production by a single gene of two or more apparently unrelated effects) or tight linkage between the different genomic loci [57]. In Chapter 3, I will build on some of the existing literature within *evolutionary economics* that deals with the evolution of intelligence and risk attitudes to argue that there are, indeed, reasons for cognitive ability and risk taking to coevolve in such a manner.

# Chapter 2

# Optimal Income Taxation with Correlated Multi-Dimensional Heterogeneity

The optimal taxation literature in the tradition of Mirrlees has largely assumed that individuals differ only in a single dimension, one that is typically interpreted as innate ability. In this chapter, I will derive rules for optimal income taxation in an environment where individuals differ along two imperfectly correlated dimensions, namely, IQ (as a proxy for innate ability) and relative risk aversion, which are seen to be negatively correlated in experimental data. As I argued in the previous chapter, this correlation is also consistent with several other observed phenomena, including the differences in the labor supply and intertemporal substitution behavior of individuals with different levels of cognitive ability, as well as differences in their reports of subjective well-being. I will first demonstrate, in a basic four-type (2×2) model, that, under certain conditions, the two-dimensional optimal taxation problem can be significantly simplified, such that the 'first-order approach' (widely used in unidimensional settings) can be applied. I then solve the model in the Rawlsian case and show that a stronger negative correlation results in lower revenue-maximizing marginal tax rates (MTRs) at the bottom of the income distribution and higher ones in the middle. To see the implications of the model for the U.S. economy and to get a better idea about revenue-maximizing MTRs at the very top with an unbounded Pareto tail, I take the 2018 March CPS data, divide the sample into a more-risk-averse and a less-risk-averse group based on whether an individual is an employee or an entrepreneur, and simulate the model using a (modified) first-order approach. I will show that the revenue-maximizing top tax rate is reduced by about 8 percentage points in the baseline case compared to a benchmark setting in which all individuals have the same coefficient of relative risk aversion. MTRs are also lowered at the bottom of the income distribution, while being raised in the middle. Consistent with the results of the 2×2 model, strengthening the correlation leads to lower rates at the bottom and higher ones in the middle, but it does not alter the rates at the very top.

Remember from Equations (1) and (2) in Chapter 1 that a type-$\theta$ individual's optimization problem (with $\theta = (w, \sigma, \alpha, \gamma)$) in most Mirrleesian taxation models is:

$$\max_{c,l} U(c, l; \theta) = u(c) - v(l) = \frac{c^{1-\sigma}}{1-\sigma} - \alpha \frac{l^{1+\gamma}}{1+\gamma} \tag{2}$$

$$s.t. \;\; c \leq y - T(y) = wl - T(wl) \tag{BC}$$

$$0 \leq l \leq \bar{l}\,, c \geq 0 \tag{NN}$$

while the planner's objective is:

$$\max_{c(\theta),y(\theta)} \int G(U(c(\theta), y(\theta); \theta), \theta) f(\theta) d\theta \tag{1}$$

$$s.t. \;\; \int y(\theta) f(\theta) d\theta \geq \int c(\theta) f(\theta) d\theta \tag{RC}$$

$$U(c(\theta), y(\theta); \theta) \geq U(c(\theta'), y(\theta'); \theta) \quad \forall \theta, \theta' \tag{IC}$$

where $l$ is labor supply (or 'work effort' in the more general sense), *w* is the individual's wage rate that reflects their innate productivity/ability, $\sigma$ is the coefficient of relative risk aversion, $\gamma$ is the inverse of the Frisch (intertemporal) elasticity of labor supply, and $\alpha$ is 'preference for leisure'. $\sigma$ is also the inverse of the EIS for consumption, and, as we saw in the previous chapter, it affects an individual's overall labor supply elasticity too (which means that differences in it are important even in deterministic and static settings). While the traditional optimal taxation literature assumes that individuals are only different in their $w$'s, my work is the first to analyze a case in which they are different in their $\sigma$'s as well, in a way that is correlated with their $w$'s.

## 2.1. Related Literature

A small subset of the existing optimal taxation literature has attempted to introduce at least one additional dimension of heterogeneity into the standard Mirrleesian model [2–13]. The existing papers have taken a variety of different approaches and tried to answer different questions, making it difficult to summarize the current state of the literature in a coherent fashion. In what comes next, I will try my best to highlight some of the more important aspects of the extant literature and how my work differs from them.

Most of the existing papers have at least one of the following characteristics: they introduce the added heterogeneity through the $\alpha$ parameter alone (which, as argued earlier, cannot be measured independently), or they impose arbitrary assumptions on the nature of the correlation between the new dimension of heterogeneity and intrinsic ability (including that there is no systematic correlation). Furthermore, all of the theoretical and most of the computational papers have used the so-called 'first-order approach' without providing a justification for why its use is appropriate (which is generally not the case in multidimensional settings). The necessary conditions for the first-order approach such as monotonicity and incentive compatibility are only verified ex-post, or not at all.

A somewhat distinct strand within this literature has focused on the implications of the empirically established [14, 136] negative correlation between IQ and the rate of time preference (or impatience) in a dynamic (i.e. multi-period) framework [58–61]. They generally provide a theoretical argument for positive capital income taxation in settings where the optimal rate would be zero otherwise. However, calibration typically shows that the rates of such taxation do not exceed 5% [60]. I will not cover this group in any more detail since they are not directly related to my work.

Sandmo (1993) [2] considers a utilitarian SWF with heterogeneity in preferences for leisure (but not in productivity), and shows that, in the full information case, the direction of redistribution depends on how the marginal utility of consumption interacts with the preference for leisure parameter. With additive separability (i.e. no interaction), redistribution is from the low-preference-for-leisure (rich) types to the high-preference-for-leisure (poor) types. He then demonstrates that these results extend to the case where the government can only redistribute using a linear income tax and a lump sum transfer that are the same for all agents (hence, moving away from the full-information assumption). Finally, he shows that if agents are also allowed to differ in their productivities and productivity is assumed to be a strictly monotone function of the preference for leisure (i.e. perfect positive or negative correlation between the two parameters), the basic ambiguity concerning the direction of redistribution remains. If, however, productivity is *strictly decreasing* in preference for leisure *and* utility is additively separable, then the tax system becomes more redistributive. As we saw in Section 1.3, there is a rough equivalent in my model for the negative relationship between productivity and preference for leisure, but the negative correlation is not perfect, and, furthermore, the planner is not restricted to linear tax schedules. Therefore, Sandmo's conclusions do not necessarily hold in my model.

Tarkiainen & Tuomala (1999) [3] perform a two-dimensional version of the first-order method and show (numerically) that with uncorrelated heterogeneity in preference for leisure and productivity and a utilitarian SWF, the tax system becomes more redistributive. Tarkiainen & Tuomala (2007) [7] extend this work by allowing the preference for leisure and productivity to be correlated through a bivariate lognormal distribution but do not provide a basis for this assumption.

Boadway, et al. (2002) [5] consider a case with uncorrelated heterogeneity along productivity and preference for leisure and four types (2×2). They further assume a utility function that is quasilinear in leisure (in order to obtain closed-form solutions) and make the two 'middle' types indistinguishable (by assuming $w_l/\alpha_l = w_h/\alpha_h$), effectively reducing the number of types to three and establishing a one-dimensional ordering between them. They allow the social planner to assign different weights to individuals with different preferences for leisure and identify the threshold weights around which there are changes in the direction of redistribution and the binding ICs ('upward/downward').

Judd, et al. (2017) [6] consider a utilitarian SWF, isoelastic utility, and two cases of multidimensional heterogeneity: 2D heterogeneity in productivity and the Frisch elasticity (5×5), and 3D heterogeneity along the previous two in addition to "basic needs", by which they mean a minimal level of consumption (3×3×3). There is no correlation between the various dimensions in either of the cases. They numerically solve these cases and conclude that the tax system becomes less redistributive, since income is now a *fuzzier* signal of ability and the social planner does not wish to redistribute to those with high ability who have low income because they also have a high preference for leisure.

Blomquist & Christiansen (2008) [8] study a case with a very general utility function and three types: high-*w*, low-leisure-preference; high-*w*, high-leisure-preference; and low-*w*, low-leisure-preference. Consumption is allowed to be a vector and individuals can have heterogeneous preferences over commodity bundles. They analyze the properties of the various screening and bunching optima without characterizing the precise conditions that give rise to those optima. They also discuss the role that commodity taxes can play particularly when a pure-income-tax system leads to bunching between the last two types.

Choné & Laroque (2010) [9] use a setting somewhat similar to [5] but with a continuum of types and demonstrate that, contrary to [4] and unlike the standard Mirrleesian model, MTRs can be negative at the bottom of the income distribution, which can serve as a justification for policies like the earned-income tax credit. Lockwood & Weinzierl (2015) [10] build on [9] as well as [94] and demonstrate that if the distribution of the relative preference for consumption over leisure rises with income (in the first-order stochastic dominance sense), then optimal MTRs with preference heterogeneity (in addition to ability heterogeneity) are lower at all incomes than without preference heterogeneity. It might appear at first that this case describes the scenario that I am investigating as well. However, they acknowledge that their technique cannot help with all dimensions of heterogeneity and also that the validity of their criterion cannot be confirmed or rejected easily with conventional economic data. Bergstrom & Dodds (2020) [13] continue along similar lines but argue that U.S. data are actually more consistent with the opposite of the criterion laid out in [10], which means optimal MTRs should be *higher* when preference heterogeneity is allowed. Both [10] and [13] rule out, by assumption, that heterogeneity in $\sigma$ might be the driving factor behind the phenomena they are trying to explain.

Jacquet & Lehmann probably come closest to what I do in Section 2.3 in their (2016) [11] and (2017) [12] papers. Wage data are taken from the CPS and the sample is divided into two groups based on either self-employment status [11] or gender [12]. Each group is assigned a different Frisch elasticity (women higher than men and the self-employed higher than the employees) and utility is assumed to be quasilinear (in $c$). Depending on which scenario is considered, optimal MTRs at the top can be higher [12] or lower [11] than the unidimensional case. However, the choice of Frisch elasticities in [11] is not buttressed by empirical evidence. Also, neither paper *proves* that the use of the first-order method is appropriate; the necessary conditions are verified ex-post.

I also want to confirm whether the $\sigma$ values reported in Burks, et al. (2009) [14] are in line what has been reported elsewhere. While those numbers ($\sigma_L = 0.29$ and $\sigma_H = 0.79$, implying a sample average of 0.54) are far below the values typically estimated in asset pricing and the business-cycle macro literature (e.g. [62–65] but see [66] for an exception), they are, nevertheless, close to the values reported in many other studies. It should also be noted that the more sophisticated models of asset pricing, such as [67] or [68], generally estimate $\sigma$ to be much lower, although still above 1. The paper most relevant to this work is Chetty (2006) [33], which looks at income and substitution effects in labor-supply behavior and arrives at a mean estimate of 0.71 for $\sigma$ in the additive utility case, and a mean of 0.97 at the upper bound of complementarity between consumption and leisure. I divide the remaining studies into four groups: experimental studies of choice over lotteries, experimental studies of games including sealed-bid auctions, studies that measure the EIS (equal to $1/\sigma$ with isoelastic utility), and everything else.

One of the most cited studies in the first group was done by Holt & Laury (2002) [69], who report that their estimates of $\sigma$ are centered around 0.3–0.5 (they do not report a mean or a median). Dave, et. al (2010) [16] use a similar method to Holt & Laury (2002) and report that nearly half of their subjects have a $\sigma$ in the 0.4–1.0 range. Harrison, et al. (2007)

[70] and Andersen, et al. (2008) [71] respectively report a mean $\sigma$ of 0.67 and 0.74 in a representative sample of Danish adults, while Dohmen, et al. (2010) [15] report a mean and median in the 0.43–0.48 range. It is worth noting that Holt & Laury (2002) conduct their experiments on a sample of U.S. university students, while the two studies mentioned next use representative samples. Since university students tend to be smarter than the general population, the fact that Holt & Laury's estimates are somewhat lower provides further evidence in support of the negative correlation between cognitive ability and risk aversion. Chapman, et al. (2018a) [22] also confirm this finding. One study that finds somewhat higher levels of risk aversion among university students is Gerhardt, et al. (2016) [129] whose estimate for $\sigma$ is 0.7 (under the no-load condition). Finally, Meissner, et. al. (2020) report an average $\sigma$ of 0.46 for a large, multi-county representative sample [134].

It is also worth mentioning that Andersen, et al. (2008) [71] use the average daily consumption of private nondurable goods as the baseline consumption/wealth in their estimation of $\sigma$, while Burks, et al. (2009) appear to have used a baseline of zero. This is consistent with Wakker (2008) [72], who argues that studies defining CRRA utility in terms of final consumption/wealth (rather than gains/losses) should arrive at larger estimates of $\sigma$. Nevertheless, unlike the asset-pricing and macro studies discussed earlier, the reported numbers are all below 1. An alternative approach was taken by Filippin & Crosetto (2016) [73] who used the 'power-expo' utility function proposed originally by Saha (1993) [74]; however, they found that preferences were well represented by CRRA and estimated $\sigma$ to be about 0.4 in most of their specifications. Studies that rely on Prospect Theory arrive at even lower estimates, with the utility function being almost linear [75, 76].

The second category of studies focus on games that involve risk, including auctions. Some of the mean $\sigma$ values reported in this category are: 0.48 in Chen & Plott (1998) [77], 0.52 in Goeree, et al. (2002) [78], 0.44 in Goeree, et al. (2003) [79], 0.46 in Goeree & Holt (2004) [80], 0.75 in Bajari & Hortacsu (2005) [81], and 0.28 in Campo, et al. (2011) [82].

In the third group, [83–85] all estimate the inverse of the EIS to be around 0.5, while Imai & Keane (2004) give an estimates of 0.75 [86]. We also have Kimball, et al. (2015) [32], who arrive at a median estimate of 0.59 and a mean estimate of 0.70.

Finally, there are studies from different domains such as SWB [87] and behavior involving mortality risk [88, 89] that also arrive at similar estimates for $\sigma$.

## 2.2. A 2×2 Model

I will assume in my first model that there are four types: A low-IQ, high-risk-aversion type (LH), a low-IQ, low-risk-aversion type (LL), a high-IQ, low-risk-aversion type (HL), and a high-IQ, high-risk-aversion type (HH). The population weight of each type $ij$ is denoted by $\pi_{ij}$ (see Figure 3). High-IQ types share a common productivity parameter $w_H$ and low-IQ types have a common $w_L$. Similarly, the high-risk-aversion types share a common risk-aversion parameter $\sigma_H$, while the low-risk-aversion types have a common $\sigma_L$.

| | **Low-Risk-Aversion ($\sigma_L$)** | **High-Risk-Aversion ($\sigma_H$)** |
|---|---|---|
| **Low-IQ ($w_L$)** | $\pi_{LL}$ | $\pi_{LH}$ |
| **High-IQ ($w_H$)** | $\pi_{HL}$ | $\pi_{HH}$ |

Figure 3. Population weights by type

If there is symmetry in the population such that:

$$\begin{cases} \pi_{LL} + \pi_{LH} = \pi_{HL} + \pi_{HH} = 0.5 \\ \pi_{LL} + \pi_{HL} = \pi_{LH} + \pi_{HH} = 0.5 \end{cases}$$

then it can be shown that:

$$\pi_{LH} = \pi_{HL} = \frac{1-r}{4}\ ,\ \pi_{LL} = \pi_{HH} = \frac{1+r}{4} \tag{7}$$

where $r$ is the correlation coefficient between $\sigma$ and $w$. I assume this type of symmetry because I want to connect my results to the correlation coefficient in a simple and intuitive way. The social planner solves:

$$\max_{c_{ij},l_{ij}} \sum_{i,j} g_{ij}\pi_{ij}U_{ij}(c_{ij}, l_{ij}) \tag{8}$$

$$s.t. \ \sum_{i,j} \pi_{ij}c_{ij} \leq \sum_{i,j} \pi_{ij}w_{ij}l_{ij}$$

$$U_{ij}(c_{ij}, l_{ij}) \geq U_{ij}(c_{i'j'}, l_{i'j'}) \quad \forall ij, i'j'$$

where $g_{ij}$ is the weight assigned to the *ij* type by the planner (with $i, j \in \{H, L\}$), and there are *twelve* distinct incentive constraints that need to be satisfied (see Figure 4).

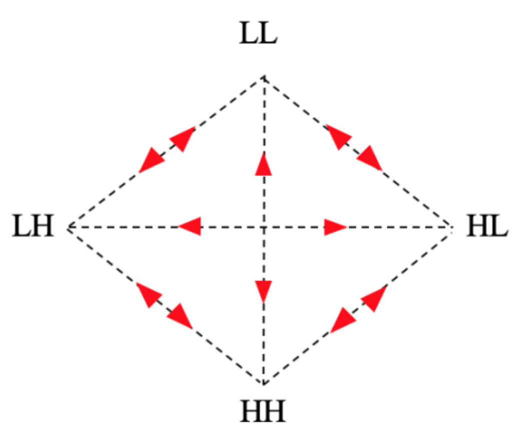



Figure 4. All twelve incentive constraints in a 2×2 setting.

I take $l = 1$ to mean a labor supply of 40 hours per week, 50 weeks per year and impose an upper bound of $\bar{l} = 2.88$ which corresponds to a maximum available time of 5760 hours per year in accordance with [45]. This implies that $w_H$ and $w_L$ will equal the annualized wage rates of the high-ability and low-ability types, respectively. Yu [90] reports, based on 1999 PSID data, that about half of the 25–44 year-old population had an education level of high school or less and an average hourly wage rate of $13.9, while the other half earned $20.3 per hour on average (in 1999 dollars). I assume that IQ is proxied by education level and base my calculations on the numbers pertaining to the younger (25–44 years old) rather than the older (45–64 years old) group of workers since differences in innate ability (as opposed to the accumulation of human capital) have a greater impact on the former This implies $w_H = \$40{,}600$ and $w_L = \$27{,}800$ ($w_H/w_L \cong 1.5$).

In order to avoid complicating the model any further, I assume that all types have the same $\gamma$ and the same $\alpha$. Following Chetty (2012) [91] and Chetty, et al. (2013) [92], and in accordance with many other papers in the optimal taxation literature, I use a baseline value of 0.5 for the Frisch elasticity. The value of $\alpha$ is chosen such that the amount of labor supply averaged across all types under competitive equilibrium is almost 35 hours per week, which roughly matched the average hours worked per week in the U.S. economy. Alternative values of $\gamma$ will be tried in the sensitivity analysis section. Note that the value of $\alpha$ will change as I change the value of the mean $\sigma$ or $\gamma$ during the sensitivity analysis. I will assume that $w$ exhibits the same correlation with $\sigma$ that IQ does, which is a simplification as the correlation coefficient between IQ and income itself is in the 0.2–0.4 range [140–142]. The heritability of IQ increases from about 45% in childhood to about

65% in young adulthood to as much as 80% later in life [143–146]. Therefore, there is a considerable innate component to IQ (and, by extension, $w$) in your prime working years.

When preferences are heterogeneous, the problem of how to choose the social welfare weights $g_{ij}$ for the different types becomes particularly acute (see [5], [9], [10], [93], and [94]). Some authors (e.g. [93, 94]) have argued that people should be held responsible for their preferences but not their abilities. Therefore, the SWF should be defined in such a way that it warrants redistribution between types with different abilities but not between types that merely differ in their preferences. Other authors, however, have not found this argument persuasive (e.g. [2]): The heritability of risk preferences (as well as personality traits in general) is only slightly less than that of IQ [20, 137–138]. In order to avoid these philosophical questions and focus instead on how the government's ability to redistribute income is impacted by the addition of $\sigma$-heterogeneity, I will use a Rawlsian or maximin-type social objective, which, in addition, is equivalent to revenue maximization [95]. Since LH is the type that earns the least income when left to their own devices, the planner's objective will be to maximize the utility of the LH type subject to the relevant constraints. Another potential problem that is avoided by choosing a Rawlsian objective is the possibility of 'reverse redistribution' (i.e. from low-ability types to high-ability types), since high-ability types also tend to have a higher marginal utility of consumption due to the negative $w$-$\sigma$ correlation. The planner's problem is therefore:

$$\max_{c_{ij},l_{ij}} U_{LH}(c_{LH}, l_{LH}) \tag{9}$$

$$s.t. \ \sum_{i,j} \pi_{ij} c_{ij} \leq \sum_{i,j} \pi_{ij} w_{ij} l_{ij} \qquad (\lambda)$$

$$U_{ij}(c_{ij}, l_{ij}) \geq U_{ij}(c_{i'j'}, l_{i'j'}) \quad \forall ij, i'j' \qquad (\mu_{iji'j'})$$

### 2.2.1. Simulating the 2×2 Model

Due to the complexity caused by multidimensional heterogeneity, I was unable to establish any general rules regarding which incentive constraints will bind and which ones won't. Therefore, I decided to start with a computer simulation. All simulations in this section were performed in MATLAB using *fmincon* and enforcing all twelve ICs. The results are shown in Figure 5–7. A few observations are in order:

1. The marginal tax rate (MTR) is always zero at the top.
2. A closer look at Figures 6(a) and (b) reveals that for 'weak' correlations (i.e. $|r| < 0.3$ [147], which is what we observe in experiments), the general pattern of MTRs seen in Figure 7 holds; that is, MTRs first rise with income and then fall to new lows. The initial rise disappears when $r$ is zero.
3. From Figure 6(c), type LL is a net taxpayer for weak correlations and a net recipient otherwise. LH and HH are always net recipients, while HL is always a net payer.
4. In terms of MTRs, the primary impact of a larger correlation coefficient is to raise them in the middle while lowering them at the low end.
5. LH and HH are bunched for $r < -0.6$ ('strong' correlation [147]); they face different MTRs at the same level of income, which creates a 'kink' in the tax schedule [96–99].

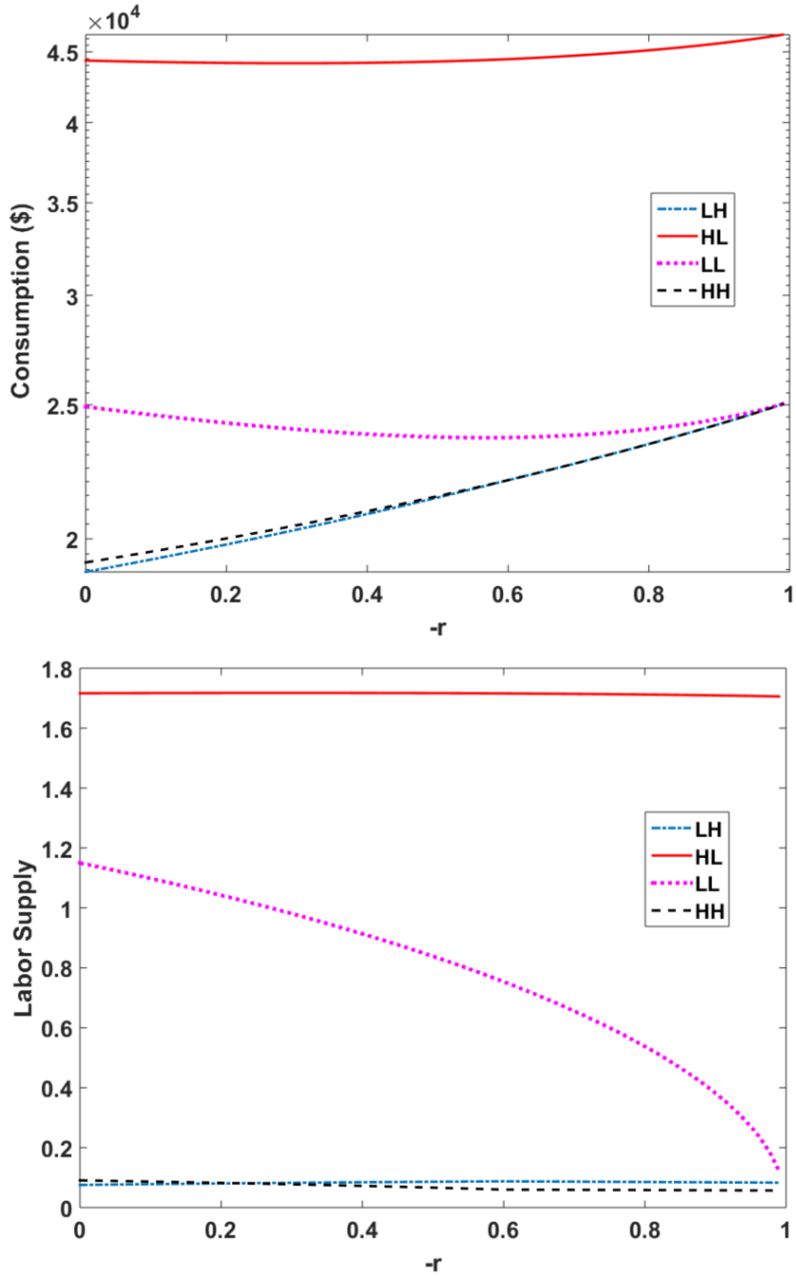
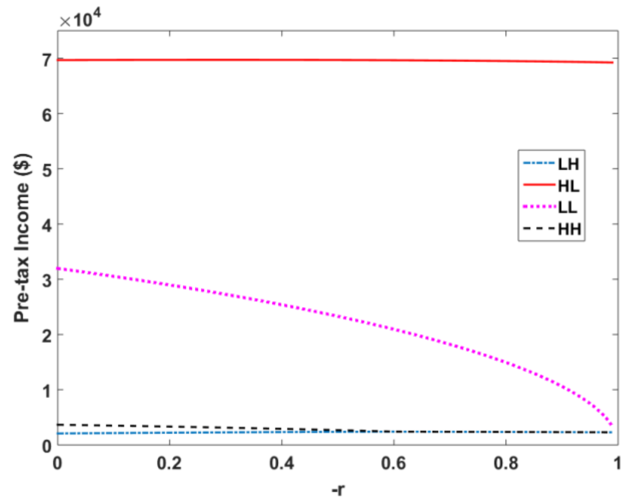
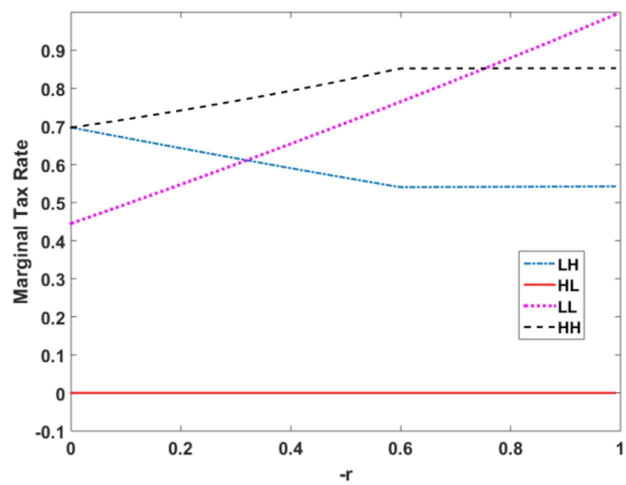


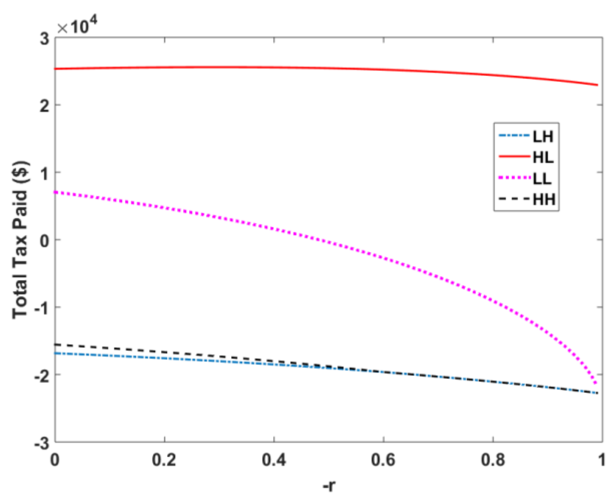

Figure 5. Top: Consumption, and Bottom: Labor-supply allocations as a function of the correlation coefficient under the Rawlsian objective (where the objective is to maximize the utility of the LH type).




(a)




(b)




(c)

Figure 6. (a) Pre-tax incomes, (b) marginal tax rates, and (c) total taxes paid under the Rawlsian objective.

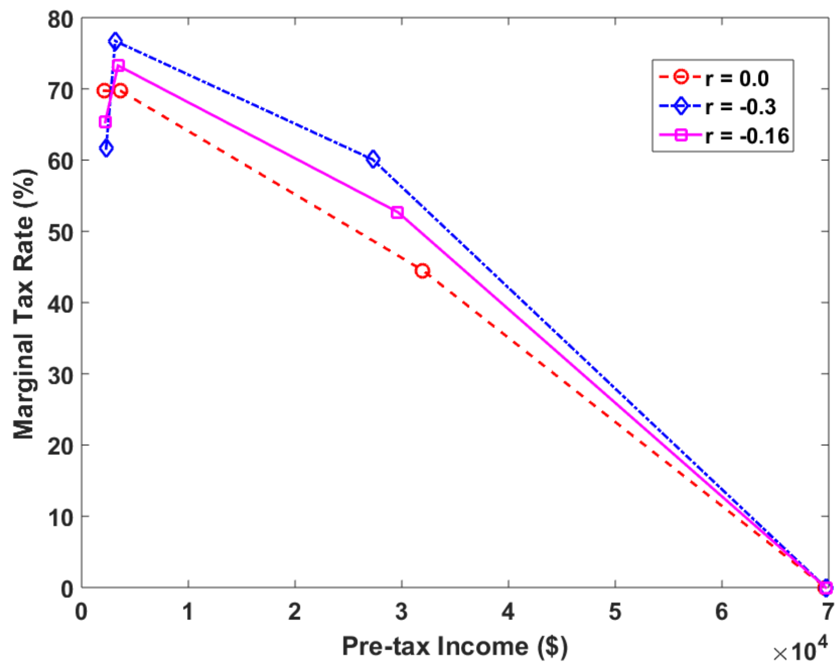



Figure 7. Revenue-maximizing (Rawlsian) marginal tax rates as a function of income for three different correlation coefficients (based on the allocations of the four types).

### 2.2.2. Sensitivity Analysis

I perform two types of sensitivity analysis in this section. For the first type, I keep the value of $(\sigma_H - \sigma_L)$ at 0.5 but increase the value of the average risk aversion ($\bar{\sigma}$) from 0.54 to higher numbers. I try two different values of $\bar{\sigma}$: 1 and 1.3. The first one, $\bar{\sigma} = 1$, is a popular choice in many macroeconomic studies and corresponds to the case where the income effect dominates the substitution effect for high-risk-aversion types, while the opposite is true for low-risk-aversion types. This would be one possible interpretation of the trends in Figure 1. The next one, $\bar{\sigma} = 1.3$, is just enough to make the income effect dominate the substitution effect for all types (the opposite of what we have with $\bar{\sigma} = 0.54$). Figure 8 shows the results for $\bar{\sigma} = 1$ and Figure 9 shows the results for $\bar{\sigma} = 1.3$. It can be seen that the seven conclusions summarized in the previous section hold for both values of $\bar{\sigma}$. The primary impact of increasing the average risk aversion is to shift up the MTR curves for all types except HL.

For the second type of sensitivity analysis I fix the risk aversion parameters and change the Frisch elasticity to 0.2 and 1, respectively, which is a range that covers most of the values used in the literature. Figures 10 and 11 show the results. It can be seen that the primary impact of a smaller Frisch elasticity is to shift the crossing point for the MTRs of the LH and HH types to the right, which means that, depending on the correlation coefficient, the initial bump in the MTRs as a function of income might disappears; this, for example, is what happens for a Frisch elasticity of 0.2 and $|r| < 0.16$.

To conclude, for weak correlations there is no bunching and MTRs are broadly declining with income. The primary impact of a stronger correlation on the MTRs in this case is to raise them in the middle while lowering them at the bottom.

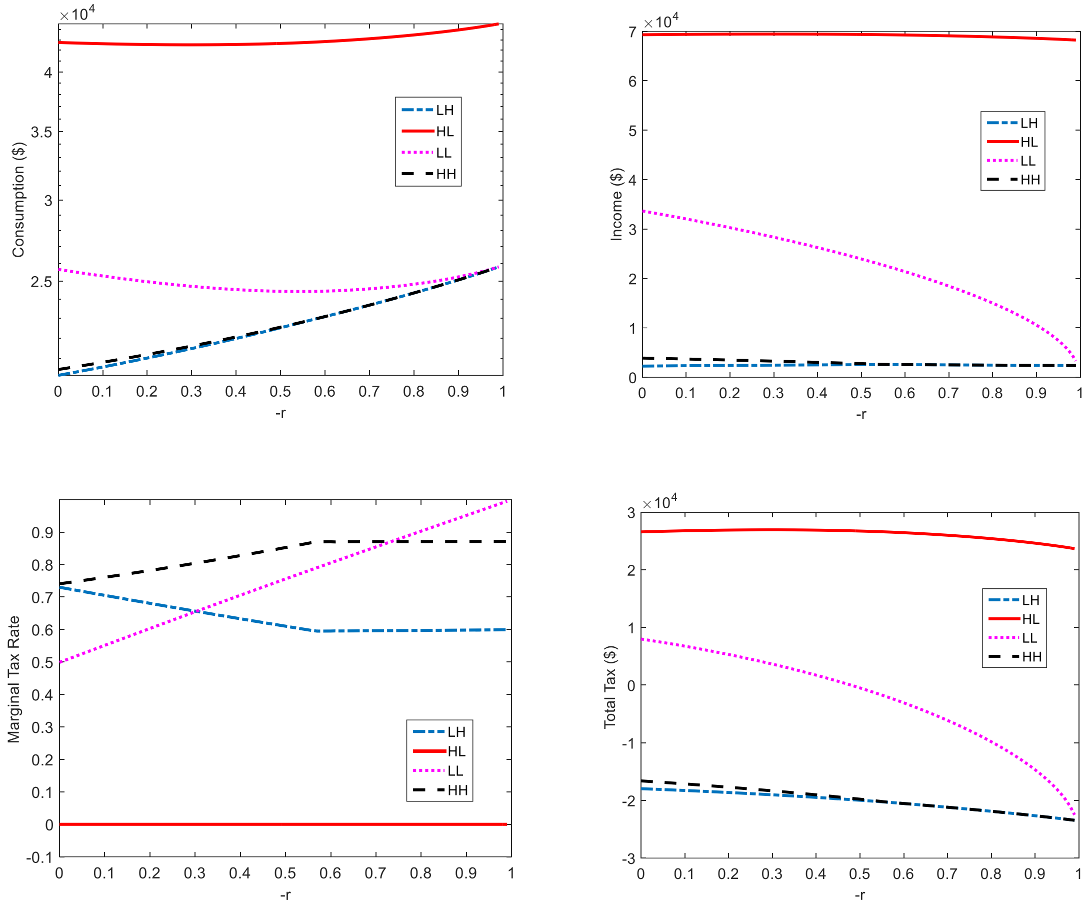



Figure 8. Sensitivity analysis for the 2×2 model with $\bar{\sigma} = 1$ and Frisch elasticity = 0.5.

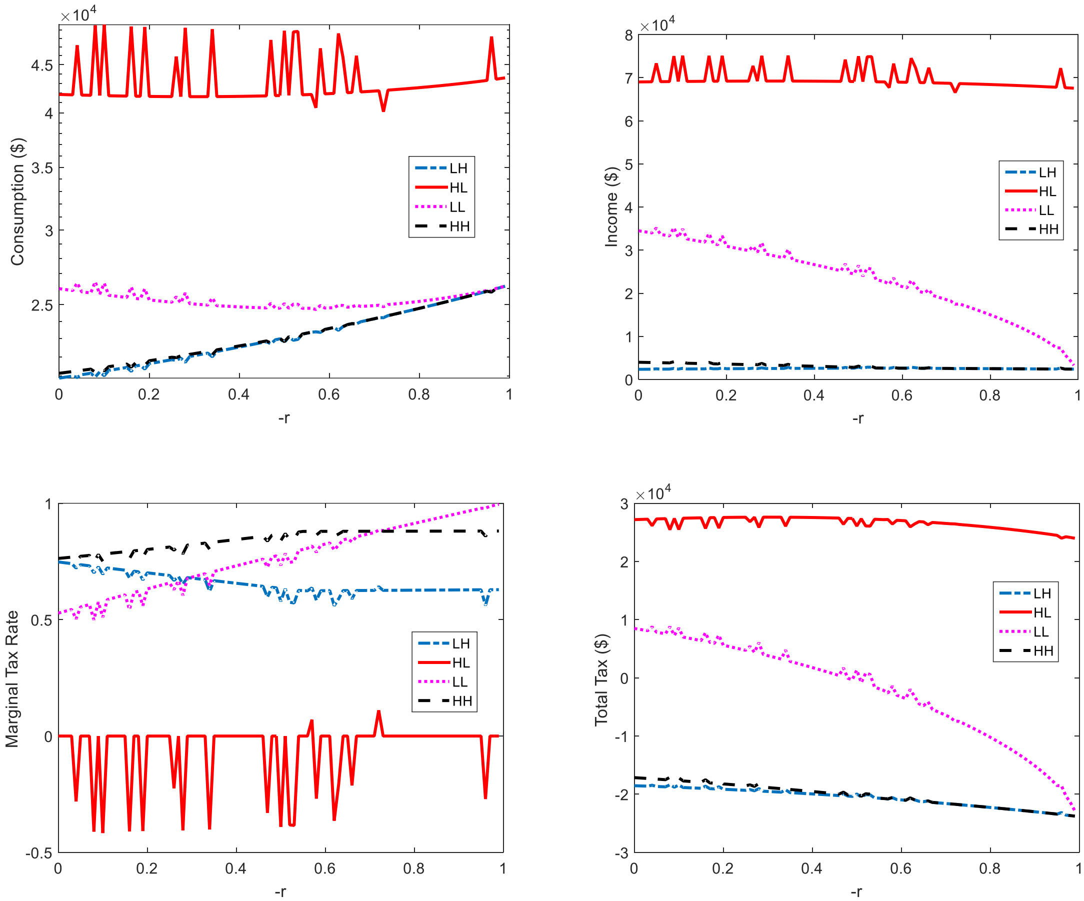



Figure 9. Sensitivity analysis for the 2×2 model with $\bar{\sigma}$ = 1.3 and Frisch elasticity = 0.5.

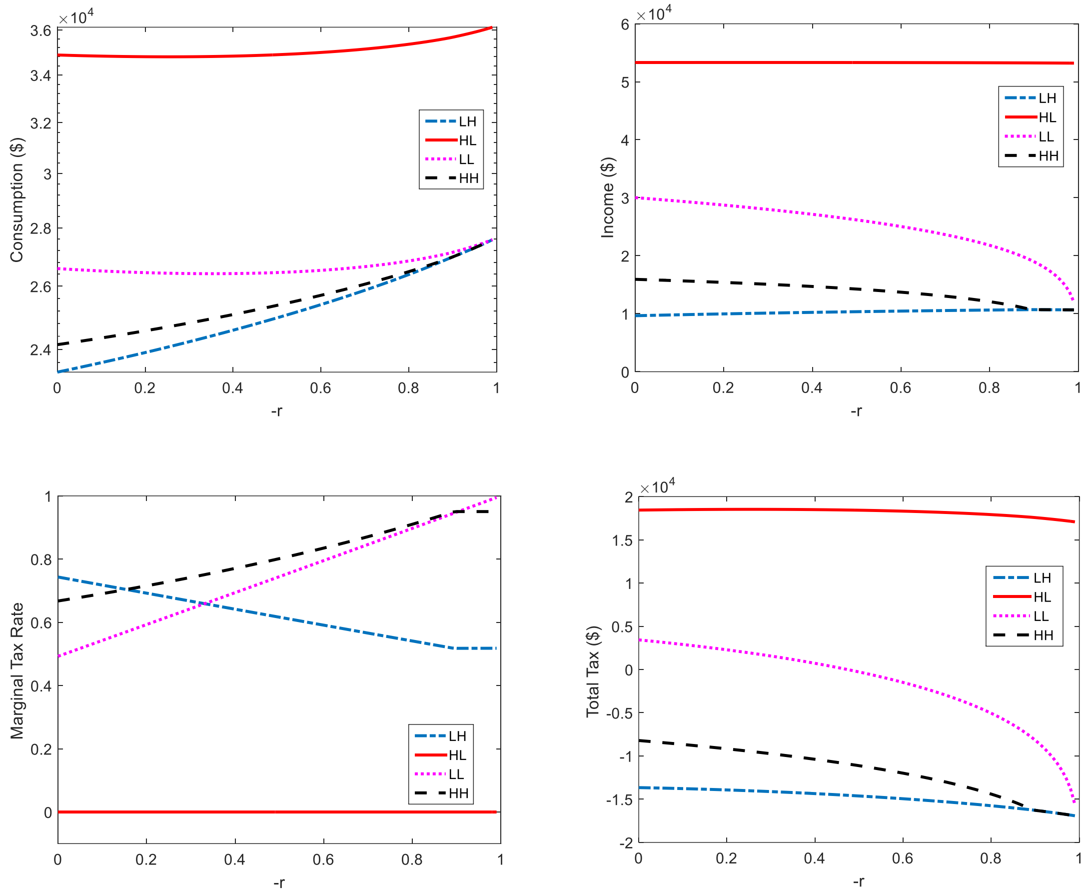



Figure 10. Sensitivity analysis for the 2×2 model with Frisch elasticity = 0.2 and $\bar{\sigma} = 0.54$.

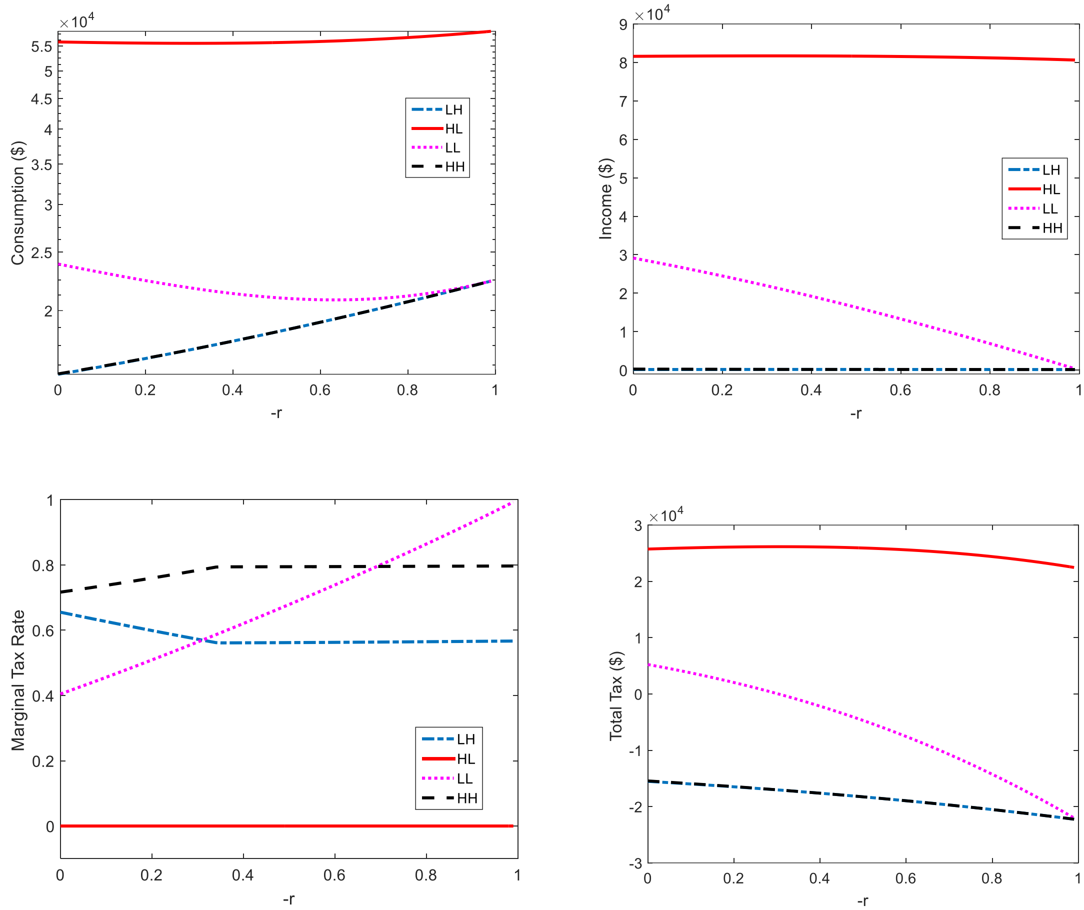



Figure 11. Sensitivity analysis for the 2×2 model with Frisch elasticity = 1 and $\bar{\sigma} = 0.54$.

(For small *r* the income of the HH type is slightly higher than that of the LH type, but the difference is not visible here.)

### 2.2.3. A Theoretical Contribution

In all of the simulations presented in the previous section, I noticed a consistent pattern of binding ICs:

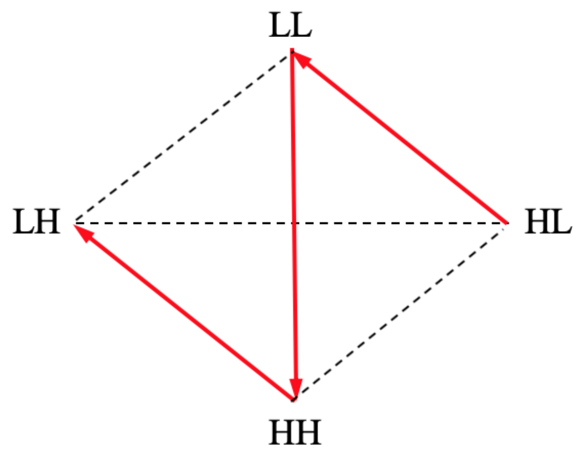



Figure 12. Binding incentive constraints in all of the simulated cases in the 2×2 model.

To analyze why this occurs, let us consider the indifference curves between income and consumption for each type and the 'single crossing' condition:

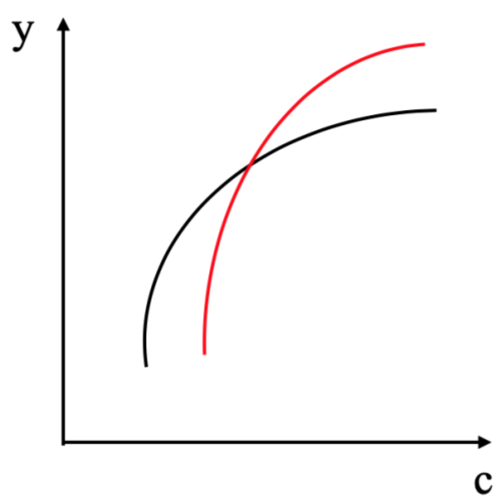



Figure 13. Income-Consumption indifference curves satisfying single crossing for two general types.

$$\frac{dy}{dc} = \frac{1}{\alpha y^{\gamma}} \frac{w_i^{\gamma+1}}{c^{\sigma_j}} \tag{10}$$

While it is easy to establish that 'within-group' single-crossing holds (LL over LH, HH over LH, HL over HH, HL over LL, and HL over LH) that does very little on its own to simplify the problem (note that $\sigma_L$-types are the 'high' types in the $\sigma$ dimension). However, we can establish a condition on *c* such that LL crosses over HH:

$$\frac{dy}{dc}(LL) > \frac{dy}{dc}(HH) \quad \text{if} \quad c^{\sigma_H - \sigma_L} > \left(\frac{w_H}{w_L}\right)^{\gamma+1}$$

$$\Longrightarrow \; c_{threshold} = \left(\frac{w_H}{w_L}\right)^{\frac{\gamma+1}{\sigma_H - \sigma_L}} \tag{11}$$

With plausible parameter values, there can *effective between-group* single-crossing between LL and HH for the relevant range of consumption allocations. The larger $\sigma_H - \sigma_L$ is compared with $\frac{w_H}{w_L}$, the more confident we can be of this result. Under such conditions, we can analyze the problem *as if* there is a type of one-dimensional ordering between the types (somewhat similar to [5]):

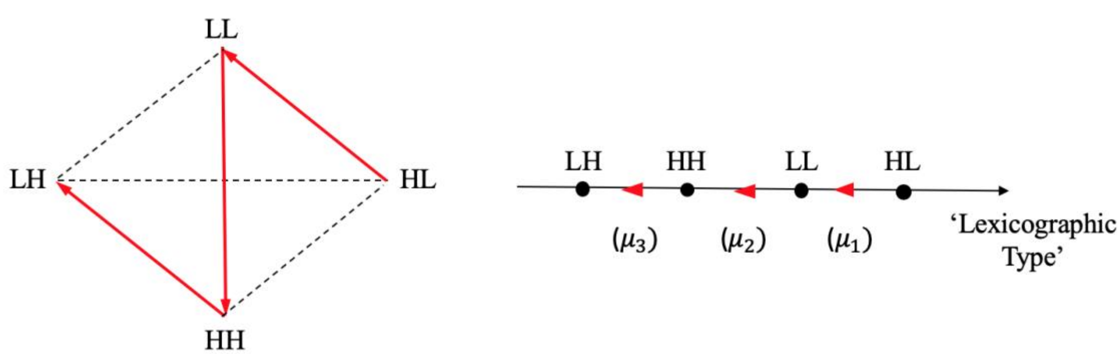



Figure 14. Ordering of types with between-group (between LL & HH) as well as within-group single-crossing in the 2×2 model.

Furthermore, assuming that utility is quasi-linear in *leisure* ($\gamma = 0$) and with a little bit of algebra, one can obtain a closed-form solution [5, 95, 99]:

$$t_{HL} = 0 \tag{12}$$

$$t_{LL} = \left(\frac{w_H}{w_L} - 1\right)\frac{1-r}{1+r} > 0 \quad \Rightarrow \quad \frac{\partial t_{LL}}{\partial r} < 0$$

$$t_{LH} = \left(\frac{w_H}{w_L} - 1\right)\frac{3+r}{1-r} > 0 \Rightarrow \quad \frac{\partial t_{LH}}{\partial r} > 0$$

$$\frac{\partial t_{HH}}{\partial r} = -\frac{t_{HH}}{\text{[A Positive Term]}} \ \Rightarrow \ \frac{\partial t_{HH}}{\partial r} < 0 \text{ as long as } t_{HH} > 0$$

$$-\frac{1}{3} < r < 0 \text{ (weak correlation):} \quad t_{LL} < t_{LH} \tag{13}$$

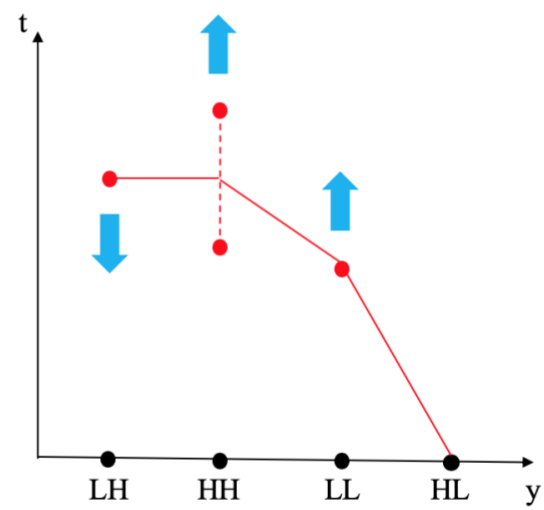



Figure 15. Effect of increasing the correlation coefficient on Rawlsian marginal tax rates by income/type.

It can be seen that the results are consistent with what we saw in Sections 2.2.1 and 2.2.2, where more plausible values of the Frisch elasticity were used (i.e. utility was *not* quasilinear in leisure). Moreover, there is a parallel between these formulas and the famous 'ABC' formula (as in Equation (16), derived using the first-order approach in the unidimensional case [100]), once you consider that the 'A' term in the ABC formula is reduced to unity with quasilinearity in leisure:

$$t_{LL} = \frac{1-r}{1+r}\left(\frac{w_H}{w_L} - 1\right) = 1.\frac{\pi_{HL}}{\pi_{LL}}.\left(\frac{w_H}{w_L} - 1\right) \tag{14}$$

$$t_{LH} = \frac{3+r}{1-r}\left(\frac{w_H}{w_L} - 1\right) = 1.\frac{1-\pi_{LH}}{\pi_{LH}}.\left(\frac{w_H}{w_L} - 1\right) \tag{15}$$

$$\frac{t}{1-t} = \underbrace{\frac{1+\varepsilon^u}{\varepsilon^c}}_{A_w}.\underbrace{\frac{1-F(w)}{wf(w)}}_{B_w}.\underbrace{\left[\frac{U_c}{1-F(w)}\int_w^\infty \frac{f(m)dm}{U_c^m}\right]}_{C_w} \tag{16}$$

## 2.3. Extension to an Infinite-Type Case

In this section, I extend the insights gained from the previous one to numerically solve a more complicated case using the first-order fixed-point algorithm provided by Mankiw, et al. (2009) [101]. Consider the following 2D distribution:

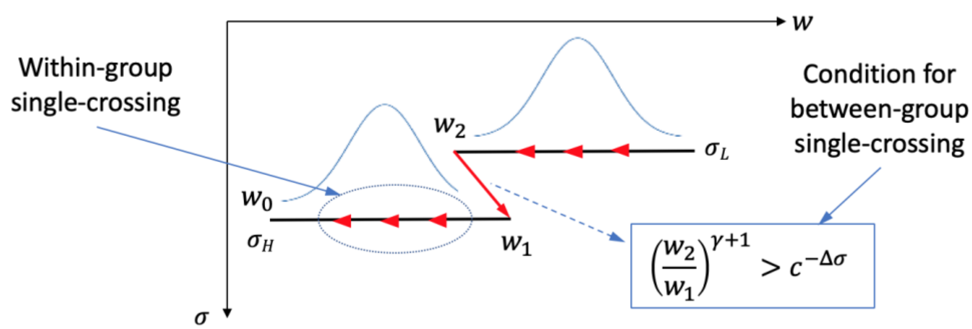



Figure 16. The 2×∞-type case analyzed in this section. The within- and between-group single-crossing conditions will ensure that the first-order simulation method can be applied to the whole problem.

Each ‘slice’ of $\sigma$ can have an arbitrary distribution of $w$ within it. I believe a natural choice for considering a discrete jump in risk aversion is to divide the population into employees ($\sigma_H$) and entrepreneurs ($\sigma_L$). Furthermore, the CPS data classifies the subjects as employees (~ 90% of the sample) or self-employed (~ 10% of the sample). It has been established that the self-employed are more risk-tolerant [102–107], have higher IQ scores [107–109], work longer hours [109–112], and earn more per hour than wage/salaried employees [109]. Note that higher risk-tolerance in this case is not merely a result of lower *absolute* risk aversion which can simply result from entrepreneurs being wealthier on average while having the same *relative* risk aversion as everybody else, but actually a result of them having a lower coefficient of *relative* risk aversion than the employees [107]. Entrepreneurs also have higher ETIs even after controlling for income and whether they itemize on their tax returns or not [113]. I take the 2018 March CPS data and approximate the hourly earnings of the employees and the self-employed with two lognormal distributions (the self-employed have a higher mean and median; then, I amend the second one at its 90th percentile (99th percentile for the overall sample; see [114]) with a Pareto tail with a thinness parameter of 1.5. It has been pointed out that more than half of the top 1% and 80% of the 0.1% of earners are active owner-managers of businesses [115]. It is also the case that the right tail of the employee distribution is dominated by non-founder CEOs, who arguably have higher *effective* ETIs due to scale and sorting effects than the rest of the employees [116–118]. Hence, I believe that when it comes to deriving top tax rates, it is sufficient to only amend the distribution of entrepreneurs with a Pareto tail. I use $\sigma_L = 0.25$ and $\sigma_H = 0.75$ so that the sample average is 0.7, in accordance with [33] while also taking a page from [14]. If the 'between-group' single-crossing condition is (as shown in Figure 16) is satisfied, then a slightly modified version of Equation (16) can be used for the fixed-point simulation algorithm in the revenue-maximizing/Rawlsian case [101]:

$$\sigma = \sigma_H\!: \;\; \frac{t^w}{1-t^w} = \frac{1+\varepsilon^u}{\varepsilon^c} . \frac{1}{wf(w)} . U_c^w \left[ \int_w^{w_1} \frac{f(m)dm}{U_c^m} + \int_{w_2}^{\infty} \frac{f(m)dm}{U_c^m} \right],$$

$$\sigma = \sigma_L\!: \;\; \frac{t^w}{1-t^w} = \frac{1+\varepsilon^u}{\varepsilon^c} . \frac{1}{wf(w)} . U_c^w \left[ \int_w^{\infty} \frac{f(m)dm}{U_c^m} \right] \tag{17}$$

Simulation results are shown in Figure 17. The top tax rate is lowered from about 77% to 69% when the second dimension of heterogeneity is introduced. Marginal tax rates are also lowered at the bottom of the income distribution, while being raised in the middle. The discontinuous behavior around $20,000 is reflective of a kink in the tax schedule, which arises due to the bunching of the highest employee type and the lowest entrepreneur type at that income level [96–99]. Figure 18 shows how compensated and uncompensated elasticities of labor supply change with income in the 2D case. It can be seen that the compensated elasticity at the very top is about 0.45, which is actually *lower* than the ETI estimate for those earning more than $100,000 per year as reported in [40] (i.e., 0.57); hence, the introduction of $\sigma$-heterogeneity in my model does not result in elasticity values that are out of the ordinary, and, in fact, allows for the higher top ETIs estimated in the literature to be partially caused by a lower $\sigma$ and partially caused by tax avoidance/evasion (see Section 1.3 for a more extensive discussion).

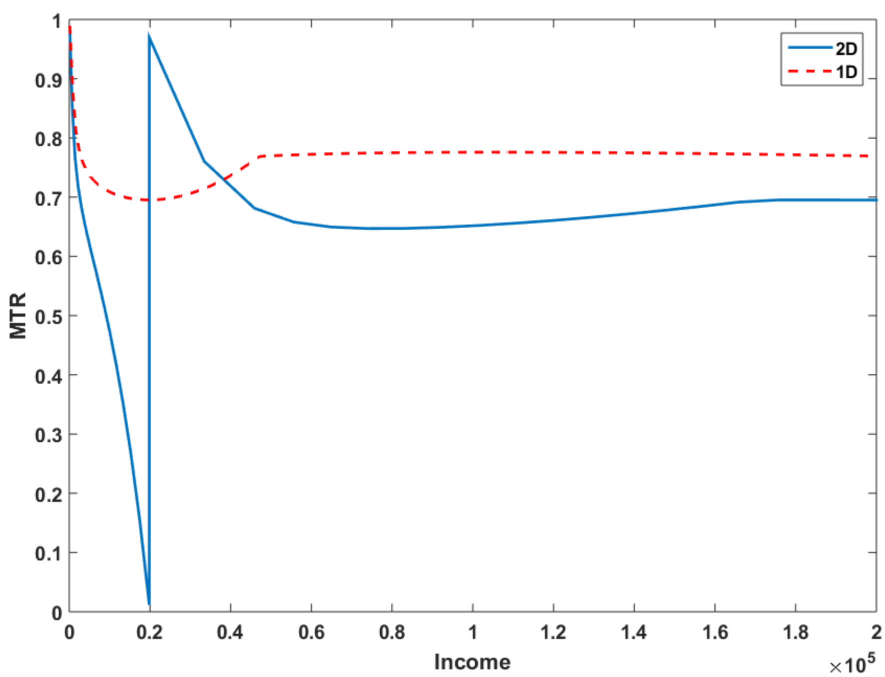



Figure 17. Revenue-maximizing marginal tax rates as a function of income in the case with no risk-aversion heterogeneity (1D) and the case with risk-aversion heterogeneity (2D) simulated in this section.

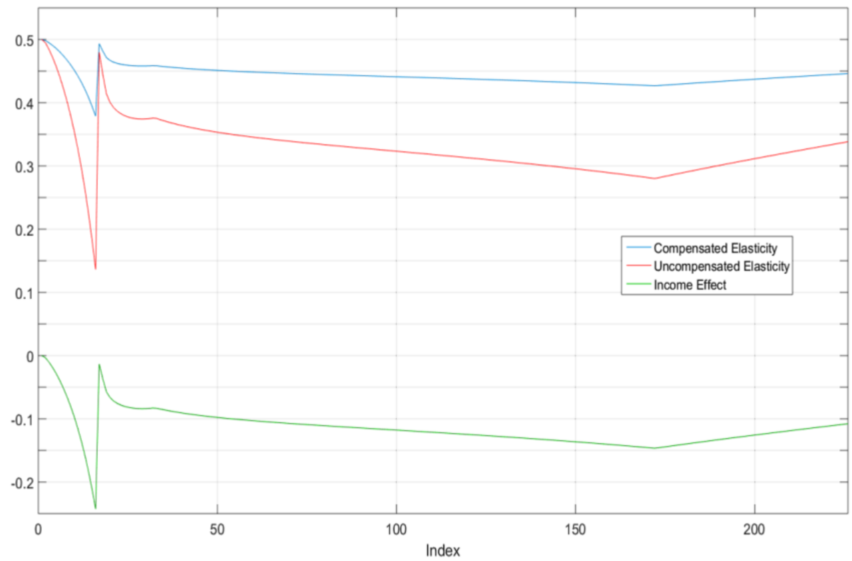



Figure 18. Compensated and uncompensated elasticities of labor supply for the 2D case from Figure 17. The income effect is just the difference between the two. (Note: Types are indexed from low to high according to their pre-tax income. This is the index shown on the x axis.)

Figure 19 shows that strengthening the correlation in the 2D case lowers the MTRs at the bottom, raises them in the middle, and lowers them at the top, while not changing them at the very top. This is consistent with the results from the 2×2 model.

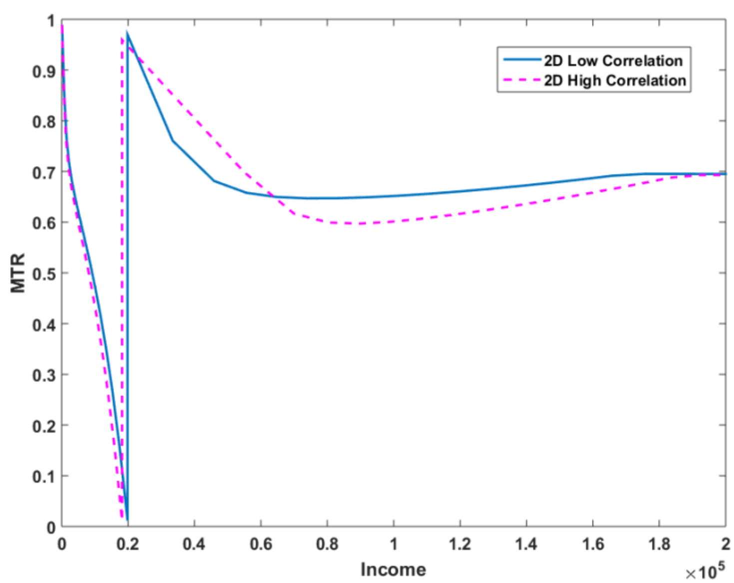



Figure 19. The effect of strengthening the $w$-$\sigma$ correlation by uniformly shifting out the $w$ curve for the $\sigma_L$ types (see Figure 16). The 'low-correlation' case is the same as the baseline 2D case in Figure 17.

## 2.4. Conclusion

I analyzed optimal Mirrleesian taxation in an environment where innate ability is imperfectly negatively correlated with individuals' coefficient of relative risk aversion, which is what we observe in experimental data. Revenue-maximizing marginal tax rates are lowered at the top and the bottom of the income distribution, while being raised in the middle compared to a benchmark in which all individuals have the same coefficient of relative risk aversion. The reduction at the very top, which is about 8 pp in my baseline case, is primarily a result of increased labor supply elasticities at that part of the income distribution. Strengthening the correlation leads to lower rates at the bottom and higher rates in the middle, but it does not alter the rates at the very top.

On a final note, it should be noted that, contra Blomquist & Christiansen (2008) [8] and Saez (2002) [119], introducing a sales tax will not help the social planner since it is preference for overall consumption (rather than a particular 'luxury' good) that is associated with higher ability. In other words, there is only one action that individuals take (choose pre-tax income, which, subject to the tax schedule they are facing, uniquely pins down their consumption). Hence, adding another tax instrument will not reveal any extra information about the individuals' hidden types [120].

# Chapter 3

# The Connection Between Cognitive Ability and Risk Attitudes: An Evolutionary Perspective

## 3.1. Introduction

In this chapter, I will build on some of the existing literature within the field of evolutionary economics that deal with the evolution of intelligence and risk attitudes (especially [121–123]) to argue that there are reasons for increased cognitive ability and increased risk taking to *coevolve*. Such "correlational selection" has been studied by evolutionary biologists in other contexts before (see, for example, [56–57, 124–125]). In short, correlational selection occurs when certain combinations of traits are favored by natural (or sexual) selection over others. However, I am not aware of any efforts so far to marry the evolutionary economics literature on risk attitudes with the idea of correlational selection from evolutionary biology. This evolutionary process should be supported by genetic correlation between the focal traits [57, 126], and, as I argued in Chapter 1, there is some suggestive evidence for such a correlation [55] (see Figure 20).

Some authors have argued for a causal relationship between cognitive ability on risk taking based on the observation that in experimental settings, subjects show a stronger preference for less risky lotteries over riskier ones when they are under cognitive load than when they aren't [18, 127–130]. However, results from the studies that use the proper *within-subject* design are only significant when the choice is between a certain payment and a lottery [127–129]. By contrast, when the choice is between two probabilistic lotteries, one riskier and one less risky, the results are not significant [129–130]. These observations appear to be more consistent with the explanation that increased preference for the certain payment under cognitive may result from the fact that evaluating lotteries is cognitively challenging, while evaluating certain outcomes is not. It should also be noted that the existence of such a causal link does not necessarily refute the existence of a coevolutionary process, as the two mechanisms can be complementary. In addition, I already argued that there is some evidence of genetic correlation between the two [55]. Finally, Branas-Garza & Rustichini (2011) report that higher exposure to testosterone is associated with both higher cognitive ability and higher risk seeking [17]. They estimate that 30–70% of the effect of testosterone on attitude to risk in males (but not in females) is mediated by cognitive ability, which still leaves some room for coevolutionary processes such as the one explored in the present chapter.

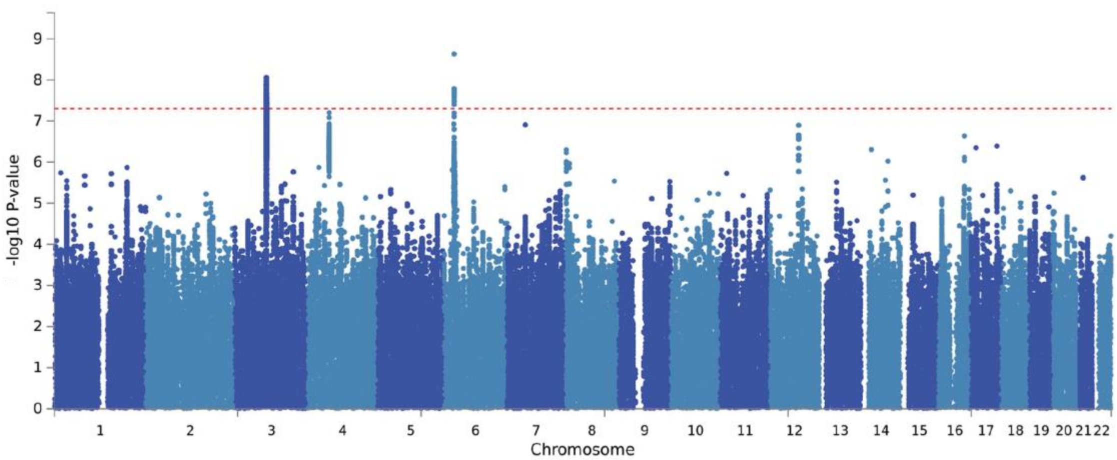



Figure 20. The 'Manhattan plot' of genomic locations reaching GWAS significance (i.e. $p < 5 \times 10^{-8}$) for self-reported risk-taking behavior (adopted from Strawbridge, et al. (2018) [55]). The hit on chromosome 3 is within the CADM2 gene, which has been found to be associated with executive functioning, information processing speed, and educational attainment. CADM2 encodes the synaptic cell adhesion molecule 2, which is important in maintaining the synaptic circuitry of the brain.

## 3.2. Model

Following the tradition in evolutionary economics, I will assume that the evolution of economically relevant traits can be analyzed as the outcome of a 'nested' optimization problem [121–123]: The individual, taking his traits (including innate abilities and preference parameters) as given, chooses some course of action or allocation in order to maximize his utility; *Nature*, on the other hand, 'chooses' the values of those innate traits such that the optimal course of action chosen by the individual would maximize the 'evolutionary fitness' of individuals of his type, which would, in the long run, tilt the composition of the population toward the 'fittest' type (i.e. those carrying the genes associated with the 'optimal' traits).

In the present work, I will abstract away from kin selection and assume that evolutionary fitness is determined by 'reproductive success', which can be quantified by the expected number of (surviving) offspring [124]. As argued in [121–122], the expected number of offspring is a *concave function of resources/consumption*, which in turn leads to the evolution of risk-averse preferences over consumption. In such an environment, concave preferences for consumption will evolve as a result of natural selection. Evolutionary fitness, defined in this manner, has at least two components: The *viability* component, which is about the probability of surviving to reproductive age, and the *fertility* component, which is about the number of mates acquired and the number of offspring produced from each mating [124]. I will assume (for the sake of analytical tractability) that each individual lives for two periods: They are born at $t = 0$, reach maturity (reproductive age) and acquire consumable resources at $t = 1$, and then use those resources to acquire mates and produce offspring until they die at $t = 2$ (see Figure 21). I will follow [121–122] in assuming that $c$ units of consumption are converted to $c^{\alpha}$ 'units of offspring' on average, with $0 < \alpha < 1$ to capture the concavity discussed above. This process is repeated every generation:

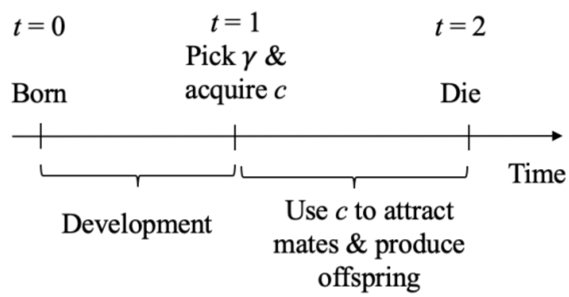



Figure 21. The lifecycle of an individual in the proposed evolutionary model.

As higher intelligence requires a larger/more complex brain, it can be thought of as an investment with an upfront cost during development [123]. This cost can come in the form of a reduced chance of survival to reproductive age or impaired development along other dimensions, as it diverts scarce resources from bodily growth. I will assume that this costs the individual $C(\theta)$ in fitness units down the road, with $\theta$ being a measure of his intelligence and $C(.)$ being an increasing and *convex* function of $\theta$ (somewhat similar to [123]). On the other hand, a higher $\theta$ can benefit the individual later in life by allowing him to convert the *same* amount of resources into a larger number of offspring. Some possible mechanisms for this are increased longevity when reproductive (for example, Deary & Der (2005) find that people with a standard-deviation disadvantage in IQ score relative to others at age 11 were only 79% as likely to live to age 76, and the relationship appears to be fully mediated by the positive association between *reaction times* and IQ [131]) or higher 'efficiency' (per resource units) in luring more fertile mates [121–122], which ultimately will result in a higher return on a given amount of resources in terms of the number of offspring. As it will become clear shortly, I am adopting this framework to explore whether I can explain a stronger tolerance for riskier lotteries by the more intelligent individuals even when the probabilities and payoffs of the lotteries are *fixed and known*, not whether more intelligent individuals are better at resource acquisition. I will assume that the higher 'fitness returns' to resources are captured by a multiplicative factor $F(\theta)$, which is an increasing and *concave* function of $\theta$ (somewhat similar to [123]). Putting all of these together, the number of offspring per adult will be given by:

$$E[d] = F(\theta).E[c^{\alpha}] - C(\theta) \tag{18}$$

At time 1, each individual is endowed with a unit of time which he can divide between a 'safe' activity that will return $R_0 = e^{r_0}$ units of consumption for sure (let us call this activity 'gathering') and a 'risky' activity which will return $R$ units of consumption subject to chance (let us call this activity 'hunting'). I will intentionally assume that $R$ is lognormally distributed to maintain mathematical tractability and build upon the existing literature on choice under uncertainty. Furthermore, this is not an unreasonable assumption since hunting is an activity that, with some probability, can yield nearly zero in terms of consumable resources (e.g. if you miss and only manage to catch a bird or squirrel along the way) but also, albeit with diminishing probability, can result in the catching of 'big game' at the other extreme, with the middle of the probability distribution corresponding to the more likely outcome of catching 'small game'. The choice facing the individual is what fraction of his time ($\gamma$) to allocate to the risky activity:

$$\max_{\gamma} u(c) = c^{1-\rho} \tag{19}$$

$$c = (1-\gamma)R_0 + \gamma R \tag{20}$$

$$R = e^r, \qquad r \sim N(\bar{r}, \sigma_r) \tag{21}$$

This is a standard portfolio choice problem with CRRA utility and has a well-known solution ($\rho$ here is the CRRA coefficient). I will make one more simplifying assumption here for the sake of mathematical tractability: Let it be the case that $R_0$ (i.e. the return to 'gathering') is so small that, regardless of the choice of $\gamma$, the 'safe' component of consumption will be nowhere near the minimum necessary to attract a mate and will be entirely spent on the individual's own survival needs. Hence, the only part of the individual's overall resources that enters the offspring production function is the 'risky' component, resulting in a modified version of Equation (18):

$$E[d] = F(\theta).E[c_r^\alpha] - C(\theta) = F(\theta).E[(\gamma R)^\alpha] - C(\theta) \tag{22}$$

## 3.3. Results

The portfolio choice problem in Equation (19) has a well-known solution [132]:

$$\gamma^* = \frac{\bar{r} - r_0 + {\sigma_r}^2}{\rho {\sigma_r}^2} \tag{23}$$

$$\mu \coloneqq E[log(c_r)] = E[log(\gamma^*)] + E[logR] = log\left(\frac{\bar{r}-r_0+{\sigma_r}^2}{\rho{\sigma_r}^2}\right) + \bar{r} \tag{24}$$

$$\sigma \coloneqq SD[log(c_r)] = SD[log(\gamma^*)] + SD[logR] = \sigma_r \tag{25}$$

Given all of the above, I will analyze nature's optimal 'choice' of $\theta$ for any level of $\rho$:

$$\max_\theta E[d] = F(\theta).E[c_r^\alpha] - C(\theta) \tag{26}$$

The resulting FOC is:

$$\frac{C'(\theta)}{F'(\theta)} = E[c_r^\alpha] \tag{27}$$

Note that the RHS of Equation (27) is the (raw) $\alpha$-th moment of a lognormal variable, which, with $\mu$ and $\sigma$ being the mean and standard deviation of the corresponding normal variable (see Equations 24–25), is equal to $e^{\alpha\mu+\alpha^2\sigma^2/2}$ . Hence the optimality condition is:

$$\frac{C'(\theta)}{F'(\theta)} = e^{\alpha\mu+\alpha^2\sigma_r^2/2} \tag{28}$$

What happens if the CRRA coefficient $\rho$ is *lower*? From Equation (24), $\mu$ is a *decreasing* function of $\rho$, hence it will go *up*. On the other hand, the second term of the sum in the exponent of the RHS in Equation (28) is independent of $\rho$. As all the terms in the exponent are positive, an increase in $\mu$ will imply an increase in the RHS. For the optimality condition to be satisfied, the LHS needs to go up as well, which, given the convexity of $C(\theta)$ and the concavity of $F(\theta)$, can only happen with an *increase* in $\theta$. Hence, more risk-tolerant individuals will be selected for a comparatively higher level of intelligence. The intuition behind this result is pretty straightforward: With convex upfront costs and concave benefits later in life, anything that amplifies the benefit side will justify a larger investment in intelligence; here, higher willingness to take risks performs that function.

Equation (12) also tells us that the optimal value of $\theta$ is more sensitive to the value of $\rho$ when $\alpha$ is larger, as the $\rho$-dependent $\mu$ variable in the exponent of the RHS is multiplied by $\alpha$. Hence, a larger $\alpha$ will result in a stronger negative correlation between $\rho$ and $\theta$. This might explain why some studies find the intelligence-risk-tolerance to be much stronger among males than females [17], as males probably face less steeply diminishing returns to additional resource/mate acquisition in terms of evolutionary fitness, and hence, can be assumed to have a larger $\alpha$ (i.e. closer to 1). This is essentially a version of the so-called "Bateman's Principles" [124, 133], which are used to explain the fact that among mammals, males are much more likely to be polygamous than females [121–122].

To conclude, I demonstrated a theoretical mechanism that leads to more risk-tolerant individuals being selected, through the process of evolution, for a comparatively higher level of intelligence than less risk-tolerant individuals. This is consistent with the observed negative correlation between IQ and risk aversion discussed throughout this thesis. Note that the proposed model does not work in the other direction, i.e., for any level of intelligence, it is optimal from a fitness perspective for nature to 'choose' the lowest possible value of the CRRA coefficient $\rho$ (in this case, $\rho = 0$, which corresponds to risk neutrality). This is probably due to the fact that the returns to the 'risky' activity in my model are bounded from below, but not from above. Hence, individuals don't face a fitness cost for having a higher tolerance for risk the way they do for having higher intelligence (through the $C(\theta)$ function). Therefore, the way forward is probably to introduce higher costs to having a higher risk-tolerance/lower $\rho$ into the model, which can be interpreted as the risk of *death* in the act of hunting or competition with other males. The results in this chapter should be viewed as exploratory, aimed at proposing an agenda for future theoretical and empirical research in evolutionary economics.

# Bibliography


1. Mirrlees, James A., “An exploration in the theory of optimum income taxation.” *The Review of Economic Studies* 38, no. 2 (1971): 175-208.

2. Sandmo, Agnar. “Optimal redistribution when tastes differ.” *FinanzArchiv/Public Finance Analysis* (1993): 149-163.

3. Tarkiainen, Ritva, and Matti Tuomala. “Optimal nonlinear income taxation with a two-dimensional population; A computational approach.” *Computational Economics* 13, no. 1 (1999): 1-16.

4. Cuff, Katherine. “Optimality of workfare with heterogeneous preferences.” *Canadian Journal of Economics* 33, no. 1 (2000): 149-174.

5. Boadway, Robin, Maurice Marchand, Pierre Pestieau, and Maria del Mar Racionero. “Optimal redistribution with heterogeneous preferences for leisure.” *Journal of Public Economic Theory* 4, no. 4 (2002): 475-498.

6. Judd, Kenneth L., Ding Ma, Michael A. Saunders, and Che-Lin Su. “Optimal Income Taxation with Multidimensional Taxpayer Types.” (2017).

7. Tarkiainen, Ritva, and Matti Tuomala. “On optimal income taxation with heterogeneous work preferences.” *International Journal of Economic Theory* 3, no. 1 (2007): 35-46.

8. Blomquist, Sören, and Vidar Christiansen. “Taxation and heterogeneous preferences.” *FinanzArchiv: Public Finance Analysis* 64, no. 2 (2008): 218-244.

9. Choné, Philippe, and Guy Laroque. “Negative marginal tax rates and heterogeneity.” *American Economic Review* 100, no. 5 (2010): 2532-47.

10. Lockwood, Benjamin B., and Matthew Weinzierl. “De Gustibus non est Taxandum: Heterogeneity in preferences and optimal redistribution.” *Journal of Public Economics* 124 (2015): 74-80.

11. Jacquet, Laurence, and Etienne Lehmann. “Optimal taxation with heterogeneous skills and elasticities: Structural and sufficient statistics approaches.” (2016).

12. Jacquet, Laurence, and Etienne Lehmann. “Optimal income taxation with composition effects.” *Journal of the European Economic Association* (2017).

13. Bergstrom, Katy, and William Dodds. *Using Labor Supply Elasticities to Learn about Income Inequality: The Role of Productivities versus Preferences.* The World Bank, 2020.

14. Burks, Stephen V., Jeffrey P. Carpenter, Lorenz Goette, and Aldo Rustichini. "Cognitive skills affect economic preferences, strategic behavior, and job attachment." *Proceedings of the National Academy of Sciences* 106, no. 19 (2009): 7745-7750.

15. Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. "Are risk aversion and impatience related to cognitive ability?" *American Economic Review* 100, no. 3 (2010): 1238-60.

16. Dave, Chetan, Catherine C. Eckel, Cathleen A. Johnson, and Christian Rojas. "Eliciting risk preferences: When is simple better?." *Journal of Risk and Uncertainty* 41, no. 3 (2010): 219-243.

17. Branas-Garza, Pablo, and Aldo Rustichini. "Organizing effects of testosterone and economic behavior: not just risk taking." *PloS One* 6, no. 12 (2011): e29842.

18. Benjamin, Daniel J., Sebastian A. Brown, and Jesse M. Shapiro. "Who is 'behavioral'? Cognitive ability and anomalous preferences." *Journal of the European Economic Association* 11, no. 6 (2013): 1231-1255.

19. Frederick, Shane. "Cognitive reflection and decision making." *Journal of Economic Perspectives* 19, no. 4 (2005): 25-42.

20. Beauchamp, Jonathan P., David Cesarini, and Magnus Johannesson. "The psychometric and empirical properties of measures of risk preferences." *Journal of Risk and Uncertainty* 54, no. 3 (2017): 203-237.

21. Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman, and Uwe Sunde. "Global evidence on economic preferences." *The Quarterly Journal of Economics* 133, no. 4 (2018): 1645-1692.

22. Chapman, Jonathan, Erik Snowberg, Stephanie Wang, and Colin Camerer. *Loss attitudes in the US population: Evidence from dynamically optimized sequential experimentation (DOSE).* No. w25072. National Bureau of Economic Research, 2018.

23. Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde. “On the Relationship between Cognitive Ability and Risk Preference.” *Journal of Economic Perspectives* 32, no. 2 (2018): 115-34.

24. Lilleholt, Lau. “Cognitive ability and risk aversion: A systematic review and meta analysis.” *Judgment & Decision Making* 14, no. 3 (2019).

25. Amador, Luis, Pablo Brañas-Garza, Antonio M. Espín, Teresa Garcia, and Ana Hernández. “Consistent and inconsistent choices under uncertainty: The role of cognitive abilities.” (2019).

26. Taylor, Matthew P. “Bias and brains: Risk aversion and cognitive ability across real and hypothetical settings.” *Journal of Risk and Uncertainty* 46, no. 3 (2013): 299-320.

27. Taylor, Matthew P. “Are high-ability individuals really more tolerant of risk? A test of the relationship between risk aversion and cognitive ability.” *Journal of Behavioral and Experimental Economics* 63 (2016): 136-147.

28. Almeida, Sergio. “Do as I Do, Not as I Say: Incentivization and the Relationship Between Cognitive Ability and Risk Aversion.” *Revista Brasileira de Economia* 73, no. 4 (2019): 413-434.

29. Andersson, Ola, Håkan J. Holm, Jean-Robert Tyran, and Erik Wengström. “Risk aversion relates to cognitive ability: Preferences or Noise?.” *Journal of the European Economic Association* 14, no. 5 (2016): 1129-1154.

30. Falk, Armin, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde. “The Preference Survey Module: A Validated Instrument for Measuring Risk, Time, and Social Preferences.” (2016).

31. Angrisani, Marco, and Maria Casanova. “Understanding Heterogeneity in Household Portfolios: The Role of Cognitive Ability and Preference Parameters.” Mimeo, USC (2011).

32. Kimball, Miles S., Fumio Ohtake, Daniel Reck, Yoshiro Tsutsui, and Fudong Zhang. “Diminishing Marginal Utility Revisited.” *Available at SSRN 2592935* (2015).

33. Chetty, Raj. “A new method of estimating risk aversion.” *American Economic Review* 96, no. 5 (2006): 1821-1834.

34. Costa, Dora L. “The Wage and the Length of the Work Day: From the 1890s to 1991.” *Journal of Labor Economics* 18, no. 1 (2000): 156-181.

35. Boppart, Timo, and Rachel Ngai. *Rising inequality and trends in leisure*. CEPR Discussion Paper no. DP12325 (2017).

36. Bick, Alexander, Nicola Fuchs-Schündeln, and David Lagakos. "How do hours worked vary with income? Cross-country evidence and implications." *American Economic Review* 108, no. 1 (2018): 170-99.

37. Boppart, Timo, and Per Krusell. "Labor supply in the past, present, and future: a balanced-growth perspective." *Journal of Political Economy* 128, no. 1 (2020): 118-157.

38. Boppart, Timo, Per Krusell, and J. K. Olsson. *Labor Supply in the Past, Present, and Future: Who and How Much?*. Working paper, Institute for International Economic Studies, Stockholm University, 2017.

39. Kimball, Miles S., and Matthew D. Shapiro. *Labor Supply: Are the income and substitution effects both large or both small?*. No. w14208. National Bureau of Economic Research, 2008.

40. Gruber, Jon, and Emmanuel Saez. "The elasticity of taxable income: evidence and implications." *Journal of Public Economics* 84, no. 1 (2002): 1-32.

41. Heim, Bradley T. "The effect of recent tax changes on taxable income: Evidence from a new panel of tax returns." *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management* 28, no. 1 (2009): 147-163.

42. Auten, Gerald, and David Joulfaian. "The Taxable Income Elasticity of High-Income Taxpayers: Evidence from a Long Panel." *Available at SSRN 1406641* (2009).

43. Weber, Caroline E. "Toward obtaining a consistent estimate of the elasticity of taxable income using difference-in-differences." *Journal of Public Economics* 117 (2014): 90-103.

44. Mertens, Karel, and José Luis Montiel Olea. "Marginal tax rates and income: New time series evidence." *The Quarterly Journal of Economics* 133, no. 4 (2018): 1803-1884.

45. Mankiw, N. Gregory, and Matthew Weinzierl. "The optimal taxation of height: A case study of utilitarian income redistribution." *American Economic Journal: Economic Policy* 2, no. 1 (2010): 155-76.

46. Ghez, Gilbert, and Gary S. Becker. "The Allocation of Time over the Life Cycle." In *The Allocation of Time and Goods over the Life Cycle*, pp. 83-132. NBER, 1975.

47. Luciano, Michelle, Mark A. Wainwright, Margaret J. Wright, and Nicholas G. Martin. “The heritability of conscientiousness facets and their relationship to IQ and academic achievement.” *Personality and Individual Differences* 40, no. 6 (2006): 1189-1199.

48. Rikoon, Samuel H., Meghan Brenneman, Lisa E. Kim, Lale Khorramdel, Carolyn MacCann, Jeremy Burrus, and Richard D. Roberts. “Facets of conscientiousness and their differential relationships with cognitive ability factors.” *Journal of Research in Personality* 61 (2016): 22-34.

49. Stanek, Kevin C. “Meta-analyses of personality and cognitive ability.” *PhD diss.*, University of Minnesota, 2014.

50. DeYoung, Colin G., Lena C. Quilty, and Jordan B. Peterson. “Between facets and domains: 10 aspects of the Big Five.” *Journal of Personality and Social Psychology* 93, no. 5 (2007): 880.

51. Boyce, Christopher J., and Alex M. Wood. “Personality and the marginal utility of income: Personality interacts with increases in household income to determine life satisfaction.” *Journal of Economic Behavior & Organization* 78, no. 1-2 (2011): 183-191.

52. Burke, Christopher J., Christian Brünger, Thorsten Kahnt, Soyoung Q. Park, and Philippe N. Tobler. “Neural integration of risk and effort costs by the frontal pole: only upon request.” *Journal of Neuroscience* 33, no. 4 (2013): 1706-1713.

53. Burke, Christopher J., Alexander Soutschek, Susanna Weber, Anjali Raja Beharelle, Ernst Fehr, Helene Haker, and Philippe N. Tobler. “Dopamine receptor-specific contributions to the computation of value.” *Neuropsychopharmacology* 43, no. 6 (2018): 1415.

54. Zénon, Alexandre, Sophie Devesse, and Etienne Olivier. “Dopamine manipulation affects response vigor independently of opportunity cost.” *Journal of Neuroscience* 36, no. 37 (2016): 9516-9525.

55. Strawbridge, Rona J., Joey Ward, Breda Cullen, Elizabeth M. Tunbridge, Sarah Hartz, Laura Bierut, Amy Horton, et al. “Genome-wide analysis of self-reported risk-taking behaviour and cross-disorder genetic correlations in the UK Biobank cohort.” *Translational Psychiatry* 8, no. 1 (2018): 1-11.

56. Lande, Russell, and Stevan J. Arnold. "The measurement of selection on correlated characters." *Evolution* 37, no. 6 (1983): 1210-1226.

57. Lande, Russell. "The genetic correlation between characters maintained by selection, linkage and inbreeding." *Genetics Research* 44, no. 3 (1984): 309-320.

58. Tenhunen, Sanna, and Matti Tuomala. "On optimal lifetime redistribution policy." *Journal of Public Economic Theory* 12, no. 1 (2010): 171-198.

59. Diamond, Peter, and Johannes Spinnewijn. "Capital income taxes with heterogeneous discount rates." *American Economic Journal: Economic Policy* 3, no. 4 (2011): 52-76.

60. Golosov, Mikhail, Maxim Troshkin, Aleh Tsyvinski, and Matthew Weinzierl. "Preference heterogeneity and optimal capital income taxation." *Journal of Public Economics* 97 (2013): 160-175.

61. Moser, Christian, and Pedro Olea de Souza e Silva. "Optimal paternalistic savings policies." *Columbia Business School Research Paper* 17-51 (2019).

62. Mankiw, N. G. "Consumer durables and the real interest rate." *Review of Economics and Statistics* (1985).

63. Mehra, Rajnish, and Edward C. Prescott. "The equity premium: A puzzle." *Journal of Monetary Economics* 15, no. 2 (1985): 145-161.

64. Cochrane, John H., and Lars Peter Hansen. "Asset pricing explorations for macroeconomics." *NBER Macroeconomics Annual* 7 (1992): 115-165.

65. Guo, Hui, and Robert F. Whitelaw. "Uncovering the risk–return relation in the stock market." *The Journal of Finance* 61, no. 3 (2006): 1433-1463.

66. Hansen, Lars Peter, and Kenneth J. Singleton. "Stochastic consumption, risk aversion, and the temporal behavior of asset returns." *Journal of Political Economy* 91, no. 2 (1983): 249-265.

67. Campbell, John Y., and John H. Cochrane. "By force of habit: A consumption-based explanation of aggregate stock market behavior." *Journal of Political Economy* 107, no. 2 (1999): 205-251.

68. Grüne, Lars, and Willi Semmler. "Asset pricing with loss aversion." *Journal of Economic Dynamics and Control* 32, no. 10 (2008): 3253-3274.

69. Holt, Charles A., and Susan K. Laury. “Risk aversion and incentive effects.” *American Economic Review* 92, no. 5 (2002): 1644-1655.

70. Harrison, Glenn W., Morten I. Lau, and E. Elisabet Rutström. “Estimating risk attitudes in Denmark: A field experiment.” *The Scandinavian Journal of Economics* 109, no. 2 (2007): 341-368.

71. Andersen, Steffen, Glenn W. Harrison, Morten I. Lau, and E. Elisabet Rutström. “Eliciting risk and time preferences.” *Econometrica* 76, no. 3 (2008): 583-618.

72. Wakker, Peter P. “Explaining the characteristics of the power (CRRA) utility family.” *Health Economics* 17, no. 12 (2008): 1329-1344.

73. Filippin, Antonio, and Paolo Crosetto. “A reconsideration of gender differences in risk attitudes.” *Management Science* 62, no. 11 (2016): 3138-3160.

74. Saha, Atanu. “Expo-power utility: A ‘flexible’form for absolute and relative risk aversion.” *American Journal of Agricultural Economics* 75, no. 4 (1993): 905-913.

75. Booij, Adam S., and Gijs Van de Kuilen. “A parameter-free analysis of the utility of money for the general population under prospect theory.” *Journal of Economic Psychology* 30, no. 4 (2009): 651-666.

76. Booij, Adam S., Bernard MS Van Praag, and Gijs Van De Kuilen. “A parametric analysis of prospect theory’s functionals for the general population.” *Theory and Decision* 68, no. 1-2 (2010): 115-148.

77. Chen, Kay-Yut, and Charles R. Plott. “Nonlinear behavior in sealed bid first price auctions.” *Games and Economic Behavior* 25, no. 1 (1998): 34-78.

78. Goeree, Jacob K., Charles A. Holt, and Thomas R. Palfrey. “Quantal response equilibrium and overbidding in private-value auctions.” *Journal of Economic Theory* 104, no. 1 (2002): 247-272.

79. Goeree, Jacob K., Charles A. Holt, and Thomas R. Palfrey. “Risk averse behavior in generalized matching pennies games.” *Games and Economic Behavior* 45, no. 1 (2003): 97-113.

80. Goeree, Jacob K., and Charles A. Holt. “A model of noisy introspection.” *Games and Economic Behavior* 46, no. 2 (2004): 365-382.

81. Bajari, Patrick, and Ali Hortacsu. “Are structural estimates of auction models reasonable? Evidence from experimental data.” *Journal of Political Economy* 113, no. 4 (2005): 703-741.

82. Campo, Sandra, Emmanuel Guerre, Isabelle Perrigne, and Quang Vuong. “Semiparametric estimation of first-price auctions with risk-averse bidders.” The *Review of Economic Studi*es 78, no. 1 (2011): 112-147.

83. Keane, Michael P., and Kenneth I. Wolpin. “The effect of parental transfers and borrowing constraints on educational attainment.” *International Economic Review* 42, no. 4 (2001): 1051-1103.

84. Gourinchas, Pierre ‐ Olivier, and Jonathan A. Parker. “Consumption over the life cycle.” *Econometrica* 70, no. 1 (2002): 47-89.

85. Gruber, Jonathan. “A tax-based estimate of the elasticity of intertemporal substitution.” *The Quarterly Journal of Finance* 3, no. 01 (2013): 1350001.

86. Imai, Susumu, and Michael P. Keane. “Intertemporal labor supply and human capital accumulation.” *International Economic Review* 45, no. 2 (2004): 601-641.

87. Gandelman, Néstor, and Rubén Hernández-Murillo. “What do happiness and health satisfaction data tell us about relative risk aversion?” *Journal of Economic Psychology* 39 (2013): 301-312.

88. Hurd, Michael D. “Mortality risk and bequests.” *Econometrica: Journal of the econometric society* (1989): 779-813.

89. Moore, Michael J., and W. Kip Viscusi. “Models for estimating discount rates for long-term health risks using labor market data.” *Journal of Risk and Uncertainty* 3, no. 4 (1990): 381-401.

90. Yu, Pei Cheng. “Optimal Retirement Policies with Present-Biased Agents.” *Available at SSRN 3156814* (2018).

91. Chetty, Raj. “Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply.” *Econometrica* 80, no. 3 (2012): 969-1018.

92. Chetty, Raj, Adam Guren, Day Manoli, and Andrea Weber. “Does indivisible labor explain the difference between micro and macro elasticities? A meta-analysis of extensive margin elasticities.” *NBER Macroeconomics Annual* 27, no. 1 (2013): 1-56.

93. Roemer, John E. "Defending equality of opportunity." *The Monist* 86, no. 2 (2003): 261-282.

94. Fleurbaey, Marc, and Francois Maniquet. "Fair income tax." *The Review of Economic Studies* 73, no. 1 (2006): 55-83.

95. Boadway, Robin, and Laurence Jacquet. "Optimal marginal and average income taxation under maximin." *Journal of Economic Theory* 143, no. 1 (2008): 425-441.

96. Lollivier, Stefan, and Jean-Charles Rochet. "Bunching and second-order conditions: A note on optimal tax theory." *Journal of Economic Theory* 31, no. 2 (1983): 392-400.

97. Weymark, John A. "Bunching properties of optimal nonlinear income taxes." *Social Choice and Welfare* 3, no. 3 (1986): 213-232.

98. Ebert, Udo. "A reexamination of the optimal nonlinear income tax." *Journal of Public Economics* 49, no. 1 (1992): 47-73.

99. Boadway, Robin, Katherine Cuff, and Maurice Marchand. "Optimal income taxation with quasi-linear preferences revisited." *Journal of Public Economic Theory* 2, no. 4 (2000): 435-460.

100. Saez, Emmanuel. "Using elasticities to derive optimal income tax rates." *The Review of Economic Studies* 68, no. 1 (2001): 205-229.

101. Mankiw, N. Gregory, Matthew Weinzierl, and Danny Yagan. "Optimal taxation in theory and practice." *Journal of Economic Perspectives* 23, no. 4 (2009): 147-74. See also: "Documentation of Simulations in 'Optimal Taxation in Theory and Practice'."

102. Stewart Jr, Wayne H., and Philip L. Roth. "Risk propensity differences between entrepreneurs and managers: A meta-analytic review." *Journal of Applied Psychology* 86, no. 1 (2001): 145.

103. Macko, Anna, and Tadeusz Tyszka. "Entrepreneurship and risk taking." *Applied Psychology* 58, no. 3 (2009): 469-487.

104. Brown, Sarah, Michael Dietrich, Aurora Ortiz-Nuñez, and Karl Taylor. "Self-employment and attitudes towards risk: Timing and unobserved heterogeneity." *Journal of Economic Psychology* 32, no. 3 (2011): 425-433.

105. Hvide, Hans K., and Georgios A. Panos. "Risk tolerance and entrepreneurship." *Journal of Financial Economics* 111, no. 1 (2014): 200-223.

106. Ahunov, Muzaffar, and Nurmukhammad Yusupov. "Risk attitudes and entrepreneurial motivations: Evidence from transition economies." *Economics Letters* 160 (2017): 7-11.

107. Van Praag, C. Mirjam, and Jan S. Cramer. "The roots of entrepreneurship and labour demand: Individual ability and low risk aversion." *Economica* 68, no. 269 (2001): 45-62.

108. Vinogradov, Evgueni, and Lars Kolvereid. "Home country national intelligence and self-employment rates among immigrants in Norway." *Intelligence* 38, no. 1 (2010): 151-159.

109. Levine, Ross, and Yona Rubinstein. "Smart and illicit: Who becomes an entrepreneur and does it pay?" *Available at SSRN* 2314667 (2013).

110. van der Zwan, Peter, Jolanda Hessels, and Cornelius A. Rietveld. "Self-employment and satisfaction with life, work, and leisure." *Journal of Economic Psychology* 64 (2018): 73-88.

111. Ajayi-Obe, Olufunmilola, and Simon C. Parker. "The changing nature of work among the self-employed in the 1990s: Evidence from Britain." *Journal of Labor Research* 26, no. 3 (2005): 501-517.

112. Hyytinen, Ari, and Olli ‐ Pekka Ruuskanen. "Time use of the self-employed." *Kyklos* 60, no. 1 (2007): 105-122.

113. Heim, Bradley T. "The responsiveness of self-employment income to tax rate changes." Labour Economics 17, no. 6 (2010): 940-950.

114. Armour, Philip, Richard V. Burkhauser, and Jeff Larrimore. "Using the Pareto distribution to improve estimates of top-coded earnings." Economic Inquiry 54, no. 2 (2016): 1263-1273.

115. Smith, Matthew, Danny Yagan, Owen Zidar, and Eric Zwick. "Capitalists in the Twenty-first Century." *The Quarterly Journal of Economics* 134, no. 4 (2019): 1675-1745.

116. Scheuer, Florian, and Iván Werning. "The taxation of superstars." The Quarterly Journal of Economics 132, no. 1 (2017): 211-270.

117. Ales, Laurence, and Christopher Sleet. "Taxing top CEO incomes." American Economic Review 106, no. 11 (2016): 3331-66.

118. Ales, Laurence, Antonio Andrés Bellofatto, and Jessie Jiaxu Wang. “Taxing Atlas: Executive compensation, firm size, and their impact on optimal top income tax rates.” *Review of Economic Dynamics* 26 (2017): 62-90.

119. Saez, Emmanuel. “The desirability of commodity taxation under non-linear income taxation and heterogeneous tastes.” *Journal of Public Economics* 83, no. 2 (2002): 217-230.

120. Renes, Sander, and Floris Zoutman. “As Easy as ABC? Multidimensional Screening in Public Finance.” (2017).

121. Rubin, Paul H., and Chris W. Paul II. “An evolutionary model of taste for risk.” *Economic Inquiry* 17, no. 4 (1979): 585-596.

122. Robson, Arthur J. “The evolution of attitudes to risk: Lottery tickets and relative wealth.” *Games and Economic Behavior* 14, no. 2 (1996): 190-207.

123. Kaplan, Hillard S., and Arthur J. Robson. “The emergence of humans: The coevolution of intelligence and longevity with intergenerational transfers.” *Proceedings of the National Academy of Sciences* 99, no. 15 (2002): 10221-10226.

124. Walsh, Bruce, and Michael Lynch. *Evolution and selection of quantitative traits*. Oxford University Press, 2018.

125. Sinervo, B., and Erik Svensson. “Correlational selection and the evolution of genomic architecture.” *Heredity* 89, no. 5 (2002): 329-338.

126. Roff, Derek A., and Daphne J. Fairbairn. “A test of the hypothesis that correlational selection generates genetic correlations.” *Evolution: International Journal of Organic Evolution* 66, no. 9 (2012): 2953-2960.

127. Whitney, Paul, Christa A. Rinehart, and John M. Hinson. “Framing effects under cognitive load: The role of working memory in risky decisions.” *Psychonomic Bulletin & Review* 15, no. 6 (2008): 1179-1184.

128. Deck, Cary, and Salar Jahedi. “The effect of cognitive load on economic decision making: A survey and new experiments.” *European Economic Review* 78 (2015): 97-119.

129. Gerhardt, Holger, Guido P. Biele, Hauke R. Heekeren, and Harald Uhlig. *Cognitive load increases risk aversion*. No. 2016-011. SFB 649 Discussion Paper, 2016.

130. Drouvelis, Michalis, and Johannes Lohse. *Cognitive abilities and risk taking: the role of preferences*. No. 20-02. 2020.

131. Deary, Ian J., and Geoff Der. “Reaction time explains IQ's association with death.” *Psychological Science* 16, no. 1 (2005): 64-69.

132. Carroll, Christopher D., *Portfolio Choice with CRRA Utility (Merton-Samuelson)*, Dec 31, 2018. Lecture Note. From the Johns Hopkins University Economics Webpage. http://www.econ2.jhu.edu/people/ccarroll/public/lecturenotes/AssetPricing/Portfolio-CRRA/ (accessed Feb 12, 2020).

133. Daly, Martin, and Margo Wilson. *Sex, Evolution, and Behavior*. (No. Sirsi) i9780871507679. Boston: Willard Grant Press, 1983.

134. Meissner, Thomas, Xavier Gassmann, Corinne Faure, and Joachim Schleich. “Individual characteristics associated with risk and time preferences-A multi-country representative survey.” (2020).

135. Chiappori, Pierre-André, and Monica Paiella. “Relative risk aversion is constant: Evidence from panel data.” *Journal of the European Economic Association* 9, no. 6 (2011): 1021-1052.

136. Shamosh, Noah A., and Jeremy R. Gray. “Delay discounting and intelligence: A meta-analysis.” *Intelligence* 36, no. 4 (2008): 289-305.

137. Bouchard Jr, Thomas J., and Matt McGue. “Genetic and environmental influences on human psychological differences.” *Journal of Neurobiology* 54, no. 1 (2003): 4-45.

138. Lykken, David T. “A more accurate estimate of heritability.” *Twin Research and Human Genetics* 10, no. 1 (2007): 168-173.

139. Chapman, Jonathan, Mark Dean, Pietro Ortoleva, Erik Snowberg, and Colin Camerer. *Econographics*. No. w24931. National Bureau of Economic Research, 2018.

140. Strenze, Tarmo. “Intelligence and socioeconomic success: A meta-analytic review of longitudinal research.” *Intelligence* 35, no. 5 (2007): 401-426.

141. Ng, Thomas WH, Lillian T. Eby, Kelly L. Sorensen, and Daniel C. Feldman. “Predictors of objective and subjective career success: A meta-analysis.” *Personnel Psychology* 58, no. 2 (2005): 367-408.

142. Nyborg, Helmuth, and Arthur R. Jensen. “Occupation and income related to psychometric g.” *Intelligence* 29, no. 1 (2001): 45-55.

143. Davies, Gail, Albert Tenesa, Antony Payton, Jian Yang, Sarah E. Harris, David Liewald, Xiayi Ke et al. “Genome-wide association studies establish that human

intelligence is highly heritable and polygenic." *Molecular Psychiatry* 16, no. 10 (2011): 996-1005.

144. Polderman, Tinca JC, Beben Benyamin, Christiaan A. De Leeuw, Patrick F. Sullivan, Arjen Van Bochoven, Peter M. Visscher, and Danielle Posthuma. "Meta-analysis of the heritability of human traits based on fifty years of twin studies." *Nature Genetics* 47, no. 7 (2015): 702-709.

145. Plomin, Robert, and Ian J. Deary. "Genetics and intelligence differences: five special findings." *Molecular Psychiatry* 20, no. 1 (2015): 98-108.

146. Sniekers, Suzanne, Sven Stringer, Kyoko Watanabe, Philip R. Jansen, Jonathan RI Coleman, Eva Krapohl, Erdogan Taskesen et al. "Genome-wide association meta-analysis of 78,308 individuals identifies new loci and genes influencing human intelligence." *Nature Genetics* 49, no. 7 (2017): 1107-1112.

147. Cohen, Jacob. "A power primer." *Psychological Bulletin* 112, no. 1 (1992): 155.