Cognitive ability, labor markets, and social policy preferences.

Matthew Dimick*
Daniel Stegmueller†

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Abstract

In this paper we argue for the centrality of cognitive ability to understanding individuals' preferences for redistribution. We develop a model in which income, unemployment, and education are all endogenous to differences in individuals' cognitive abilities. We test our argument using a large-scale, representative panel study from Germany. We develop a Bayesian approach to estimate the effect of ability on redistribution preferences. We then decompose the treatment effect for preferences into components due to treatment-induced changes in labor market choices and outcomes. Our results demonstrate the fundamental importance of ability for redistribution preferences, and underscore that ignoring the fact that labor market outcomes are endogenous to ability is a threat to valid inference in current standard political economy models.

*SUNY Buffalo Law School, `mdimick@buffalo.edu`
†University of Mannheim, `mail@daniel-stegmueller.com`

I. Introduction

It has been the basic tenet of political economics that the preferences of citizens (and, ultimately, their vote) are shaped by economic conditions. Institutionally, the locus for these conditions is the labor market, undoubtedly the single most important source of individuals' economic well-being. Consequently, a wave of recent research seeks to link individuals' economic conditions to their preferences for social spending, social insurance, or redistribution. The list of conditions studied includes a wide range of economic variables, such as income, unemployment risk, skill specificity, and education. While we agree with the emphasis placed on economic attributes of citizens, we caution that these are usually the result of individual choices and actions. However, empirical studies in political economy usually take circumstances as exogenously given and analyze individuals' responses to them, e.g., when analyzing the effect of income on redistributive preferences. Thus, they miss the impact of fundamental forces driving both citizens' economic circumstances and preferences.

In this paper, we present a general theoretical framework for linking individuals' economic conditions to their redistributive preferences. We go beyond simply claiming that economic conditions are endogenous. Instead we develop (and test) an explicit model, which shows *why* and *how* labor market factors, such as wages, unemployment rates, and education, are endogenous to individuals' cognitive ability. While different individuals possess a diverse range of capabilities, general cognitive ability (or intelligence) is the fundamental (uni-dimensional) factor driving individual differences in the endowment of skills and the ability to acquire new ones (Gustafsson 1984; Carroll 1993; Johnson and Bouchard 2005; Borghans et al. 2008; Nisbett et al. 2012).

The link between cognitive ability and preference parameters should not be ignored. It contributes to our understanding of preferences, by moving 'further back' in the causal chain. In contrast to non-cognitive skills, such as personality, and other attributes of "character" (Borghans et al. 2008), general cognitive ability changes little over the life-cycle. It is an innate individual trait, which remains stable after childhood, (e.g., Hopkins and Bracht 1975; Schuerger and Witt 1989). While we certainly do not claim for cognitive abilities to be an Aristotelean "unmoved mover" in explanations of preferences, they do describe basal individual differences, which substantively influence the economic choices individuals make and which environments they find themselves in over the course of their lives (e.g., Gottfredson 2002; Heckman, Stixrud, and Urzua 2006). Thus, we argue, they should be considered as a fundamental factor shaping individuals' preferences for redistribution. Our contribution in this paper is to develop both theory and empirical illustrations of the mechanisms linking ability to preferences.

There is ample evidence showing that a sizable part (around 50%) of the variation in cognitive ability is due to differences in individuals' inherited genetic make-up and that (purely additive) environmental factors play a more limited role (see, e.g., the summaries in Bouchard and McGue 1981; Deary, Johnson, and Houlihan 2009). Environmental factors matter as an interaction with genetic factors (genotype-environment correlations), making it likely that individuals' genetic composition contributes to the experiences individuals create and the environments they sort into (Plomin 1999). But note that our argument developed here does not presuppose a form of "genetic determinism". Individual traits, including cognitive ability, are malleable at young ages and even at in *in utero* conditions (Phillips and Shonkoff 2000; Knudsen et al. 2006). Individuals' cognitive capacities at different ages depend on previous investments in them (Cunha and Heckman 2007). Thus, they can be affected by social interventions, from early development and care programs for disadvantaged children (e.g., Blau and Currie 2006; Heckman and Krueger 2003), to nutritional programs, to efforts to reduce exposure to pollution. The fact that social programs can successfully affect individual cognitive ability also makes transparent that we do not claim that the *distribution* of ability is itself exogenous to politics. To the contrary, analyzing the institutional and political origins of cross-national differences in ability distributions emerges as an important avenue of further research from the findings presented in this paper.

Our paper proceeds as follows. Section II introduces our theoretical model. Section III details how we translate our theoretical propositions into empirically testable statements. Section IV describes the German Socio-Economic Panel, a high-quality household panel we use to estimate our statistical model, which is described in detail in Section V. Results are presented in Section VI, and we describe a number of robustness tests in Section VII. In the concluding section of our paper we not only discuss our results, but also outline how our model can be extended to cover further research questions.

II. Model

Consider a measure-one continuum of workers, distinguished by their *ability*. Ability is denoted $\theta \in \Theta = \mathbf{R}_+$ and has cumulative distribution $F(\theta)$, probability density $f(\theta)$, and a finite expectation. Each worker has an identical von Neumann-Morgenstern utility function $u(c)$ over final consumption. We assume that u is twice continuously differentiable, strictly increasing, and weakly concave.

There is a larger continuum of potential firms that open job vacancies. To endogenize the cost of a vacancy, we assume that each firm has access to a production technology $f : (0,\infty) \to (0,\infty)$ that requires one worker and capital $k > 0$ to produce $\theta f(k)$ units of the consumption good. One can think of $\theta f(k)$ as the output produced either by the combination of worker ability and the firm's capital investment or alternatively as the combination of the worker's ability with the firm's investment in some skill-specific job vacancy. The function f is continuously differentiable, strictly increasing, and strictly concave and satisfies the standard conditions for an interior solution: $\lim_{k\to 0} f(k) = 0$, $\lim_{k\to 0} f'(k) > 1$, and there exists $\bar{k}_\theta$ such that $\theta f'(\bar{k}_\theta) = 1$. The large number of firms ensures free entry, so aggregate profits are zero in equilibrium.

Workers and firms come together through search in the labor market. As in Acemoglu and Shimer (1999), Moen (1997), or Montgomery (1991), we assume that firms post wages prior to being matched with employees and that workers apply for jobs facing the profile of posted wages.[3] Following both the theoretical and empirical literature of labor market frictions, we assume a constant returns to scale matching function $m(u, v)$ that depends on the number of searching workers u and the number of vacancies posted by firms v. We define $q \equiv u/v$, $q \in [0,\infty)$, the ratio of searching workers to the number of vacancies, as the expected *queue length*. Given the assumption of constant returns to scale in the matching function, a worker is hired with probability $\mu(q) \equiv m/u$, where $\mu : [0,\infty] \to [0,1]$ is continuously differentiable and decreasing. Intuitively, longer queue lengths—more searching workers for a given job—reduce the probability of being hired. In contrast, a firm fills a vacancy with probability $\eta(q) \equiv m/v = q\mu(q)$, where $\eta : [0,\infty] \to [0,1]$ is continuously differentiable and increasing. In this case, longer queue lengths increase the probability of filling a vacancy. In addition to these standard assumptions, we also assume that

[3] As long as wage setting and capital investments are simultaneous, our results are identical to other wage-setting scenarios, in particular to the cases where s-specific monopoly unions set wages *ex ante* to maximize workers' expected utility or where workers and firms bargain *ex post* over the wage and the bargaining advantages of each side satisfy the Hosios (1990) condition.

$\eta(q)$ is strictly a concave function. This helps to simplify and focus our analysis on questions of interest.[4]

When employed, workers' consumption is denoted c_E; when unemployed, c_N. Firms that hire a worker produce $\theta f(k)$, while firms that fail to fill their vacancy produce nothing and incur only the cost of capital $-k$. Workers that are employed by a firm receive a wage, $w \in [0, \infty)$. In addition, workers also receive transfers from the government, denoted b. The government operates a linear tax, τ, $\tau \in [0,1]$ and redistributes the proceeds to all individuals, employed or unemployed, in equal, lump-sum transfers. There is no corporate tax and profits, if any, are retained. The government is subject to a balanced budget constraint:

$$b = \tau \bar{y} \tag{1}$$

where $\bar{y}$ denotes average income, denoted as:

$$\bar{y} \equiv \int_0^{\infty} \mu(q(\theta))\, w(\theta) dF(\theta) \tag{2}$$

We can also write the consumption equations as follows:

$$c_E \equiv (1-\tau)w + b \tag{3}$$

and

$$c_N \equiv b \tag{4}$$

To summarize the model, the timing of events is as follows:

1. Individuals choose their most preferred tax rate, τ, under a balanced-budget constraint, which allocates the revenue in equal, lump-sum transfers, b, to all individuals regardless of employment status.

2. With expectation of zero profit, firms make irreversible investments in capital, k, anticipating the probability of hiring a worker, and post a wage, w.

3. Workers apply to jobs with posted wages, forming queues, q, to maximize their consumption utility.

[4] Both of the most commonly assumed functional forms for the matching function—the Cobb-Douglas and the exponential functions—imply that $\eta(q)$ is concave.

A. Equilibrium

This section analyzes the preceding model, which we solve through backward induction. An equilibrium in our model is defined by the following equations:

$$\max_{k,\,w,\,q} \eta(q)(\theta f(k) - w) - k \tag{5}$$

subject to

$$U = \mu(q)u((1-\tau)w + b) + (1-\mu(q))u(b) \tag{6}$$

and

$$\eta(q)(\theta f(k) - w) - k = 0 \tag{7}$$

taking τ and b as given.

Then moving back to the policy preference stage, b is solved via equation (1) and the equilibrium tax rate is the one that maximizes the utility of the individual, defined by the following equation:

$$\max_{\tau} \mu(q)u((1-\tau)w + b) + (1-\mu(q))u(b) \tag{8}$$

Proposition 1. *An equilibrium exists and is unique. In any equilibrium, the following characteristics hold:*

1. *The labor market endogenously segments into* Θ *different submarkets, yielding a distinct wage,* w_θ*, and queue length,* q_θ *for each type,* θ*.*

2. *There exists a critical value of the tax rate,* $\tau_e > 0$*, that maximizes the economy's aggregate (average) output.*

Proof. See Appendix A.1

The proof for this proposition establishes the existence of equilibrium values for capital investments (k), wages (w), queue lengths (q) (and therefore unemployment rates $[1-\mu(q)]$), and social policy preferences (τ^*). *All* of these variables are endogenous to preferences (u) and abilities (θ). Our model is therefore more general than the otherwise similar models of Moene and Wallerstein (2001) and Iversen and

Soskice (2001), where all of these variables, except the social-spending ideal points, are exogenous.[5]

Two features characterize any equilibrium. First, the labor market endogenously separates into Θ different submarkets, with distinct wages, capital investments, and unemployment rates in each. In other words, a type-θ *chooses* to search in a type-θ submarket because such a market maximizes her expected utility. In addition, the equilibrium is characterized by a critical value of the tax rate that maximizes the economy's output. In this economy, as in Acemoglu and Shimer (1999)—and the arguments of much of the Varieties of Capitalism literature—some level of unemployment insurance is necessary for maximizing output. The reason for this is that without unemployment insurance risk averse workers apply for low-risk, low-wage (low-productivity) jobs. With some positive amount of insurance, workers are more willing to take the risk of applying to high-risk, high-wage (high- productivity) jobs. As we shall see more clearly in the next proposition, however, there is a limit to insurance. Too high a tax rate will encourage "too much" search, create too many vacancies, and thereby lower output. Thus, there is a cost of social spending which guarantees the equilibrium existence of an ideal tax rate below 1.

B. Comparative Statics

Having established and characterized the equilibrium, we turn now to the comparative statics of the model. We begin by analyzing the effects of ability on income and unemployment rates. The model predicts that wages are higher for higher ability workers because firms post higher wages hoping to attract more able applicants. In addition, unemployment rates are lower for more able applicants because the expected cost of a vacancy for a high-ability worker is lower than for a low-ability worker.

It is intuitive that income and employment rates would be increasing in ability. But we need a mechanism to make the connection precise. After all, in a perfectly competitive labor market, there would be no unemployment at all—for workers of any ability—and wages would simply be determined by the worker's marginal productivity. When we use a matching model of the labor market to investigate these relationships,

[5]Note that the uniqueness of the equilibrium follows from the assumptions on the matching function we have made, in particular the concavity of $\eta(q)$. Without this assumption, an equilibrium still exists, as shown by Acemoglu and Shimer (1999), but may not be unique. Since this would substantially reduce the tractability of the model, particularly at the social-policy stage, we think the additional assumption is worth the small loss in generality.

we can begin to understand why high ability workers are employed with greater probability. Furthermore, in a matching model, wages are typically not equal to marginal productivity, so the link between ability and income is less obvious.

These statements about the relationship between ability, income, and unemployment rates are captured by the following proposition.

Proposition 2. *(1) The employment rate, μ, is increasing, and conversely the unemployment rate, $1-\mu$, is decreasing in ability, θ; (2) income (or wage rate), w, is increasing in ability, θ.*

Proof. See Appendix A.1

Our next proposition analyzes the effects of income and unemployment rates on individuals' social-spending preferences. This next proposition follows closely from the previous one. Consistent with other arguments in the literature, both formal and nonformal, our model predicts that preferences for social spending are decreasing in income and increasing in the unemployment rate. Because higher-income individuals benefit less from redistributive social spending, they demand less of it. Likewise, individuals with higher expected unemployment prefer both greater social insurance as well as more redistribution because their expected incomes are lower.

While our model is consistent with these previous findings, the real payoff is in being able to link them back to different ability types. Hence, because our model predicts that higher ability workers will have higher incomes and lower unemployment rates, our model predicts that higher ability workers will prefer less redistribution than lower ability workers. If this prediction turns out to be true, we further expect that some significant amount of this effect goes through workers' labor market conditions.

Proposition 3 states these hypotheses slightly more formally:

Proposition 3. *Preferences for social spending are (1) decreasing in the employment rate, μ (increasing in the unemployment rate, $1-\mu$); (2) decreasing in income (or wage rate), w. Therefore, from Proposition 2, social spending preferences are decreasing in ability.*

Proof. See Appendix A.1

C. Education

Until this point, our model makes predictions for the effects of ability on income, unemployment, and, through these two variables, social spending preferences. We now incorporate education into the model. Suppose that acquiring education increases a worker's productivity by a rate $h \geq 1$. The productivity of an educated worker is therefore $\theta_\varepsilon \equiv \theta h$. Essentially, we assume that education makes a higher ability person proportionally more productive than a lower ability individual. Let r, $r \in R = \mathbf{R}_+$, be the benefit foregone in pursuing an education. The benefit has cumulative distribution $G(r)$ and probability density $g(r)$ with finite distribution. In the specific case we examine, the forgone benefit r is best thought of as nonmonetary (time spent at the beach rather than studying). We assume that r is distributed identically and independently of ability, θ. Workers do not acquire education if it makes them worse off, so we impose the condition that education must make a worker at least as well off as her best utility without education: $U_\varepsilon \geq U_{-\varepsilon}$.

Proposition 4. *(Education) For each type-θ there exists a critical value of r, denoted r^*, that gives the equilibrium proportion of workers acquiring education, $G(r^*)$. $G(r^*)$ is increasing in θ. Income and employment continue to be increasing in θ. For workers of the same type, $U^*_\varepsilon(\theta) = U^*_{-\varepsilon}(\theta, r^*)$, $\int_r U^*_\varepsilon(\theta) dG(r) \geq \int_r U^*(\theta) dG(r)$, $w^*_\varepsilon(\theta) \geq w^*_{-\varepsilon}(\theta)$, and $q^*_\varepsilon(\theta) < q^*_{-\varepsilon}(\theta)$.*

Since every worker will invest in education if it makes her better off, there is some threshold value of r, denoted r^*, which indicates a type-θ worker that is indifferent between acquiring and not acquiring education. This value of r is increasing in an individual's ability type. This follows from our assumption about the interaction between ability, θ, and education, h. The impact of education on a higher-ability worker is larger than a low-ability worker, and this implies that her wages and employment rates rise to a proportionally larger degree. Therefore, a greater share of higher-ability types acquire education.

This proposition also compares workers of the same type who do and do not acquire education. First, as follows from the above, the utility of workers with education is equal to the worker who is just indifferent about acquiring education. Also, education increases productivity, and through wages and employment rates, increases utility compared to a submarket without the possibility of education.

Overall, because the share of educated workers is increasing in ability type, and because of the positive effect of education on wages and employment, we expect education to have a negative effect on social spending preferences.

III. Empirical Strategy

We now turn to an empirical test of our model. Our main proposition connects individuals' ability to preferences by explicating how ability shapes labor market outcomes. Thus, our empirical approach needs to trace the full path from ability through the labor market on social preferences. In the following we use the potential outcomes framework to outline how ability affects policy preferences via labor market outcomes (Imai et al. 2011; VanderWeele and Vansteelandt 2009).[6] Imagine a simplified scenario where individual i ($i = 1, \dots, N$) possesses a preferred level of social policy ω_i, which is a function of ability θ. Different (counterfactual) ability levels are denoted by θ_i and θ_i'. Realized values of confounding factors $\mathbf{X}_i$ are denoted by $\mathbf{x}_i$. A straightforward estimate of the *total effect* of ability on preferences is

$$TE = E(\omega_i(\theta_i'|\mathbf{x}_i) - \omega_i(\theta_i|\mathbf{x}_i)), \tag{9}$$

i.e., the expected (counterfactual) difference in social policy preferences for, say, high and low ability holding other confounding variables constant.

To understand *how* ability shapes preferences, we need to move beyond estimating total effects. In testing the argument that labor market outcomes are the primary mechanism linking skills to policy preferences, we separate the effect of ability mediated via labor market outcomes from the vast number of alternative mechanisms that could link ability to preferences (Imai et al. 2011: 769). More precisely, denote by $M_i(\Theta_i = \theta_i|\mathbf{Z}_i = \mathbf{z}_i)$ an individual's labor market position as function of ability, θ_i, and other realized background factors, $\mathbf{z}_i$. The (average) effect of skills on social policy

[6] General identification results for this setup are discussed in Imai, Keele, and Yamamoto (2010). Some researchers rightly caution about the empirical difficulty of studying mechanisms (see exemplarily, Green, Ha, and Bullock 2010). We emphasize that in our view (and that of Imai, Keele, and Yamamoto 2010) the key benefit of clearly defining mechanisms in a potential outcomes framework is that it lays bare the identifying assumptions needed. We state these assumptions explicitly and conduct sensitivity analyses to see how robust our results are against their violations.

preferences that is due to labor market outcomes – the *mediated effect* – is given by

$$ME = E(\omega_i(\theta_i, M_i(\theta_i'|\mathbf{z}_i)|\mathbf{x}_i) - \omega_i(\theta_i, M_i(\theta_i|\mathbf{z}_i)|\mathbf{x}_i)), \tag{10}$$

i.e., the change in preferences caused by a change in labor market outcomes resulting from a change in ability levels from θ to θ' while holding labor market confounders ($\mathbf{z}_i$) and preference confounders ($\mathbf{x}_i$) constant.

The *remaining (or: direct) effect* of ability on preferences is calculated by holding labor market outcomes at a constant ability level

$$DE = E(\omega_i(\theta_i', M(\theta_i|\mathbf{z}_i)|\mathbf{x}_i) - \omega_i(\theta_i, M(\theta_i|\mathbf{z}_i)|\mathbf{x}_i)). \tag{11}$$

It represents all mechanisms other than labor market outcomes linking ability to social policy preferences.[7]

In section V we present the statistical model used to estimate these effects in detail. Before doing so we describe the unique data set that enables our analyses.

IV. Data

We use individual-level panel data from the German Socio-Economic Panel (SOEP), a longitudinal representative survey of German households conducted since 1984.[8] It is unique in that it provides both—measures of intelligence or ability and measures of social policy preferences. SOEP also provides high-quality data on individuals' labor

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[7]The previous discussion lays out the causal counterfactual definition of our argument and is independent of the specific statistical model used to estimate it (cf. Imai, Keele, and Yamamoto 2010). Its value lies not only in providing a clear definition of what we want to know, but also in making explicit the two identifying assumptions needed to estimate these quantities (Imai et al. 2011). The first is the standard assumption that, after conditioning on included observables, there are no unobserved confounders that change with treatment (e.g., ability) and affect preferences or labor market outcomes. The second assumption concerns the mediating variables, namely labor market outcomes. It requires that no unobserved confounders affect both preferences and labor market status after conditioning on observables. Since *both* assumptions have to be made jointly to estimate mediated effects, (Imai et al. 2011) refer to them as 'sequential ignorability.' In most empirical applications these conditions are likely to be violated. However, we can use sensitivity analyses to gauge how violations of these identifying assumptions influence our results. We discuss these problems in more detail in the appendix, where we also present sensitivity plots (as suggested by Imai, Keele, and Yamamoto 2010).

[8]For details see `/www.diw.de/en/soep`.

market activities, such as income, work experience, and unemployment spells. In addition to a core set of questions, additional modules related to specific topics are fielded. Relevant to our topic are a battery of welfare preference items contained in the 2002 wave, and, for the first time, a test of cognitive abilities administered to a subset of individuals in 2006.[9] In the following we describe the data on cognitive abilities and redistribution preferences. The number of individuals who participated in all necessary waves and which are interviewed using CAPI in 2006 (and thus eligible for participating in the cognitive test) is 4,444. In order to create a homogeneous sample, we focus on 1,636 working-age males.[10] Of those 343 refused to participate in the cognitive ability test. We treat item-nonresponse as part of our measurement models, thus our final sample size is 1,636 respondents.[11]

Ability measures. We rely on an adapted version of a standard psychological symbol-digits correspondence test (Lang et al. 2007; Schupp et al. 2008), which corresponds to a sub-module of the widely used Wechsler Adult Intelligence Scale (WAIS).[12] It captures the concept of 'fluid intelligence', which represents general analytical performance, and is 'fluid' in the sense that it is productive over a wide range of domains (Cattell 1987: 97). More precisely, fluid intelligence is understood as "the ability to perceive complex relations, reduce complex correlates, form concepts, develop aids, reason, abstract, and maintain span of immediate apprehension in solving novel problems" (Rindermann 2007: 462). Thus, by representing the ability to learn rather than simply the stock of already acquired knowledge, fluid intelligence corresponds closely to the role of ability, θ, in our theoretical model (Almlund et al. 2011: 40).

After extensive pre-testing, a symbol-digit test (SDT) was administered in 2006 to the subset of individuals surveyed via computer-assisted interviewing. In the

[9]The obvious downside is that cognitive skills are measured after preferences. However, evidence suggests that fluid intelligence (as used in this paper) represents essentially innate abilities and is stable after childhood, independent of one's environment (e.g., Hopkins and Bracht 1975; Schuerger and Witt 1989). Furthermore, we also conduct a robustness test where ability is measured net of age effects, which produces almost identical results.

[10]A proper analysis including women would have to solve the selection problem of female labor market participation, or present separate analyses for men and women (which would increase the paper's length and complexity). But note that simply including all women does not change our core results.

[11]In a robustness check we use listwise deletion of missing values producing a sample size of 1,105. Results are indistinguishable between both data sets.

[12]More precisely it corresponds to the symbol-digit- modalities-test (Smith 1995), adapted for use in a large-scale population survey (see below).

implemented version test, respondents have to match numbers to symbols. Nine symbols corresponding to nine numbers are displayed permanently on the screen, and individuals have to match numbers to a stream of displayed symbols as quickly as possible.[13] The frequency of correct matches is assessed in three 30-second intervals, yielding an "ultra-short" 90-second test (Lang et al. 2007; Schupp et al. 2008). While such a short test cannot provide the same level of detail as longer test batteries (such as the widely used AFQT), it is well suited for application in a *general* survey, where participation is voluntary and question time limited. Pre-tests have shown that scores obtained from this ultra-short test correlate highly with established long-form psychological ability tests (Lang et al. 2007; von Rosenbladt and Stocker 2005). Its shortness will result in less precise measurements of individual ability. In our measurement model, described below, this uncertainty is taken into account in all parts of the model.[14]

Social policy preferences. We use the 2002 wave of the SOEP, which provides a set of items tapping if individuals prefer the private market or the state as provider of financial security for people of old age, for families, for individuals needing care, in case of illness, or in case of unemployment. Response categories range from 'only the private market' to 'only the state'. These items have been used as proxy measures for preferences by Alesina and Fuchs-Schündeln (2007). In contrast to their work our model allows for measurement error in these proxies. We argue that responses to these items are driven by individuals' underlying social policy preferences: individuals who prefer a more active welfare state, which spends more on social services, will respond positively to those items. This underlying policy preference should be captured using an appropriate measurement model (e.g., Ansolabehere, Rodden, and Snyder 2008; Jackman 2008), as described in the following section.

Labor market outcomes. A respondent's education choice is represented by a 4-category variable (based on the International Standard Classification of Education). Its levels are: (1) elementary and lower secondary education, (2) upper secondary education, vocational education, (3) post-secondary and advanced vocational training, (4) college (BA/MA/PhD). We measure earnings as the sum of respondents' monthly earnings from labor in the current year. In order to abstract from temporary earnings

[13] Classical psychological tests usually require individuals to choose symbols. This procedure is reversed in the SOEP to enable data entry using standard CAPI tools.

[14] See Jackman (2008: section 4) for a discussion of the biases when ignoring measurement uncertainty.

shocks in the current cross-section (such as exogenous shocks in macro-economic conditions), we smooth individuals' earnings by averaging over ±3 years. To capture the probability of experiencing unemployment, we use information in the panel to construct a variable indicating if a respondent has experienced spells of unemployment in the past calendar year.

Controls. We include a number of individual and household characteristics as controls in various parts of our model. These include, age, living in eastern Germany, household size, and family background (such as parental education). More detailed definitions and descriptive statistics of all covariates is available in Appendix A.7.

V. Statistical Model

We estimate the effect of ability on policy preferences ω_i of individual i ($i = 1, \ldots, N$) living in state s ($s = 1, \ldots, S$) via the following equation:

$$\omega_{is} = \eta_1 \theta_i + \boldsymbol{\gamma}' \mathbf{m}_i(\theta_i) + \boldsymbol{\zeta}' \mathbf{x}_i + \xi_s + \epsilon_i \tag{12}$$

where $\mathbf{x}_i$ are control variables capturing heterogeneity between individuals; $\mathbf{m}_i$ is a vector of endogenous labor market outcomes, which is a function of ability (detailed below); and θ is cognitive ability. Both preferences and ability are not directly observable, but have to be captured by appropriate measurements described next.

A. Redistribution preferences

The majority of studies on individual policy preferences uses a single survey item. Often born out of limitations of survey design or coverage, this widespread practice has some drawbacks. Preferences are captured only imperfectly when using a single survey item as dependent variable. Using multiple items is preferable since it leads to an improved measurement of social policy preferences (cf. Ansolabehere, Rodden, and Snyder 2008; Jackman 2008). Furthermore, jointly estimating measurement model equations together with substantive model equations takes measurement error into account and yields more conservative standard errors (Skrondal and Laake 2001). Following recent research (e.g., Treier and Jackman 2008; Stegmueller 2011), we employ an ordinal probit item response theory model, which expresses preferences as an unobserved (latent) variable, θ, which generates observed categorical survey responses to policy questions (for an introduction to Bayesian IRT models, see Jackman 2009: ch.9). We model response y^r_{si} of individual i to each question s ($s = 1, \ldots, S$), which has T_q categories, as a function of a threshold and a discrimination parameter:[15]

$$y^r_{si} = \Phi(\tau^r_{st} - \lambda^r_s \omega_i) \tag{13}$$

Here τ_{st} are item thresholds, λ_s are item discrimination parameters, and Φ is the normal CDF. To ensure that the model reflects the ordinal nature of survey items, $\boldsymbol{\tau}^s_s$ is a vector of thresholds for item s with length $T_s - 1$ with a strictly monotonous ordering constraint, such that $\tau_{sa} < \tau_{sb}, \forall a < b, \forall s$. The latent variable $\boldsymbol{\omega}$ represents individuals' social policy ideal points. Its location and scale are identified by specifying its distribution as normal with fixed variance, $\boldsymbol{\omega} \sim N(0, 1)$. This latent variable strategy is preferable over using simple sum-scores as it includes measurement uncertainty in the model.

B. Measuring ability

We model ability via a linear factor model for cognitive ability, following recent work in economics by Heckman and colleagues (e.g., Carneiro, Hansen, and Heckman 2003; Heckman, Stixrud, and Urzua 2006; Cunha, Heckman, and Schennach 2010).[16] In the measurement equation for ability, we assume that measurements made using the Symbol-Digit-Test are generated by latent continuous cognitive abilities. More precisely, let y^a_{ci} be the number of correct number-symbols pairs in each 30 second block c ($c = 1, \ldots, C$) achieved by individual i. Then, responses are modeled as a function of an individual's latent cognitive ability θ_i:

$$y^a_{ci} = \mu_c + \lambda^a_c \theta_i + \boldsymbol{\delta}' \boldsymbol{w}_i + \epsilon^a_c \tag{14}$$

[15] To avoid a proliferation of variables and coefficients in the remainder of the paper, we use superscripts to denote the equation they belong to (e.g. 'r' for social policy preference equations, 'l' for labor income, etc.)

[16] In a more complex measurement model setup Heckman, Stixrud, and Urzua (2006) allow for reverse causality between schooling and cognitive and non-cognitive skills, since many of their subjects were still at school when completing the tests. In our case all individuals still in school are excluded from the analysis, and we therefore do not extend our model in that direction. We do, however, allow for endogenous schooling, i.e. we model the fact that schooling is a choice influenced by latent cognitive and non-cognitive ability.

Here, λ^a are discrimination or loading parameters indicating how latent ability produces observable test responses, μ_c are test means, and ϵ_c^a are residuals with zero mean and variance ψ_c^a. In the following application we restrict $\mu_c = 0$ since we use standardized values from the cognitive abilities test. Location and scale of the latent ability variable are fixed by using a standard-normal prior distribution, $\theta \sim N(0,1)$.[17] One might question the normality assumption for ability. In a robustness tests we show that a model that allows for non-normal factors (using a finite mixture of normals) leads to quite similar ability effect estimates.

If $\boldsymbol{\delta} = \mathbf{0}$ equation (14) describes a classical linear measurement equation with expectation $\mu_c + \lambda_c^a \theta_i$ and residual variances ψ_c^a. In an extension of the classic measurement model approach, we allow for the effect of confounders $\boldsymbol{w}_i$ affecting measurements via the bias parameter δ (Skrondal and Rabe-Hesketh 2004). For example, one might be worried that foreigners perform worse in ability tests, not because of their true ability, θ but simply because language difficulties make it harder to understand instructions.

C. Endogenous schooling, income, and unemployment experience

When analyzing social policy preferences, economic outcomes such as income or earnings, unemployment experiences, and choice of education are not exogenous. Rather, they are substantially shaped by ability. Using US panel data Heckman, Stixrud, and Urzua (2006) demonstrate how a variety of economic and social outcomes are determined by cognitive skills. We model economic outcomes relevant to policy preferences as functions of cognitive ability. As an "added bonus" including behavioral outcomes in our ability measurement equation (in addition to psychological test items) improves measurements of ability, since test items and behavior are exchangeable sources of identification (e.g. Heckman, Stixrud, and Urzua 2006; Cunha, Heckman, and Schennach 2010).

Education We model individuals' education choice via an underlying utility function and a set of cutoff points (for similar specifications see Machin and Vignoles 2005; Cameron and Heckman 1998). For each individual i, we record his or her highest choice of education certificate, y_i^e, such as vocational or high school education.

[17] Alternatively, one could fix one of the λs and freely estimate the variance. We prefer this approach since it normalizes the distribution of latent ability and makes easier the visual comparisons in plots presented below.

Individuals obtain an education certificate $s \in \{1, \ldots, S\}$ if the latent index I lies between two cutoff values τ_s^e. We let $D(s) = 1$ if $y_i^e = s$. Cutoffs are ordered such that $\tau_s^e \leq \tau_{s+1}^e (s = 1, \ldots, S-1)$. Thus, the choice of education certificate is given by[18]

$$D(1) = \mathbf{1}(I \leq \tau_1), D(s) = \mathbf{1}(\tau_{s-1} \leq I < \tau_s), D(S) = \mathbf{1}(\tau_{s-1} \leq I). \tag{15}$$

To capture the effect of ability on education, we model the latent index via the following linear specification

$$I = \boldsymbol{\alpha}^{e\prime} \mathbf{z}_i^e + \beta^e \theta_i + \epsilon_i^e, \tag{16}$$

where $\mathbf{z}_i^e$ is a vector of control variables such as immigration status and parental background with coefficients $\boldsymbol{\alpha}^e$. The effect of cognitive ability on obtained education is captured by β_1^e. Finally, residuals ϵ^e are normally distributed with zero mean and unit variance.

Income As argued before, cognitive ability determines an individual's productivity and performance and is thus an important part of his earning function (Griffin and Ganderton 1996). We model an individual's labor income y_i^l as function of standard variables such as work experience and immigration status collected in $\mathbf{z}_i^l$ and of ability,θ_i:

$$y_i^l = \boldsymbol{\alpha}^{l\prime} \mathbf{z}_i^l + \beta^l \theta_i + \epsilon_i^l. \tag{17}$$

Here, β^l captures the effect of ability on earnings, while $\boldsymbol{\alpha}^l$ represents the effect of other relevant factors. Residuals ϵ_i^l are zero-mean normally distributed with estimated variance ψ^l.

Unemployment Researchers modeling unemployment dynamics often rely on random effects specifications to capture effects of unobserved factors such as ability. Having measures of cognitive ability allows us to model these previously unobserved effects directly. We model the propensity of experiencing unemployment y_i^u via a probit equation:

$$y_i^u = \Phi(\tau^u + \boldsymbol{\alpha}^{u\prime} \mathbf{z}_i^u + \beta^u \theta_i), \tag{18}$$

[18] $\mathbf{1}(a)$ is an indicator function equal to 1 if a is true and 0 otherwise.

where τ^u is a threshold or intercept, $\mathbf{z}_i^u$ is a vector of control variables, such as immigration status and age, with associated coefficients $\boldsymbol{\alpha}^u$. The effect of an individual's cognitive ability, θ_i is captured by β^u.

This completes the specification of the skills measurement model. The model setup implies that conditional on control variables in $\mathbf{z}_i$, the dependence across all measurements, choices, and outcomes is due to $\boldsymbol{\theta}$. Controlling for this dependence in equations (14) – (18) means controlling for endogeneity in the model (Heckman, Stixrud, and Urzua 2006: 424).

D. Estimation

We specify and estimate this system of equations in a Bayesian framework (for introductions see Gill 2014 or Jackman 2009). We assign proper (hyper-) priors to all model parameters such that our inference relies only on the data (i.e., we use vague prior values; details are in appdendix A.9)

We estimate the model using MCMC sampling using a standard Gibbs sampler with Metropolis steps for updating the probit threshold vectors. We run two chains for 200,000 iterations, discarding the first half as burn-in. To reduce memory usage, we thin each chain by a factor of 20. Visual inspection as well as diagnostics of the resulting $2 \times 10,000$ samples suggested by Gelman and Rubin (1992) and Geweke (1992) show no signs for absence of convergence. Furthermore, we conducted an "insurance run" (Gill 2008) running the sampler for 500,000 iterations – yielding identical results.

VI. Results

In this section we describe the results of our model starting with characteristics of our ability and preference measurements. Readers solely interested in tests of our propositions find these in subsection C.

A. Ability and labor market outcomes

Estimates for our measurement equations for ability are given in Table 1. It shows estimates (posterior means) and highest posterior density regions, which can be seen as the Bayesian analogue to the classical confidence interval.[19] Panel (A) shows the relationship between latent ability, θ, and observed symbol-digit-test performance. The first column ("θ effects") shows the marginal effects, λ^a, of a change in ability on test performance. Not surprisingly, they are strongly related: a unit increase in ability leads to almost one more symbol being entered correctly in each 30-second test block. The residual variances, ψ^a, are rather small, suggesting that a one-dimensional latent ability factor explains the majority of the variance in observed test performance.[20]

Figure 1, panel (A), shows the resulting distribution of ability in the population. It plots kernel density estimates of the distribution of posterior means of all respondents' θ_is. The plot shows considerable individual variation in latent ability. A substantial portion of respondents has low levels of ability of more than one standard deviations below the population mean (which is normalized to zero), especially among those with no high school education. At the other end of the distribution are individuals with high levels of ability, one found predominantly among the higher educated. But one should also note the existence of lower educated individuals with high latent ability and (especially) of highly educated individuals with lower ability. This suggests that using education as proxy for ability or productivity in models explaining policy preferences is bound to produce rather unreliable results.

Panel (B) of Table 1 shows how (latent) ability produces individuals' observed education choice and labor market outcomes. In order to save space, we omit estimates of controls included in each labor market outcome equation, and only show effects of ability. While we will present more intuitively interpretable quantities of interest below, a first look at our structural parameter estimates reveals the importance of ability. Starting with education, our results provide supporting evidence for sorting into education based on ability. At every level of education choice, and holding other confounding factors constant, ability increases the utility of education, as evidenced by the significant β^e coefficient. In line with our proposition, increasing ability is connected with increased earnings (the coefficient β^l is positive) and a decreasing propensity of experiencing unemployment (the coefficient β^u is negative). The relationship between latent ability and observed labor market outcomes is significantly

[19] More precisely, a region R is a $100(1-\alpha)$ percent HPD region (not necessarily contiguous) for parameter θ if (1) $P(\theta \in R) = 1-\alpha$ and (2) $P(\theta_1) \geq P(\theta_2)$ for all $\theta_1 \in R$ and $\theta_2 \notin R$, i.e., it yields an interval estimate with the added requirement that each value in the interval is larger than those outside of it (Gill 2014: 46).

[20] This agrees with a dimensional analysis of test scores using eigenvalue decomposition, which also suggests a single-factor model. See appendix A.8.

Table 1: Measurement system for latent ability. Posterior means and 95% highest posterior density regions. Panel (A) shows the relationship of θ to cognitive test performance. Panel (B) shows the relationship of θ to observed labor market outcomes.

		θ effects			Tresholds/Residuals	
(A) Ability indicators						
SDT 1-30 sec.	λ_1^a	0.891	[0.845,0.940]	ψ_1^a	0.234	[0.210,0.260]
SDT 31-60 sec.	λ_2^a	0.953	[0.909,0.998]	ψ_2^a	0.096	[0.078,0.114]
SDT 61-90 sec.	λ_3^a	0.890	[0.842,0.938]	ψ_3^a	0.226	[0.201,0.250]
(B) Ability outcomes						
Labor income	β^l	0.122	[0.082,0.161]	ψ^l	0.365	[0.337,0.395]
Unemployment	β^u	−0.174	[−0.260,−0.091]	τ^u	0.354	[0.284,0.422]
Schooling	β^e	0.098	[0.031,0.168]	τ_1^e	−1.072	[−1.155,−0.990]
				τ_2^e	0.603	[0.534,0.677]
				τ_3^e	1.035	[0.952,1.115]

Note: Control variable δ in ability indicator equations estimate as -0.352 ± 0.098. Controls $\boldsymbol{\alpha}$ in labor market outcome equations in panel (B) not shown to save space. Full table available in appendix A.10.

different from zero, as indicated by the fact that the highest posterior density regions for both earnings and unemployment do not include zero.

Figure 1 illustrates the importance of ability by presenting easier to interpret quantities of interest. Panel (B) plots the predicted probability of obtaining a college degree (BA/MA) as function of ability holding other factors constants. Increasing ability by one standard deviation (from the population mean) raises the probability of obtaining higher education by almost 5 percentage points. At the lower end of the ability spectrum the probability of finishing college is 15 percent, while at the higher end of the ability spectrum it rises to almost 30 percent. In panel (C) we plot the expected value of a respondent's monthly net earnings (smoothed over ±3 years). This plot shows the centrality of ability for labor market outcomes. Even after accounting for other factors, such as work experience and immigration status, moving from one standard deviation below to population mean to one standard deviation above increases net monthly earnings by almost 400 Euros. Panel (D) shows the effect of ability on unemployment risk. Here we plot the predicted probability that a respondent experiences spells of unemployment holding other factors constant. We find a substantial effect of ability. Moving up one standard deviation in the ability

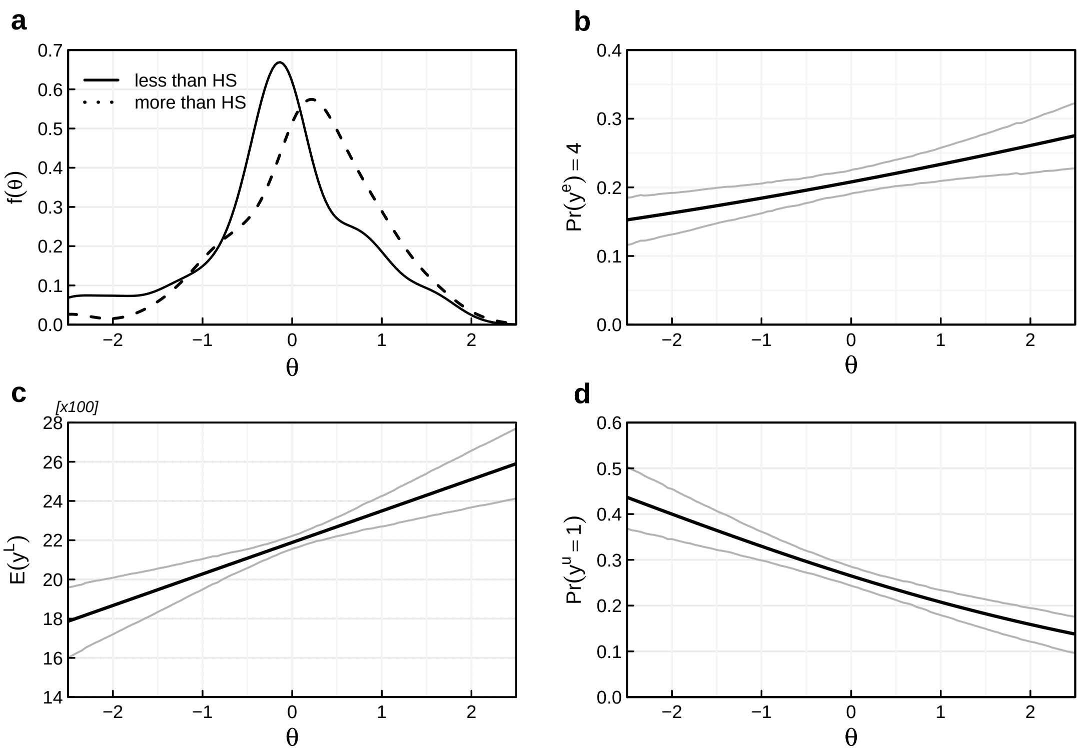

Figure 1: Population distribution and labor market effects of ability. Panel (a) shows kernel density plot of θ for respondents without and with high school (and above) degrees. The sorting into education based on (latent) ability is also illustrated in panel (b) which shows the probability of choosing college education at increasing deciles of θ. Panel (c) shows the effect of ability on labor income; panel (d) shows the effect on the probability of experiencing unemployment.

distribution reduced unemployment risk by more than five percentage points. Even more dramatic is a comparison at the tails of the ability distribution. Those at the bottom (say, two standard deviations below average) have a 40 percent chance of experiencing spells of unemployment, while those at the top have a chance of around 15 percent.

B. Social policy preferences

We now turn to our measurement of social policy preferences. Table 2 shows estimates for the ordinal IRT model of social policy preferences. We find that latent preferences are most strongly related to statements regarding state responsibility for financial security for the sick, the old, and those needing care. The relationship of $\boldsymbol{\omega}$ to state responsibility for financial security of families is somewhat weaker, but still unequivocally non-zero. Estimates of thresholds for each item are spread widely over the support of $\boldsymbol{\omega}$, thus providing information on respondents' social policy ideal points ranging from clear "support" to "opposition" to redistributive social policy.

We plot the estimated social policy ideal points of each individual in panel (A) of Figure 2 and their population density (estimate via a Gaussian kernel evaluated over a 200-point grid) in panel (B). Figure 2 confirms that our model captures a wide range of social policy preferences. While the majority of respondents have ideal points within one standard deviation from the population average (which is normalized to zero), a seizable share of respondents hold more extreme social policy preferences. This is especially the case for those supporting redistributive social policy (i.e., larger values of ω), as can be clearly seen in the density plot in panel (B).Figure 2 also shows that preferences for different individuals come estimated with different levels of uncertainty, which can result from missing data, or from inconsistent response behavior to the social spending items. Simply using single items or sums of items ignores this uncertainty. Our model takes this into account at all stages of estimation.

C. Ability effects on preferences

With measures of ability, θ and social policy preferences, ω, in hand, we can now turn to the test of proposition 3. Panel (A) of Table 3 shows several model specifications of the total effect of ability on social policy preferences, while panel (B)

Table 2: Ordinal IRT measurement equation for social policy preferences. Posterior means with highest posterior density regions.

	Discrimination parameter λ_i^r			Thresholds τ_{it}^r		
Sick	λ_1^r	1.139	[1.006,1.269]	τ_{11}	−1.744	[−1.973,−1.524]
				τ_{12}	0.601	[0.391,0.803]
				τ_{13}	1.971	[1.721,2.222]
Unemployed	λ_2^r	0.764	[0.672,0.855]	τ_{21}	−1.955	[−2.147,−1.775]
				τ_{22}	−0.234	[−0.376,−0.091]
				τ_{23}	0.900	[0.754,1.051]
Care	λ_3^r	1.020	[0.907,1.139]	τ_{31}	−2.116	[−2.335,−1.878]
				τ_{32}	0.377	[0.203,0.565]
				τ_{33}	1.756	[1.543,1.971]
Old	λ_4^r	1.271	[1.119,1.425]	τ_{41}	−1.887	[−2.152,−1.629]
				τ_{42}	0.767	[0.546,0.999]
				τ_{43}	2.174	[1.902,2.465]
Families	λ_5^r	0.575	[0.502,0.653]	τ_{51}	−1.195	[−1.321,−1.060]
				τ_{52}	0.672	[0.556,0.796]
				τ_{53}	1.612	[1.470,1.758]

Notes: Based on 5,000 MCMC samples.

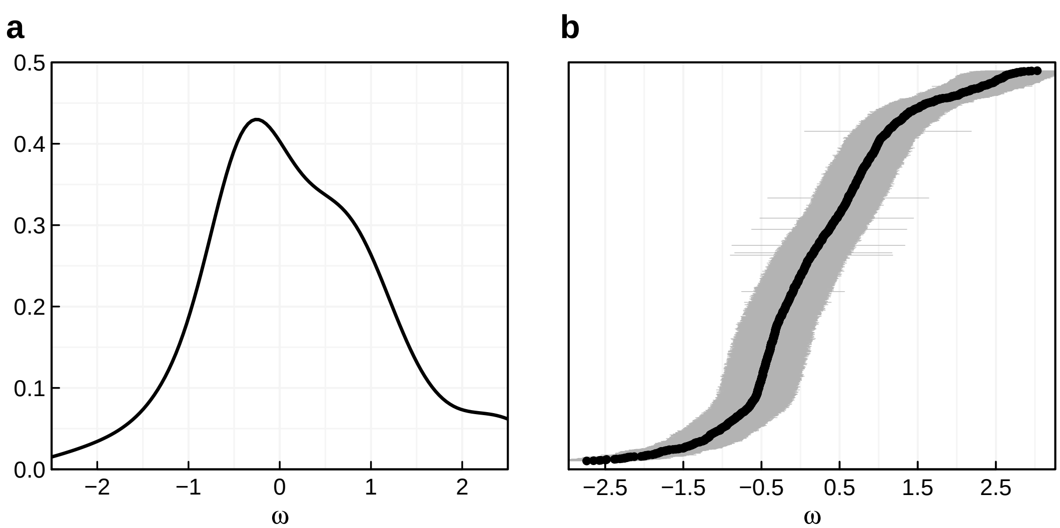

Figure 2: Social policy ideal points. Panel (A) shows the population distribution of social policy preferences via a Gaussian kernel density estimate. Panel (B) shows posterior means and standard deviations of each ω_i estimate.

decomposes this effect into what is transmitted via labor market outcomes and other unspecified channels.

Total effect of ability Estimates displayed in panel (A) provide clear evidence for the negative impact of ability on preferences. We find that individuals with higher ability prefer a less redistributive social policy. Note that our model setup already accounts for endogenous sorting into education, and endogenous labor market outcomes. Specification (1) does not include any additional variables in the preference equation, while specification (2) adds a number of basic individual characteristics, such as age, household size, immigration status, and if a respondent is divorced. Specification (3) adds more extended controls (at the risk of increasing endogeneity problems) such as being self-employed or a union member. All three specifications agree. The effect of a marginal change in ability on social spending preferences is -0.12 ± 0.04, which is significantly different from zero (in both the substantive and statistical sense). Inspecting highest posterior density regions similarly shows that the estimate of that parameter does not include zero.

To show the effect of ability on social policy preferences graphically, we simulate the expected population level of social policy preferences at each level of ability. We calculate social policy preferences for respondents who were born in Germany and are currently living in West Germany (which is economically more prosperous). All other individual characteristics are set to population average values. Figure 3 shows the resulting expected values together with their uncertainty represented by lines for the 90 percent HPD regions. The distribution of ability is indicated by the gray-shaded polygon for reference. This plot once more underscores the significant effect of ability on social spending preferences. Moving a respondent up on standard deviation from the mean of the ability distribution makes him or her prefer markedly less redistributive policies.

Decomposition of ability effect In proposition 3 we argued that the affect of ability on social spending preferences operates *via* labor market outcomes. We put this proposition to a stricter test by decomposing the total effect of ability on preferences into two channels (cf. section III). One channel represents the systematic effect of ability on preferences via labor market outcomes endogenous to a respondent's ability; the other channel represents the (possibly many) mechanisms not considered by our theoretical model (cf. Imai et al. 2011: 769). Results of this decomposition are shown in panel (B) of Table 3. It expresses in a single estimates what was apparent from

Table 3: Effect of ability on social policy preferences. Posterior means, posterior standard deviations in parentheses, HPD regions in brackets.

	(1)	(2)	(3)
(A) Total effect			
Ability	−0.116	−0.122	−0.126
$E(\omega_i(\theta_i'\|\mathbf{x}_i) - \omega_i(\theta_i\|\mathbf{x}_i))$	(0.035)	(0.037)	(0.039)
	[−0.173,−0.057]	[−0.184,−0.063]	[−0.202,−0.050]
(B) Effect decomposition			
Ability via labor market	−0.063	−0.059	−0.049
$E(\omega_i(\theta_i, M_i(\theta_i'\|\mathbf{z}_i)\|\mathbf{x}_i) - \omega_i(\theta_i, M_i(\theta_i\|\mathbf{z}_i)\|\mathbf{x}_i))$	(0.013)	(0.013)	(0.012)
	[−0.083,−0.042]	[−0.079,−0.037]	[−0.074,−0.026]
Ability via other channels	−0.054	−0.063	−0.077
$E(\omega_i(\theta_i', M(\theta_i\|\mathbf{z}_i)\|\mathbf{x}_i) - \omega_i(\theta_i, M(\theta_i\|\mathbf{z}_i)\|\mathbf{x}_i))$	(0.035)	(0.037)	(0.040)
	[−0.112,0.003]	[−0.125,−0.003]	[−0.156,0.001]
Basic controls[a]	no	yes	yes
Extended controls[b]	no	no	yes

Notes: Calculated based on estimates from equation (12) using eqns. (9), (10), and (11).
a Controls included are age, household size, immigration status, being divorced.
b Controls included are age, house ownership, union membership, self-employment, and currently living in East Germany.

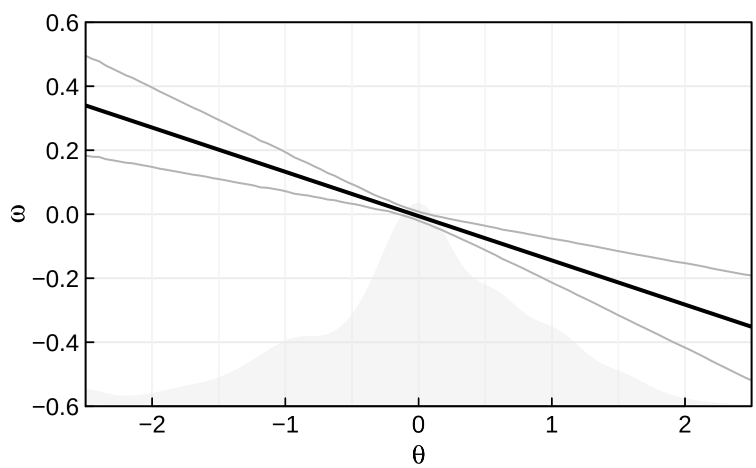

Figure 3: Total effect of ability on social policy preferences. Expected values and 90 percent HPD regions.

our previous discussion of the individual elements making up proposition 3: ability is a central driver of preferences *through* its effect on labor market outcomes. The effect of ability on policy preferences that is channel via the labor market is estimated as -0.06.[21] Its highest posterior density region is clearly bound away from zero, indicating the significance of the ability-labor market channel. Quantitatively, our results mean that almost 50% of the total effect of ability is due to its effect on labor market outcomes.

VII. Robustness Tests

In this section we present a number of alternative specifications to test the robustness of our main conclusions. We consider the role of religion as non-economic factors shaping preferences, industry effects, life-cycle effects on ability, as well as the possibility that our (normal) functional form assumption for the distribution of ability is incorrect.

A. Religion / second dimension

In our first robustness test we include religion, which was stressed by previous research on redistribution (Scheve and Stasavage 2006; Stegmueller et al. 2012; Stegmueller 2013). While relevant for individuals' preference formation, we expect religion to have an additional effect, largely unconnected to the ability-preferences nexus. We estimate a model that includes religion, in the form of indicator variables for the three largest denominations in Germany: Catholics, Protestants, and other denominations. Those not identifying with any denomination are the reference group. We find our estimate of the total effect of ability on preferences is virtually unchanged. We find an estimate of -0.126 with a posterior standard deviation of 0.04.

[21] We conducted robustness checks for violations of the sequential ignorability assumption. We use the procedures outlined in Imai, Keele, and Tingley (2010); Imai, Keele, and Yamamoto (2010) adapted to our more demanding model setup (and implemented in a Bayesian framework). In the next iterations of this paper we will present more detailed plots showing estimated indirect effects under a range of violations; for now we note that our result still obtains when setting ρ (the degree of confounding) to values in the (rather wide) range of -0.5 to 0.5.

B. Industry effects

In our second robustness test we allow for the possibility that a respondent's industrial sector shapes his or her preferences. This means that it is employment in certain industries itself—rather than sorting into industrial sectors based on ability, income prospects, or unemployment risk—that shapes social spending preferences. We account for this possibility by including industry fixed effects for nine major industrial sectors. Under this specification, we estimate the total effect of ability on social policy preferences as -0.109 with a posterior standard deviation of 0.04.

C. Time stability of ability

We stated before that we (had to) assume that fluid intelligence remains rather stable after early adulthood. However, inasmuch as there is a decline of fluid intelligence later in the life-cycle that is not accounted for in our model, we would overestimate the effect of ability on labor market outcomes and preferences. To investigate how much this violation affects our results we estimate a model where ability is a function of age, by replacing θ_i with $f(\theta_i|a_i)$ where a_i is an individual's age. The functional form of this dependence is left unspecified. In our robustness test we approximate it with a simple natural spline with three degrees of freedom (but simpler forms yield no different results). While there is indeed some evidence for the instability of ability due to age, our estimate of the total effect of ability on preferences is -0.127 with a slightly decreased posterior standard deviation of 0.038.

D. Nonparametric ability distribution

One may question how our results are affected by our choice of a normal prior for ability, which was essentially done out of convenience and not derived from our theoretical model. While our Bayesian approach allows the data to overwhelm the prior to produce non-normal posterior distributions of θ, this functional form assumption could be problematic. Imagine a population that is composed of two clearly separated ability types, leading to a bimodal ability distribution. Imposing the assumption of a single-peaked normal distribution would shrink extremely low and high ability types towards the overall ability mean, thus possibly biasing the estimated effect of ability on preferences. We jettison the normality assumption by modeling the distribution of θ non-parametrically using a finite mixture of normals prior (Ferguson

1983):

$$\theta \sim \sum_k \pi_k N(\mu_k^a, \phi_k^a), \;\; k = 1, \ldots, K. \tag{19}$$

This specification allows for very flexible functional forms, including heavy tails and multi-modality (Rossi 2014: 3). Our Bayesian implementation of this model follows the indicator approach first introduced by Diebolt and Robert (1994). The full hierarchical structure is:

$$\theta \sim N(\mu_{z_i}^a, \phi_{z_i}^a) \tag{20}$$

$$z_i \sim \text{MN}(\boldsymbol{\pi}) \tag{21}$$

$$\boldsymbol{\pi} \sim \text{Dirichlet}(\boldsymbol{\alpha}) \tag{22}$$

$$\mu_1^a = 0, \, \phi_1^a = 1 \tag{23}$$

The distribution of θ is a mixture of K normal distributions. For each individual, an indicator variable z_i shows to which mixture component this individual belongs. These indicator variables follow a K-multinomial distribution with category probabilities π, which have the Dirichlet distribution with parameter vector $\boldsymbol{\alpha}$ as their conjugate prior. The first component θ mean is fixed to zero and its variance normalized to one for identification.

In our implementation we set $K = 3$. Our choice is guided by the desire to allow extreme ability types at both ends of the spectrum, in addition to the standard normally distributed types centered over zero. We set $\boldsymbol{\alpha} = (1, 1, 1)$ indicating that the component probability $\boldsymbol{\pi}$ is equidistributed. Figure 4 shows the distribution of θ resulting from this model as histogram and as kernel density estimate (the blue line). A standard normal distribution is added for comparison (red line). Figure 4 reveals clear deviation from normality, especially at the lower end of the ability spectrum, where a normal prior located far fewer individuals than we actually observed. However, even the flexible 3-component model produces a uni-modal distribution of ability, suggesting that our original normal prior choice might serve as a decent approximation.

Of greater interest than the distribution itself is the question if allowing for a more flexible distributional form changes our effect estimates. In our non-parametric model we estimate the effect of θ on social policy preferences as -0.083 with a standard deviation of 0.029.

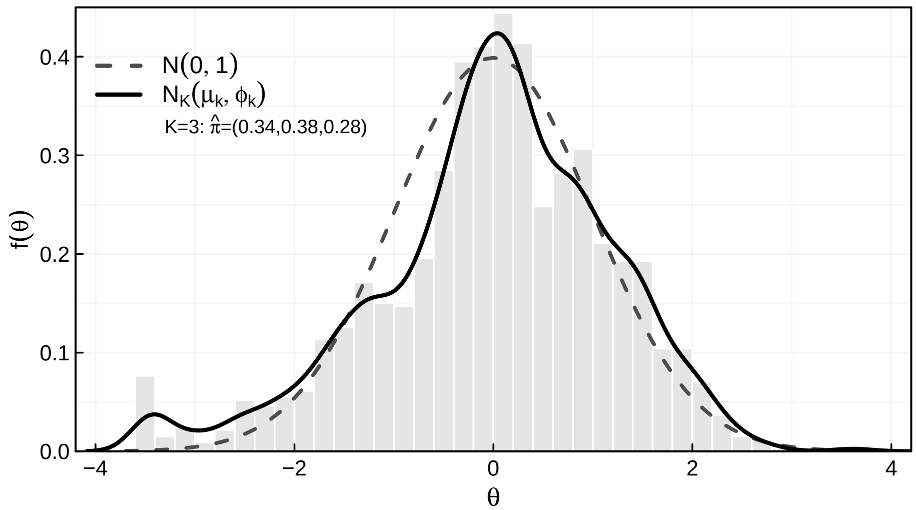

Figure 4: Nonparametric estimate of θ via 3-component mixture of normals prior.

VIII. Conclusion

In this paper we have argued for the centrality of cognitive ability to understanding individuals' preferences for redistribution. We have derived testable prepositions which we analyzed using a large-scale, representative panel study and an empirical model, in which measured individual heterogeneity in ability translates into preferences. Our econometric specification accounts for individual-specific unobserved effects, allows for the fact that cognitive ability measurements are imperfect, and explicitly accounts for endogeneity of labor market outcomes. Our results demonstrate the fundamental importance of ability for redistribution preferences. Ability is a fundamental aspect of individuals' preferences, and this is in seizable parts due to how cognitive ability shapes labor market outcomes. Ignoring the fact that labor market outcomes are endogenous to ability is a threat to valid inference in current standard political economy models.

Most importantly, understanding the path from ability to preferences on the *micro* level can enhance our understanding of *macro*-level political-economic relationships. In following we show how the macro-level implications of our argument reconcile an otherwise disparate set of theoretical arguments and empirical findings about the cross-national determinants of redistribution. To begin, the well-known result of Meltzer and Richard (1981) predicts that redistribution will increase as the distance between median and mean incomes increases. This is often interpreted as meaning that redistribution will increase as inequality grows. In contrast, Moene and Wallerstein (2001), assuming that transfers are provided as insurance and that individuals are sufficiently risk averse, argue that redistribution will decrease as inequality grows. More recently, Lupu and Pontusson (2011) argue that it is not the level of inequality but the structure of inequality that matters for redistribution. They contend that redistribution will increase when the relative income distance between the middle class and the poor is smaller than the distance between the middle class and the rich, a condition they refer to as *skew*. Finally, Rehm, Hacker, and Schlesinger (2012) argue that popular support for the welfare state depends on the correlation between economic disadvantage (income inequality) and economic insecurity (unemployment risk). Welfare state support is weaker (stronger) when this correlation is stronger (weaker).

The following proposition demonstrates how a simple change in the ability distribution (in particular, one that favors low ability types versus middle and high types) can unify all of these arguments into a single theory of redistribution.

Proposition 5. ***(Redistribution)*** *Consider two continuous ability distributions, $F_A(\theta)$ and $F_B(\theta)$. Suppose that (1) $\int y(\theta)dF_A(\theta) = \int y(\theta)dF_B(\theta)$ and (2) for all $\theta \subset [\theta_0, \theta_1]$, such that $0 < \theta_0 < \theta_1 \leq \theta_{m,A}$, $f_B(\theta) > f_A(\theta)$, while for all $\theta \subset [\theta_0, \theta_1]^c$, $f_B(\theta) < f_A(\theta)$. Then the following statements are true:*

1. *The difference between the median and mean income is higher under B than A.*
2. *The skewness (third central moment) of the expected income distribution is higher under B than A.*
3. *Expected income inequality is lower under B than A (B Lorenz dominates A).*
4. *The covariance of income and the employment rate is lower under B than A, which implies that the correlation between them can be lower as well.*
5. *Social spending and redistribution is higher under B than A.*

The first condition defines distribution A as a mean-preserving spread of distribution B. The second condition says that more income is concentrated under distribution B than A to those with abilities less than the median ability of A. From these two conditions the enumerated results obtain.

Because more income is concentrated below the median ability of *A* in *B* than *A*, and yet mean income under both distributions is the same, the distance between median and mean income increases. Since the mean-median distance and skewness are closely related, it is not surprising that skewness also increases, a point not acknowledged by Lupu and Pontusson (2011). It also follows simply from *B* being a mean-preserving contraction of *A* that income inequality and employment rate inequality are lower under *B* than *A*. These two results imply that the correlation of income inequality and unemployment risk is lower under *B* than *A*, a point not acknowledged by Rehm, Hacker, and Schlesinger (2012). Finally, all of these results are consistent with *B* having more redistribution than *A*. This follows from the increase in the median-mean distance as in the Meltzer and Richard (1981) argument. Thus, an increase in the median-mean distance, contrary to widespread belief, is not inconsistent with a reduction in inequality, a point not acknowledged by Moene and Wallerstein (2001).

In conclusion, our model provides a general framework for analyzing a wide range of political-economy phenomena. It can be readily deployed to analyze and test a variety of labor market institutions—wage-setting institutions, employment protection legislation, vocational education and training, active labor market policy—something that we hope to do in future work.

A. Appendix

A.1. Proof of Proposition 1

We divide the proposition into several lemmata to ease the exposition of the proof

Lemma 1. *There exists a unique equilibrium* $\{k^*_\theta, w^*_\theta, q^*_\theta\}$ *in each submarket* θ.

A convenient way to solve this problem is to first find the optimal capital choice, which is given by

$$\eta(q^*)\theta f'(k^*) = 1 \tag{24}$$

This equation clearly implies that k^* is increasing in θ as well as q, since η is increasing in q. This solves for k^*. From here, there are a number of routes to solve the model. We first solve for w^*. First note that the workers utility constraint (6) implies a positive relationship between w and q by the implicit function theorem:

$$\frac{dq_\theta}{dw_\theta} = \frac{-\mu(q_\theta)u'(c)(1-\tau)}{\mu'(q_\theta)[u(c)-u(b)]} \tag{25}$$

Then maximizing firm profit in equation (5) with respect to the wage gives the first-order condition:

$$\eta'(q_\theta)\frac{dq_\theta}{dw_\theta}[\theta f(k)-w] - \eta(q_\theta) = 0 \tag{26}$$

Using equation (25) and $\eta(q) = q\mu(q)$, we can then rewrite equation (26) as:

$$\beta(q_\theta)\frac{u(c)-u(b)}{u'(c)(1-\tau)} = (1-\beta(q_\theta))(\theta f(k^*)-w) \tag{27}$$

where $\beta(q_\theta) \equiv -q_\theta\mu'(q_\theta)/\mu(q_\theta)$ is the elasticity of the employment rate with respect to the queue length and $\beta(q_\theta) \in (0,1)$ from our assumptions on m. Thus the wage is a weighted difference of the firm's surplus and the worker's surplus divided by the marginal benefit of an increase in the wage.

This solves the wage, and, knowing the wage, we can use the firm's zero-profit condition in (7) to pin down the equilibrium queue length. It is easy to verify that a higher w implies a larger q: fewer firms post vacancies when wages are higher, making queue lengths longer. Since $\eta(q)$ is concave, a unique value of q is associated with each w. This ensures the uniqueness of the equilibrium.

Lemma 2. *Aggregate per capita output, $\bar{y}$, is a strictly quasiconcave function of τ.*

From equation (27), the left-hand side is decreasing in τ for any given value of $\bar{y}$. To restore the equality, w must therefore increase. From firms' zero-profit condition, an increase in w implies an increase in q.

Lemma 3. *For each θ, an equilibrium social spending choice τ^*_θ exists and is unique.*

We turn now to workers' social spending preferences. Applying the envelope theorem, this gives the first-order condition for τ as

$$\mu(q_\theta)u'(c)(\bar{y}+\tau\bar{y}_\tau - w_\theta) + (1-\mu(q_\theta))u'(b)(\bar{y}+\tau\bar{y}_\tau) = 0 \tag{28}$$

If left-hand side of (28) is negative at $\tau = 0$, then $\tau^*_\theta = 0$. Otherwise, $\tau^*_\theta \in (0, \tau_{\max}]$. Rearranging we get a useful expression for the first-order condition:

$$1 - \left(\frac{\mu(q_\theta)}{1-\mu(q_\theta)}\right)\left(\frac{u'(c)}{u'(b)}\right)\left[\frac{w_\theta}{\bar{y}} - (1+\xi(\bar{y},\tau))\right] + \xi(\bar{y},\tau) = 0 \tag{29}$$

where $\xi(\bar{y},\tau) \equiv \bar{y}_\tau(\tau/\bar{y})$ is the elasticity of public funds with respect to the tax rate.

Next, $\tau_{\max} < 1$. From equation (27), w is increasing in τ. From the zero-profit condition, $q \to \infty$ as w reaches its upper bound. Hence $\bar{y} \to 0$ as $\tau \to 1$. This further implies that $c \to 0$ and $b \to 0$ as $\tau \to 1$. Hence, $\tau_{\max} < 1$.

Finally, maximizing the output of the economy requires $\tau = \tau_e > 0$. It is a well-known result in the labor market matching literature that maximizing output is equivalent to maximizing workers' expected income. In this case, maximizing aggregate per capita, or average, output implies maximizing $\bar{y}$ in equation (2). This also implies maximizing worker utility when $u(\cdot)$ is linear. From Acemoglu and Shimer (1999), when u_2 is a concave transformation of u_1, then in equilibrium $w_2 < w_1$ and $q_2 > q_1$. Hence, in any equilibrium with $b = \tau = 0$, output will not be optimal.

Acemoglu and Shimer (1999) also show that efficient, i.e., output-maximizing insurance exists. Let $\bar{\theta}$ be the ability level of the average worker. Since $\bar{y} = \mu(q_\theta)w_\theta$, we can rewrite (29) as

$$1 - \left(\frac{\mu(q_\theta)}{1-\mu(q_\theta)}\right)\left(\frac{u'(c)}{u'(b)}\right)\left[\frac{w_\theta}{\bar{y}} - (1+\xi(\bar{y},\tau))\right] + \xi(\bar{y},\tau) = 0 \tag{30}$$

when social spending is targeted to the unemployed ($\chi = 0$). Rearranging this equation gives:

$$1-\left(\frac{\mu(q_s)}{1-\mu(q_s)}\right)\left(\frac{u'((1-\tau)w_s)}{u'(b)}\right)\frac{w_s}{\bar{z}}+\xi(\bar{z},\tau)=0 \tag{31}$$

where $\xi(\bar{z},\tau)\equiv\bar{z}_\tau(\tau/\bar{z})$ is the elasticity of public funds with respect to the tax rate. This formulation of the f.o.c. is convenient, since it captures the three critical effects of Proposition 3. The term $\mu(q_s)/(1-\mu(q_s))$ captures the effect of unemployment risk. The $u'((1-\tau)w_s)/u'(b)$ term is the marginal rate of substitution between employed and unemployed consumption, and captures the effect of risk aversion. The $w_s/\bar{z}$ term is the ratio between individual income and average government revenues, which captures the (pure) income effect.

When government transfers are provided to all individuals ($\chi = 1$), the first-order condition is:

$$\mu(q_s)u'((1-\tau)w_s+b)(\bar{y}+\tau\bar{y}_\tau-w_s)+(1-\mu(q_s))u'(b)(\bar{y}+\tau\bar{y}_\tau)=0 \tag{32}$$

Rearranging, we get an equation analogous to (31):

$$1-\left(\frac{\mu(q_s)}{1-\mu(q_s)}\right)\left(\frac{u'((1-\tau)w_s+b)}{u'(b)}\right)\left[\frac{w_s}{\bar{y}}-(1+\xi(\bar{y},\tau))\right]+\xi(\bar{y},\tau)=0 \tag{33}$$

This second-order conditions are satisfied. Following again Acemoglu and Shimer (1999), some positive level of transfers (targeted or universal) increase output in the economy, so at $\tau = 0$, the first-order conditions are positive. In contrast, at $\tau = 1$ no one would work, and the elasticity of public funds terms would become infinitely negative.

$\square$

A.2. Proof of Proposition 2

An equilibrium for a type θ worker is a tangency between a worker's indifference curve and a firm's zero-profit condition. Therefore, it is straightforward to show that where $\theta_1 > \theta_2$ for any $(\theta_1,\theta_2)\in\Theta$ the zero-profit condition in the type-θ_1 submarket lies everywhere above the curve in the type-θ_2 submarket in $\{q,w\}$ space. Since workers' indifference curves have positive slope, this implies $w(\theta_1) > w(\theta_2)$ and $q(\theta_1) < q(\theta_2)$, which in turn implies $\mu(\theta_1) > \mu(\theta_2)$.

This result is somewhat counterintuitive because queue lengths are increasing with the wage. However, a higher θ also allows firms to earn greater profits, even while paying higher wages, and from the zero-profit condition, this induces more firms to enter the market, which drives down q.

$\square$

A.3. Proof of Proposition 3

We employ monotone comparative statics (Milgrom and Shannon 1994; Ashworth and Bueno de Mesquita 2006).

Beginning with income, differentiate the first-order condition in equation (x) with respect to w. This gives, after rearranging:

$$\mu(q_\theta)\left[\left(\frac{u''(c_E)}{u'(c_E)}\right)(\bar{y} + \tau\bar{y}_\tau - w_\theta) - 1\right] \tag{34}$$

Clearly, as long as $-u''(c_E)/u'(c_E) < -1/(\bar{y} + \tau\bar{y}_\tau - w_\theta)$ for all $w \in [0, \infty]$, then this expression will be negative, and τ^*_θ will be decreasing in w.

Next, we examine employment μ and unemployment $1 - \mu$. Differentiating the first-order condition in equation (x) with respect to μ, we obtain:

$$u'(c_E)(\bar{y} + \tau\bar{y}_\tau - w_\theta) - u'(b)(\bar{y} + \tau\bar{y}_\tau) \tag{35}$$

which is unambiguously negative. Hence, τ^*_θ is decreasing in μ and increasing in $1 - \mu$.

From Proposition 2, τ^*_θ is decreasing in θ through its effects on w and μ.

$\square$

A.4. Proof of Proposition 4

First, for given θ, $\theta h \geq \theta$. From Proposition 2, this implies $w^*_\varepsilon(\theta) \geq w^*_{-\varepsilon}(\theta)$ and $q^*_\varepsilon(\theta) < q^*_{-\varepsilon}(\theta)$. Hence for a type-$(\theta, r = 0)$ person, the condition for acquiring education, $U_\varepsilon \geq U_{-\varepsilon}$, is clearly satisfied. However, as $r \to \infty$, there will exist some r^* such that $U_\varepsilon < U_{-\varepsilon}$ for all $r > r$. This is because for all finite θ, U_ε is finite, but $U_{-\varepsilon}$ is strictly increasing and $\lim_{r\to\infty} U_{-\varepsilon} = \lim_{r\to\infty} \mu u(c+r) + (1-\mu)u(b+r) = \infty$. By the intermediate value theorem, there exists some r^* such that $U_\varepsilon(\theta) = U_{-\varepsilon}(\theta, r^*)$.

Next, the returns to education are increasing in ability. For instance, for any θ, the difference in ability between getting an education and not is $h(\theta - 1) > 0$ which is clearly increasing in θ. This implies that the difference $U_\varepsilon - U_{-\varepsilon}$ for all $r \leq r^*$ is likewise increasing in θ. This in turn implies that both r^* and $G(r^*)$ are also increasing in θ.

Aggregate utility increases with education. Take the difference of $\int_r U_\varepsilon^*(\theta) dG(r)$ and $\int_r U^*(\theta) dG(r)$ and rewrite as

$$\left(\int_0^{r^*} U_\varepsilon^*(\theta) dG(r) + \int_{r^*}^{\infty} U_\varepsilon^*(\theta) dG(r)\right) - \left(\int_0^{r^*} U^*(\theta) dG(r) + \int_{r^*}^{\infty} U^*(\theta) dG(r)\right).$$

From the above, this reduces to $\int_0^{r^*} U_\varepsilon^*(\theta) dG(r) - \int_0^{r^*} U^*(\theta) dG(r)$, and is positive.

Finally, we take note that the presence of $r > 0$ implies $U_{-\varepsilon}(\theta, r) \neq U(\theta)$. This is because r is a kind of "asset" that increases risk-taking behavior. Therefore, $w_{-\varepsilon}^*(\theta, r) > w^*(\theta)$ and $q_{-\varepsilon}^*(\theta, r) > q^*(\theta)$. Intuitively, because ability does not change, workers are on the same zero-profit curve. With the asset, wages are higher, but queue lengths are also longer.

$\square$

A.5. Proof of Proposition 5

The difference between the median and mean income is higher under B than A. This follows from the second condition. Because more of the income is concentrated below the median of *A*, it necessarily requires that the ability of the person with median income under *B* is lower than in *A*.

The skewness (third central moment) of the expected income distribution is higher under B than A. Formally, skewness is defined as the third central moment of a distribution, or:

$$\Sigma \equiv E\left[\left(\frac{Y - \bar{y}}{\sigma}\right)^3\right] = \frac{\int_0^{\infty} (y(\theta) - \bar{y})^3 dF(\theta)}{(\int_0^{\infty} (y(\theta) - \bar{y})^2 dF(\theta))^{3/2}} \tag{36}$$

First, since a mean-preserving spread increases the variance of a distribution, $\sigma_B < \sigma_A$, which increases skewness by decreasing the denominator in (36). Second, from the previous step, we have

Expected income inequality is lower under B than A (B Lorenz dominates A). Write the Lorenz curve of the expected income distribution as:

$$L(p) = \int_0^{\infty} \frac{y(\theta)dF(\theta)}{\bar{y}} \tag{37}$$

From condition (2), we have $L'_B(p) > L'_A(p)$ for all $\theta < \theta_{m,A}$ and $L'_B(p) < L'_A(p)$ for all $\theta > \theta_{m,A}$. This implies that the $L_B(p)$ curve lies everywhere above the $L_B(p)$ curve, and hence that income distribution of B Lorenz dominates A.

The correlation between income and employment is smaller under B than A.

Social spending and redistribution is higher under B than A. This result follows simply from the Meltzer and Richard (1981) argument that an increase in the difference between median mean incomes will increase the preferred tax rate of the median voter.

A.6. Calcuation of effect decomposition

This section describes how we calculate direct and total indirect effects (Robins 2003) of equations (11) and (10) from our model estimates.[22] Consider our model in simplified form with one covariate of interest (treatment), x_i, a mediating variable (preferences), m_i, and confounders, c_i. We estimate the following system of equations:

$$y_i = \beta_0 + \beta_1 x_i + \lambda m_i + \beta_2 c_i \tag{38}$$

$$m_i = \gamma_0 + \gamma_1 x_i + \gamma_2 c_i + \epsilon_{2i}. \tag{39}$$

with

$$\epsilon_{2i} \sim N(0, \sigma^2_{\epsilon_2}) \tag{40}$$

[22]Imai, Keele, and Tingley (2010); Imai, Keele, and Yamamoto (2010); Imai et al. (2011) call these average causal mediated effects for the treated and average direct effects for the control, while Pearl (2001) calls them total natural indirect effects and pure natural direct effects. See Imai, Keele, and Tingley 2010 and Muthen and Asparouhov 2014 for an extended discussion on their computation.

Take the general expression used in the formulas for direct and indirect effects (eq. (11) and (10)), $E(Y(x, M(x'))|C = c)$. As these quantities are not expressed conditional on M, we need to integrate over M:

$$
\begin{aligned}
E(Y(x,M(x'))|C=c) &= \int_{-\infty}^{\infty} (\beta_0 + \beta_1 m + \beta_2 x + \beta_3 c) && (41)\\
&\quad \times f(m; \gamma_0 + \gamma_1 x' + \gamma_2 c, \sigma_2^2) \partial M && (42)\\
&= \beta_0 + \beta_2 x + \beta_3 c + \beta_1 E(M|X = x', C = c) && (43)
\end{aligned}
$$

Indirect effect Denote two values of a treatment by x and x' (e.g., low vs. high ability). The indirect effect (eq. 10) is :

$$E[(Y(x', M(x')) - Y(x', M(x))|C] = \beta_1 \gamma_1 \tag{44}$$

Direct effect The direct effect (eq. 11) is

$$E[Y(x', M(x)) - Y(x, M(x))|C] = \beta_2 \tag{45}$$

The total effect is then simply $\beta_1 \gamma_1 + \beta_2$

A.7. Descriptive statistics

Table A.1 gives means (and standard errors) of covariates used in our model, separately for the pooled estimation sample, and for individuals who did (not) participate in cognitive testing. The final column provides the probability of test refusal as function of observables.

Table A.1: Means of full sample, test-participants and non-participants. Probability of cognitive test refusal. Estimates and standard errors.

	Estimation sample	Test participants	Test refusers	Refusal mfx[a]
Age	46.891	46.389	48.903	0.001
	(0.238)	(0.264)	(0.538)	(0.001)
Income[b]	1.540	1.509	1.671	0.003
	(0.025)	(0.026)	(0.071)	(0.011)
Education				
Elementary	0.164	0.151	0.213	0.062
	(0.006)	(0.006)	(0.015)	(0.024)
General vocational	0.517	0.525	0.486	–[c]
	(0.008)	(0.009)	(0.018)	
Vocational + degree	0.120	0.122	0.110	−0.029
	(0.005)	(0.006)	(0.011)	(0.024)
Higher education	0.188	0.189	0.186	0.010
	(0.006)	(0.007)	(0.014)	(0.025)
Work experience	18.658	18.259	20.257	0.001
	(0.227)	(0.253)	(0.509)	(0.001)
Grown up East	0.160	0.164	0.142	−0.048
	(0.006)	(0.007)	(0.013)	(0.040)
Living East	0.144	0.146	0.138	0.063
	(0.006)	(0.006)	(0.012)	(0.053)
HH size	2.797	2.809	2.749	−0.005
	(0.020)	(0.023)	(0.046)	(0.007)
House owner	0.525	0.519	0.551	0.030
	(0.008)	(0.009)	(0.018)	(0.017)
Foreigner	0.093	0.079	0.150	0.112
	(0.005)	(0.005)	(0.013)	(0.033)
Divorced	0.068	0.066	0.074	0.028
	(0.004)	(0.004)	(0.009)	(0.030)
Unemployment exp.	0.309	0.308	0.315	−0.004
	(0.007)	(0.008)	(0.017)	(0.017)
Union member	0.178	0.180	0.170	−0.012
	(0.007)	(0.007)	(0.014)	(0.020)
Self-employed	0.072	0.066	0.093	0.097
	(0.004)	(0.004)	(0.010)	(0.034)
N	3912	3131	781	3912

[a] Probit model for test refusal; displayed are marginal effects. Correctly classified cases: *****%.
[b] In 1000 constant Euros
[c] Reference category

Table A.2: Items used in measurement models

Item	Missing %
(A) Symbol correspondence test	
SCT correct 1-30 sec.	20.97
SCT correct 31-60 sec.	20.97
SCT correct 61-90 sec.	20.97
(B) State responsibility for financial security	
When Sick	0.43
In Old-Age	0.61
When unemployed	0.61
When Requiring Care	0.67
For Family	0.67

A.8. Dimension analysis of measurement items

In order to check if our choice of one-dimensional factor models for ability and preferences is appropriate, we analyze the dimensionality of our measurement items by examining the eigenvalues of their correlation matrix.

Panel (A) of Table A.2 lists items used in our ability measurement model. About 21% of respondents refuse to participate in the test. We treat non-response as part of our model (i.e., we impute at each step of our MCMC sampler). In the following we use only complete responses. In order to examine if our one-dimensional measurement system is appropriate we calculate the eigenvalues of the correlation matrix of the 3 ability measurements items. Results are displayed in Figure A.1. Using Kaiser's (1960) criterion, as well as the visual inspection of the pattern of eigenvalues, suggests that a one-factor model provides a good summary of the data. See (Heckman 1995) for the same conclusion.

Exact wording of items used in the redistribution measurement model are given in panel (B) of Table A.2. Items are originally recorded on five point agree–disagree scales, but since the lowest categories are very sparsely populated we collapsed responses to four categories (this does not influence our final results, but removes thresholds to be estimated from the IRT model). Nonresponse is low for all items. Eigenvalues of the correlation matrix of the 6 preference measurements are given in Figure A.2. Using Kaiser's criterion, as well as the visual inspection of the pat-

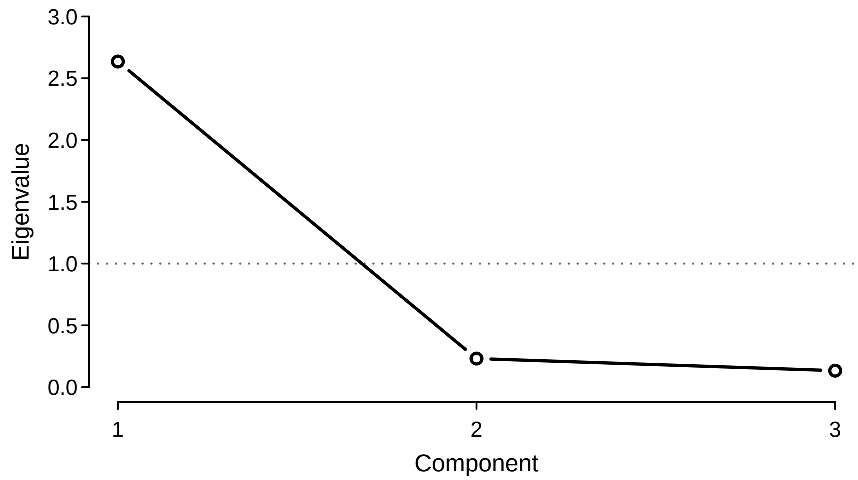

Figure A.1: Eigenvalues of ability measurement items.

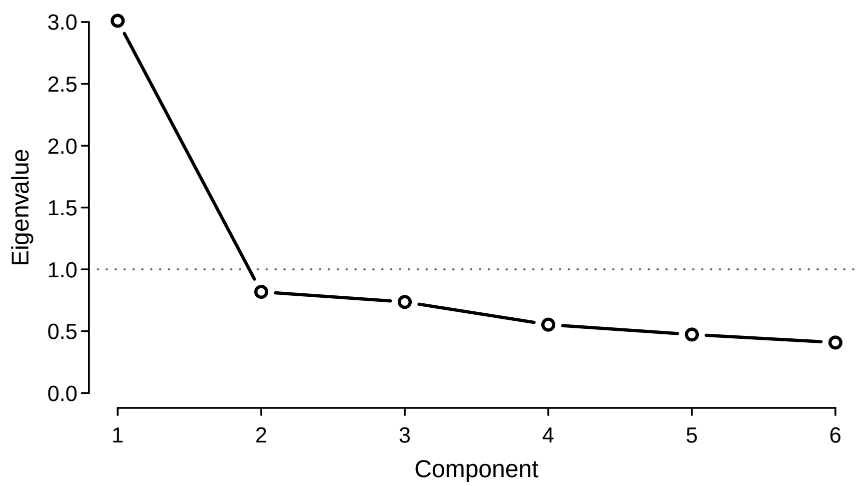

Figure A.2: Eigenvalues of preference measurement items.

tern of eigenvalues, suggests that a one-factor model of social policy preferences is appropriate.

A.9. Prior specification

We elicit priors for coefficients of latent variables in measurement equations by choosing parametrization of a half-normal distribution such that parameters are expected to have mean 0.5 and values greater than 10 occur with a low probability of $p = 0.1$: $\lambda^c, \lambda^n, \lambda^r \sim N_+(0.5, 7.413)$. This represents an a priori expectation of a non-zero relationship between latent skills and their observable manifestations, and orients the latent variables (e.g., such that higher test scores are related to higher latent cognitive skills). Note that this restriction does in no way influence our results (since the latent factors are rotation invariant through their relation to the outcome equations). For threshold parameters in probit equations, we choose parameters for the normal distribution such that values lie in the interval $[-10, 10]$ with probability $p = 0.9$: $\tau^r, \tau^n, \tau^u \sim N(0, 6.08)$. Residuals in equations with continuous left hand side variables are drawn from an inverse Gamma distribution $\epsilon^l, \epsilon^r \sim \Gamma^{-1}(1, 2)$. A zero-centered normal prior with large variance ensures regression type estimates for all control variables in my policy preferences equation, $\gamma_v \sim N(0, 100)$. The same prior is used for controls in skill outcome measurement equations $\alpha^u, \alpha^l, \alpha^e \sim N(0, 100)$. Finally, priors for coefficients for effects of ability in economic outcomes and choice equations and in the policy preferences equation are normally distributed with prior mean zero and a large variance $\beta^l, \beta^e, \beta^u, \eta \sim N(0, 100)$. Given the relatively large sample size of more than a thousand cases, the data dominate these priors, and results are insensitive to prior perturbations. We conducted robustness tests using a different Gamma prior specifications for residuals (shape and scale = 0.001); priors for coefficients with variances 10 times larger; and lambda priors with mean 0. Results are indistinguishable from the ones presented here.

A.10. Complete tables of estimates

[todo]

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