Time Discounting, Savings Behavior and Wealth Inequality[*]

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Abstract

The distribution of wealth in society is very unequal and has important economic and political consequences. According to standard life-cycle savings theory, differences in time discounting behavior across individuals can play an important role for their position in the wealth distribution. Empirical testing of this hypothesis has been difficult because of serious data limitations. We overcome these limitations by linking an experimental measure of time discounting for a large sample of middle-aged individuals to Danish high-quality administrative data with information about their real-life wealth over the life-cycle as well as a large number of background characteristics. The results show that individuals with relatively low time discounting are persistently positioned higher in the wealth distribution. The relationship is of the same magnitude as the association between years of education and the position in the wealth distribution, and it robustly persists after controlling for a large number of theoretically motivated confounders such as education, risk aversion, school grades, income, credit constraints, initial wealth, and parental wealth. These findings support the view that individual differences in time discounting affect individuals' positions in the wealth distribution through the savings channel.

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1 Introduction

Why some people are rich while others are poor is of fundamental interest for economics and the social sciences. One important hypothesis from standard theory is that differences in people's time discounting lead to differences in wealth because those who place a larger weight on future payoffs save more and thus accumulate more wealth. Macroeconomic research suggests that this relationship between time discounting and wealth inequality operating through the savings channel is quantitatively important and that it can contribute to explaining why wealth is more unequally distributed than income (Krusell and Smith 1998; Carroll et al. 2017). It also shows that heterogeneity in time discounting potentially plays an important role in the propagation of business cycles and the effects of stimulus policies because impatient individuals tend to run down wealth and have limited opportunities to smooth consumption (Carroll et al. 2014; Krueger et al. 2016).

This paper examines empirically whether and to what extent differences in how much people discount the future are associated with wealth inequality, and whether the savings channel plays a key role in explaining this relationship. Until now, it has been difficult to measure the relationship between differences in how people discount the future and their wealth status due to data limitations. We tackle this problem by measuring patience – defined as behaviorally revealed time discounting – for about 3,600 mid-life Danish individuals[1] using established incentivized experimental elicitation methods and combining these measures with Danish administrative data containing detailed longitudinal information about individuals' real-life wealth as well as a large number of control variables. These data are maintained by Statistics Denmark and known to be of a high quality (Card et al. 2010). The income and wealth data are third-party reported directly from employers, banks, financial intermediaries, etc. to the tax authorities who use them for tax assessment and selection for audit (Leth-Petersen 2010; Kleven et al. 2011; Chetty et al. 2014a).

Experimental evidence – starting with the famous marshmallow experiments measuring delayed gratification in children in the 1960s up to recent research using intertemporal choices to reveal discounting behavior of adults – points to pervasive heterogeneity in time discounting across individuals (Mischel et al. 1989; Barsky et al. 1997; Frederick et al. 2002; Harrison et al. 2002; Sutter et al. 2013; Attema et al. 2016; Carvalho et al. 2016; Falk et al. 2018). Moreover, experimental measures of the discounting of future monetary payments predict real life outcomes such as individuals' smoking behav-

[1] We deliberately invited people from cohorts now in mid-life so that we can expect the timing of education and retirement to have less influence on wealth ranking and where observed income is arguably a good proxy for permanent income.

ior and BMI/obesity (Chabris et al. 2008, Lawless et al. 2013); students' completion of apprenticeship programs (Backes-Gellner et al. 2017); adolescents' propensity to consume alcohol, buy cigarettes, and violate the school's code of conduct (Sutter et al. 2013); and individuals' level of credit card debt (Meier and Sprenger 2010), suggesting that these measures contain relevant information about how individuals evaluate intertemporal trade-offs.

We document a sizeable association between individuals' patience and their positions in the within-cohort wealth distribution.[2] In accordance with standard life-cycle savings theory the evidence further suggests that savings behavior explains a major part of this association. The 1/3 of the subjects who are the most patient are on average positioned six-seven percentiles higher in the wealth distribution than the 1/3 of the subjects who are the least patient, and the 1/3 of the subjects in the middle group are, on average, positioned in between the two other groups in the wealth distribution. Moreover, the relationship between patience and the position in the wealth distribution is robust both across different measures of time discounting[3] and to the inclusion of housing and automobile wealth. The relationship also holds for subcategories of wealth such as financial wealth, and is remarkably stable over the 15-year period where we measure subjects' wealth (2001-2015), which is consistent with the notion that deep and stable underlying forces shape this wealth ranking.

To assess the strength of the relationship between patience and the position in the wealth distribution, we compare it with the association between wealth inequality and educational attainment. Arguably, educational attainment is one of the most important predictors of lifetime inequality (Huggett et al. 2011). When comparing the 1/3 of the subjects with the lowest education level (compulsory schooling level or only slightly more) to the 1/3 with the highest education level (college degree or more), we find a difference of seven percentiles in the wealth distribution, similar in magnitude to the association between patience and the position in the wealth distribution. Taken at face value, this could simply reflect that discounting and educational attainment are correlated, but, as we show in a multivariate analysis, the relationship between discounting and the position in the wealth distribution is only slightly smaller when we control for education.[4] At the same time, parental wealth is known to be a very strong predictor

[2]Throughout the paper, when we use the terms wealth rank, wealth position, or rank in the wealth distribution, we always mean the within-cohort percentile rank of individuals.

[3]We exposed subjects to choice tasks with three different combinations of time horizons. This allows us to construct three different measures of time discounting. All three measures lead to the same conclusion regarding the influence of time discounting on wealth rank. Note also, that we focus in this paper on identifying individuals' "long-run" patience (i.e, the "exponential part" of time discounting), and we are not interested in identifying present bias (which would require different experimental elicitation methods; see Augenblick et al. 2015).

[4]We are interested in the role of time preferences for wealth rank via the savings channel. To identify this channel, we need to control for education because education affects permanent income and the timing of income independently of individuals'

of individual wealth (Charles and Hurst 2003). Individuals with parents belonging to the highest 1/3 of the parental wealth distribution are positioned 15 percentiles higher than individuals with parents in the lowest 1/3 of the wealth distribution. Thus, patience is roughly as powerful as education in predicting a person's position in the wealth distribution and half as powerful as parental wealth.

In the context of standard life-cycle savings theory, patient individuals save more and become, ceteris paribus, wealthier at all points in the life-cycle compared to impatient individuals. In practice, however, the association between patience and wealth could also arise because of a correlation between patience and permanent income, the timing of income, wealth transfers, initial wealth, or risk preferences. We therefore collected data to control for all of these factors in order to isolate the savings channel. Even after having controlled for a comprehensive set of theoretically motivated covariates, our results reveal a significant relationship between time discounting and wealth inequality with an association between patience and wealth position that accounts for at least 80 percent of the bivariate relationship across all specifications.

Our sample is large in an experimental context, but too small to study the dynamics in the very top of the wealth distribution. However, we find a significant relationship between patience and being located in the top 10% of the wealth distribution, and we also show that patience is a significant predictor of different sub-components of net wealth such as the amount of liquid assets held. To identify the savings channel, we also examine the role of credit constraints because they play an important role in explaining observed savings behavior (Zeldes 1989) and because borrowing limits constrain net wealth from below. Individuals may become credit constrained because of income shocks, but as recent research suggests, credit constraints may also be self-imposed because relatively impatient individuals have less savings and are more likely to face credit constraints (Carroll et al. 2014, 2017). More generally, the propagation of shocks is typically stronger in an environment where discount factors are heterogeneous because credit constraints affect more people (Krueger et al. 2016). Consistent with these hypotheses, we find that individuals who are relatively impatient are more likely to be subject to constraints. In one test, we follow the previous empirical literature (e.g., Johnson et al. 2006; Leth-Petersen 2010) and consider people to be affected by constraints if they hold liquid funds worth less than one month's disposable income (hard credit constraint). We find a strong negative association between patience and this measure of constraints over the entire period for which we have wealth data. In fact, the share of credit constrained individuals is considerably larger among the 1/3 least patient subjects compared to the 1/3 most patient ones in

savings behavior. But, of course, time preferences may also affect individuals' education levels and therefore the overall effect of time preferences on wealth rank may in fact be larger than what the savings channel captures.

each of the 15 years of the study. The fact that credit constraints more largely affect the most impatient individuals for such a long period of time suggests that the fundamental long-run characteristics of these individuals — such as their degree of impatience — underlies this pattern.[5]

The existence of a considerable share of people with credit constraints has interesting testable implications for the role of time discounting in people's position in the wealth distribution. In particular, people who are regularly subject to credit constraints cannot further reduce their net wealth position by borrowing money. This means that the variation in patience among the part of the population disproportionately affected by credit constraints is likely to have only limited effects on their wealth positions. In contrast, the savings and borrowing behavior of the part of the population not subject to credit constraints can vary more freely and their patience levels therefore have much more scope for influencing their wealth positions. The data nicely bear out the prediction that credit constraints mute the relationship between patience and the position in the wealth distribution. For subjects who hold liquid assets worth less than one month's disposable income, the patience measure is no longer a significant predictor of wealth positions. In contrast, for subjects with liquid wealth corresponding to more than one month's disposable income, the impact of patience on the wealth position becomes much larger: moving from the lowest to the highest level of patience in this group increases the wealth rank position by 12 percentiles.

Our measure of patience is based on individuals' choices among time dated monetary payments. An important question is, therefore, whether the elicited variation in time discounting across individuals simply reflects variation in market interest rates or credit constraints (Frederick et al. 2002; Cohen et al. 2016) such that homogenous preferences could explain our empirical results. This explanation is, however, rather implausible for the following reasons: First, if our patience measure simply reflected individual-specific market interest rates, it should completely lose its power to explain individuals' position in the wealth distribution if we control for individual interest rates. To address this question, we acquired access to individual account level data with information about outstanding debt and interest payments during the calendar year, which enabled us to calculate the marginal interest rates for each individual in our sample (Kreiner et al. 2018). If we include this variable as a control in our regression, the patience measure is still a highly significant and sizeable predictor of individuals' position in the wealth distribution. Second, we observe that substantial variation in our patience measure remains in the part of the population that is constrained, i.e., has liquid wealth of less than one month's disposable

[5] In particular, the persistence with which credit constraints disproportionately affect impatient individuals makes it unlikely that transitory negative shocks at the time when we elicited discount rates are responsible for people's experimentally revealed impatience.

income. It is thus unlikely that the patience measure simply reflects credit constraints. In addition, if our patience measure contains meaningful information about individuals' time preferences such that it affects the position in the wealth distribution through the savings/borrowing channel, then the variation in our patience measure should primarily affect the wealth position of people who are not constrained, which is exactly what we find.

Third, if individual-specific variation in market interest rates or credit constraints are hypothesized as drivers behind the patience measure, one must ask where this variation in interest rates and constraints could come from. One possibility is that it could come from adverse transitory shocks to income or wealth that affect individuals' creditworthiness. However, we find that high-discounting individuals are *persistently* more likely to be affected by constraints *over a* 15-*year period*, which does not seem compatible with *transitory* shocks having caused a high market interest rate. Alternatively, the variation could be due to long-term differences between individuals in, say, levels of income, initial wealth, or parental wealth, but the association between patience and wealth exists after controlling for these differences.

Therefore, taken together, we believe that the above evidence suggests that patience as measured in our experiment is likely to play a significant role in explaining people's position in the wealth distribution. To further corroborate this interpretation, we examined the determinants of individuals' positions in the wealth distribution in another sample of 2,550 subjects from the 1952-1955 cohorts. We have a survey measure of time discounting for these individuals, collected when they were 18-21 years old, i.e., the time discounting measure was taken roughly 30 years *before* the period for which we examine wealth data. As in our original sample, individual differences in time discounting predict *persistent* differences in individuals' wealth over the period 2001-2015. This shows that our results are robust to the timing of the measurement of individuals' patience.

Our study relates to the literature in public finance and macroeconomics documenting wealth inequality and trying to understand its causes and consequences. This literature documents that wealth inequality is enormous, persistent, and considerably larger than income inequality (e. g., Piketty and Saez 2014). Work on understanding the driving forces behind wealth inequality has focused on differences across people in income processes, wealth transfers, saving propensities, capital returns, and public policy (e.g. Heathcote et al. 2009; Piketty 2014; Hubmer et al. 2016; Boserup et al. 2016, 2018; Fagereng et al. 2018; De Nardi and Fella 2017). Traditional macroeconomic models of consumption and savings with heterogeneous agents assume that agents are homogeneous in terms of preferences and the stochastic properties of the income process (Heathcote et al. 2009; De Nardi and Fella 2017). A common feature of this class of models is that individuals face different shock sequences and thereby realizations of income, which lead them to make different consumption-savings decisions. Initial conditions may vary across individuals, for example by allowing for heterogeneity in initial wealth or innate productivity, which add additional potential for heterogeneity in consumption and savings choices. As relatively good data on earnings are widely available, this has been the preferred way to introduce heterogeneity. An alternative way to introduce heterogeneous "initial conditions" is to let preferences vary across individuals, keeping the assumption that each individual's preferences are fixed (Krusell and Smith 1998; Carroll et al. 2017). These macro models show that even a limited degree of heterogeneity in time discounting can generate a significant increase in wealth inequality compared to the reference case with homogeneous preferences and that the assumption of heterogeneous time discounting significantly improves the match with the empirically observed wealth distribution.

Our contribution relative to this literature is that we provide independent measures of individuals' actual time discounting. This enables us to (i) document a persistent association between differences in time discounting and wealth rank that is robust to different measures of discounting and wealth, (ii) assess the quantitative influence of individuals' patience on wealth position relative to factors such as education and parental wealth, (iii) show that the existence of credit constraints strongly mutes the influence of heterogeneous time discounting as predicted while magnifying it for those unaffected by constraints, and (iv) identify the savings channel as the likely mechanism behind the influence of heterogeneity in time discounting on people's positions in the wealth distribution. In addition, based on an independent sample and a different measure of subjective discounting elicited in the early 1970s, we show that differences in time discounting significantly predict individuals' wealth rank 30 years later.

Our paper is also related to the experimental literature on the elicitation of time preferences. This literature has documented large heterogeneity in time discounting across individuals (e.g. Attema et al. 2010; Abdellaoui et al. 2010; Epper et al. 2011; Andreoni and Sprenger 2012; Abdellaoui et al. 2013; Augenblick et al. 2015; Attema et al. 2016; Harrison et al. 2002) and that the elicited discount rates predict real life outcomes (Chabris et al. 2008; Meier and Sprenger 2010; Lawless et al. 2013; Sutter et al. 2013; Backes-Gellner et al. 2017). However, none of these papers attempt to identify the sources of wealth inequality, i.e., they do not address questions (*i*)–(*iv*) mentioned above.

The remainder of the paper is organized as follows. The next section illustrates within a basic life-cycle savings model why we should expect a positive association between patience and wealth inequality, and it points to factors we need to control for if we want to isolate the mechanism operating through the savings channel empirically. Section 3 presents the sampling scheme, the experimental design, and the register data on wealth and characteristics of the participants. Section 4 presents the empirical results and section 5 features different robustness checks. Section 6 concludes.

2 Association between time discounting and wealth in theory

This section illustrates within a simple neoclassical, deterministic life-cycle savings model how heterogeneity across individuals in subjective discounting is expected to generate differences in savings behavior leading to permanent differences in wealth levels across individuals at all ages. It also points to other factors that may generate a relationship between time discounting and wealth, which we need to control for if we want to isolate the effect operating through the savings channel. Finally, we discuss various extensions of the simple framework.

2.1 A basic neoclassical model of individual life-cycle savings

Assume that an individual chooses spending $c(a)$ over the life-cycle $a \in (0, T)$ so as to maximize the discounted utility function

$$U = \int_0^T e^{-\rho a} u\left(c\left(a\right)\right) da, \quad u\left(c\left(a\right)\right) \equiv \frac{c\left(a\right)^{1-\theta}}{1-\theta} \tag{1}$$

where $u\left(\cdot\right)$ is instantaneous utility, θ is the coefficient of relative risk aversion, and ρ is the rate of time discounting reflecting the degree of impatience. The flow budget constraint is

$$\dot{w}\left(a\right) = rw\left(a\right) + y\left(a\right) - c\left(a\right), \tag{2}$$

where $y\left(a\right)$ is income excluding capital income, $w\left(a\right)$ is wealth, r is the real interest rate yielding capital income $rw\left(a\right)$. Utility (1) is maximized subject to the budget constraint (2), a given level of initial wealth $w\left(0\right)$ and the No Ponzi game condition, $w\left(T\right) \geq 0$. The solution is characterized by a standard Euler equation/Keynes-Ramsey rule, which may be used together with the budget constraint to derive the following closed-form relationship between an individual's wealth level at age a in the life-cycle and the different wealth determinants (see Appendix A):

$$w\left(a\right) = Y\left(\gamma\left(a\right) - \frac{1-e^{\frac{r(1-\theta)-\rho}{\theta}a}}{1-e^{\frac{r(1-\theta)-\rho}{\theta}T}}\right)e^{ra}, \tag{3}$$

where Y is lifetime resources equal to the present value of income over the life-cycle plus initial wealth, while $\gamma(a)$ is the share of lifetime resources received by the individual up to age a:

$$Y \equiv \int_0^T y(a) e^{-ra} da + w(0), \quad \gamma(a) \equiv \frac{\int_0^a y(\tau) e^{-r\tau} d\tau + w(0)}{Y}.$$

It follows from equation (3) that the wealth level of an individual $w(a)$ starts at the given initial value $w(0)$ and goes to 0 at the end of the life span. The wealth level may both increase or decrease when going through the life-cycle (higher a), and it may become negative (this happens for example, if initial wealth is zero, $w(0) = 0$, and income equals zero, $y(a) = 0$, at the beginning of the period, in which case wealth starts by decreasing from its initial level of zero). The main prediction follows from the wealth equation (3) (see Appendix A):

Differences in time discounting across people (ρ) *generate differences in savings behavior* $(c(a)$ profiles$)$ *that generate inequality in wealth* (cross-sectional variation in $w(a)$), *with patient people having most wealth at all points in the life-cycle* (a) *conditional on the other wealth determinants* $(Y, \gamma(a), T, r, \theta)$.

This shows that subjective discounting and wealth is related through the savings channel. Differences in wealth may also arise because of differences across people in permanent income Y, time profile of income $\gamma(a)$, (expected) lifetime T, real interest rate r on savings, and the CRRA parameter θ reflecting the degree of intertemporal substitution in consumption. These factors are potential confounders that we would like to control for in order to isolate the role of the savings channel for the association between time discounting and wealth inequality. If, for example, patient individuals attain higher education levels and therefore higher permanent income Y, then this creates a positive relationship between patience and wealth beyond the savings mechanism. On the other hand, more education would normally also imply a steeper income profile, which in isolation reduces the level of wealth at a given age (due to lower values of $\gamma(a)$ in equation 3).

Note that differences in the CRRA preference parameter θ have ambiguous effects on wealth as shown in Appendix A. A higher θ reduces wealth if $r > \rho$ and increases wealth if $r < \rho$. Intuitively, a higher θ implies a stronger preference for consumption smoothing, which flattens the consumption profile. If the initial consumption profile is increasing (decreasing), occurring when $r > \rho$ ($r < \rho$), then this increases (decreases) consumption in the first part of life leading to lower (higher) wealth over the life-cycle.

Note also that the theory does not imply a clear relationship between differences in patience and the cross-sectional variation in consumption/savings levels. Patient individuals have, ceteris paribus, lower consumption levels early in life and higher consumption levels later in life compared to impatient individuals.

2.2 Extensions

Income shocks: The model only allows for deterministic variation in income over the life-cycle. This contrasts with standard macro models of wealth inequality where income develops stochastically and is uninsurable (De Nardi and Fella 2017). This gives variation in wealth beyond the income determinants in the above model (Y,$\gamma(a)$) and mutes the relationship between discounting and wealth. Nevertheless, as described in the introduction, Krusell and Smith (1998) and others show that heterogeneity in discounting behavior may improve the ability of macro models to explain wealth inequality.

Endogenous income and human capital formation: We have assumed exogenous income. Work effort and human capital accumulation may well be related to impatience (Blinder and Weiss 1976), which would affect wealth beyond the savings mechanism described in the model above. However, this does not necessarily change the above result. Consider, for example, the following extension of the basic model where an individual chooses the share of time spent on work $l^y(a)$, human capital formation $l^h(a)$ and leisure $l^u(a)$ at all ages a such that $l^y(a) + l^h(a) + l^u(a) = 1$. Income now depends on hours worked and the level of human capital $h(a)$, which depends on time spent on education:

$$\begin{aligned} y &= f\left(h(a), l^y(a)\right), \\ \dot{h}(a) &= g\left(h(a), l^h(a)\right), \quad h(0) \text{ given,} \end{aligned}$$

where $f(\cdot)$ and $g(\cdot)$ are production functions with standard properties. Finally, the utility function is extended with utility from leisure such that

$$U = \int_0^T e^{-\rho a}\left[u\left(c(a)\right) + v\left(l^u(a)\right)\right] da,$$

where $v(\cdot)$ is a concave function. In this case, the first order condition for spending again gives the standard Keynes-Ramsey rule and when combined with the budget constraint (2), we again obtain the wealth expression (3). Hence, it is still the case in the extended model that a correlation between wealth and subjective discounting reflects the mechanism going through the savings channel if we just condition on the other wealth determinants, since controlling for permanent income Y and the income profile parameter $\gamma(a)$ capture the mechanisms going through income and human capital.

Wealth transfers: Inter vivo transfers and bequests influence wealth inequality (De Nardi 2004; Boserup et al. 2016; 2018). The model does not explicitly include wealth transfers, but wealth transfers received may be included in $y(a)$, in which case the wealth expression (3) is unchanged. In a similar vein, we may interpret $c(a)$ as spending including transfers. From an empirical point of view, transfers only matter for the results if they are correlated with subjective discounting (after controlling for income and the other wealth determinants described above). If, for example, more patient individuals are also more prone to save in order to leave bequests, this then creates a positive relationship between patience and wealth running through savings. Thus, the main prediction is the same although savings are motivated by giving consumption possibilities to others in the future rather than own future consumption.

Credit constraints: In the simple model, each individual may borrow and lend at a fixed interest rate r (which could vary across individuals). A large literature has theoretically and empirically examined the role of credit constraints for savings behavior and the persistent effects of business cycle shocks (Zeldes 1989; Leth-Petersen 2010; Krueger et al. 2016). To see the implications of including a (hard) credit constraint, consider the special case where consumers can never have negative wealth, i.e. $w(a) \geq 0$ for all $a \in (0, T)$. Assume initial wealth $w(0)$ is zero and income is constant, $y(a) = y$ for all a. For patient individuals with $\rho < r$, the constraint is not binding, because they would wish to have an increasing consumption profile, implying that the wealth equation (3) still applies. For impatient individuals with $\rho > r$, wealth becomes zero at all points in the life-cycle, $w(a) = 0$ for all a. These individuals would prefer a decreasing consumption profile over the life-cycle, but they will end up consuming their current income because of the credit constraint. All individuals with $\rho > r$, but different degrees of impatience ρ, will then end up having the same wealth at all points in time (zero in this case). As this example illustrates, credit constraints may imply that the most impatient individuals (ρ above some threshold) are constrained from borrowing, and that therefore patience and wealth become uncorrelated within this group.

A "softer" version of credit constraints is that the interest rates on loans are larger than on deposits and that more borrowing implies higher (marginal) interest rates, reflecting that marginal lending is less likely to be covered by collateral and more likely to be subject to default. This implies that the marginal interest rate on additional funds for consumption is (weakly) decreasing in the level of wealth, corresponding to $r(w)$ where $r'(w) \leq 0$. As more impatient individuals are more willing to pay a higher interest rate, we would ceteris paribus expect a correlation between subjective discounting and the marginal interest rates across individuals.

In the empirical analysis, we use measures of both hard and soft credit constraints to examine whether a correlation between time discounting and the propensity to be constrained exists, and we analyze whether time discounting is associated with wealth inequality after controlling for credit constraints.

3 Experimental design, sample and data

Our empirical analysis combines experimental data and administrative register data. The Danish research infrastructure makes this possible, whereby data can be linked across modes of data collection using social security numbers. We use standard experimental techniques to measure time discounting and risk attitudes for a sample drawn from the population. We then link this information at the individual level to administrative records with longitudinal information on wealth and income over the life-cycle and other individual characteristics that may be important according to the theory in section 2. This section describes the sampling scheme, the design and implementation of the experiment, and the register data.

3.1 Sample and recruitment for the experiment

Respondents were recruited by sampling individuals from the Danish population register satisfying the following two criteria: (*i*) born in the period 1973-1983, and (*ii*) residing in the municipality of Copenhagen (Københavns Kommune) when they were seven years old. Statistics Denmark, the central authority on Danish statistics, provided a data set of all individuals who met these two sample criteria. The data set contained names, current addresses, and civil registration numbers. All individuals in the gross sample received a personal invitation letter in hard copy from the University of Copenhagen.[6] The letter informed subjects about a unique username and password needed to log in to a web page, the expected time to complete the experiment, and contact information for support.[7] Subjects were also informed that the could earn money by participating in the study and that that the overall payment would depend on their choices.

We invited a total of 27,613 subjects to participate in the online experiment that took place in February 2015.[8] 4,190 (15.17 percent) of all invitees logged in to our experimental platform. The vast majority

[6]The invitation letter and an English translation are available in Appendix B.1.

[7]An extensive pretesting phase preceded the main experiment. This phase comprised focus groups and a series of pilot experiments. We used these pretests to improve the task presentation, to calibrate the choice situations, and to obtain expected times for completion.

[8]Only 424 (1.54 percent) of the 27,613 invitation letters were returned.

(3,717 or 88.71 percent) of subjects who did so successfully completed the experiment and received a payment. Our analyses include a total of 3,620 subjects.[9] Participation rates at this level are common for similar experimental studies (e.g. Andersson et al. 2016 report 11%). Sections 3.3 and 5 analyze selection into the experiment.

Subjects who followed the web link in the invitation letter arrived at a login page. After successful login, a single page with introductory instructions appeared. These instructions described the outline of the experiment and payment modalities. Subjects were also presented with a graphical depiction of a wheel they had to spin at the end of the experiment. They were told that the spin of the wheel at the end would determine the choice situation that would count for payment, and, hence, that any of the choice situations could be picked for payment. The online experiment included three preference elicitation tasks to measure time, risk, and social preferences. Each task was accompanied by short video instructions and comprehension questions. The three blocks appeared in individualized random order. Within each block, the set of choice situations was once again randomized. This paper focuses on the time task, which is described in detail in the next subsection. In some of the analyses, we include information from the risk task, which is described in Appendix B.4.[10]

The median completion time was 47 minutes. Our elicitation tasks involved real monetary incentives. We used an experimental currency and informed the subjects that 100 points corresponded to 25 Danish kroner (DKK).[11] This provided us more flexibility for calibration of the choice situations. At the end of the experiment, the subject spun the wheel in order to determine the choice situation relevant for payment. The random choice situation where the wheel stopped was then displayed together with the subject's decision, and the points were exchanged into money. Payment was done via direct bank transfer at the relevant date (details follow below). Possible payments considering all three tasks ranged from 88 to 418 DKK. The average amount paid out was 245 DKK.

3.2 Measuring patience

We use standard money-earlier-or-later experiments to elicit patience. These experiments are well-suited for implementation on an internet platform. We describe the choice tasks and how they are used to

[9] For the linkage between experimental and register data, it is important that the people who participated in the experiment are identical to the people who were invited. To check that the correct person participated in the experiment, the respondents were asked to state their gender and year of birth as the first thing after logging in to the experiment. 38 respondents were excluded from the analysis because their stated gender and/or year of birth were not identical to the information in the register data. In addition, we excluded 59 persons without the required register data information (typically immigrants).

[10] The results reported in this paper do not use data from the social task. Results, not reported here, did not suggest any significant relationship between social preferences and wealth inequality.

[11] 1 USD $\simeq$ 6.5 DKK at the time of the study.

measure patience below.

Time tasks: Our measurement of intertemporal choice behavior is based on convex time budgets (Andreoni and Sprenger 2012). We depict intertemporal choices graphically and present only a single allocation choice per page. We used a total of 15 independent choice situations that differed in terms of payment dates and interest payments.

Figure 1 depicts screenshots of a typical choice situation. The left panel shows a typical choice screen in its initial state. The right panel presents the same situation after selection of an allocation. At the beginning of each choice situation, each subject was endowed with ten colored 100-point blocks. These ten blocks were allocated to the earlier of the two payment dates (in Figure 1a: "in 8 weeks"). The subject then had the possibility to move some (or all) of the ten blocks to the later date (in Figure 1a: "in 16 weeks"). When shifting a block into the future, the subject was compensated by a (situation-specific) interest payment. That is, each 100-point block's value increased once it was deferred to the later point in time. In the example depicted in Figure 1, each block allocated at the later point in time has a value of 105 points. The subject thus had to decide how many of the ten blocks he wanted to keep for earlier receipt, and how many of the blocks he wanted to postpone for later receipt. Figure 1b presents an example selection. In this example, the subject chose to allocate four 100-point blocks for receipt in 8 weeks, and save the remaining six 100-point blocks for receipt in 16 weeks. Deferring the receipt of the latter six blocks led to a total interest payment of $6 \cdot 5 = 30$ points. Choices were made by clicking (or touching) the respective block, after which a horizontal bar appears that could be moved up and down. Alternatively, it was possible to use the keyboard or the buttons at the very top. Once a definitive choice was made, the subject clicked on the "Confirm" button at the bottom right. The decision was then stored in the database and it was no longer possible to amend the choice. The next (randomly selected) choice situation was presented thereafter. Once all 15 choice situations had been presented, the experiment continued with the next task or the end-of-experiment questionnaire.

Figure 1: Example of choice situation

(a) Initial screen

(b) Selected option

Notes: The figure shows screenshots of a typical choice situation. The left panel shows a typical choice screen in its initial state. The right panel presents the same situation after selection of an allocation.

The literature on experimental measures of time and risk preferences has pointed out that "choice bracketing" or the "narrow bracketing of choice situations" governs individuals' choices. Choice bracketing means that individuals treat decisions "one at a time" and do not integrate them into their broader choice sets, i.e., they tend to neglect the set of choices available outside a given choice situation (Kahneman and Lovallo 1993; Read et al. 1999). For example, one important reason for observing risk aversion at small experimental stakes is that individuals typically do not integrate their lifetime wealth into the decision situation when deciding about whether to accept a gamble.[12] Note however, that choice bracketing is not just a feature of behavior in the laboratory. It occurs, for example, in insurance markets (Cicchetti and Dubin 1994)[13] and college admissions (Simonsohn and Gino 2013), and also appears to play an important role in stock markets (Benartzi and Thaler 1995; Barberis et al. 2006). The wide prevalence of choice bracketing means that one can retrieve meaningful measures of subjective risk aversion and time preferences by putting subjects in laboratory choice situations with monetary gambles and dated monetary payments, respectively, and that these measures can then be used to predict other behaviors inside or outside the laboratory. In particular, the experimental measure will have predictive

[12] If individuals integrated their lifetime wealth into the experimental choice situation, they should be risk neutral because the experimental stakes are negligible relative to their lifetime wealth, i.e., their utility function is basically linear for the experimental stake levels.

[13] Cicchetti and Dubin (1994) examine individuals' purchases of insurance against the possibility of malfunctions in their home telephone wiring. They report that people pay 45 cents each month to insure against an expected loss of 26 cents a month, which reflects a 1/200 chance of losing \$55. When viewed from a monthly perspective, this amount of risk aversion appear not unreasonable. However, from the perspective of lifetime wealth, the risk involved appears negligible, making it difficult to rationalize risk averse behavior without referring to narrow bracketing.

power to the extent to which subjective preferences measured in the experiment reveal an individual's general tendency to value risk and time in other domains.

Choice situations in our experiment involved three different payment dates: "today", "in 8 weeks", and "in 16 weeks". Combinations of all three payment dates were used. We decided to state delays in terms of weeks (instead of months) to prevent possible weekday effects. The compiled list of transactions were then sent electronically to the bank for implementation of the payout. Subjects knew that the payment was initiated either on the same day, or exactly 8 or 16 weeks later. Hence, the payment dates shown on the screen refer to the points in time where the transactions were actually initiated. It took one day to transfer the money to the subject's "NemKonto", which is a publicly registered bank account that every Danish citizen possesses and which is typically used as the salary account. Exceptions were non-banking days, such as weekends or holidays. In this case, the transaction occurred on the subsequent banking day.

The interest rates applied varied across choice tasks. For example, the five choice tasks asking subjects to choose between receiving payments in 8 weeks or 16 weeks had rates of return in the interval 5-25 percent (amounting to annualized interest rates in the range of 34-282 percent). This range of interest rates is similar to those used in the other studies reviewed in the introduction. Moreover, Appendix B.3 shows that the distribution of choices made by the participants in our internet experiment is very similar to the choice distribution in the lab experiment of Andreoni and Sprenger (2012). Potentially, discount rates for larger stake sizes would be lower due to the so-called "magnitude effect" (e.g. Frederick et al. 2002). However, for our purpose of examining the link between patience and wealth inequality, only the ordering of the subjects according to their time discounting is relevant. The magnitude effect would arguably change the size of the elicited discount rates, but there is no reason to believe that it would change the relative position of the subjects.

Patience measure: We use a simple patience index based on the mean number of blocks saved for later receipt to measure an individual's degree of patience. We compute the patience index for the five choice situations in the time frame with allocations between $t_1 = 8$ weeks and $t_2 = 16$ weeks:[14]

$$\phi_{\text{patience}} = \text{mean}\left(\frac{z_1}{10}, ..., \frac{z_5}{10}\right), \tag{4}$$

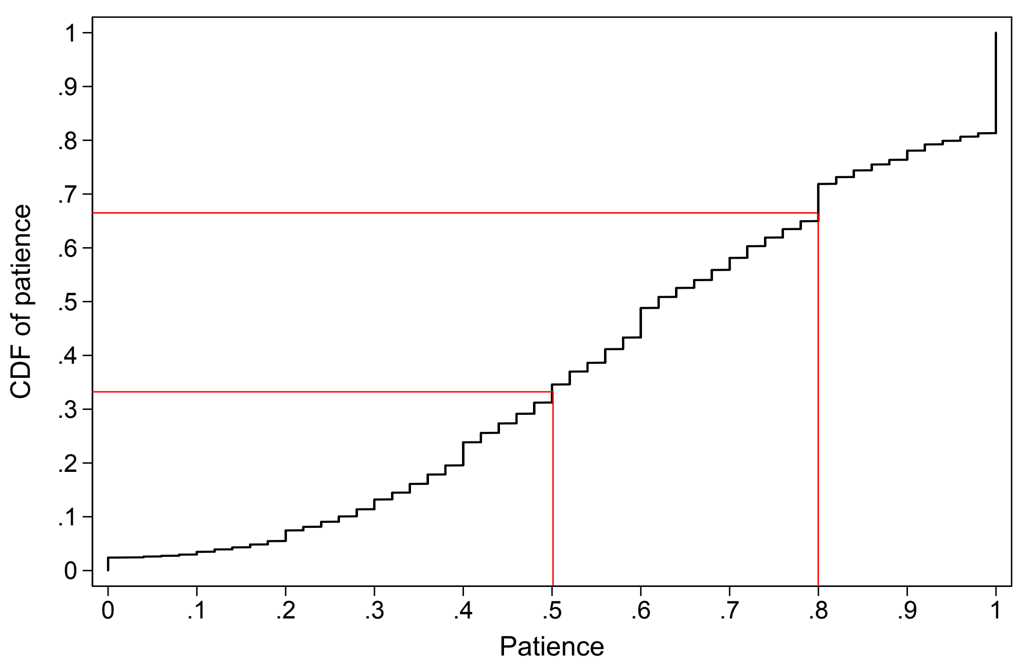
where z_i denotes the number of blocks saved in task i, and where we divide each choice by the total number of blocks so that $\phi_{\text{patience}} \in [0, 1]$. Higher values of ϕ_{patience} indicate greater patience. Due to the

[14]The allocations are labeled choiceId $\in \{11, ..15\}$ in Table A1 of Appendix B.2.

discreteness of our measures (10 blocks to allocate in each of the 5 choice situations), our index can take values in steps of 1/50. By construction, censoring occurs at both ends of the scale, making it impossible to detect lower and higher discount rates than those offered in the experiment. Figure 2 depicts the cumulative distribution of the patience index. It reveals substantial heterogeneity across the individuals in the sample with the exception of the top end of the distribution where 18 percent of the individuals saved all blocks in all five choice situations. Figure 2 also shows tertile cut-off points, which are used in the empirical analyses to split individuals into high, medium, and low patience groups in order to be able to illustrate the differences in outcomes across these groups graphically.

In the robustness section 5.2, we show that our results are robust to using the choices based on the time frames "today" versus "in 8 weeks" and "today" versus "in 16 weeks", to basing the aggregation of individual choices on the median instead of the mean, and to ranking the individuals according to structurally estimated discount factors obtained from a random utility model estimated on the choice data.

Figure 2: Distribution of the patience index



Notes: The figure shows the cumulative distribution of the patience index computed from expression (4) using the experimental data. The red lines indicate tertile cut-off points.

3.3 Register data information on wealth and other characteristics

The choice data from the experiment is linked at the individual level with administrative register data at Statistics Denmark.[15] The register data contains demographic characteristics and longitudinal information about annual income and values of assets and liabilities at the end of each year for each individual. The income and wealth information is based on third party reports to the Danish tax authorities. For instance, employers report earnings, government institutions report transfer payments, and banks, mortgage institutions, mutual funds, and insurance companies report values of assets and liabilities. The value of assets includes bank deposits, market value of listed stocks, bonds and mortgage deeds in deposit, and value of property assessed by the tax authorities using land and real estate registries. The value of liabilities includes all debt except debt to private persons. The data contains information about adult individuals (age$\geq$18) over the period 1980-2015. Wealth accumulated in pension accounts and estimated car values are available as of 2014. In the robustness section, we show that the inclusion of these components has minor effects on the main results.

The Danish wealth data has been used previously for research examining credit constraints (Leth-Petersen 2010; Kreiner et al. 2018), retirement savings (Chetty et al. 2014a), accuracy of survey responses (Kreiner et al. 2015), effects of bequests on wealth inequality (Boserup et al. 2016), and effects of wealth taxation on wealth accumulation (Jakobsen et al. 2018). Wealth inequality has been reasonably stable in Denmark over the 35-year observation period, with the top 10% richest owning between 50 and 80 percent of wealth depending on the definition of wealth and the sample considered (Boserup et al. 2016; Jakobsen et al. 2018).

Table 1 provides summary statistics for our respondents (column a), and compares their characteristics to those of non-respondents (columns b-c) and a 10% random sample of the full population of this age group (columns d-e). The respondents' median wealth level is slightly higher than the median of their annual gross income. People in the bottom 10% of the distribution have negative net wealth. Percentile 95 of the wealth distribution is about five times the median. The corresponding ratio for the income distribution is less than 2, showing that wealth is much more concentrated than income. The respondents are slightly older, less likely to be single, and slightly more highly educated compared to non-respondents. Wealth and income of the respondents are higher throughout the distributions. In general, the differences are smaller when we compare respondents to the random sample of the population. For example, the difference in median wealth is less than 1 percent. Section 5 provides evidence

[15] In practice, the experimental data was merged with the administrative data by Statistics Denmark using a link between usernames provided in the invitation letters and the civil registration numbers of the individuals. The final data set where the personal identifiers are removed is stored on servers at Statistics Denmark enabling data analysis through a secure interface. The participants were not informed that the data from the experiment would be linked with the administrative register data. The Danish Data Protection Agency approved the research project and this procedure.

suggesting that our main results are not very sensitive to the differences in sample composition shown in Table 1.

Table 1: Means of selected characteristics

	(1) Respondents vs. non-respondents			(2) Respondents vs. 10% of population	
	(a) Respondents	(b) Non-respondents	(c) Difference, (a)-(b)	(d) Population	(e) Difference, (a)-(d)
Age	37.32	36.46	0.86	37.37	-0.05
Woman (=1)	0.50	0.49	0.01	0.51	-0.01
Single (=1)	0.28	0.38	-0.10	0.28	0.00
Dependent children (=1)	0.61	0.57	0.04	0.63	-0.02
Years of education	14.89	14.16	0.73	14.64	0.25
Gross income distribution					
p5	135745	98974	36772	130343	5402
p25	287472	234966	52506	270900	16572
p50	383040	341611	41429	360132	22908
p75	484472	434678	49795	456263	28209
p95	720178	654999	65179	700517	19661
Wealth distribution					
p5	-337615	-351123	13507	-241803	-95812
p25	93898	48919	44978	144177	-50280
p50	487002	317400	169602	483217	3785
p75	1066942	800074	266868	972420	94522
p95	2397821	2024448	373373	2254289	143532
Observations	3620	23626	27246	67539	71159

Notes: Variables are based on 2015 values. The random 10% sample of the Danish population is drawn from individuals born in the same period (1973-1983) and not included in the gross sample (i.e., did not live in the capital city of Copenhagen or the surrounding area when they were seven years old). (=1) indicates a dummy variable taking the value 1 for individuals who satisfy the description given by the variable name. Wealth denotes the value of real estate, deposits, stocks, bonds, mortgage deeds in deposit, cars, and pension accounts minus all debt except debt to private persons. The tax assessed values of housing is adjusted by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. Gross income refers to annual income and excludes capital income. The table includes individuals for whom a full set of register variables is available.

4 Empirical results

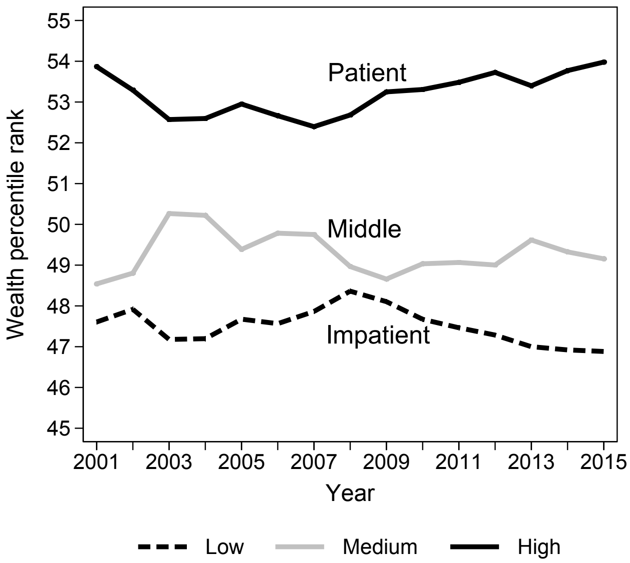
In this section, we present the empirical findings. First, we derive the overall association between time discounting and wealth inequality. Informed by theory, we then introduce a large number of control variables with the aim of isolating an association between patience and wealth inequality operating through the savings channel. We also analyze whether the elicited patience predicts if individuals are among the top 10% of the wealthiest, and we present a large number of robustness analyses.

4.1 Overall association between time discounting and wealth inequality

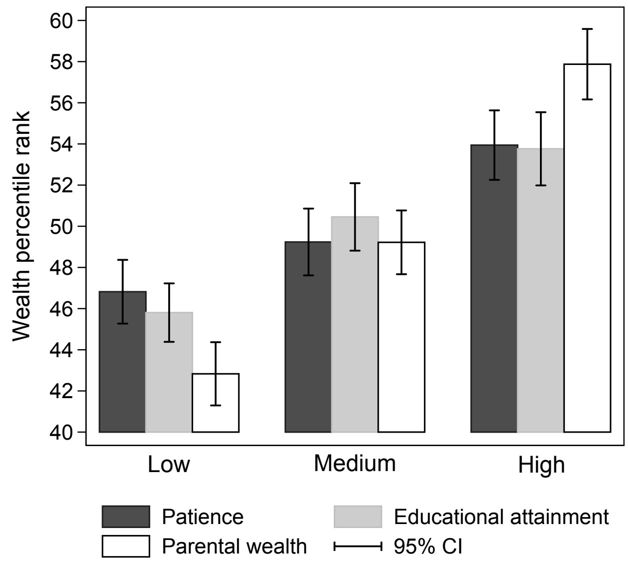
Most of our analysis is based on measuring the relationship between individuals' elicited time discounting and their positions in the wealth distribution, measured by the individual's percentile rank in the within cohort×time distribution of the sample (e.g. Chetty et al. 2014b). This measure has several advantages: it compares an individual's wealth with the wealth of others from the same cohort and at the same point in time, thereby controlling for life-cycle and time trends in wealth; it works well with zero and negative observations that are common in wealth data; and it is a very robust measure (insensitive to outliers and unaffected by monotone transformations of the underlying data). Figure 3a presents graphical evidence of the association between the elicited patience measure and the position in the wealth distribution of the individuals in the sample for each year in the period 2001-2015. In the figure, the sample is split into three equally sized groups according to the size of the patience measure such that the "High" group includes the most patient individuals in the sample, "Low" the least patient individuals and "Medium" includes individuals with patience measures between the "High" and "Low" groups. The figure shows that the individuals' patience ordering predicts the position in the wealth distribution, so that the group average of the most patient individuals is consistently at the highest position in the wealth distribution, followed by the group with medium patience, and with the most impatient individuals on average attaining the lowest position in the wealth distribution. Comparing the percentile rank position among the most patient with the rank position among the least patient in Figure 3a reveals a difference of about 6-7 wealth percentiles throughout the 15 year period that the data spans.

Figure 3: Time discounting, educational attainment, and wealth inequality

(a) Patience and position in the wealth distribution



(b) Patience vs. education and parental wealth



Notes: Panel a shows the association between elicited patience and the position in the wealth distribution in the period 2001-2015. The position in the distribution is computed as the within cohort×time percentile rank. The sample is split into three equally sized groups according to the tertiles of the patience measure such that "High" includes the 33 percent most patient individuals in the sample, "Low" the 33 percent most impatient individuals and "Medium" the group in between the "High" and "Low" groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. Panel b compares the patience-wealth association to the education-wealth association and to the parental wealth-wealth association. The subject's wealth is measured in 2015, educational attainment equals years of completed education, and parental wealth is measured when the subject was eighteen years old. The individuals in the sample are split into three equally sized groups according to patience, years of education, and parents' position in their wealth distribution, respectively. Cut-offs for the education groups (years): Low [8, 14]; Medium [14, 16.5]; High [16.5, 21] where the numbers refer to years of completed education.

To assess the magnitude of the association between patience and wealth inequality, we compare it to the association between educational attainment levels and wealth inequality. Huggett et al. (2011) argue that educational attainment is one of the most important factors contributing to lifetime inequality. Figure 3b splits the sample into three equally sized groups according to educational attainment as measured by the number of years of completed education. The group with least education has completed 8-14 years of education, while the group with most education has completed 16.5-21 years of education. Comparing the groups with the lowest and the highest level of educational attainment shows a difference of six to seven wealth percentiles, which is comparable to the association with patience. We also compare the association between patience and wealth to the relationship between parental wealth and child wealth. It is well-known from the intergenerational literature that parental wealth is a strong predictor of child wealth (Charles and Hurst 2003; Clark and Cummins 2014; Adermon et al. 2018). Figure 3b also splits the sample into three equally sized groups according to parental wealth. Individuals with parents in the top 1/3 of the parental wealth distribution are positioned 15 percentiles higher in the child wealth distribution than individuals with parents in the lowest 1/3 of the parental wealth distribution. In other words, based on the bivariate correlations, heterogeneity in time discounting and in education appear to be roughly equally important for individuals' wealth rank, whereas parental wealth is roughly twice as important.

4.2 Isolating the savings channel

4.2.1 Role of education and income

The bivariate association between patience and wealth inequality in Figure 3 is potentially caused by higher savings propensities of patient individuals as predicted by life-cycle savings theory, but it could also exist because patient individuals invest more in education, thereby attaining higher income and wealth, or because of the other mechanisms described in the theory section 2. We therefore turn to multivariate regressions and sequentially add control variables with the aim of isolating an association between patience and wealth inequality operating through the savings channel. We focus on the wealth percentile rank at the end of the observation period in the regressions. At this point in the life-cycle, individuals have completed their education and income is arguably a good proxy for permanent income (Haider and Solon 2006).[16] The results are presented in Table 2. Column 1 presents the result from a simple bivariate regression of the wealth percentile on the patience measure. It shows that moving from the lowest to the highest level of patience in the sample is associated with a difference of some eleven wealth percentiles, and this association is statistically significant at the 0.1 percent level.

[16]We also ran regressions with wealth data covering the whole period 2001-2015. The results are presented in section 5.3 and confirm the results presented in Table 2.

Table 2: Patience and wealth inequality

Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	11.37***	9.68***	9.56***	10.42***	9.33***	9.21***	9.46***	9.50***
	(1.73)	(1.75)	(1.75)	(1.83)	(1.80)	(1.79)	(1.80)	(1.81)
Risk aversion							2.70	2.90
							(2.10)	(2.11)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gross income decile dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
Parental wealth decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Wealth at age 18 decile dummies	No	No	No	No	No	Yes	Yes	Yes
Demographic controls	No	No	No	No	No	No	No	Yes
Constant	42.81***	39.51***	39.34***	37.66***	33.36***	29.06***	27.58***	28.34***
	(1.16)	(1.82)	(2.08)	(2.58)	(2.98)	(3.16)	(3.38)	(3.50)
Observations	3620	3620	3620	3330	3330	3330	3330	3330
Adj. R-squared	0.01	0.02	0.03	0.03	0.07	0.08	0.08	0.08

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. The measurement of patience is described in expression (4). Ranks in the wealth and income distributions are computed within-cohort in 2015. Gross income does not include capital income. School grades are self-reported by the respondents on our online platform. Parental wealth is measured when respondents were 18 years old. “Demographic controls” include a gender dummy, a dummy for being single, and a dummy for having dependent children. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

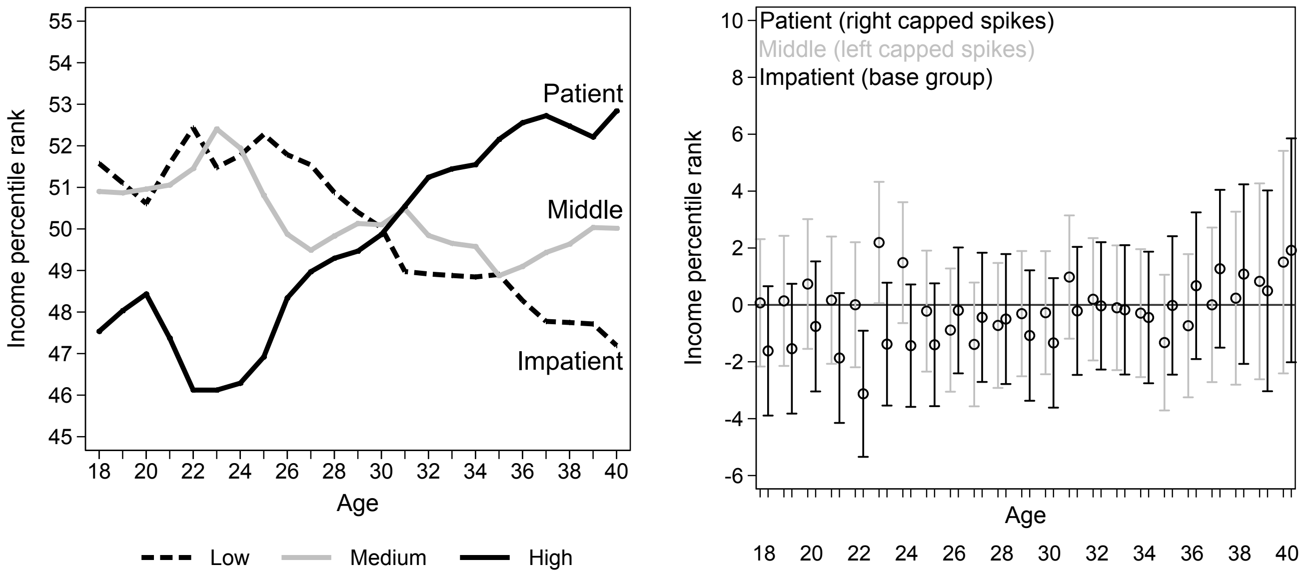
Patient individuals may be more prone to have delayed incomes by choosing longer education. Conversely, education may also contribute to patience. The data shows a significant positive correlation between patience and educational attainment. The average years of education for the low patience group is 14.3, while it is 15.3 years for the high patience group. In this way, education is also a marker for patience as suggested by Lawrance (1991). Column 2 includes flexible dummies for educational attainment as control variables. The coefficient on the patience measure decreases somewhat, but it is still large with a value of 10 percentiles. Thus, the relationship between patience and wealth exists beyond education.

According to the basic theory, differences across individuals in the level of permanent income and in the time profiles of income are important for the cross-sectional variance in wealth. A higher permanent income is associated with a higher position in the wealth distribution at all ages. However, holding total lifetime income fixed, an increasing profile of income leads to a lower position in the wealth distribution at all ages compared to a flat income profile. Figure 4a plots the position in the within-cohort income ranks for the respondents at different ages and separately for the three patience groups defined in Figure 3. The panel shows that the most patient group on average has a steeper income profile over the age interval 18-40. They start out being ranked lower in the income distribution than the less patient groups, but at age 40 they are positioned about 6 percentiles higher than the low patience group, suggesting that these individuals have a higher level of permanent income. It turns out that the controls for educational attainment capture these differences in timing of income and levels of permanent income to a large extent. To see this, consider Figure 4b, which plots coefficients from regressions of the (within age group and year) labor income percentile rank on the patience group dummies, where "low patience" is the reference group, and a fully flexible set of dummies for years of completed education. Panel b shows that the differences across the three patience groups in the level and the slope of income are washed out by controlling for educational attainment. This suggests that including a detailed set of dummies for educational attainment in Table 2, column 2, adequately controls for the differences in permanent income and in timing of income observed in the raw data.

Figure 4: Relationship between discounting behavior and income over the life-cycle

(a) Unconditional

(b) Conditional on education



Notes: Panel a shows the position in the within-age-group-and-year labor income distribution for the respondents over the life-cycle separately for three patience groups. The sample is split into three equally sized groups according to the tertiles of the patience measure such that "High" includes the 33 percent most patient individuals in the sample, "Low" the 33 percent most impatient individuals and "Medium" the group in between the "High" and "Low" groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. Panel b plots coefficients from regressions of 'within-age-group-and-year labor income percentile rank' on the patience groups and fully flexible "years of education" dummies. "Middle" and "Patient" indicate the "Medium" and "High" patience groups, respectively. "Low" patience is the base group. Capped spikes represent 95% CI. The panel shows that the income paths for the three patience groups are leveled out when controlling for education.

In column 3 of Table 2, we further control for income differences by including decile dummies for the position in the within-cohort income distribution (gross income excluding capital income). The inclusion of these dummies hardly affects the parameter on the patience measure.[17] Recent evidence suggests that cognitive ability is correlated with time discounting and risk attitudes (Dohmen et al. 2010).[18] In column 4, we add decile dummies for school grades. This increases the estimate of the patience parameter.

4.2.2 Controlling for parental wealth and initial wealth

Wealth accumulation may also be influenced by transfers from parents (Boserup et al. (2016)), which may help explain why wealth is more concentrated than income (De Nardi 2004). We do not directly observe bequests and *inter vivo* transfers in the data. However, if the variation in family transfer payments across

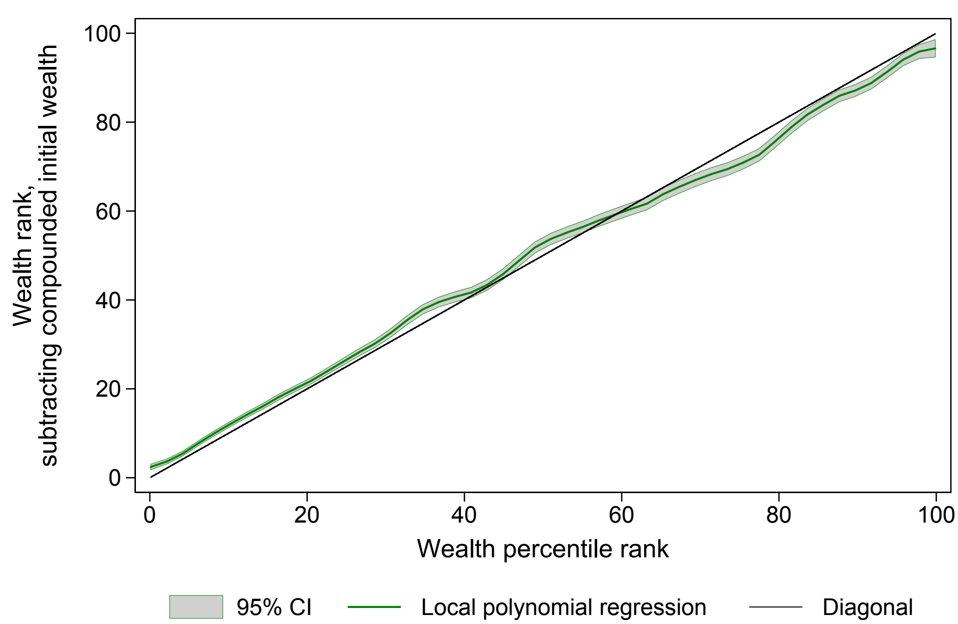
[17] We have also constructed a figure corresponding to Figure 3a, but where wealth is normalized by income in 2015 before calculating the position in the wealth distribution. This graph also shows that the most patient individuals are persistently located higher in the distribution of wealth-income ratios than the less patient individuals.

[18] The association between risk preferences and ability has recently been questioned (Andersson et al. 2016).

individuals is a function of parental wealth, this information can be used as a proxy. Column 5 includes decile dummies for the within-cohort parental wealth measured when individuals are 18 year old. The coefficient on the patience measure remains largely unchanged, indicating a nine percentile increase in the wealth rank associated with moving from the bottom to the top of the patience distribution.[19]

Theoretically, initial wealth is another potential confounding factor if we want to isolate the role of the savings channel. Figure 5 plots the percentile rank of wealth in year 2015 *less* wealth holdings at age 18 (the age of majority) against the wealth percentile rank in year 2015. We compound wealth at age 18 with a relatively high real interest rate (5 percent) to make sure that we do not underestimate the potential effect of initial wealth. The graph lies close to the 45 degree line implying that initial wealth has a negligible effect on the position in the wealth distribution in year 2015, in line with the evidence in Boserup et al. (2018). Table 2, column 6 includes decile dummies for the within-cohort wealth rank at age 18. Consistent with the graphical evidence, the inclusion of these controls does not affect the parameter on patience in any important way.

Figure 5: Importance of initial wealth at age 18



Notes: Local polynomial regression of the percentile rank of wealth in 2015 less wealth holdings at age 18 on wealth percentile rank (2015). Wealth at age 18 is compounded by a real interest rate of 5 percent.

[19]We obtain the same result if we confine the sample to individuals where both parents are alive in 2015, see Appendix C.1. This rules out that wealth differences are driven by inheritance from parents.

4.2.3 Risk preferences and demographic controls

We also elicited risk preferences in the experiment. Section 2 shows that the CRRA parameter has ambiguous effects on wealth depending on the relative size of the rate of time preference and the real interest rate on savings. Irrespective of the theoretical association between risk aversion and wealth, existing studies suggest that risk aversion and patience are correlated (e.g. Leigh 1986; Anderhub et al. 2000; Eckel et al. 2005). In our data, elicited risk aversion is also correlated with elicited patience, and risk aversion could therefore potentially confound the association between wealth and patience. Column 7 includes our experimental measure of risk aversion among the control variables. Again, our parameter of interest is left virtually unchanged and remains strongly significant.

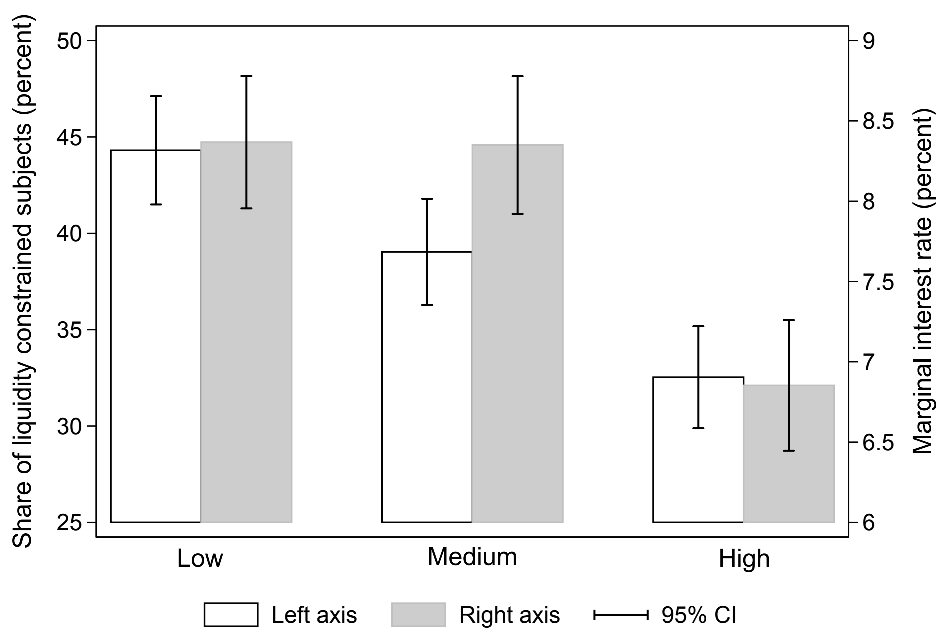
Column 8 includes a set of additional demographic controls for gender, single status, and dependent children. This does not impact the patience parameter estimate either.

4.2.4 Role of financial markets

So far, we have focused on controlling for heterogeneity in economic resources entering into the intertemporal budget set of the individuals. In this section, we focus on potential differences in the slope of the budget constraint. Theory predicts that relatively impatient people wish to borrow more and, therefore, face a higher risk of being credit constrained. This potential relationship between patience and credit constraints may contribute to the propagation of business cycle shocks and the impact of stimulus policy (Carroll et al. 2014; Krueger et al. 2016). It also implies that credit constraints can mute the relationship between patience and wealth as shown in section 2. In this section, we analyze whether the elicited degree of patience in the experiment is related to credit constraint tightness measured with the register data, and whether this influences the relationship between patience and wealth. We also use the register data to control for heterogeneity in asset returns. Finally, we address whether it might be the case that the time discounting elicited in the experiment only measures market interest rates faced by the subjects rather than heterogeneity in true time discounting.

Credit constraints are inherently difficult to measure, as they are defined by the shadow value of liquidity, which is not observed. We follow the previous literature and apply two different proxies for liquidity constraints. Our first measure is a dummy variable for the respondent holding liquid financial assets corresponding to less than one month's disposable income. This measure has routinely been applied in the literature (e.g. Zeldes 1989; Johnson et al. 2006; Leth-Petersen 2010). However, it is not necessarily a good measure of the shadow value of liquidity, as people can have different access to credit and therefore effectively face constraints that affect them with different intensity even if they are otherwise observationally equivalent. Therefore, we also use a measure capturing the interest rate on marginal liquidity (local slope of the budget set). This 'marginal interest rate' is based on account level data with information about debt, deposits, and interest payments during the year. We calculate an average interest rate for each account of an individual. For people with debt accounts, we select the highest interest rate among debt accounts as the marginal interest rate. For people without debt, we select the lowest interest rate among their deposit accounts based on the logic that this is the cheapest source of liquidity. Kreiner et al. (2018) show that the computed interest rates match actual interest rates set by banks and that this measure of liquidity constraint tightness improves the ability to predict spending responses to a stimulus policy. Details about the construction of the marginal interest rate and its distribution are presented in Appendix C.2 and Kreiner et al. (2018).

Figure 6: Patience and the probability of being credit constrained

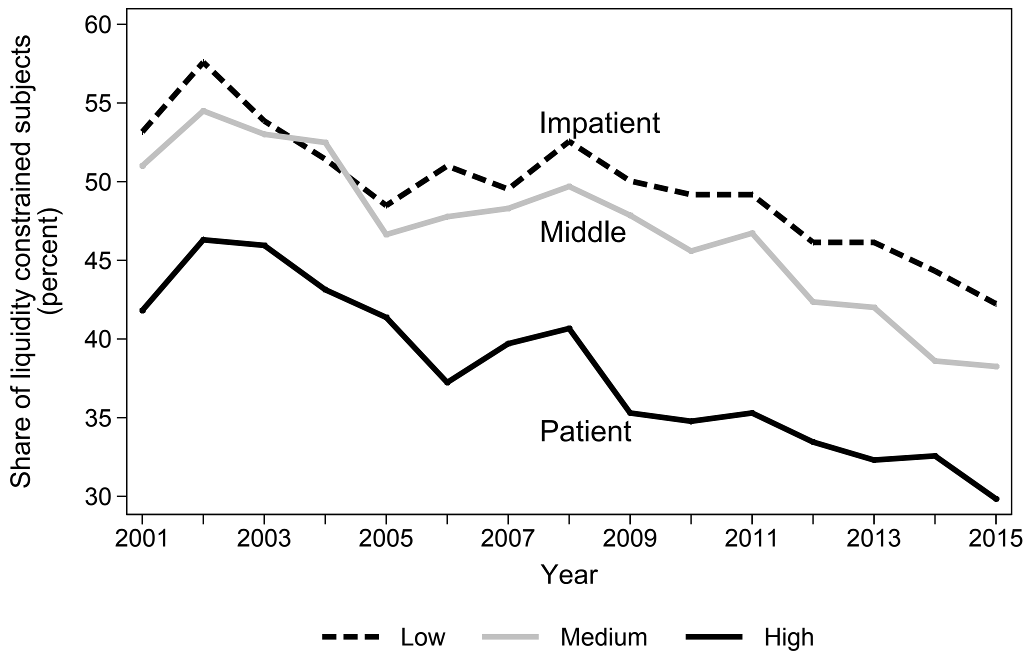


Notes: The white bars show the association between elicited patience and the propensity to hold liquid assets worth less than one month's disposable income in 2014. The sample is split into three equally sized groups according to the tertiles of the patience index such that "High" includes the 33 percent most patient individuals in the sample, "Low" the 33 percent most impatient individuals and "Medium" the group in between the "High" and "Low" groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. The grey bars show the association between elicited patience and the marginal interest rate in 2014 for the three patience groups.

Figure 6 illustrates the association between patience and the indicators for being affected by constraints. As above, we split the sample into three equally sized groups according to the magnitude of the experimental patience measure and calculate the fraction observed with liquid assets worth less than one month's disposable income (white bars) and the average of the marginal interest rates faced by the individuals (grey bars). The graph shows that 33 percent of the individuals in the most patient group are observed with a low level of liquid assets in real-life compared to 45 percent with a low level of liquid assets in the least patient group. This is consistent with the theoretically motivated proposition that impatient people save less and hence are more likely to end up in a situation where they are affected by liquidity constraints. Turning to the association between the patience measure and the marginal interest rate, the overall pattern is confirmed. The most patient group faces, on average, a marginal interest rate of slightly less than 7 percent, while the least patient group faces a marginal interest rate of about 8.5 percent.

We compute the two measures of credit constraints before collecting the experimental data about patience. This leaves open the possibility that elicited patience is a response to an adverse shock, which has led a patient individual to drive down his liquid assets and, consequently, transitorily behave as if he were impatient. Figure 7 shows the fraction of people who are recorded with liquid assets worth less than one month's disposable income for the period 2001-2015 for each of the three patience groups. The graph shows that the propensity to be observed with low levels of liquid assets generally declines for all three groups over time. This reflects the fact that people in the sample are in the early stages of their life-cycle and accumulate more assets as they grow older. More importantly, the figure shows that in each of the 15 years the share of credit constrained individuals is considerably larger among the 1/3 least patient subjects compared to the 1/3 most patient ones. Such persistence is difficult to rationalize with short term shocks.

Figure 7: Prevalence of liquidity constraints across levels of patience, 2001-2015



Notes: The figure shows the association between elicited patience and the frequency of individuals within each patience group who are observed with liquid assets corresponding to less than one month's disposable income. The sample is split into three equally sized groups according to the tertiles of the patience index such that "High" includes the 33 percent most patient individuals in the sample, "Low" the 33 percent most impatient individuals and "Medium" the group in between the "High" and "Low" groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0].

To investigate how direct measures of constraints might affect the position in the wealth distribution, we split the sample according to the dummy variable indicating whether the respondents hold liquid assets worth more or less than one month's disposable income and repeat the regressions from Table 2 separately for the two groups. The results are reported in Table 3. Columns 1 and 2 report results from the subsample holding liquid assets worth more and less, respectively, than one month's disposable income. We include the full set of controls that were also included in Table 2, column (8) in these regressions. Consistent with theory, we find that elicited patience is no longer predictive of the wealth percentile rank for the subgroup where credit constraints are likely to be binding, column (2). However, the association between patience and wealth is much stronger than in the pooled sample for the group who are unlikely to be affected by constraints, column (1), cf. Table 2. In fact, the results presented in Table 3, column (1) suggest that moving from the lowest level of patience to the highest level is associated with an increase in the position in the wealth distribution of more than 12 percentiles. The dummy variable for holding high/low levels of liquid assets arguably does not capture the entire effect of constraints, since the intensity of constraints is likely to vary within the two groups. We include the marginal interest rate among the regressors to control for the intensity of constraints in columns 3 and 4. Recent evidence suggests that some individuals are better at obtaining high returns on savings (Fagereng et al. 2018). Therefore, we also include asset returns among the regressors. It is computed for each individual by adding dividend income received in 2014 to realized and unrealized capital gains/losses from the start to the end of the year, and then dividing by the market value of the assets. For both the high (column 3) and the low (column 4) liquid asset groups, the parameter on the marginal interest rate is significant and negative such that a higher marginal interest rate is associated with a lower wealth rank. The asset return coefficient is positive in both cases. The inclusion of the marginal interest rate and asset returns mutes the parameter estimate on patience, but it remains highly significant and of a magnitude indicating that the most patient person is ranked about nine wealth percentiles higher than the least patient person in the sample consisting of people holding liquid assets corresponding to at least one month's disposable income. The parameter estimate on patience remains insignificant for the low liquid asset group. The evidence presented in Table 3 is consistent with the theoretical conjecture that credit constraints mute the relationship between patience and the position in the wealth distribution. Moreover, when controlling for the marginal interest rate and the asset returns, which arguably capture the slope of the intertemporal budget constraint, we still find a strong association between patience and wealth inequality.

These findings also speak to the issue about whether differences in elicited time discounting simply reflect variation in real-life market interest rates facing the individuals who participated in the online experiments (Frederick et al. 2002, Krupka and Stephens 2013). The fact that patience significantly predicts the wealth percentile rank after controlling directly for the market interest rate suggests that discounting behavior elicited with experimental methods not only reflects market interest rates, but also differences in time preferences.

Table 3: Wealth percentile rank, patience and credit constraints

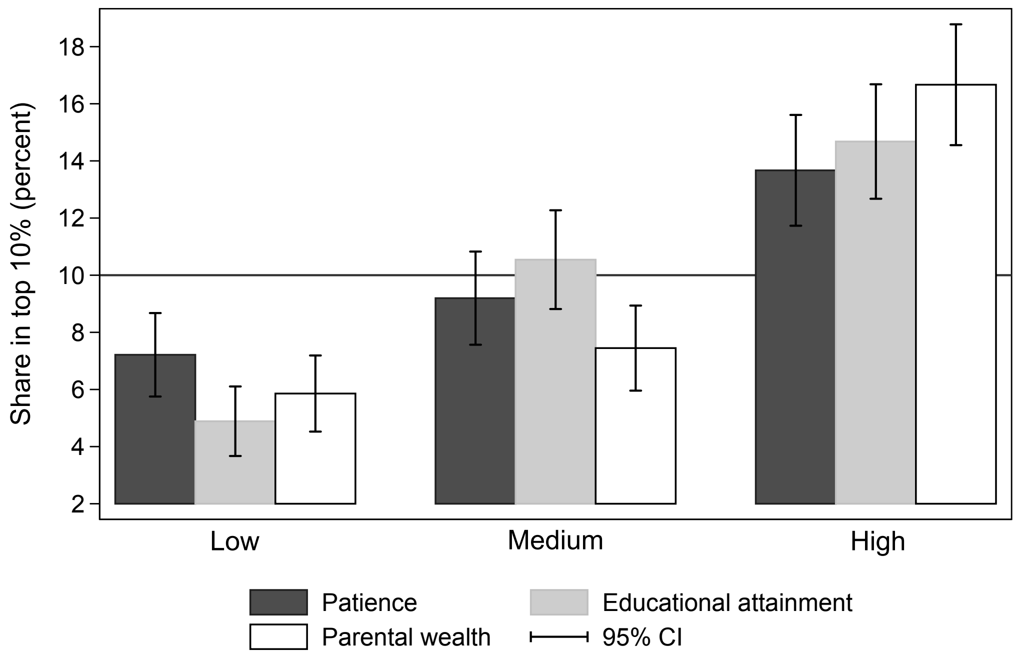
Dep. var.: Wealth percentile rank Liquid Assets:	(1) High	(2) Low	(3) High	(4) Low
Patience	12.31***	-1.11	8.83***	-0.44
	(2.47)	(2.41)	(2.34)	(2.33)
Risk aversion	5.75*	-1.82	3.49	-1.72
	(2.77)	(2.91)	(2.63)	(2.87)
Interest rate on liquidity			-1.68***	-0.72***
			(0.11)	(0.08)
Rate of return on stocks			0.17	1.09*
			(0.20)	(0.52)
Year dummies for educational attainment	Yes	Yes	Yes	Yes
Gross income decile dummies	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	Yes	Yes	Yes	Yes
Parental wealth decile dummies	Yes	Yes	Yes	Yes
Wealth at age 18 decile dummies	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes
Constant	21.57***	41.94***	43.73***	51.72***
	(5.90)	(4.38)	(5.64)	(4.36)
Observations	2017	1274	2017	1274
Adj. R-squared	0.07	0.03	0.18	0.08

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Columns 1 and 3 report estimation results on the subsample of respondents who are recorded holding liquid assets worth more than one month's disposable income in 2014. Columns 2 and 4 report estimation results on the subsample holding liquid assets worth less than one month's disposable income in 2014. Percentile ranks in the wealth and income distributions are computed within-cohort in 2015. Marginal interest rates and asset returns are measured in 2014. Gross income does not include capital income. School grades are self-reported by the respondents on our online platform. Parental wealth is measured when respondents were 18 years old. "Demographic controls" include three variables: a gender dummy, a dummy for being single, and a dummy for having dependent children. The number of observations included in this table is slightly lower than the number of observations included in Table 6. This is because the register data does not allow the construction of the dummy indicator for liquidity constraints because disposable income is recorded to be negative. Furthermore, the number of observations is reduced when entering the marginal interest rate, as some of the detailed account-specific information is missing for some individuals.

4.3 The top 10 percent wealthiest

A sizable literature has studied the concentration of wealth at the top of the distribution. For example, Piketty and Saez (2014) find that the share of total wealth owned by the wealthiest ten percent has been in the range 60-90 percent over the last 150 years in the US and Europe. In order to examine whether there is an association between our patience measure and the propensity to be in the top end of the wealth distribution, Figure 8 displays the fraction of respondents who belong to the wealthiest ten percent within the three patience groups defined in the previous section. The figure shows that about seven percent in the least patient group are among the wealthiest ten percent in the sample, whereas 14 percent of the individuals categorized to be among the most patient individuals belong to the wealthiest ten percent in the sample. Again, we compare the association with the corresponding associations for education and parental wealth. Among the 1/3 of individuals with the highest level of education, 15 percent belong to the ten percent wealthiest, whereas 5 percent is so among the 1/3 with the lowest level of education. Similarly, about 16 percent of the children among the top third in terms of parental wealth belong to the wealthiest ten percent, whereas 6 percent among the bottom 1/3 in terms of parental wealth belong to the top 10 percent most wealthy individuals in the sample. Thus, while the association between patience and the propensity to be among the wealthiest ten percent is not quite as pronounced, it is of the same order of magnitude as the association between education and the position in the wealth distribution, and the picture is roughly similar when comparing to the association between being among the wealthiest ten percent and parental wealth. In Appendix C.3, we show regressions corresponding to the regressions presented in Table 2, but where the dependent variable is a dummy variable indicating whether the respondent belongs to the wealthiest ten percent. The results show that patience is statistically significant, also when controlling for the same set of control variables as in Table 2. Due to the limited sample size, it is impossible to credibly examine how patience is related to the propensity to belong to the group of the very wealthy, say, to the top 0.1%.

Figure 8: Relationship between patience and being among the top 10% wealthiest



Notes: The black bars show the association between elicited patience and the propensity to be among the wealthiest ten percent in the sample (top ten percent in the within-cohort wealth distribution, 2015). The sample is split into three equally sized groups according to the tertiles of the patience index such that "High" includes the 33 percent most patient individuals in the sample, "Low" the 33 percent most impatient individuals and "Medium" the group in between the "High" and "Low" groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. The grey bars show the association between the propensity to be among the wealthiest ten percent in the sample and educational attainment, where the individuals in the sample are split into three equally sized groups according to how many years of education they have completed. Cut-offs for the education groups (years): Low [8, 14]; Medium [14, 16.5]; High [16.5, 21] where the numbers refer to years of completed education. The white bars show the association between the propensity to be among the wealthiest ten percent in the sample and parental wealth, where the individuals in the sample are split into three equally sized groups according to their parents' positions in the parental wealth distribution. Parental wealth is measured when the subject was eighteen years old.

5 Additional analyses and robustness checks

This section presents a series of robustness checks corroborating our main findings. First, we use an alternative data source where time discounting was elicited by survey in 1973 and reproduce some of our main results, thereby addressing the pertinent question of whether it is important for our key results that individual time discounting in the experiment is measured at the end of the observation period. Second, we consider other ways of measuring patience in the experiment. Finally, we examine the robustness of our core results to the definition of wealth, to the observation period, and to selection into participation in the experiment.

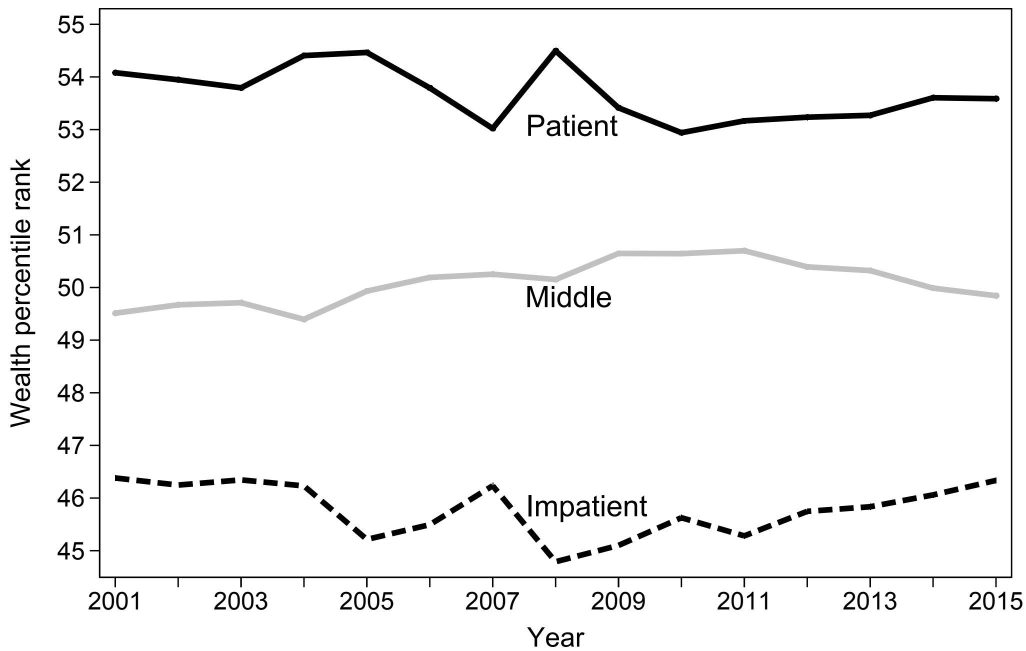
5.1 Does time discounting measured early in the life-cycle predict future position in the wealth distribution?

This section uses data from the Danish Longitudinal Survey of Youth (DLSY). The DLSY survey contains a crude measure of time discounting collected in 1973 for a sample consisting of 2,550 individuals from the 1952-1955 cohorts.[20] The survey data is merged with administrative records covering the same period as the core analysis. In this way we examine whether an alternative measure of time discounting collected when individuals are 18-21 years old is predictive of future inequality in wealth observed when they are about 45-60 years old. The respondents in the 1973 survey were asked, among other things, the following question: *If given the offer between the three following jobs, which one would you choose?* (*i*) *A job with an average salary from the start.* (*ii*) *A job with low salary the first two years but high salary later.* (*iii*) *A job with very low salary the first four years but later very high salary.* We interpret this question about the preference over the timing of income streams as a proxy for time discounting, where respondents answering (*iii*) are the most patient and respondents answering (*i*) are the least patient. This aligns with the interpretation of the "money earlier or later" experiments to elicit time discounting. In Appendix C.4, we demonstrate a strong correlation between patience elicited with the survey question and patience elicited in the incentivized experiment using a sample of respondents who participated in the experiment and were also asked the survey question.

Figure 9 shows the average position in the wealth distribution for each of the three patience groups defined by the three answers to the survey question in the DLSY sample. The figure shows that the ordering of the individuals into groups according to their time discounting in 1973 predicts the position in the wealth distribution in the period 2001-2015, so that the group average of the most patient individuals is consistently at the highest position in the wealth distribution, followed by the group with medium patience, and with the least patient individuals on average attaining the lowest position in the wealth distribution. The difference in the average wealth rank position of the most patient and the least patience is about 7 to 8 wealth percentiles. The persistence and magnitude resemble the pattern observed in Figure 3a.

[20]For details, see https://dlsy.sfi.dk/dlsy-in-english/. 82 percent of the sample belongs to the 1954 cohort, while the rest are recruited from the 1952, 1953, and 1955 cohorts.

Figure 9: Time discounting in 1973 and position in the wealth distribution 2001-2015



Notes: The figure shows the association between time discounting elicited in the Danish Longitudinal Survey of Youth (DLSY) in 1973 and the position in the wealth distribution in the period 2001-2015. The position in the wealth distribution is computed as the within-cohort percentile rank in the sample. The three groups are defined based on the answers to the question: *If given the offer between the three following jobs, which one would you choose? (i) A job with an average salary from the start. (ii) A job with low salary the first two years but high salary later. (iii) A job with very low salary the first four years but later very high salary.* 665 respondents preferred a flat income profile (impatient). 1,157 preferred a steeper profile (middle), and 728 preferred the steepest profile (patient).

The association shown in Figure 9 represents only a bivariate relationship. Table 4 presents a series of regressions of the wealth percentile rank on dummy variables for the DLSY patience groups and controls for income, education, and initial wealth. Column 1 shows results from a regression corresponding to Figure 9, i.e. without control variables included, and the regression estimates confirm that there are statistically significant differences between the low patience group and the medium and high patience groups. Column 2 includes a full set of dummies for the number of years of completed education, and column 3 adds income decile dummies. The size of the parameters on the patience dummies are somewhat lower in these specifications with education and income controls, but they are still sizable and the parameter on the high patience dummy variable is significant at the five percent level. In column 4, decile dummies for wealth measured in 1983 (first occurrence of individual-level wealth data) are added to the control set in order to control for initial wealth. This mutes the parameters on the patience group dummies slightly, but the high patience group parameter is still significant at the five percent level. Finally, column 5 includes demographic controls, but the overall picture is the same as in the previous column.[21]

In summary, the results from using a very early measure of patience confirms the findings from the core analysis based on experimental elicitation of time discounting that relatively patient individuals are consistenly positioned higher in the wealth distribution.

Table 4: Patience in 1973 and position in the wealth distribution, 2001

Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)
Patience, high	7.21***	4.58**	3.81*	3.28*	2.99*
	(1.54)	(1.57)	(1.56)	(1.50)	(1.51)
Patience, medium	3.20*	2.65	1.88	1.66	1.48
	(1.34)	(1.36)	(1.35)	(1.30)	(1.31)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes
Gross income decile dummies	No	No	Yes	Yes	Yes
Wealth decile dummies, 1983	No	No	No	Yes	Yes
Demographic controls	No	No	No	No	Yes
Constant	46.50***	40.72***	33.70***	25.93***	26.84***
	(1.04)	(1.57)	(1.99)	(2.80)	(2.91)
Observations	2548	2548	2548	2548	2548
Adj. R-squared	0.01	0.04	0.05	0.12	0.12

Notes: OLS regressions. Dep. var.: Within-cohort wealth percentile rank in 2001. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Two patience dummies are included in the regressions. These are based on the time discounting question in DLSY, see notes to Figure 9. Dummies for medium and high patience are included, low patience is the reference group. The regressions are based on 2001, which is the first year in Figure 9. By then, the individuals in the DLSY sample (born 1952-1955) were in their mid-life such that it is comparable to the scenario in our core analysis. Ranks in the wealth and income distributions are computed within-cohort. "Demographic controls" include a gender dummy, a dummy for being single, and a dummy for having dependent children. Two observations are dropped because of missing wealth data in 1983.

5.2 Sensitivity to other ways of measuring patience in the experiment

Our patience measure is based on the subset of choice tasks where the subjects were asked to choose between payouts 8 and 16 weeks from the experiment date. As described in section 3 we also confronted subjects with trade-offs that involved payouts made as soon as possible after the experiment, where the delay only pertained to the time required to administer the transfer to the participant's account. In Table 5, we construct patience measures based on all possible combinations of the payment dates that we exposed subjects to ("today", "in 8 weeks", and "in 16 weeks"). Columns 1-3 present results from regressions based on choice tasks with alternative combinations of payment dates. Column 1 reproduces Table 2, column 8. Columns 2-3 present estimates based on regressions where the patience measure is based on alternative choice task horizons. The parameter estimates on patience are stable across these

[21] It is impossible to control for parental wealth, as the link between parents and children only exists for cohorts born in 1960 and later.

regressions.

Some 18 percent of the sample always postpone payments, cf. Figure 2. In order to verify that individuals who always defer payments do not drive our main result, we reestimate our preferred specification, cf. column 1, on a subsample omitting these individuals. The results from this estimation are reported in Table 5, column 4. At 8.79, the parameter estimate on patience is close to the estimate from the preferred specification.

Our preferred patience measure is constructed using a mean-aggregator, cf. equation 4. We construct a patience index using a median aggregator in column 5. In this case, the parameter estimate on patience is attenuated somewhat, now indicating a six rank point difference when moving from the least to the most patient individual in the sample, but the parameter is also estimated precisely and is significant in this case.

As a final robustness check, we estimated discount rates structurally using a random utility model. We refer to Appendix C.5 for details. In order to make the scale comparable to our patience index, we rank the estimated discount rates and use the discount rate rank as a regressor. The results are presented in column 6. The patience parameter based on this alternative measure is precisely estimated, and it indicates that moving from the least patient to the most patient individual in the sample is associated with an increase of almost eight rank points in the wealth distribution, which is close to what we find in the preferred specification. Overall, our results are robust to alternative ways of calculating a measure of patience.

Table 5: Patience and wealth inequality. Other patience measures

Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)	(6)
Patience measure:	8 vs. 16 weeks	0 vs. 16 weeks	0 vs. 8 weeks	8 vs. 16 weeks, $\neq 1$	8 vs. 16 weeks, median	Rank of estimated discount rate
Patience	9.50***	9.51***	9.66***	8.79***	5.76***	7.66***
	(1.81)	(1.96)	(1.86)	(2.34)	(1.51)	(1.86)
Risk aversion	2.90	2.98	2.89	4.02	2.49	1.95
	(2.11)	(2.11)	(2.10)	(2.47)	(2.11)	(2.30)
Year dummies for educational attainment	Yes	Yes	Yes	Yes	Yes	Yes
Gross income decile dummies	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth decile dummies	Yes	Yes	Yes	Yes	Yes	Yes
Wealth at age 18 decile dummies	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	28.34***	28.01***	27.93***	26.69***	30.87***	38.14***
	(3.50)	(3.58)	(3.55)	(3.85)	(3.45)	(3.58)
Observations	3330	3330	3330	2709	3330	2848
Adj. R-squared	0.08	0.07	0.08	0.06	0.07	0.08

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. “Patience, 8 vs. 16 weeks” is the standard measure referred to as “Patience” in the other tables and figures. Ranks in the wealth and income distributions are computed within-cohort in 2015. School grades are self-reported by the respondents on our online platform. Parental wealth is measured when respondents were 18 years old. “Demographic controls” include three variables: a gender dummy, a dummy for being single, and a dummy for having dependent children.

5.3 Sensitivity to definition of wealth, observation period, and selection into the experiment

Table 6 shows the results from a number of additional robustness checks. The first column in Table 6 reproduces column 8 from Table 2, i.e. the specification with the richest set of control variables included. The dependent variable in this specification is based on net wealth ranks calculated using 2015 data. In that analysis, we focus on the latest year in the sample because we want to characterize the association between elicited patience and wealth for individuals who have reached a life stage where their current income is as close to its "permanent level" as possible, and where their financial position is not dominated by early life decisions such as undertaking education and entering the labor market. However, Figure 3a showed evidence that the bivariate association between patience and wealth is stable over a much longer period, 2001-2015. In Table 6, column 2, we re-estimate the reference model reported in column 1 using annual observations for the entire data period 2001-2015. Consistent with the impression provided by Figure 3a, the multivariate results are robust to this change, although the parameter of interest is slightly smaller than in the preferred specification.

The theory presented in section 2 characterizes wealth as being held in just one asset. A natural interpretation is that it reflects net wealth, which is the wealth concept we have used in the analysis so far. An alternative interpretation is that it reflects financial assets. In column 3 we re-estimate the reference specification using financial assets, consisting of stocks, bonds, and deposits, as the basis for constructing the position in the wealth distribution. Also for this outcome we find that the positive relationship between patience and the ranking in the financial asset distribution is similar to the result obtained in the reference specification based on net wealth.[22]

Column 4 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. This is done to account for the fact that the tax assessed values may be somewhat below market values (Leth-Petersen 2010). The estimate of the patience parameter attenuates slightly but the parameter is precisely estimated and is within two standard deviations from the reference estimate in column 1. The wealth data including housing and financial wealth are consistently third-party reported for an exceptionally long period. However, they lack two components of wealth that are potentially important for assessing wealth inequality, wealth kept in the car stock and wealth accumulated in pension accounts. Data docu-

[22] In agreement with the results presented in Figure 3a, the more patient respondents are consistently ranked higher in the financial asset distribution relative to their less patient peers over the period 2001-2015 (not reported).

menting these two components has recently become available, but only from 2014 onwards. In column 5, we include the value of the car stock among assets and calculate the net wealth rank based on 2015 data. The patience parameter is close to the estimate in column 4.

Table 6: Patience and wealth inequality. Robustness analyses

Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	9.50***	6.59***	11.11***	7.65***	7.37***	5.73***	8.40***	8.04***
	(1.81)	(1.28)	(1.59)	(1.75)	(1.74)	(1.58)	(1.83)	(1.90)
Risk aversion	2.90	1.47	2.30	3.15	2.84	2.29	2.16	2.87
	(2.11)	(1.48)	(1.85)	(2.01)	(2.00)	(1.86)	(2.15)	(2.19)
Year dummies for educational attainment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gross income decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth at age 18 decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	No	Yes	No	No	No	No	No	No
Constant	28.34***	33.36***	9.33**	26.00***	24.73***	13.54***	30.80***	28.13***
	(3.50)	(5.31)	(3.17)	(3.34)	(3.33)	(3.04)	(3.54)	(3.63)
Observations	3330	48891	3330	3330	3330	3330	3330	3330
Adj. R-squared	0.08	0.09	0.28	0.14	0.15	0.30	0.07	0.08

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Column 1 reproduces column 8 form Table 2. Column 2 includes annual data on wealth for the period 2001-2015. Standard errors are clustered at the individual level in this column. Column 3 considers only financial assets, ie. stocks, bonds, and deposits. Column 4 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. Column 5 includes the value of the car stock. Column 6 includes both the value of the car stock and wealth held in pension accounts. In column 7, the dependent variable is constructed on the baseline wealth measure (as in column 1), but the equation is estimated using inverse probability weighting where probability weights are based on respondents vs. non-respondents. Column 8 presents results estimated using inverse probability weighting where the weights are based on respondents vs. population. Ranks in the wealth and income distributions are computed within-cohort. School grades are self-reported by the respondents on our online platform. Parental wealth is measured when respondents were 18 years old. "Demographic controls" include three variables: a gender dummy, a dummy for being single, and a dummy for having dependent children.

We further include wealth kept in pension accounts in column 6. This addition slightly mutes the point estimate of the patience parameter. There are good reasons why adding pension wealth would attenuate the estimate. 90 percent of contributions to pension accounts are made to illiquid employer organized pension accounts (Kreiner et al. 2017), and the contributions are predominantly determined by collective labor market agreements. As Chetty et al. (2014a) document, the majority responds passively to these savings mandates, i.e. they do not adjust other types of savings in response to these savings mandates.

Only a fraction of the subjects whom we invited to participate in the experiment accepted the invitation, and this can potentially imply that our sample is selected and not representative of the population at large. In column 7 we re-estimate the reference specification from column 1 using propensity score weighting, where the propensity scores measure the propensity to participate in the experiment for all the subjects who were invited. The propensity scores are estimated using variables created from information available in the administrative registries accessible for both participants and non-participants: year dummies for educational attainment, decile dummies for income, parental wealth, and wealth at age 18 as well as age dummies, a gender dummy, a dummy for being single, and a dummy for having dependent children. The results presented in column 7 are close to the estimate from the reference specification. In Column 8 we construct propensity scores measuring the propensity to be in the experiment compared to the population at large. As with previous cases, we find no important deviations from the benchmark model. The propensity score weighting approach is based on the assumption that the selection into the experiment can be adequately captured by the set of covariates on which the propensity score is estimated. To the extent that this is a reasonable assumption, our results do not appear too specific to the sample for which we elicit patience measures. In total, Table 6 presents a series of alternative estimates designed in order to check the validity of our main finding showing that elicited patience is associated with wealth inequality and that the magnitude of the association is non-trivial.

6 Concluding remarks

According to standard life-cycle savings theory, differences in how much people discount the future generate differences in savings behavior and thereby wealth inequality. Data limitations previously prevented the examination of a direct link between empirical time discounting measures and wealth inequality operating through the savings channel. We address this problem by analyzing a unique combination of data with information about individuals' time discounting and real-world wealth for a large sample of middle-aged individuals in Denmark. Subjective measures of patience are elicited using standard experimental methods and linked to longitudinal administrative wealth records for a period covering 15 years.

Our measures of time discounting indicate substantial heterogeneity in individuals' patience, and we show that individuals with a high level of patience are systematically positioned higher in the wealth distribution in each year over the 15 year period for which we have individual wealth data compared to those who have low levels of patience. The association between patience and the position in the wealth distribution is robust and significant for all our measures of time discounting, of the same magnitude as the correlation between education and wealth and, on average, roughly half as large as the influence of parental wealth on the wealth rank. The association also exists after controlling for education, risk aversion, income, initial wealth and parental wealth, suggesting that the savings mechanism is important. Moreover, we replicate the significant association between discounting and wealth position in an independent data set in which the patience measure – collected in the early 1970s – predicts differences in individuals' wealth 30 years later.

We also find that people with a relatively low level of patience are more likely to be persistently affected by liquidity constraints. This is consistent with models where impatient people run down their assets in order to keep current spending relatively high, implying that they face a higher risk of becoming credit constrained (Krueger et al., 2016; Carroll et al., 2017). In this sense, liquidity constraints are to some extent self-imposed as described in these models. In addition, individuals who are persistently affected by liquidity constraints have limited opportunities to further reduce their wealth levels through the borrowing/savings channel. This implies that the variation of patience levels among the subset of individuals who are persistently affected by credit constraints is predicted to mute the relationship between patience and the wealth rank – a prediction that is nicely borne out by the data. In contrast, if we limit our analysis to the subset of individuals who are not credit constrained (i.e., where the savings/borrowing channel is "fully operative"), we find that the influence of differences in time discounting is roughly 50% higher than in the overall sample.

Thus, taken together, our results suggest that differences in individuals' time discounting play a significant role for their wealth rank and they point, more generally, to the potential importance of incorporating heterogeneous time discounting into models of consumption and savings behavior as originally suggested by Krusell and Smith (1998) and recently applied by Hubmer et al. (2016), Krueger et al. (2016), Carroll et al. (2017), De Nardi and Fella (2017) and Alan et al. (2017).

Our results indicate that the elicited patience measures contain important and relevant information about the order of subjects' evaluations of intertemporal trade-offs that are predictive of subjects' wealth position. Therefore, making a direct link between experimentally elicited discounting behavior and the discount rates entering models of aggregate savings behavior would appear to be a natural next step. However, taking this step is likely to be a challenge in practice. As is well-known in the experimental literature (Frederick et al. 2002), discount rates elicited under relatively small stakes are typically much larger than discount rates that are implied by aggregate models of discounting. However, insofar as the ordering of patience derived from small stake choice tasks is the same as it would be in a setting with large stakes, the experiments can credibly elicit the ordering of individuals in terms of their discounting behavior, as done in our analyses.

This paper provides a positive analysis of the relationship between discounting behavior and wealth inequality. The normative consequences of the results are, however, not obvious although effects of discount rate heterogeneity may have implications for macroeconomic policies and policies that provide insurance against shocks. Our results suggest that households with high discount rates are more likely to face liquidity constraints such that they are less able to smooth consumption over the business cycle. Thus, business cycle shocks may impose asymmetric costs on households with high and low discount rates and the costs of business cycles may be larger in the presence of discount rate heterogeneity. Therefore, the existence of discount rate heterogeneity and its effects on wealth may have a bearing on the desirability and the effectiveness of macroeconomic policies, the design of insurance institutions, and policies that aim at increasing the savings of poor households.

Appendices

A Theory

A.1 Derivation of equation (3)

The solution to the maximization problem is characterized by the standard Euler equation/Keynes-Ramsey rule

$$\frac{\dot{c}(a)}{c(a)} = \frac{r-\rho}{\theta}, \tag{5}$$

and the transversality condition $w(T) = 0$. By integrating the flow budget constraint (2), we obtain the following intertemporal budget constraint

$$w(a) = e^{ra}\left[w(0) + \int_0^a y(\tau) e^{-r\tau} d\tau - \int_0^a c(\tau) e^{-r\tau} d\tau\right]. \tag{6}$$

By evaluating (6) at $a = T$ and using $w(T) = 0$ in the optimum, we obtain

$$Y \equiv w(0) + \int_0^T y(\tau) e^{-r\tau} d\tau = \int_0^T c(\tau) e^{-r\tau} d\tau.$$

By integrating (5), we obtain

$$c(a) = c(0) e^{\frac{r-\rho}{\theta}a}, \tag{7}$$

which is substituted into the above equation in order to get

$$Y(0) = c(0) \int_0^T e^{\frac{r(1-\theta)-\rho}{\theta}\tau} d\tau.$$

By solving the integral and isolating $c(0)$, we obtain

$$c(0) = Y(0) \frac{\rho + r(\theta - 1)}{\theta\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta}T}\right)}. \tag{8}$$

Next, we substitute equation (7) into (6), which gives

$$w(a) = e^{ra}\left[w(0) + \int_0^a y(\tau) e^{-r\tau} d\tau - c(0) \frac{\theta}{r(1-\theta)-\rho}\left(e^{\frac{r(1-\theta)-\rho}{\theta}a} - 1\right)\right],$$

and we use expression (8) to substitute for $c(0)$, which gives

$$w(a) = e^{ra}\left[w(0) + \int_0^a y(\tau)\, e^{-r\tau} d\tau - Y \frac{1 - e^{\frac{r(1-\theta)-\rho}{\theta} a}}{1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}}\right].$$

Finally, this equation is rewritten to (3) by using the definition of $\gamma(a)$.

A.2 Relationship between wealth and impatience

Differentiating (3) with respect to ρ gives:

$$\frac{\partial w(a)}{\partial \rho} = -Y \frac{\frac{a}{\theta} e^{\frac{r(1-\theta)-\rho}{\theta} a}\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right) - \frac{T}{\theta} e^{\frac{r(1-\theta)-\rho}{\theta} T}\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} a}\right)}{\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right)^2} e^{ra} \tag{9}$$

$\frac{\partial w(a)}{\partial \rho} \leq 0$ iff

$$\begin{aligned} a e^{\frac{r(1-\theta)-\rho}{\theta} a}\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right) - T e^{\frac{r(1-\theta)-\rho}{\theta} T}\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} a}\right) &\geq 0 \iff \\ a\left(e^{\frac{\rho - r(1-\theta)}{\theta} T} - 1\right) - T\left(e^{\frac{\rho - r(1-\theta)}{\theta} a} - 1\right) &\geq 0 \iff \\ \frac{e^{kT} - 1}{T} - \frac{e^{ka} - 1}{a} &\geq 0 \end{aligned}$$

where $k \equiv \frac{\rho - r(1-\theta)}{\theta}$. The function $\frac{e^{ka}-1}{a}$ equals k when $a \to 0$ (which may be seen by applying l'Hôpital's rule) and is increasing in a for all values of $k \neq 0$.[23] For $T > a$, this implies that $\frac{e^{kT}-1}{T} > \frac{e^{ka}-1}{a}$.

A.3 Relationship between wealth and the intertemporal elasticity of substitution

Differentiating (3) with respect to θ gives:

$$\begin{aligned} \frac{\partial w(a)}{\partial \theta} &= -Y \frac{\frac{a}{\theta} e^{\frac{r(1-\theta)-\rho}{\theta} a}\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right) - \frac{T}{\theta} e^{\frac{r(1-\theta)-\rho}{\theta} T}\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} a}\right)}{\left(1 - e^{\frac{r(1-\theta)-\rho}{\theta} T}\right)^2} e^{ra} \frac{r-\rho}{\theta} \\ &= \frac{r-\rho}{\theta} \frac{\partial w(a)}{\partial \rho}, \end{aligned}$$

[23]The derivative equals $\frac{e^{ka}(ka-1)+1}{a^2}$, which is never zero if $k \neq 0$ and positive for $ka = 1$ and also positive for $ka = -1$. Thus, the derivative is always positive implying that the function is increasing in a.

where the last equality comes from equation (9). We know from Appendix A.2 that $\partial w_a / \partial \rho \leq 0$. Hence, $\partial w_a / \partial \theta \leq 0$ if $r > \rho$, $\partial w_a / \partial \theta \geq 0$ if $r < \rho$ and $\partial w_a / \partial \theta = 0$ if $r = \rho$. QED.

B Experiment

B.1 Invitation letter

Figure A1: Invitation letter

ØKONOMISK INSTITUT
KØBENHAVNS UNIVERSITET

[redacted]

FEBRUAR 2015

ØKONOMISK INSTITUT

ØSTER FARIMAGSGADE 5,
BYGNING 26
1353 KØBENHAVN K

TLF 35 33 02 77

analyse@econ.ku.dk

Dataansvarlig: Søren Leth-Petersen,
Professor

Kære [redacted],

Københavns Universitet inviterer dig til at deltage i en undersøgelse på internettet. Undersøgelsen er en del af et forskningsprojekt, der handler om at forstå grundlaget for danskernes økonomiske beslutninger. Vi ved allerede meget mere om folks privatøkonomiske beslutninger, end vi gjorde før den finansielle krise, men der er stadig meget, vi mangler at forstå – og det er derfor, vi spørger om din hjælp.

Det tager ca. 30-50 minutter at gennemføre undersøgelsen. Når du er færdig, vil du typisk modtage et præmiebeløb, og det vil automatisk blive overført til din NemKonto. Beløbets størrelse afhænger bl.a. af de valg, som du træffer i undersøgelsen og vil i gennemsnit svare til en god timeløn.

Undersøgelsen foregår på internettet. Du vil bl.a. blive bedt om at tage stilling til spørgsmål om opsparing og investering. Reglerne bliver forklaret, når du har logget ind. Undersøgelsen er åben for deltagelse til og med fredag d. 27. februar 2015.

Datatilsynet har godkendt forskningsprojektet, hvilket betyder, at vores procedurer opfylder persondatalovens krav til behandling af data. En vigtig del af Datatilsynets krav er, at dine svar bliver behandlet anonymt. For at sikre dig anonymitet har vi dannet et tilfældigt brugernavn til dig. For at deltage skal du logge ind på hjemmesiden: **analyse.econ.ku.dk.**

Brugernavn: deltager5795 Password: n4mw9!uay

Invitationen er personlig, og vi beder derfor om, at du ikke videregiver brugernavn og password til andre. Du er velkommen til at kontakte os, hvis du har problemer med at logge ind eller har yderligere spørgsmål. Du kan ringe til projektkoordinator Gregers Nytoft Rasmussen på telefonnummer 35 33 02 77 mandag-torsdag kl. 14.00-17.30 eller skrive til adressen analyse@econ.ku.dk.

Med venlig hilsen

Søren Leth-Petersen
Projektleder, professor

English translation of the invitation letter:

Dear «name»,

University of Copenhagen invites you to participate in a study on the Internet. The study is part of a research project about understanding the basis for the Danes' financial decisions. We already know a lot more about people's personal financial decisions than we did before the financial crisis, but there is still much we need to understand - and that is why we are asking for your help.

It takes about 30-50 minutes to complete the study. When you are finished, you will typically receive prize money and it will be automatically transferred to your NemKonto. The amount depends, i.a., on the choices that you make during the study and will on average correspond to a decent hourly wage.

The study is conducted on the Internet. You will consider questions concerning savings and investments, among other things. The rules will be explained once you have logged in. The study is open for participation through «date».

The Data Protection Agency has approved the research project, which means that our procedures comply with the Act on Processing of Personal Data. An important part of the Data Protection Agency's requirements is that your answers will be treated anonymously. To ensure anonymity, we have formed a random username for you. To participate, please log in at the following website: **analyse.econ.ku.dk**.

Username: «username» Password: «password»

The invitation is personal and we therefore ask you not to pass on username and password to others. Please feel free to contact us if you are having trouble logging in or have any further questions. You can call project coordinator Gregers Nytoft Rasmussen at phone number 35 33 02 77 Monday-Thursday 2:00 p.m. – 5:30 p.m. or write to the address analyse@econ.ku.dk.

Sincerely yours,

Søren Leth-Petersen

Project manager, professor

B.2 Choice situations for time task

Table A1 presents a list of all choice situations in the time task. 'x1' is the value of a block allocated at 't1'. 'x2' is the value of a block allocated at 't2'. 't1' and 't2' are delays in months. As mentioned above, however, the presentation of delays occurred in weeks. 'delay' is equal to the difference between 't2' and 't1'. 'rate' is the annual discount rate imputed by the relative values of the blocks. It is defined as $\left(\frac{x_2}{x_1}\right)^{\frac{12}{t_2-t_1}} - 1$. 'slope' denotes the slope of the budget line in ('x1', 'x2')-space, i.e. $-\frac{x_2}{x_1}$.

Table A1: Time choice situations

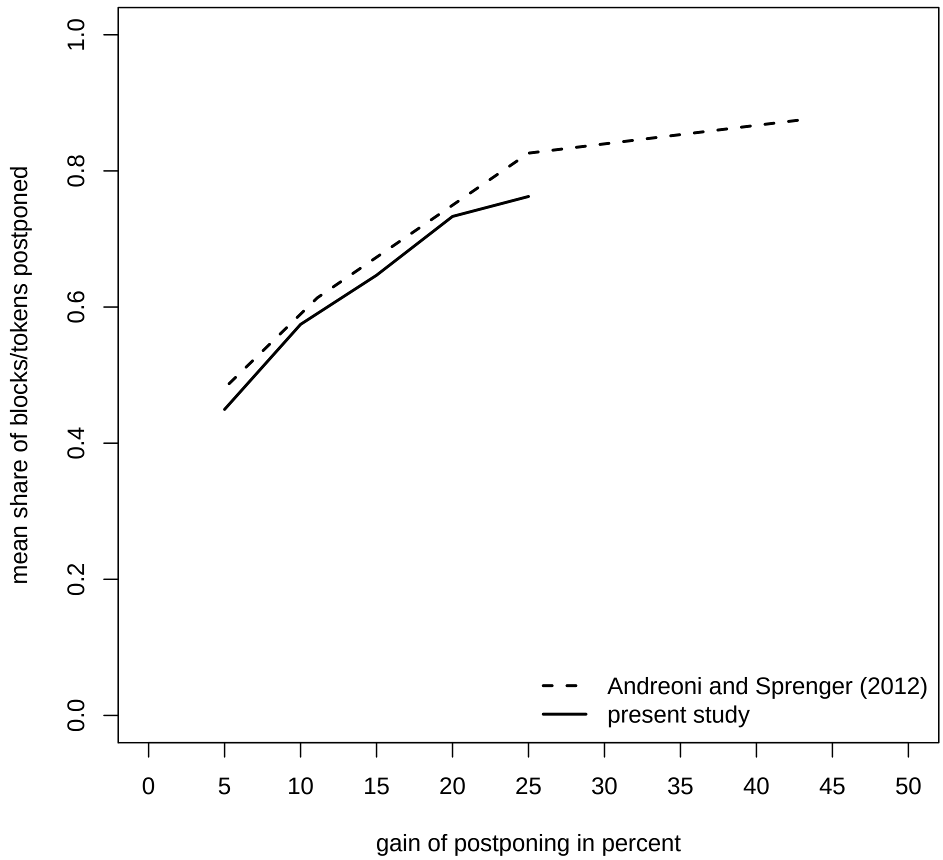
choiceId	x1	x2	t1	t2	delay	rate	slope
1	100	105	0	2	2	0.340	-1.050
2	100	110	0	2	2	0.772	-1.100
3	100	115	0	2	2	1.313	-1.150
4	100	120	0	2	2	1.986	-1.200
5	100	125	0	2	2	2.815	-1.250
6	100	105	0	4	4	0.158	-1.050
7	100	115	0	4	4	0.521	-1.150
8	100	125	0	4	4	0.953	-1.250
9	100	135	0	4	4	1.460	-1.350
10	100	145	0	4	4	2.049	-1.450
11	100	105	2	4	2	0.340	-1.050
12	100	110	2	4	2	0.772	-1.100
13	100	115	2	4	2	1.313	-1.150
14	100	120	2	4	2	1.986	-1.200
15	100	125	2	4	2	2.815	-1.250

B.3 Comparing experimental results to previous work

In this appendix, we compare our choice data from the time discounting experiment to similar choice data from a related study (Andreoni and Sprenger 2012 [AS]). There are some differences between the budget choice designs and the selected populations, but we show that overall behavior found in the two data sets appears to be both qualitatively and quantitatively very similar. Our patience measure is constructed using five choice situations. In each of these five choice situations, subjects chose to allocate 10 blocks between an earlier point in time (8 weeks, i.e. 56 days in the future) and a later point in time (16 weeks, i.e. 112 days in the future). Subjects in the AS study faced a series of related budget choices. They were asked to allocate 100 tokens between two different payment dates in each of these budget choices. For comparability, we pick the most similar delays in their experiment, namely 35 and 70 days. In addition to different delays and different number of blocks/tokens to allocate, the two studies vary with respect to the subject sample and the presentation format. Specifically, the AS sample consists of 97 San Diego undergraduates, whereas our study uses data from 3,620 middle-aged individuals from the general Danish population. In their experiment, subjects were presented an ordered list of allocation choices with fixed payment dates on each screen. In contrast, we displayed each allocation choice in our study separately on a new screen. The five allocation choices we use to construct our index were interleaved with other choices involving different payment dates, and they appeared in randomized order. Furthermore, we held the value of an earlier block fixed at 100 points, whereas AS fixed the price of a future token for each date configuration.

Figure A2 juxtaposes the average share of blocks/tokens that subjects postponed to the later date as a function of the relative gain measured in percent from delaying it. In both experiments, it is as expected that the higher the compensation ('gain of postponing'), the more the subjects are willing to postpone gratification. Importantly, the average behavior found in the the two data sets appears to be both qualitatively and quantitatively very similar.

Figure A2: Comparing choices in experiment to existing work

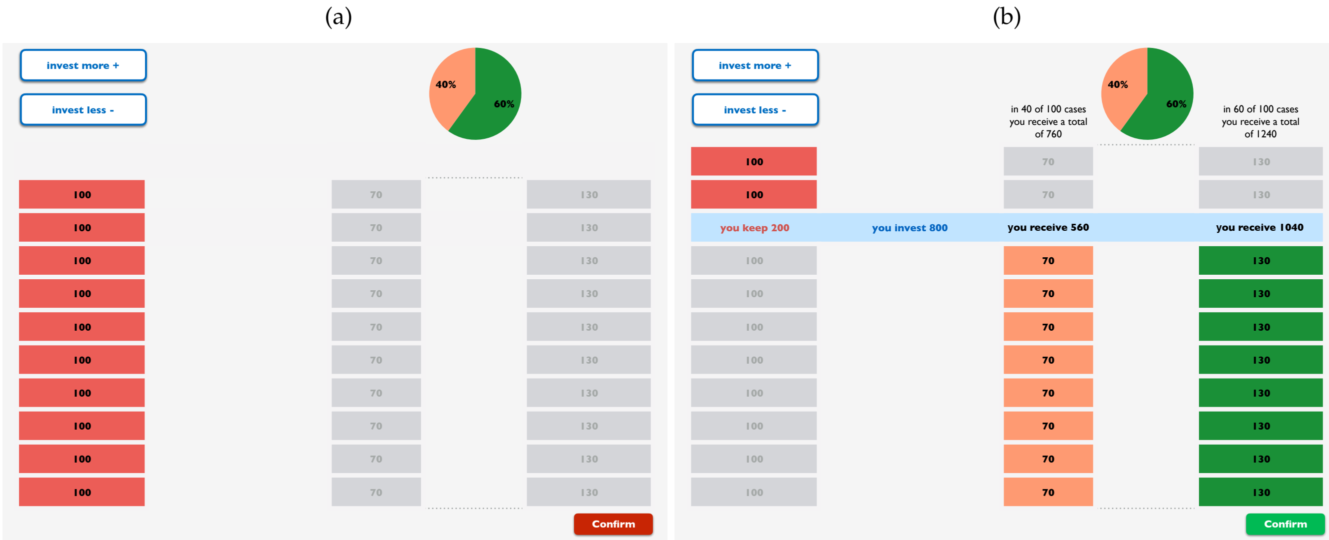


Notes: The figure shows the average share of blocks/tokens postponed to the later date by the subjects as a function of the relative gain measured in percent from delaying it. For our data, the gain is calculated as the value of a later block in points measured in percent of the point value of a sooner block. For Andreoni and Sprenger (2012) the gain is calculated as the price of a later token in percent of the price of a sooner token.

B.4 Risk task and risk aversion measure

Risk task: We use investment games (IGs) similar to Gneezy and Potters (1997) to measure risk aversion. The main differences to their setup are: (*i*) that we used a graphical interface to present the investment choice, and (*ii*) that we varied both probabilities of winning and rates of return across the choice situations. A typical choice situation is depicted in Figure A3. The left panel shows the initial state of a choice situation. The subject was endowed with ten 100-point blocks positioned at the very left of the screen and could then decide how many of these blocks to invest in a risky asset. The (binary) risky asset, depicted on the right-hand side of the choice screen, resulted in either a good outcome or a bad outcome. In the example, the good outcome occurred with probability 60% (illustrated by the wheel on top of the risky asset) and yielded 130 points for each invested 100-point block. The bad outcome occurred with probability 40% and yielded 70 points for each invested 100-point block. The user interface worked in the same way as in the time task.

Figure A3: Risk choice task. Initial screen (a) and selected option (b)



A total of 15 choice situations were implemented. They varied in terms of probabilities and rates of return. Table A2 presents a list of all choice situations in the risk task. 'vb' is the value of a block. 'm1' is the multiplier in case the good state occurs, in which case the new value of a block is vb*m1. 'm2' is the multiplier in case the bad state occurs, in which case the new value of a block is vb*m2. 'p' is the probability of the good state. 'mev' is the expected multiplier, $mev = p \times m_1 + (1-p) \times m_2$. 'msd' standard deviation of the multiplier, $msd = \sqrt{p \times (m_1 - mev)^2 + (1-p) \times (m_2 - mev)^2}$. 'mskew' is the skewness of the multiplier, $mskew = \frac{p \times (m_1 - mev)^3 + (1-p) \times (m_2 - mev)^3}{msd^3}$. 'slope' is the slope of the budgets, i.e. the ratio of prices, $slope = \frac{m_2 - 1}{m_1 - 1}$.

Like in the other tasks, choice situations in the risk task appeared in individualized random order. If the random choice situation picked in the payment stage was a risky choice situation, the subject was again confronted with her choice. The choice could not be reverted at this stage, however. The subject was then asked to resolve uncertainty in the present situation. This was done by spinning the wheel on top of the risky asset. The final payout corresponded to the sum of the safe account and the resolved outcome of the originally risky account. Payments were transferred directly to subjects' NemKonto on the next banking day.

Risk aversion measure: We construct a risk aversion index as follows: We take all choice situations with zero skewness, i.e. with probability 0.5 (choiceId 1, 4, 7, 14 and 15 in Table A2). We then normalize and

Table A2: Risk choice situations

choiceId	vb	m1	m2	p	mev	msd	mskew	slope
1	100	1.21	0.81	0.5	1.010	0.200	0.000	-0.905
2	100	1.41	0.91	0.2	1.010	0.200	1.500	-0.220
3	100	1.11	0.61	0.8	1.010	0.200	-1.500	-3.545
4	100	1.31	0.71	0.5	1.010	0.300	0.000	-0.935
5	100	1.61	0.86	0.2	1.010	0.300	1.500	-0.230
6	100	1.16	0.41	0.8	1.010	0.300	-1.500	-3.688
7	100	1.35	0.75	0.5	1.050	0.300	0.000	-0.714
8	100	1.65	0.90	0.2	1.050	0.300	1.500	-0.154
9	100	1.20	0.45	0.8	1.050	0.300	-1.500	-2.750
10	100	1.50	0.40	0.6	1.060	0.539	-0.408	-1.200
11	100	1.72	0.62	0.4	1.060	0.539	0.408	-0.528
12	100	1.45	0.35	0.6	1.010	0.539	-0.408	-1.444
13	100	1.67	0.57	0.4	1.010	0.539	0.408	-0.642
14	100	1.51	0.50	0.5	1.005	0.505	0.000	-0.980
15	100	1.61	0.60	0.5	1.105	0.505	0.000	-0.656

aggregate using the mean.[24] We define:

$$\phi_{\text{risk aversion}} = \text{mean}\left(\frac{z_1}{10}, ..., \frac{z_5}{10}\right),$$

where z_i denotes the number of blocks kept in the safe account in choice situation i. $\phi_{\text{risk aversion}}$ is an index of risk aversion with $\phi_{\text{risk aversion}} \in [0, 1]$. Higher values of $\phi_{\text{risk aversion}}$ indicate greater risk aversion and a $\phi_{\text{risk aversion}}$ of zero indicates minimum risk aversion (or, more precisely, a degree of risk aversion below the one implied by $z = 1$ in all situations).

C Empirical results

C.1 Main result for subjects with both parents still alive

In this section, we document that the parameter on patience is robust to including only observations for individuals where both parents are still alive. Table A3, column 1 repeats Table 2, column 5, and Table A3, column 2 performs the corresponding estimation but on the subset of observations where respondents' parents are both still alive. As is seen from the table, the results are for all practical purposes similar, and we take this as an indication that inheritance does not drive the correlation between the wealth rank and our patience measure.

[24] Using the median does not change our results.

Table A3: Patience and wealth inequality. For a subsample of individuals with both parents alive

Dep. var.: Wealth percentile rank	(1)	(2)
Patience	9.33***	8.05***
	(1.80)	(2.28)
Year dummies for educational attainment	Yes	Yes
Gross income decile dummies	Yes	Yes
Self-reported school grades decile dummies	Yes	Yes
Parental wealth decile dummies	Yes	Yes
Wealth at age 18 decile dummies	No	No
Demographic controls	No	No
Constant	33.36***	33.67***
	(2.98)	(3.86)
Observations	3330	2178
Adj. R-squared	0.07	0.06

Notes: OLS regressions. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. The measurement of patience is described in expression (4). Ranks in the wealth and income distributions are computed within-cohort in 2015. Gross income does not include capital income. School grades are self-reported by the respondents on our online platform. Parental wealth is measured when respondents were 18 years old.

C.2 Marginal interest rates

Here we present details about the construction of marginal interest rates. We obtained access to administrative register data from the Danish tax authority containing information on the value of loans at the end of 2013 and 2014 for all loans that the respondents held in Denmark. In addition, the data comprise interest payments during 2014 at the individual loan level. This allows us to approximate the interest rate paid on each loan as $r_{i,l} = \frac{R^{14}_{i,l}}{\frac{1}{2}(D^{13}_{i,l}+D^{14}_{i,l})}$, where $R^{14}_{i,l}$ is the sum of interest payments on loan l for individual i during 2014, $D^{13}_{i,l}$ is the value of the loan at the end of 2013, and $D^{14}_{i,l}$ is the value of the loan at the end of 2014. We only include non-mortgage loans and require a minimum denominator in the above equation of 1,000 DKK. The resulting interest rates are censored at the 5th and the 95th percentiles. Our approximation of the interest rate is exact if the debt evolves linearly between 2013 and 2014. If it does not, the computation of the interest rate may introduce a measurement error.

For respondents with loan accounts, we define the marginal interest rate as the highest calculated loan account-specific interest rate. If a respondent only has deposit accounts, we define the marginal interest rate as the smallest account-specific interest rate among the calculated account-specific interest rates for that respondent. The rationale is that the cost of liquidity is given by the loan account with the highest interest rate if a respondent has loan accounts, whereas the cost of liquidity for a respondent who only has deposit accounts is determined by the account where the lowest return is earned. Table A4 shows the distribution of the computed marginal interest rates.

Table A4: Distribution of marginal interest rates

Percentile	p5	p25	p50	p75	p95
Marginal interest rate	0.00	0.97	6.25	12.73	22.79

C.3 The top 10 percent wealthiest

Table A5 shows regressions corresponding to those presented in Table 2. However, the dependent variable in Table A5 is a dummy variable indicating whether the respondent belongs to the wealthiest ten percent. Even after controlling for the full set of covariates in column 8, the results show that going from minimum to maximum patience (0 to 1) is associated with an increase of five percentage points in the probability of belonging to the wealthiest ten percent in a birth cohort. The effect of patience is significant at the 0.1 percent level.

Table A5: Top 10% wealthiest

Dep. var.: Dummy for top 10% of the wealth distribution	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	0.09***	0.07***	0.06***	0.06***	0.06**	0.05**	0.05**	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Risk aversion							0.01	0.01
							(0.02)	(0.02)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gross income decile dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
Parental wealth decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Wealth at age 18 decile dummies	No	No	No	No	No	Yes	Yes	Yes
Demographic controls	No	No	No	No	No	No	No	Yes
Constant	0.04***	-0.02	-0.02	-0.01	-0.02	-0.05*	-0.06*	-0.06*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	3620	3620	3620	3330	3330	3330	3330	3330
Adj. R-squared	0.01	0.03	0.05	0.05	0.07	0.09	0.09	0.09

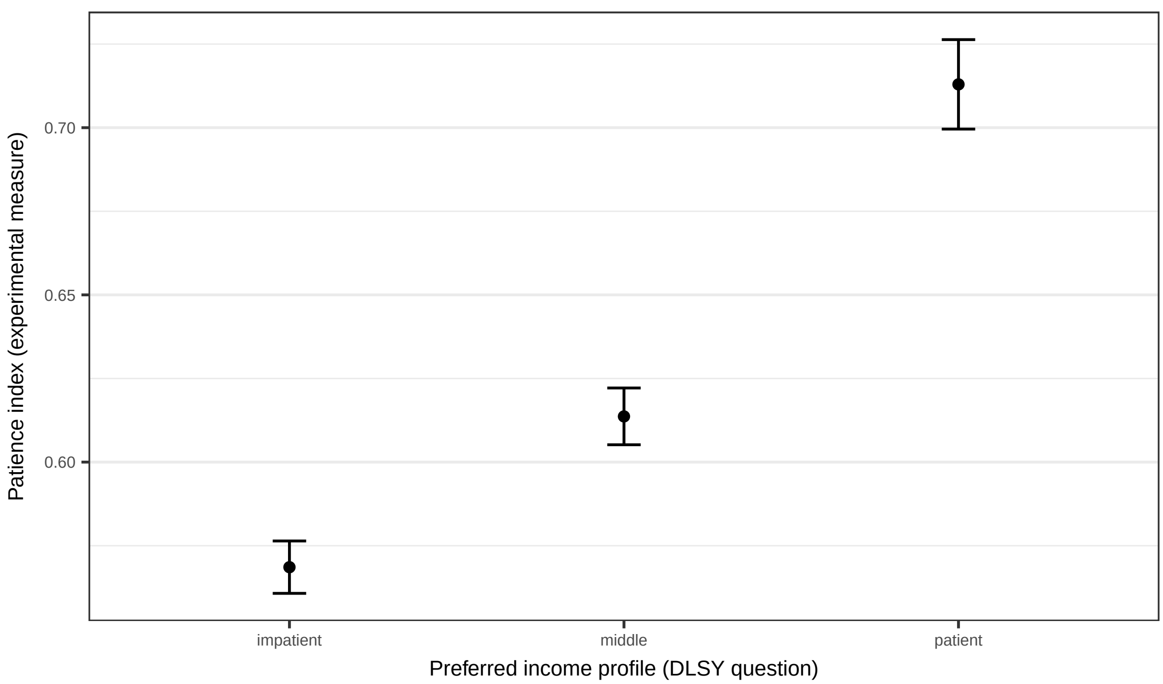
Notes: OLS regressions. Dep. var.: Dummy for top 10% of the within-cohort wealth distribution, 2015. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Ranks in the wealth and income distributions are computed within-cohort. Gross income does not include capital income. School grades are self-reported by the respondents on our online platform. Parental wealth is measured when respondents were 18 years old. “Demographic controls” include three variables: a gender dummy, a dummy for being single, and a dummy for having dependent children. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

C.4 Comparing patience measured in the DLSY survey and in the experiment

In this appendix, we compare patience elicited with the DLSY survey questions to the patience elicited in the experiment. We do this with data from a large-scale online study conducted during the year 2018. 4,152 Danes of the cohorts with birth year 1967 to 1986 completed the study. In addition to the DLSY survey measure described in section 5.1, the study also included an experimental time task with real monetary incentives. With the exception that there were 100 blocks instead of 10 to be allocated between two points in time in each of the choice situations, the time task was identical to that described in section 3. For comparability, we bin the 100 blocks into 10, and then construct our patience index based on the $t_1 = 2$ months vs. $t_2 = 4$ months allocations.

Figure A4 depicts the arithmetic means (dots) of our patience index conditional on the three possible responses in the DLSY question, and 95% confidence intervals (whiskers). It shows that responses in the DLSY question and choices in the real-incentivized, experimental time task are highly and significantly correlated.

Figure A4: Comparison of DLSY and experimental measure



C.5 Structural estimation of patience

In this appendix, we describe the structural estimation of patience used in the sensitivity analysis in section 5.2. Consider the decision problem from the subject's perspective. Define a choice situation S

(see rows in Table A1) as a tuple of attributes (x_1, t_1, x_2, t_2), where x_1 and x_2 denote the value (points) of a block materializing at the earlier point in time t_1 and the later point in time t_2, respectively. Delays will be reported in months.

Assuming additively separable time discounting, a subject's choice z is the outcome of the maximization problem

$$\max_{z \in \{0,1,...,10\}} d(t_1)u(w_1) + d(t_2)u(w_2)\,,$$

subject to the budget constraint

$$w_2 = -\frac{x_2}{x_1}(w_1 - 10x_1)\,,$$

where $w_1 = (10 - z)x_1$ and $w_2 = z \cdot x_2$ denote the total number of points allocated to t_1 and t_2, respectively. Therefore, $z \in \{0, 1, ..., 10\}$ indicates the number of blocks saved to the later point in time. In our setup, it holds that $x_1 = 100$ points in every choice situation. The slope of the budget lines is thus given by $-\frac{x_2}{100}$.

To be able to compare estimated discount rates with our nonparametric index of patience, we first restrict attention to choice situations with payment dates $t_1 = 2$ months and $t_2 = 4$ months. In order to make the model operational, we have to assume specific functional forms for the discount function $d(t)$ and the utility function $u(w)$. Assuming continuous compounding, $d\,(t)$ is specified as

$$d(t) = e^{-\rho \frac{t}{12}}\,,$$

where ρ is the annualized discount rate. We further assume that utility is linear in outcomes, i.e. $u(w) = w$. Since, for all choice situations, it holds that $x_1 < x_2$, discount rates are bounded from below at zero. Note that a single choice situation S only informs us about whether an individual is more or less patient than a certain threshold (see the rates listed in Table A1). The fact that we observe multiple choices per subject and that these choice situations vary with respect to their implicit interest rates permit us to bound the discount rate to an interval.

Until now, we have considered a deterministic model. To incorporate the possibility of errors, we have to make an assumption about the stochastic nature of choices. To do this, we assume random utility with additively separable choice noise (McFadden 1974, 1981). Denoting S_z as the temporal points allocation arising from choice z in a specific situation, the utility of S_z is given by $U(S_z) = d(t_1)u((10 - z)x_1) + d(t_2)u(z \cdot x_2)$. We presume that the utility of a temporal stream of outcomes equals $V(z) = U(S_z) + \varepsilon_z$, with ε_z being an i.i.d. random variable representing error in evaluating utility.

Under the assumption that ε_z follows a Type I extreme value distribution with (inverse) scale (precision) parameter λ, and $z' \neq z$, an individual chooses allocation z if $V(z) > V(z')$. This yields the choice probability Prob$(\cdot)$ of allocation z:

$$\text{Prob}(z) = \text{Prob}(U(S_z) - U(S_{z'}) > \varepsilon_{z'} - \varepsilon_z)) = \frac{e^{\lambda U(S_z)}}{\sum_{k=0}^{10} e^{\lambda U(S_k)}} .$$

We estimate the model using maximum likelihood. The objective function to be maximized is equal to

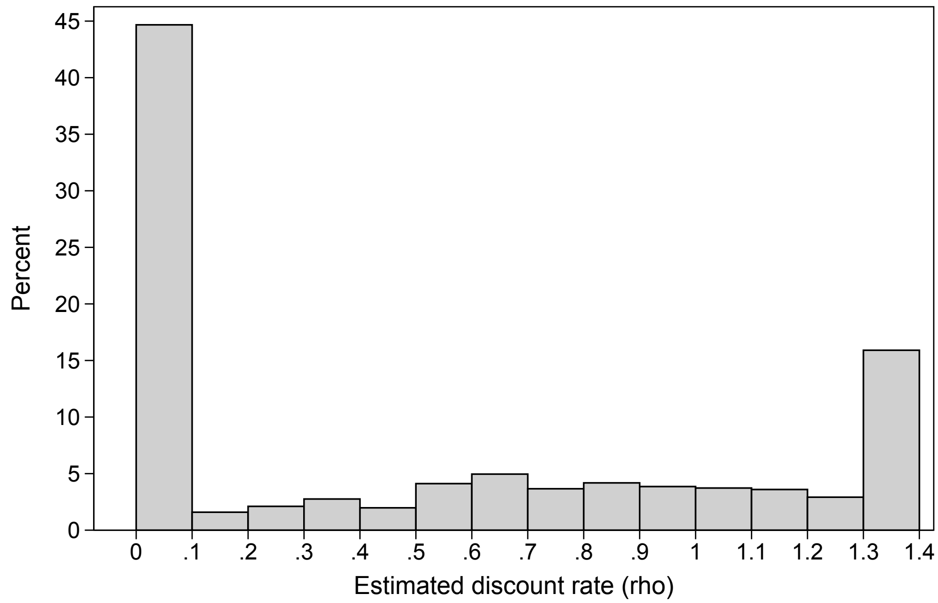
$$f(\mathcal{S};\theta) = \prod_{j=1}^{m} \prod_{k=0}^{10} \text{Prob}(z)^{1[S_z = S_k]} ,$$

where θ denotes the vector of parameters to be estimated, the first product multiplies over all m choice situations in $\mathcal{S}$, and the second product multiplies over all eleven possible allocations. Note that the stochastic specification of the model introduces an additional precision parameter λ, which is constrained to be positive. $\lambda = 0$ represents random choice. In this case, choice probabilities follow a uniform distribution over the eleven possible allocations. Large λ's, on the other hand, indicate higher precision.

We report results for 3,087 subjects for whom we were able to obtain parameter estimates. Figure A5 depicts the distribution of estimated discount rates. It includes subjects who always chose to keep or save all blocks in all choice situations. For these subjects, we set the actual discount rate to the maximum and minimum possible discount rate, respectively. The mean of the estimated discount rates in the sample is 0.52 per annum. Table 5 shows that we obtain similar results when we use the rank of the estimated discount rates instead of the the patience index as a right-hand side variable in the wealth regressions.

We have also estimated a version of the structural model where we use a CRRA subutility function $u(w)$ and included the concavity parameter among the estimated parameters. This exercise resulted in discount rates very similar to those reported here, and with more or less the same association between patience and wealth as reported in Table 5.

Figure A5: Distribution of structurally estimated discount rates



Notes: 3,087 observations. Mean = 0.52.

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