Time Discounting and Wealth Inequality*

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Abstract

We use standard experimental methods to elicit how much people discount the future for a large sample of middle-aged individuals in Denmark and link it to information about their real-life wealth over a 15-year period obtained from administrative registers. The results show that individuals with relatively low time discounting are consistently positioned higher in the wealth distribution. The association between time discounting and the position in the wealth distribution is significant and of the same magnitude as the association between length of education and the position in the wealth distribution, and it exists after controlling for education, school grades, income, initial wealth, parental wealth, and credit constraints. Our results are consistent with the prediction of standard life-cycle savings theory that differences in time preferences generate differences in savings behavior and thereby wealth inequality.

Keywords: Wealth inequality, discounting behavior, preference heterogeneity, experimental methods, register data

JEL codes: C91, D15, D31, E21

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1 Introduction

Are differences in how people discount the future associated with wealth inequality? We address this question by combining experimental data providing information about individuals' patience—defined as behaviorally revealed time discounting—and administrative data with detailed information about their real-life wealth. Our study is motivated by standard life-cycle savings theory predicting that patient individuals save more and therefore become more wealthy. Experimental evidence—starting with the famous Marshmallow experiments measuring delayed gratification in children in the 1960s and up to recent research using, for example, monetary 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; Andreoni and Sprenger 2012; Sutter et al. 2013; Augenblick et al. 2015; Attema et al. 2016; Carvalho et al. 2016). Macro models suggest that such heterogeneity in time discounting can have significant effects on wealth inequality (Krusell and Smith 1998; Carroll et al. 2017), and therefore also have consequences for the propagation of business cycle shocks and for the effects of stimulus policy (Carroll et al. 2014; Krueger et al. 2016). We provide a first link between these two literatures by demonstrating a strong association between individuals' patience and their positions in the wealth distribution, and by providing evidence suggesting that a major part of this association is explained by savings behavior in accordance with standard life-cycle savings theory.

The analysis is carried out in Denmark where it is possible to link subjective information about an individual's behavior elicited in controlled experiments with administrative records providing longitudinal information about actual wealth and income over the life-cycle as well as information about education, school grades, initial wealth, parental background, the likelihood of being credit constrained and demographics. People born during 1973-1983 in the capital city of Copenhagen were invited in February 2015 to participate in an online, incentivized experiment designed to elicit patience and risk attitudes. About 3,600 individuals participated in the experiment, making it a large sample in an experimental context. We invited people from cohorts now in mid-life where we expect the ranking of wealth across individuals to be less influenced by the timing of education and retirement and where observed income is arguably a good proxy for permanent income (Haider and Solon 2006). We use simple, standard experimental methods that are well-suited to elicit behavior in online experiments. Specifically, we elicit individual time discounting by letting individuals choose between receiving monetary payments early (0 or 8 weeks) or late (8 or 16 weeks). The experimental data is linked to the Danish administrative data, which is maintained by Statistics Denmark and of a high quality (Card et al. 2010). The income and wealth components 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).

The experimentally elicited patience of the individuals is strongly correlated with wealth inequality, measured by the percentile rank of the individuals in the within-cohort distribution (e.g. Chetty et al. 2014b). The 1/3 of the subjects who are most patient are on average positioned six percentiles higher in the wealth distribution than the 1/3 of the subjects who are 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. The relationship between our elicited patience measure and the position in the wealth distribution is remarkably stable over the 15-year period where we measure their wealth.

To assess the magnitude of the relationship, we compare it with the association between wealth inequality and educational attainment, which arguably is one of the most important predictors of life-time 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. This suggests that patience is roughly as good as education in predicting a person's 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 controlling for education.

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 do find a significant relationship between patience and the propensity to be in the top 10% of the wealth distribution, and we also show that patience is correlated with different sub-components of net wealth.

In the context of standard life-cycle savings theory, patient individuals save more and become more wealthy at all points in the life cycle. In this framework, 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 use experimental methods to elicit time discounting, but in practice it is impossible to create random variation in time discounting across individuals that can be used to make causal inference about the impact of time discounting on wealth formation. Instead, we include a large battery of controls including education, school grades, income, initial wealth, parental wealth, and elicited risk attitudes in order to isolate the effect operating through the savings channel. Our results show that even after having controlled for a comprehensive set of theoretically motivated covariates a very significant relationship between time discounting and wealth inequality is consistently present.

Net wealth may be constrained from below by borrowing limits. The presence of credit constraints is a leading explanation for observed savings behavior (Zeldes 1989; Johnson et al. 2006). Individuals may become credit constrained because of income shocks, but as pointed out by recent research, credit constraints may also be self-imposed because relatively impatient individuals have less savings and are more likely to be affected by 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 more people are affected by credit constraints (Krueger et al. 2016). Consistent with these hypotheses, we find that individuals who are relatively impatient are more likely to be affected by credit constraints. In one test, we follow the previous empirical literature (e.g., Leth-Petersen 2010) and consider people as being affected by constraints if they are observed holding liquid funds worth less than one month of disposable income (hard credit constraint). We find a strong negative association between patience and this credit constraint measure over a 15 year period. We also use information about loans and deposits of the individuals to compute the interest rate on marginal liquidity for each individual (soft credit constraint) and show that this is also negatively correlated with elicited patience.

An important question is whether the elicited variation in time discounting across individuals simply reflects variation in market interest rates/credit constraint tightness unrelated to time preferences, cf. discussions in Frederick et al. (2002) and Cohen et al. (2016), such that the empirical results could be explained in a setting where agents have homogeneous preferences. We find this explanation unlikely: First, the variation in market interest rates would have to come from the budget sets if preferences are homogeneous; for example, an adverse transitory shock to income or wealth could affect the market rate facing the individual because of a decrease in creditworthiness. However, we find that high-discounting individuals are persistently more likely to be affected by credit constraints over a 15-year period, which does not seem compatible with transitory shocks having caused a high market interest rate. Second, the variation in market interests could be due to long term differences between individuals in, say, levels of income or initial wealth, but the association between patience and wealth exists after controlling for such differences. We also include the hard and soft measures of credit constraints as control variables in the wealth rank regressions, and still find a strong association between the elicited time discounting and the position in the wealth distribution.

Finally, we provide evidence suggesting that the observed relationship between patience and wealth is robust to the timing at which patience is elicited. Using a survey measure of time discounting collected in 1973 for the 1954 cohort in another sample, we show that this early measure of patience also predicts persistent differences in wealth of the individuals over the period 2001-2014.

The next section provides a more detailed description of the relationship to the existing literature. Section 3 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 that we need to control for if we want to isolate empirically the mechanism operating through the savings channel. Section 4 presents the sampling scheme, the experimental design, and the register data on wealth and characteristics of the participants. Section 5 presents the empirical results and different robustness checks. Section 6 concludes.

2 Relationship to literature

Our study relates to the experimental literature measuring subjective preference parameters and to the public finance and macro literature documenting wealth inequality and trying to understand its causes and consequences.

Public finance and macro literature: A large literature documents that wealth inequality is substantial and more unequally distributed than income. The share of total wealth owned by the 10 percent wealthiest has been in the range of 60-90 percent over the last 150 years in both the US and in Europe (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, 2017; Fagereng et al. 2016; De Nardi and Fella 2017). Traditional macro-economic models of consumption and savings with heterogeneous agents assume 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 preferences of each individual is fixed. Economists have historically been treating preferences as stable over time and as similar among people, and have been reluctant to introduce preference heterogeneity in order to make models fit the data better. The background for this position has been that it is difficult to discipline such an exercise when no direct information about preferences is available (Stigler and Becker 1977; Heathcote et al. 2009). Recently, the interest in studying heterogeneity in behavior and preferences has increased. Krusell and Smith (1998) present one of the earliest examples of a macro model with heterogeneous time preferences, and show that a limited degree of heterogeneity in time discounting can generate a significant increase in wealth inequality compared to the reference case with homogeneous preferences. A recent example is Carroll et al. (2017) showing that a model with identical preferences falls short of matching the degree of wealth inequality, while adding modest heterogeneity in impatience significantly improves its ability to fit the wealth distribution. Our contribution relative to this literature is that we use experiments to provide an independent measurement of the heterogeneity in time discounting across individuals and testing whether this can predict the position of the individuals in the real-world wealth distribution.

Experimental literature: The behavioral economics literature has made much progress on quantifying and modeling time preferences at the individual level (e.g. Attema et al. 2010; Bleichrodt et al. 2009; Abdellaoui et al. 2010; Epper et al. 2011; Andreoni and Sprenger 2012; Abdellaoui et al. 2013; Augenblick et al. 2015; Halevy 2015; Attema et al. 2016). Experimental research documents pervasive cross-sectional heterogeneity in time discounting among various populations, contexts and elicitation methods (see Barsky et al. (1997); Sutter et al. (2013); Ubfal (2013), and the articles cited above), albeit this research does not link the distribution of time discounting to the wealth distribution.

A standard concern about extrapolating the results from experimental studies to real life is that experimental studies are usually based on relatively small samples, often consisting of student subjects, see e.g. the discussion in Exadaktylos et al. (2013). In contrast, our study of the origins of wealth inequality requires an experiment with a comparatively large and rich sample from the population.

Another concern is that experimentally elicited measures of preferences are potentially context-specific and the result of the specific laboratory setting applied (e.g. Hardisty et al. 2013; Augenblick et al. 2015). Frederick et al. (2002) summarize the earlier experimental literature measuring subjective time discounting and discuss a number of challenges associated with the elicitation of such preferences. To alleviate measurement concerns, some studies have confronted elicited experimental preference measures with subjects' real world decisions. These studies, however, typically do not focus on savings behavior. For example, Chabris et al. (2008) show that individual discount rates predict inter-individual variation in health-related field behaviors, for example exercise, BMI, and smoking. Lawless et al. (2013) find that elicited time preferences for money predicts smoking cessation and obesity. Backes-Gellner et al. (2017) confront elicited patience with real-life data on student outcomes such as program completion and find that elicited patience predicts real-life outcomes. Overall, very few studies have been able to confront elicited subjective discount factors with data on real-life wealth, and, in particular, rich wealth information from third-party data sources. Exceptions are Meier and Sprenger (2010) who find that (present-biased) time preferences correlate with credit card borrowing, Meier and Sprenger (2012) who find that the degree of time discounting predicts repayment of credit as measured by FICO credit scores, and Carvalho et al. (2016) who document a link between time discounting (specifically, present bias) and access to liquidity prior to and after payday.

A related issue is the fungibility of money. Some authors (Frederick et al. 2002; Augenblick et al. 2015) have argued that, since money can easily be transferred back and forth in time, choices over monetary outcomes may not reflect time preferences very well. This issue can potentially be addressed by eliciting preferences using choices over consumption rather than monetary flows. For instance, Augenblick et al. (2015) suggest the allocation of real effort over time for measuring time preferences.[1] Related tasks have been used in Carvalho et al. (2016) and Augenblick and Rabin (2017). Cohen et al. (2016) discuss the different approaches and argue that both methods do come with their own problems. We opted for monetary outcomes in this study for practical reasons. Our intent to elicit time discounting of a broad, middle-aged sample from the population using an internet-based, real-incentivized experiment made it necessary to implement a short and simple task that does not require extensive time efforts from participants. Specifically, we wanted to avoid that subjects had to repeatedly return to our web platform to complete time-consuming real-effort tasks. We expected that a real-effort experiment would have led to substantial selection and attrition, potentially affecting those subjects with highest opportunity costs.[2]

[1]Relatedly, other studies (e.g. McClure et al. (2007)) administered juice to thirsty subjects.

[2]Our data collection was preceded by substantial pretesting. In particular, we started with various standard tasks (smaller sooner vs. larger later choices presented as lists, and budget choices) with varying presentation formats. In a series of focus groups with subjects from the general population we assessed the different elicitation method. Based on the feedbacks we received, we improved the presentation format, visual depiction and instructions of our elicitation task. What resulted is the graphical allocation choice task presented in the next section, and a video introducing the subject to the decision task (see the transcript in the appendix). Our pilots and comprehension questions indicated that subjects understood the task well and quickly.

3 Association between time discounting and wealth in theory

This section illustrates within a simple neoclassical, deterministic life-cycle savings model why we should expect heterogeneity across individuals in subjective discounting to generate differences in savings behavior and therefore in wealth levels at all ages. It also points to other factors that may generate a relationship between time discounting and wealth, and that 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.

3.1 A basic neoclassical model of individual life-cycle savings

Assume 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 the wealth level of an individual 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 $\gamma\left(a\right)$ is the share of lifetime resources received by the individual up to age a:

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

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). From the wealth equation (3) follows the main prediction (see Appendix B):

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 counfounders if we want to measure 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 reduce the level of wealth at a given age (due to lower values of $\gamma(a)$ in the formula).

Note that differences in the CRRA preference parameter θ have ambiguous effects on wealth as shown in Appendix C. 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 point to a clear relationship between differences in patience and the cross-sectional variation in consumption levels. Patient individuals have, ceteris paribus, lower consumption levels early in life, but higher consumption levels later in life compared to impatient individuals.

3.2 Extensions

Income shocks: The model allows only for deterministic variation in income over the life-cycle. This is in contrast to 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.

Borrowing constraints: The model has a perfect capital market with the same real interest rate r for all borrowing and savings. A large literature has examined theoretically and empirically the role of borrowing 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 (hard) borrowing constraints, consider in our simple model 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 implying borrowing over the life-cycle. However, since borrowing is not possible because of the borrowing constraint they will end up consuming their current income. 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, borrowing constraints may imply that the most impatient individuals (ρ above some threshold) are constrained from borrowing, and therefore that patience and wealth becomes uncorrelated within this group.

A "softer" version of borrowing 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 borrowing constraints to examine whether there exists correlation between time discounting and the propensity to be borrowing constrained, and we analyze whether time discounting is associated with wealth inequality after controlling for borrowing constraints.

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 above model. 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

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

where $v(\cdot)$ is a concave function. In this case, the first order condition for spending gives again the standard Keynes-Ramsey rule and when combined with the budget constraint (2), we again obtain the wealth expression (3). Hence, in the extended model it is still the case 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 the mechanisms going through income and human capital are captured by controlling for permanent income Y and the income profile parameter $\gamma(a)$.

Wealth transfers: Inter vivo transfers and bequests influence wealth inequality (De Nardi 2004; Boserup et al. 2016; 2017). 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 then this creates a positive relationship between patience and wealth running through savings. Thus, the main prediction is the same. The only difference is that the savings are motivated by giving consumption possibilities to others in the future rather than own future consumption.

4 Experimental design and data

Our overall approach is to measure time discounting and risk attitudes using experimental techniques for a stratified sample drawn from the population and linking this information at the individual level to administrative records with third-party reported longitudinal information about wealth and income over the life-cycle as well as information about education, parental wealth and demographic characteristics in order to explore whether differences in elicited patience are predictive of differences in observed wealth. Combining experimental data with administrative register data is made possible by the Danish research infrastructure, whereby data can be linked across modes of data collection using social security numbers. This section describes the sampling scheme, the experimental design and its implementation, and the register data.

4.1 Sample and recruitment for the experiment

We recruited respondents by sampling from the Danish population register individuals 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, i.e. we sent out invitations to the complete birth cohorts meeting the sampling requirements. Statistics Denmark, the central authority on Danish statistics, provided a data set of all individuals who met the sample criteria. The data set contained names, current addresses, and civil registration numbers. We invited everyone in the gross sample to participate by sending personal invitation letters in hard copy. Each letter contained a unique username and password combination needed to log in to a web page through which the experiments was conducted. Upon receiving the invitation letter invitees could decide to participate by logging in to the web page.

We invited a total of 27,613 subjects for participation in our online experiment taking place in February 2015.[3] 4,190 (15.17 percent) of all invitees logged in to our experimental platform. The vast majority (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 3,634 subjects.[4]

[3]Only 424 (1.54 percent) of the 27,613 invitation letters bounced back.

[4]It is important for the linkage between experimental and register data that the people who participated in the experiment

We employed the following recruiting procedure: Subjects received an official invitation from the University of Copenhagen by letter mail.[5] It informed subjects about the login details, the expected time to complete the experiment and contact information for support.[6] Subjects were informed that the payment for participating in the study would depend on their choices, and that the final payment would, on average, correspond to a decent hourly wage.[7]

Subjects who followed the web link in the invitation letter arrived at a login page. Upon 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 determines the choice situation that counts for payment, and, hence, that any of the choice situations could be picked for payment. There were three elicitation tasks, a time task, a risk task and a social task. 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. Our main focus in this paper is the time task, which is described in detail in the next subsection. A description of the risk task can be found in Appendix F. The present study does not use data from the social task.

The average completion time was 46.85 minutes. It took the fastest subject 21.25 minutes to complete the experiment. The distribution of completion times has positive skew. We did not prevent subjects from taking breaks during the experiment session. However, once they logged in for the first time, they were required to finish the experiment within a two week time frame. Our elicitation tasks involved real monetary incentives. During the study, we used an experimental currency. 100 points corresponded to 25 Danish kroner (DKK).[8] This provided us more flexibility for calibration of the choice situations. To determine the choice situation relevant for payment, subjects spun a wheel containing all the choice situations they were confronted with. The random choice situation at which the wheel stopped was then displayed together with the subject's decision. Then, the points were exchanged into money. Payment was done via direct bank transfer at the relevant date (details follow below). When converting from

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 45 persons without the required register data information (typically immigrants).

[5] An English translation of the invitation letter is available in Appendix D.

[6] The main experiment was preceded by an extensive pretesting phase. This phase comprised of 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.

[7] We left the exact range of amounts open to not induce reference points.

[8] 1 USD $\simeq$ 6.5 DKK at the time of the study.

points to DKK, we rounded the amount up to the next unit. Possible payments considering all three tasks ranged from 88 to 418 DKK. The average amount paid out was 245.23 DKK. A distribution of payments can be found in Appendix G.

4.2 Measuring patience

To elicit an index for time preferences we exposed subjects to a series of choice tasks. The data generated by these tasks serve as an input for our behavioral measure of patience, which we describe in more detail below.

4.2.1 Time task

To elicit intertemporal choice behavior, we use convex time budgets (Andreoni and Sprenger 2012). Our presentation format differs from what was proposed originally in that we depict intertemporal choices graphically and present only a single allocation choice per page.[9] 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-points blocks. These ten blocks were allocated at 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 these 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-points 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-points blocks in 8 weeks, and save the remaining six 100-points blocks for receipt in 16 weeks. Deferring the receipt of the latter six blocks led a total interest payment of $6 \cdot 5 = 30$ points. Choices were made by clicking (or touching) the respective block, and then moving around the horizontal savings bar. 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

[9] We also avoid the simultaneous presentation of dates and delays. This is motivated by previous results (Read et al. 2005) reporting behavioral differences between these two presentation formats.

no longer possible to revert 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.

Choice situations involved three different payment dates: “today”, “in 8 weeks”, and “in 16 weeks”. Combinations of all three payment dates were used in the experiment. We decided to state delays in terms of weeks (instead of months) to prevent possible weekday effects. The payments were consolidated on a per-day basis. 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 at 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 at the subsequent banking day.

The interest rates applied varied across choice tasks. For example, for the five choice tasks asking subjects to choose between receiving payments in 8 weeks or 16 weeks had rate of returns in the interval 5-25 percent (amounting to annualized interest rates in the range of 16-282 percent). This range of interest rates is similar to those used in other studies reviewed in the literature section. Moreover, in appendix L, we show that the distribution of choices made by the subjects in our experiment is very similar to the distribution of choices in 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, our results rely only on the ordering of the subjects according to their time discounting. 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.

4.2.2 The patience measure

The collected choice task data enable us to calculate a non-parametric measure of patience.[10] That is, we construct a measure that is specific to each individual in our sample, and this measure is based on choice data only and does not involve auxiliary assumptions on the structure of individual preferences. Our patience index is constructed by taking the choice variable z, i.e. the number of blocks saved for late receipt. We then normalize and aggregate the measure across the various choice situations. Aggregation is performed using the median, which ensures that our measure is robust to single outliers in choices. Results are close to identical if we take the arithmetic mean instead. For constructing our *patience* measure, we take the five choice situations that involve allocations between $t_1 = 8$ weeks and $t_2 = 16$ weeks.[11] In the robustness section we show that our results are robust to using indices based on trade-offs between "today" and "in 8 weeks", or "today" and "in 16 weeks".

Our patience index is defined as follows:

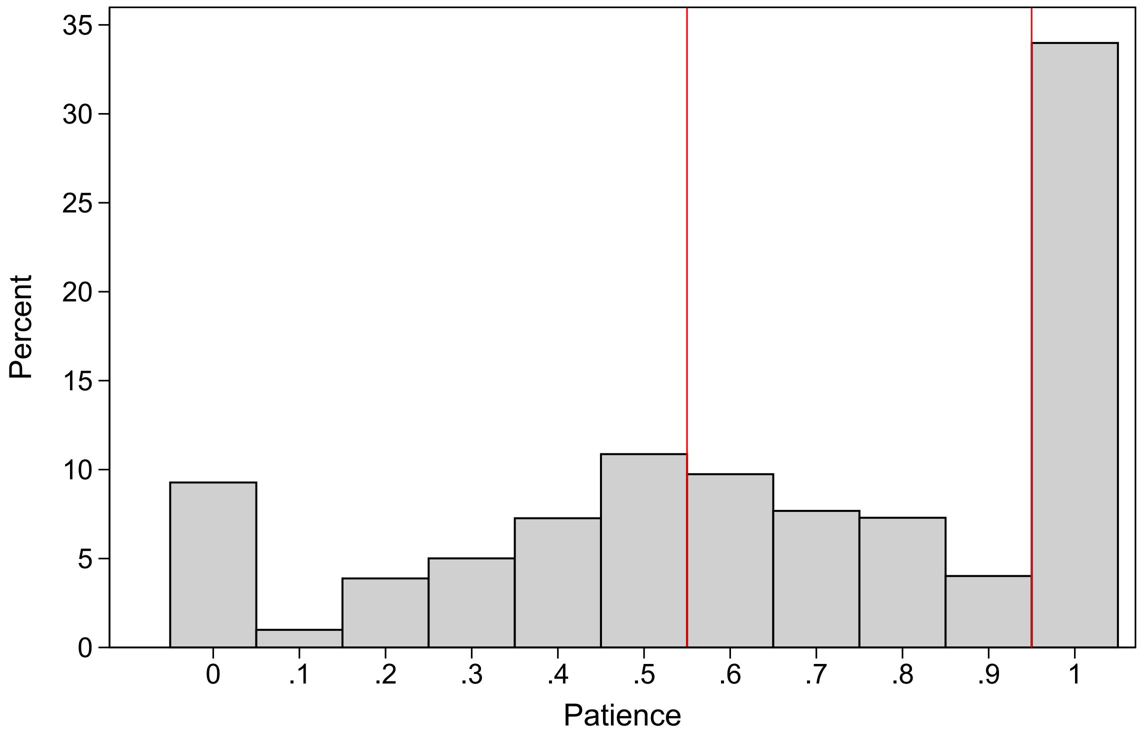
$$\phi_{\text{patience}} = \text{median}\left(\frac{z}{10}\right) , \tag{4}$$

where z denotes the number of blocks allocated at the later point in time, i.e. in 16 weeks, and where $\phi_{\text{patience}} \in [0, 1]$. Higher values of ϕ_{patience} indicate greater patience. Due to the discreteness of our measures (10 blocks were allocated), our index can take values in $1/10$th steps. By construction, censoring occurs at both ends of the scale, i.e. it is not possible to detect negative values or values larger than what the experimental scenarios span. The histogram in Figure 2 depicts the distribution of our patience index. Importantly, we find substantial heterogeneity across the individuals in the sample. In Section 5, we study whether this variation in elicited patience can predict the positions of the individuals in the wealth distribution. The vertical lines in Figure 2 indicate tertile cut-off points. In many of our empirical analyses we split the patience index in tertiles of high, medium and low patience in order to facilitate visualization.

[10]We refer to our index as "patience" and not "time preferences" to include the possibility that other factors than deep preferences affect the revealed time discounting (see e.g. the discussions in Frederick et al. 2002 and Epper 2015).

[11]These are labeled choiceId $\in \{11, ..15\}$ in Table A1 of Appendix E.

Figure 2: Histogram of patience index



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

4.3 Register data and the measurement of wealth and other characteristics

The choice data from the experiment is linked with Danish administrative register data at the individual level.[12] The register data contains demographic characteristics and information from the income tax register. The income tax register includes information on annual income as well as the values of assets and liabilities at the end of each year. The value of assets includes assessed property value, market value of stocks, bonds and mortgage deeds in deposit and bank deposits. The value of liabilities includes all debt except debt to private persons. All the register data are third-party reported. For instance, employers report earnings, government institutions report transfer payments, and information on assets and liabilities is reported by financial institutions. The data in the registers are organized as a panel data set so that it is possible to observe income, assets, and liabilities back in time for the respondents in the experiment. The data cover the period 1980-2014 and includes everyone who is at least 18 years

[12]The participants were not informed that the data from the experiment would be linked with the administrative register data. The Danish Data Protection Agency has approved the research project and this procedure. To merge the experimental data with the register data, the usernames provided in the invitation letters were translated into anonymized civil registration numbers.

old. There are two components of wealth that the data described so far does not include. One is wealth accumulated in pension accounts and the other is wealth kept in cars. These two components have become available as of 2014, and in the robustness section we examine if the inclusion of these two components affect our findings when we confine the analysis to be based only on wealth observed in 2014.

In total, we sent out 27,613 invitations and reached 3,634 participants giving a gross participation rate of 13%. Participation rates at this level are common for similar experimental studies (e.g. Andersson et al. 2016 report 11%). The sample selected to receive invitations to participate in the experiment was sampled from the population register. We therefore know the identity of participants as well as invitees who did not respond to the invitation. As a result, we are able to compare the characteristics of the participants and non-participants. This is done in Table 1, which contains summary statistics. Compared to non-participants, participants are slightly older, are less likely to be single, and have slightly longer education. The magnitudes of these differences appear to be relatively small. Participants, however, have a significantly higher level of income, net wealth and liquid assets than non-participants. In Table 1, column (d) we list the corresponding statistics for a 10 percent random sample from the Danish population in order to assess how representative our sample is of the Danish population at large. Compared to the random sample from the population, the sample of respondents is on average slightly younger, less likely to have children staying at home, have slightly longer education, and have higher income. The median level of wealth is lower, but the overall variance is larger. Overall, the respondents appear to be more similar, on average, to the random sample from the population than the gross sample. In section 5.5, we investigate whether the results are sensitive to the differences in sample composition documented 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	36.32	35.45	0.87	36.38	-0.06
Woman (=1)	0.50	0.49	0.01	0.50	0.00
Single (=1)	0.29	0.39	-0.10	0.29	0.00
Dependent children (=1)	0.57	0.52	0.05	0.60	-0.03
Years of education	14.65	13.93	0.72	14.46	0.19
Gross income (median)	369923.40	331215.30	38708.10	350046.80	19876.60
Liquid assets (median)	29898.20	21639.40	8258.80	26941.00	2957.20
Wealth distribution					
p5	-357104.20	-378243.70	21139.50	-276244.80	-80859.40
p25	58746.17	22666.69	36079.48	103225.30	-44479.13
p50	386146.00	251551.40	134594.60	397204.50	-11058.50
p75	886077.90	663706.30	222371.60	829476.00	56601.90
p95	2128028.00	1749405.00	378623.00	1969143.00	158885.00
Observations	3634	23823	27457	67588	71222

Notes: Variables are based on 2014 values. The random 10 percent sample of the Danish population is drawn among those who are not in the gross sample (i.e., did not live in Copenhagen Municipality when they were seven years old), but who were born in the same period (1973-1983). (=1) indicates a dummy variable which takes 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. These ratios are calculated for each of 98 municipalities. Gross income refers to annual income and excludes capital income. Liquid assets include bank deposits and market values of stocks and bonds. The table includes individuals for whom a full set of register variables is available.

5 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 number of control variables with the aim of isolating the part of the association operating through the savings channel. Next, we examine the role of credit constraints and whether heterogeneity in discounting predicts if individuals are among the top 10% wealthiest. Finally, we present a number of robustness analyses.

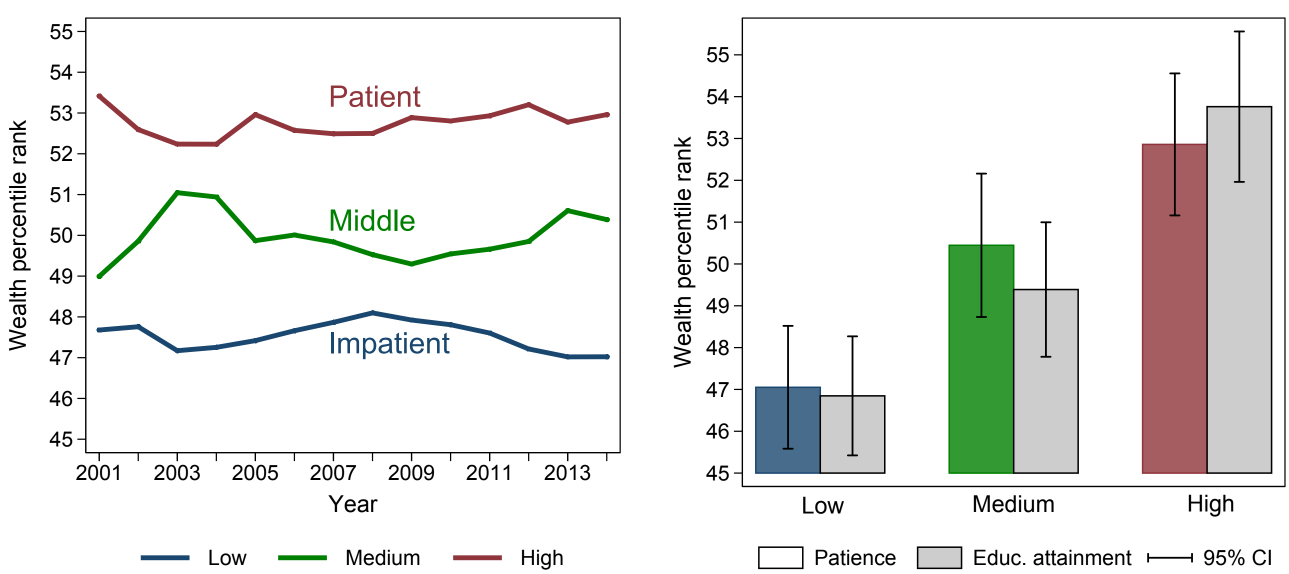
5.1 Overall association between time discounting and wealth inequality

Most of our analysis is based on measuring the relationship between elicited time discounting of the individuals and their positions in the wealth distribution, measured by the percentile rank of the individual in the within cohort×time distribution of the sample (e.g. Chetty et al. 2014b). This wealth rank measure has several advantages: it compares the wealth of an individual with wealth of others from the same cohorts and thereby controls for life-cycle differences in wealth, it works well with zero and negative observations that are common in wealth data, and it is a very robust measure as it is 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 2001-2014. 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 patience ordering of the individuals predicts the position in the wealth distribution, so that the group average of the most patient individuals consistently is 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 five to six wealth percentiles.

Figure 3: Time discounting, educational attainment and wealth inequality

(a) Patience and position in the wealth distribution

(b) Patience vs. education



Notes: Panel a shows the association between elicited patience and the position in the wealth distribution in the period 2001-2014. The position in the wealth distribution is computed as the percentile. The sample has been split into three approximately equally sized groups according to the tertiles of the subjective discount factor 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 [0.6, 0.9]; High [1.0]. Panel b shows the association between the position in the wealth distribution (average over 2012-2014) and educational attainment, where the individuals in the sample have been 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]; High (16, 21] where the numbers refer to years of completed education.

In order to assess the magnitude of the association between time discounting and wealth inequality we compare it with 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 life time inequality. In Figure 3b, we have split the sample into three equally sized groups according to educational attainment as measured by the number of years of completed education. The groups with least education has completed 8-14 years of education while the group with most education has completed 16-21 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. Thus, the predictive power of the elicited patience measure is comparable to education.

5.2 Including other predictors of wealth inequality

The bivariate association between patience and wealth inequality in Figure 3 may be due to higher savings propensities of patient individuals as predicted by life-cycle savings theory, but it may also arise because of other mechanisms as described in the theory section 3. We therefore turn to multivariate regressions and sequentially add control variables in an attempt to isolate the part of the association operating through the savings channel. In the regressions, we focus on the wealth percentile rank at the end of the observation period. At this point in the life cycle, we expect the ranking of wealth to be less influenced by the timing of education, and income is arguably a good proxy for permanent income (Haider and Solon 2006). [13] The results are presented in Table 2. Column 1 presents the result from a simple bivariate regression of the wealth percentile on patience. Consistent with the graphical evidence, we find that moving from the lowest to the highest level of patience in the sample is associated with a difference of eight wealth percentiles, and this relationship is statistically significant at the 0.1 percent level.

[13] We have also run the regression presented in Table 2 using the wealth data covering the whole period 2001-2014. The results are presented in Section 5.4 and confirm the results presented in Table 2.

Table 2: Patience and wealth inequality

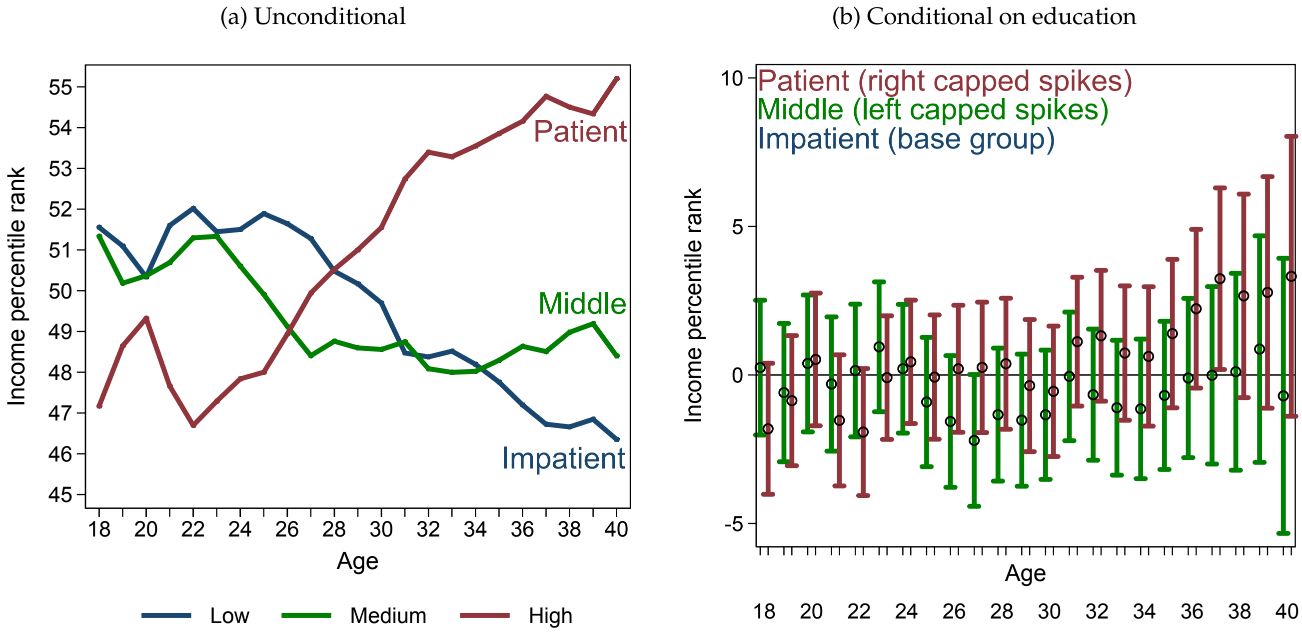
Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	8.14***	6.62***	6.45***	6.88***	6.46***	5.89***	6.09***	6.07***
	(1.44)	(1.46)	(1.47)	(1.54)	(1.51)	(1.50)	(1.51)	(1.51)
Risk aversion							2.99	3.12
							(1.92)	(1.92)
Year dummies for educational attainment	No	Yes	Yes	Yes	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
Wealth at age 18 decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Parental wealth decile dummies	No	No	No	No	No	Yes	Yes	Yes
Demographic controls	No	No	No	No	No	No	No	Yes
Constant	44.68***	42.86***	43.93***	43.09***	37.26***	35.31***	33.70***	34.17***
	(1.03)	(1.67)	(1.97)	(2.47)	(2.66)	(3.09)	(3.26)	(3.39)
Observations	3634	3634	3634	3360	3360	3360	3360	3360
Adj. R-squared	0.01	0.02	0.03	0.02	0.05	0.07	0.07	0.07

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. For each respondent, wealth and gross income are measured as averages over the period 2012-2014. Gross income does not include capital income. Parental wealth is measured as the average over the period when the respondent was 7-14 years old. 'Demographic controls' include three variables: a gender dummy, a dummy for being single in 2013, and a dummy for having dependent children in 2013. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

In Figure 3b, we compared the magnitude of the association between patience and the position in the wealth distribution with the magnitude of the association between schooling and the position in the wealth distribution. As discussed in the theory section, the most patient individuals might be more prone to delay income by choosing more education. Reversely, education may also contribute to patience. The data shows a statistically 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). In column 2, flexible dummies for educational attainment are included as control variables. The coefficient on the patience measure decreases somewhat, but remains highly significant and not statistically different from the coefficient in column 1. Thus, the relationship between patience and wealth exists beyond education.

According to the basic theory, the cross-sectional variance in wealth potentially also depends on permanent income and the profile of income over time. In Figure 4a, we plot the position in the within-cohort income distribution for the respondents across different ages and separately for the three patience groups that were 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 they pick up and by age 40 they are positioned about 6 percentiles higher, suggesting a higher level of permanent income for these individuals. Such a pattern, where patient individuals have relatively steep income profiles while less patient individuals have relatively flat income profiles, is consistent with a positive relationship between time discounting and choice of education. The fact that more patient individuals have higher permanent income potentially implies that the positive association between wealth and patience can exist without these individuals saving more relative to their permanent income. On the other hand, the difference in the time profile of income implies in isolation a negative association between wealth and patience. It turns out that the controls for educational attainment to a large extent capture these differences in timing of income and levels of permanent income. To see this consider Figure 4b plotting 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 including a fully flexible set of dummies for years of completed education. The figure shows that the differences across the three patience groups in level and 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 differences in permanent income and for differences in the timing of income that are observed in the raw data.

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



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 has been split into three approximately equally sized groups according to the tertiles of the subjective discount factor 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 [0.6, 0.9]; High [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 with-in cohort income distribution (gross income excluding capital income). The parameter on the patience measure is hardly affected by the inclusion of these dummies.[14] Recent evidence suggests that cognitive ability is correlated with time discounting and risk attitudes (Dohmen et al. 2010).[15] In column 4, we add decile dummies for school grades. This does not change the estimate of the patience parameter.

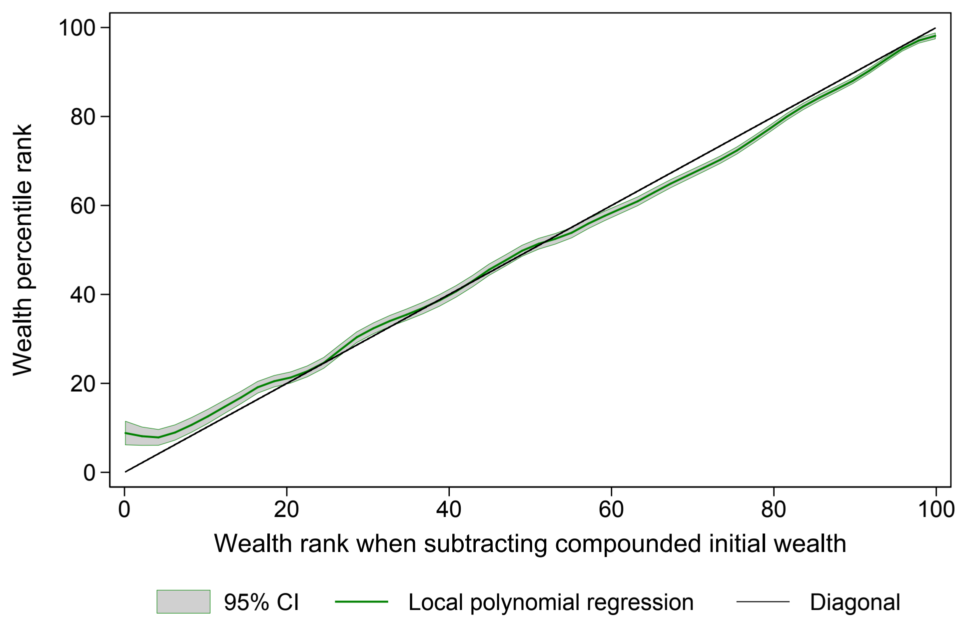
Theoretically, initial wealth is another potential confounding factor if we want to isolate the role of the savings channel. Figure 5 plots the wealth percentile rank in year 2014 against the percentile rank of wealth in year 2014 *less* wealth holdings at age 18, the age of majority. In constructing this figure,

[14]We have also constructed a figure corresponding to Figure 3, but where wealth is normalized by average income 2012-2014 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.

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

we have compounded wealth at age 18 with a considerable real interest rate (5 percent) to make sure that we do not underestimate the potential effect of initial wealth. If the wealth rank in 2014 was fully determined by initial wealth then the curve in the diagram would be flat. On the contrary, 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 2014. In Table 2, column 5 we include decile dummies for the within-cohort wealth rank at age 18. Consistent with the graphical evidence presented in Figure 5, 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 wealth percentile rank (2014) on the percentile rank of wealth in 2014 less wealth holdings at age 18. Wealth at age 18 has been compounded by a real interest rate of 5 percent.

Wealth accumulation may also be influenced by transfers from parents. We do not directly observe bequests and inter vivo transfers in the data. However, such transfers are likely correlated with initial wealth and parental wealth. In column 6 we add decile dummies for the within-cohort parental wealth. This does not affect the parameter estimate associated with the patience measure significantly. While we do not directly observe transfers from parents to children, we are able to exploit the longitudinal aspect of our administrative data. If parents make transfers to their children then that should create a negative correlation between adjustments in parental wealth and child wealth (Kolodziejczyk and Leth-Petersen 2013). This test is reported in Appendix I and does not show evidence of transfers from parents to children.

In the experiment we also elicited risk preferences. Theoretically, the association between risk aversion on wealth is not clear. According to the theory presented in section 3, 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. The model predicts a positive effect of the CRRA parameter on wealth if the rate of time preference is greater than the real interest rate on savings, $\rho > r$, and a negative effect if the rate of time preference is smaller than the real interest rate on savings, $\rho < r$. In Appendix H we perform an implicit test of this prediction: For each patience group, we regress the net wealth percentile rank on the experimental measure of risk aversion. Consistent with the model prediction, the less patient the group is, the more positive the effect of risk aversion on relative wealth is. Irrespective of the theoretical association between risk aversion and wealth, previous studies have shown evidence 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. In column 7 we include our experimental measure of risk aversion among the control variables. Again, our parameter of interest is left virtually unchanged and remains strongly significant.

Finally, in column 8 we include a set of additional demographic controls for gender, single status, and dependent children. The inclusion of these variables does not impact the patience parameter estimate either.

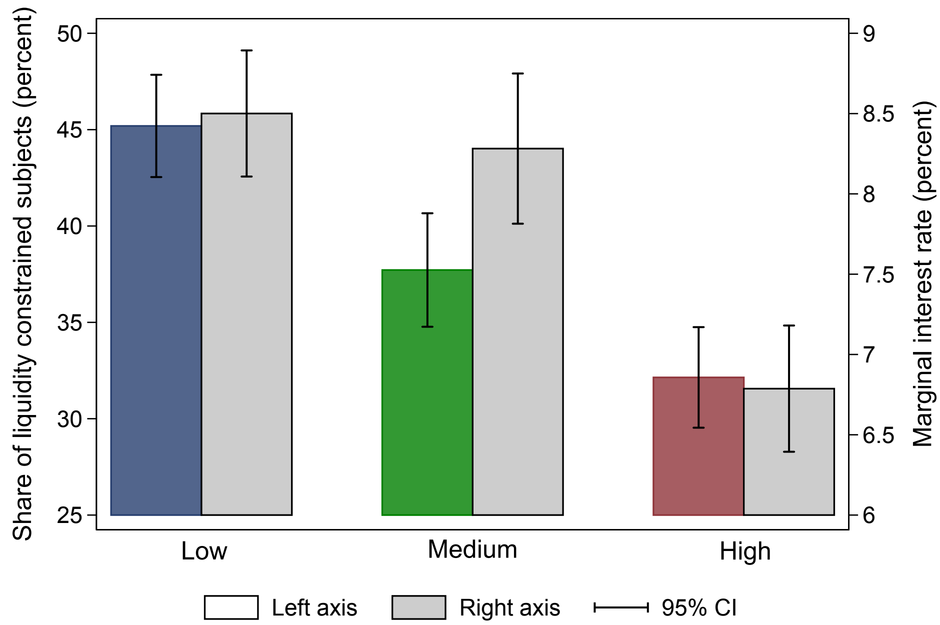
In summary, we find that the pattern depicted in Figure 3 is statistically significant and that the relationship between patience and the position in the wealth distribution is robust to the inclusion of a large number of covariates capturing other explanations of the association between patience and wealth inequality than the savings channel. The difference between the most patient and the most impatient is 8 percentiles without the controls and 6 percentiles when including the controls. The implies that a large part of the association may be explained by differences in savings behavior as suggested by life-cycle savings theory.

5.3 Role of liquidity constraints

Theory informs that people who are relatively patient will save relatively more and therefore face a smaller risk of being liquidity constrained, or, conversely, that people who are relatively impatient are more likely to be affected by liquidity constraints. This potential relationship between patience and liquidity constraints may contribute to the propagation of business cycle shocks and the effects of stimulus policy (Carroll et al. 2014; Krueger et al. 2016) and it implies that liquidity constraints can mute the relationship between patience and wealth. In this section, we analyze whether elicited patience and liquidity constraints are related and whether this influences the relationship between patience and wealth. We also address whether it might be the case that the time discounting elicited in the experiment only measures market interest rates faced by the subjects instead of heterogeneity in true time discounting.

Liquidity 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 worth of 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. We therefore also construct a measure of the marginal interest rate, which is arguably a better proxy for the marginal price of liquidity. To construct this we exploit that we have access to account level data with information about outstanding debt and interest payments during the year. We use this to calculate an average interest rate for each account that we observe for the individual. For people with debt accounts we pick the highest interest rate among debt accounts as the marginal interest rate. For people who do not have debt we pick the lowest interest rate among their deposit accounts based on the logic that this is the cheapest source of liquidity. This measure has been proposed by Kreiner et al. (2016) who document that it is able to match interest rates set by banks and to predict spending responses to a stimulus policy. In Appendix K we present more details about the construction of the marginal interest rate.

Figure 6: Patience and the probability of being credit constrained

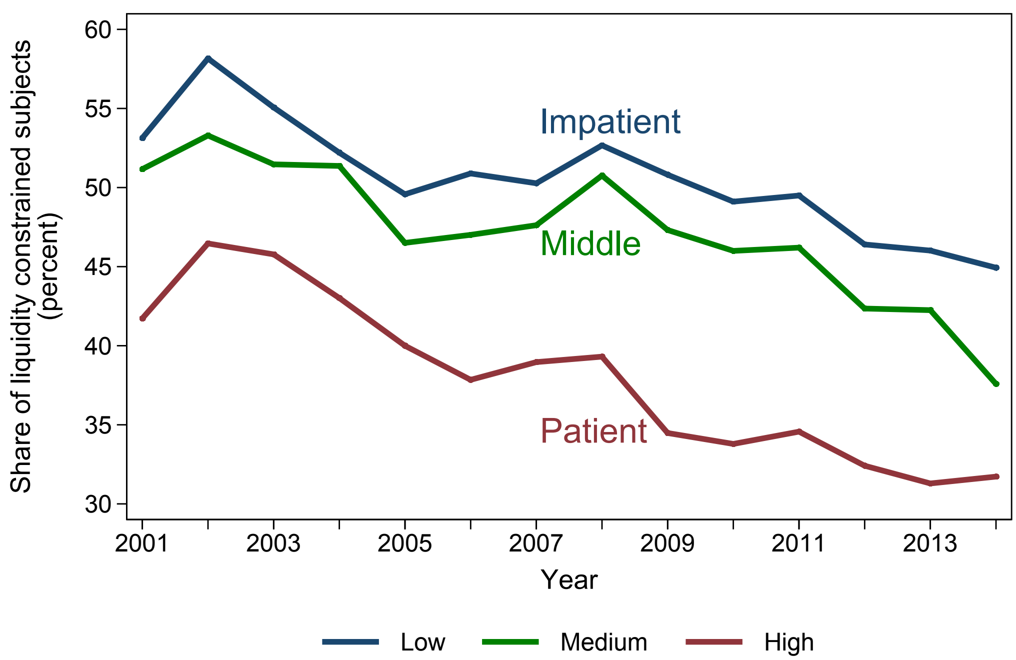


Notes: The colored bars show the association between elicited patience and the propensity to hold liquid assets worth less than one month of disposable income in 2014. The sample has been split into three approximately equally sized groups according to the tertiles of the patience index such that 'High' 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 [0.6, 0.9]; High [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 done previously, we split the sample into three equally sized groups according to the magnitude of the experimental patience measure and calculate the fraction who are observed with liquid assets worth less than one month of disposable income (colored 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 while 45 percent are observed 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 about 7 percent while the least patient group faces a marginal interest rate of about 8.5 percent.

The two measures of liquidity constraints are measured before the experimental data about patience is collected. This leaves open the possibility that elicited patience is a response to an adverse shock, which has lead a patient individual to drive down his liquid assets and, consequently, transitorily behave as if he is impatient. Figure 7 shows the fraction of people who are recorded with liquid assets worth less than one month of disposable income for the period 2001-2014 for each of the three patience groups. The graph shows that the propensity to be observed with low levels of liquid assets is generally declining 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 people who are classified as relatively patient are persistently, i.e. over a period of 14 years, recorded as being less likely to be affected by constraints. Such persistence is difficult to rationalize with short term shocks.

Figure 7: Prevalence of liquidity constraints across levels of patience, 2001-2014



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 of disposable income. The sample has been split into three approximately 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 [0.6, 0.9]; High [1.0].

In order 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 of 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 of disposable income. Consistent with theory, we find that for the subgroup where liquidity constraints are likely to be binding, column (2), elicited patience is no longer predictive of the wealth percentile rank. However, for the group who are unlikely to be affected by constraints, column (1), the association between patience and wealth is much stronger than in the pooled sample, cf. Table 5. In fact, the results presented in 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 almost 11 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. In columns 3-4 we include the marginal interest rate among the regressors to control for the intensity of constraints. For both the high (column 3) and the low (column 4) asset group, the parameter on the marginal interest rate is significant and negative such that a higher marginal interest rate is associated with a lower wealth. The inclusion of the marginal interest rate mutes the parameter estimate on patience, but it remains highly significant and of a magnitude indicating that the most patient person is ranked seven wealth percentiles higher than the least patient person in the sample consisting of people holding liquid assets corresponding to at least one month of disposable income. For the low liquid asset group, the parameter estimate on patience remains insignificant. In columns 5-6 we introduce the additional control variables also used in column 8 of Table 5. This leaves the parameter estimates on patience virtually unchanged. The evidence presented in Table 3 is consistent with the theoretical conjecture that liquidity constraints will mute the relationship between patience and the position in the wealth distribution.

The findings presented here also speak to the issue about whether differences in elicited time discounting simply reflects variation in real-life market interest rates facing the individuals who have participated in the online experiments (Frederick et al. 2002). For example, Krupka and Stephens (2013) use a survey-elicited measure of time discounting and show that it reflects the market interest rates faced by the individuals at the time of the survey rather than actual time discounting. The fact that patience significantly predicts the wealth percentile rank after controlling directly for the market interest rate indicates that discounting behavior elicited with experimental methods does not only reflect market interest rates, but also differences in time preferences.

Table 3: Wealth percentile rank, patience and liquidity constraints

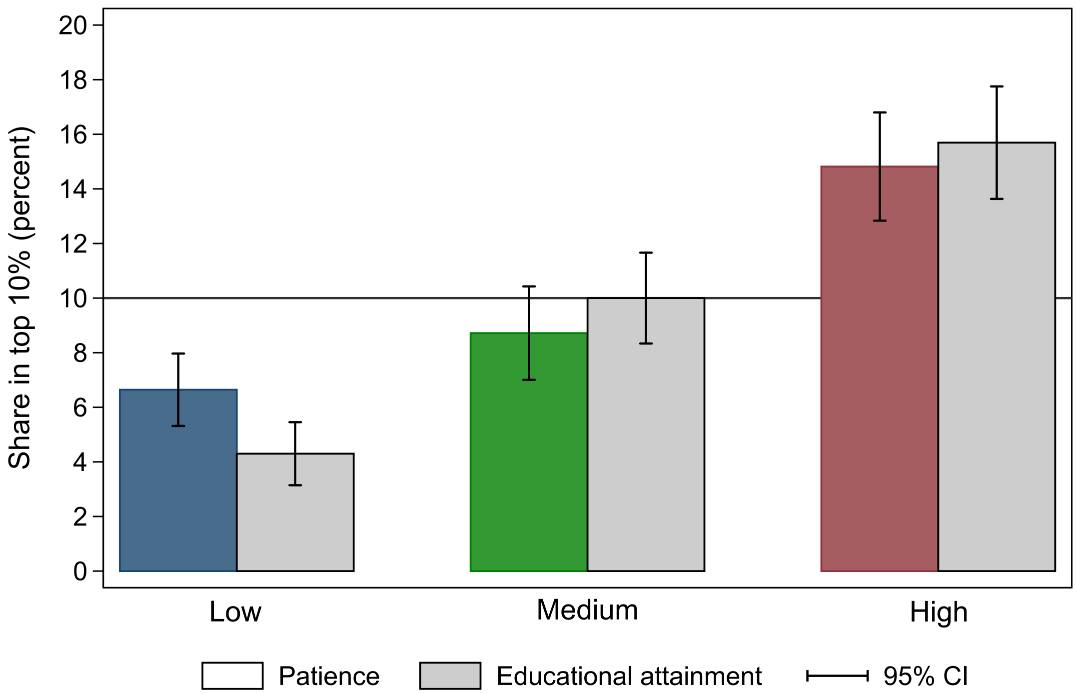
Dep. var.: Wealth percentile rank Liquid Assets:	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
Patience	10.90***	-2.81	7.04***	-2.92	6.50***	-0.99
	(1.98)	(1.89)	(1.82)	(1.84)	(1.92)	(1.95)
Marginal interest rate			-1.98***	-0.75***	-1.87***	-0.82***
			(0.10)	(0.08)	(0.11)	(0.09)
Risk aversion					4.17	-1.62
					(2.31)	(2.62)
Year dummies for educational attainment	No	No	No	No	Yes	Yes
Gross income decile dummies	No	No	No	No	Yes	Yes
Self-reported school grades decile dummies	No	No	No	No	Yes	Yes
Wealth at age 18 decile dummies	No	No	No	No	Yes	Yes
Parental wealth decile dummies	No	No	No	No	Yes	Yes
Demographic controls	No	No	No	No	Yes	Yes
Constant	49.52***	40.64***	62.86***	49.32***	50.82***	52.68***
	(1.48)	(1.31)	(1.50)	(1.59)	(5.28)	(4.19)
Observations	2226	1400	2198	1392	2034	1286
Adj. R-squared	0.01	0.00	0.18	0.06	0.20	0.09

Notes: OLS regressions. Column (1), (3), (5) are estimated on the subsample of respondents who are recorded holding liquid assets worth more than one month of of disposable income. Column (2), (4), (6) are estimated on the subsample holding liquid assets worth less than one month of of disposable income. 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. For each respondent, wealth and gross income are measured as averages over the period 2012-2014. Gross income does not include capital income. Parental wealth is measured as the average over the period when the respondent was 7-14 years old. 'Demographic controls' include three variables: a gender dummy, a dummy for being single in 2013, and a dummy for having dependent children in 2013. The number of observations included in this table is slightly lower than the number of observations included in Table 5. 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. The number of observations is further reduced by 36 observations when entering the marginal interest rate. This is because some of the detailed account specific inforamation was missing for these observationa. Finally the number of observations is reduced further when moving to columns 5-6. As reported in the notes to Table 2 this is because some of the respondents did not report school grades.

5.4 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 10 percent wealthiest 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 we display in Figure 8 the fraction of respondents who belong to the ten percent wealthiest within the three patience groups defined in the previous section. The figure shows that in the least patient group about six percent belong to the ten percent wealthiest in the sample whereas 15 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 that for education, and while the association between patience and the propensity to be among the ten percent wealthiest is not quite as stark, it is of the same order of magnitude and significant in economic terms. In Appendix J, 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 ten percent wealthiest. 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 very wealthy, say, top 0.1%.

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



Notes: The colored bars show the association between elicited patience and the propensity to be among the ten percent wealthiest in the sample (top ten percent in the within-cohort wealth distribution, 2012-2014). The sample has been split into three approximately 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 [0.6, 0.9]; High [1.0]. The grey bars show the association between the propensity to be among the ten percent wealthiest in the sample and educational attainment, where the individuals in the sample have been 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]; High (16, 21] where the numbers refer to years of completed education.

5.5 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 is elicited by survey back in 1973 and reproduce some of our main results, thereby adressing 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 return to the experimental data and examine the robustness of our core results to the definition of wealth, to accounting for selection into participating in the experiment, and to the exact timing of the payments in the experiment. Finally, we provide additional evidence suggesting that wealth transfers from parents to children are generally small, and therefore unlikely to be a major driver behind the association between elicited patience and position in the wealth distribution.

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

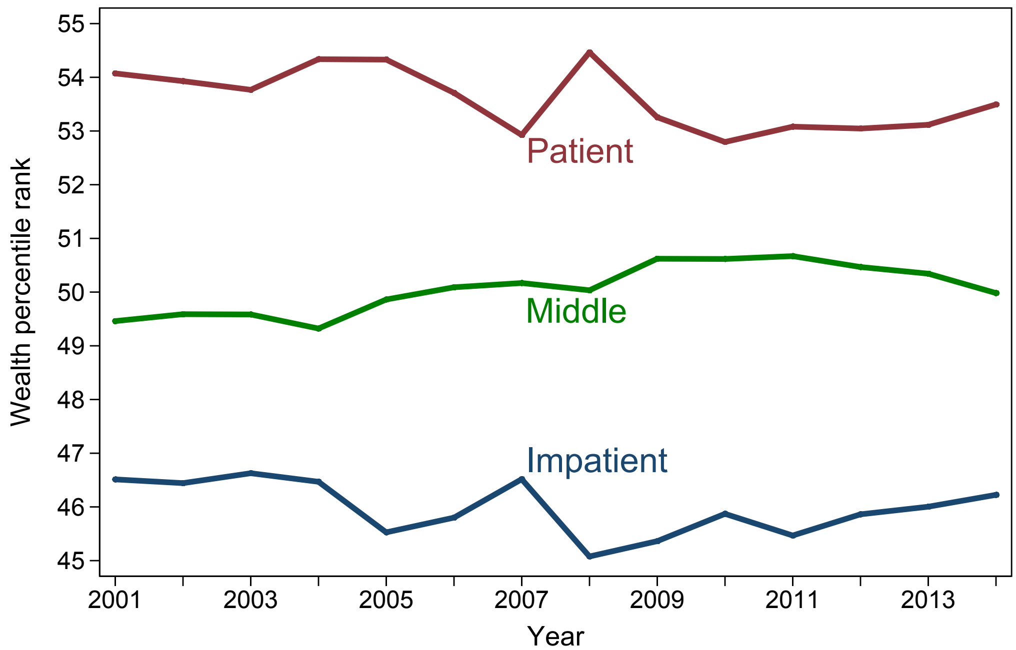
This section uses data from the Danish Longitudinal Survey of Youth (DLSY). The DLSY survey contains a crude measure of time discounting collected in 1973 for a sample consisting of 2,389 individuals from the 1952-1955 cohorts.[16] The survey data is merged with administrative records covering the same period as the core analysis. In this way we can examine whether an alternative measure of time discounting collected at a very early point in time relative to when wealth is measured is predictive of future wealth inequality. In the 1973 survey, the respondents were, among other things, asked 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 crude proxy for time discounting, where respondents answering (*iii*) are the most patient and respondents answering (*i*) are the least patient. This aligns with the normal interpretation of experiments using timing of monetary payments to elicit time discounting.

Figure 9 shows the average position in the wealth distribution for each of the three groups defined by the three answers to the question. 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

[16] Interviews are also made at several other points in time. 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.

2001-2014, so that the group average of the most patient individuals is consistenly 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 6 to 7 wealth percentiles. The persistence and magnitude resemble the pattern observed in Figure 3a.

Figure 9: Time discounting in 1973 and position in the wealth distribution 2001-2014



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 2001-2014. The position in the wealth distribution is computed as the with-in 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.* 620 respondents preferred a flat income profile (impatient). 1,091 preferred a steeper profile (middle), and 678 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 significant at conventional levels of significance. In column 4, decile dummies for wealth measured in 1983 are added to the control set in order to control for initial wealth. This mutes the medium patience group slightly and leaves it significant only at the ten percent level, while the high patience group parameter is still significant at the five percent level. Finally, column 5 includes demographic controls, which does not affect the estimates of the parameters of interest in any important way.[17]

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, 2012-2014

Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)
Patience, medium	4.08**	3.48*	2.74*	2.62+	2.37+
	(1.39)	(1.39)	(1.38)	(1.34)	(1.36)
Patience, high	7.07***	4.33**	3.59*	3.21*	3.10*
	(1.60)	(1.61)	(1.60)	(1.55)	(1.55)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes
Gross income decile dummies, 1998-2000	No	No	Yes	Yes	Yes
Wealth decile dummies, 1983	No	No	No	Yes	Yes
Demographic controls	No	No	No	No	Yes
Constant	46.16***	39.27***	33.08***	22.14***	22.89***
	(1.08)	(1.69)	(2.07)	(2.93)	(3.03)
Observations	2384	2384	2384	2384	2384
Adj. R-squared	0.01	0.05	0.07	0.14	0.14

Notes: OLS regressions. Dep. var.: Within-cohort wealth percentile rank computed from average wealth over 2012-2014. Robust standard errors in parentheses. + p<0.10, * 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. Ranks in the wealth and income distributions are computed within-cohort. Demographic controls include a dummy for being single in 2013 and a dummy for being female. 5 observations are dropped because of missing income data in 1998-2000 or missing wealth data in 1983.

5.5.2 Sensitivity analysis of core results

We now return to the core analysis and perform a number of robustness checks. The results from these are presented in Table 5. The first column in Table 5 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 over the period 2012-2014. In that analysis, we focus on the latest years in the sample, because we want to characterize the association between elicited patience and wealth for individuals who have reached into a life stage where their current income is as close to its

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

‘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, 2001-2014. In Table 5, column 2, we re-estimate the reference model reported in column 1 using annual observations for the entire data period 2001-2014. Consistent with the impression provided by Figure 3a, the multivariate results are robust to this change. The association between the position in the asset distribution and patience is highly statistically significant and of the same magnitude as the corresponding estimate in Table 2.

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 the reference specification is re-estimated 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.[18]

Column 4 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses to account for the fact that the tax assessed values may be somewhat below market values (Leth-Petersen 2010). These ratios are calculated for each of 98 municipalities. The estimate of the patience parameter is largely unaffected relative to 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 documenting these two components has recently become available, but only for 2014. In column 5, we include the value of the car stock among assets and calculate the net wealth rank based only on 2014 data. The patience parameter is slightly smaller than the reference estimate presented in column 1 but not significantly different from it.

[18]In agreement with the results presented in Figure 3, the more patient respondents are persistently ranked higher in the financial asset distribution relative to their less patient peers over the period 2001-2014 (not reported).

Table 5: Patience and wealth inequality. Robustness analyses

Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	6.07***	4.49***	6.68***	5.34***	5.21***	4.11**	5.38***	5.34**
	(1.51)	(1.07)	(1.29)	(1.49)	(1.47)	(1.34)	(1.54)	(1.67)
Risk aversion	3.12	0.30	1.15	3.06	2.31	2.60	3.58	4.06
	(1.92)	(1.34)	(1.64)	(1.89)	(1.84)	(1.66)	(1.96)	(2.11)
Year dummies for educational attainment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gross income decile dummies, 2012-2014	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wealth at age 18 decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental wealth 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
Gross income decile dummies	No	Yes	No	No	No	No	No	No
Constant	34.17***	56.98***	11.88***	31.50***	29.27***	17.19***	34.29***	33.81***
	(3.39)	(3.31)	(2.94)	(3.36)	(3.33)	(3.03)	(3.53)	(3.95)
Observations	3360	46192	3360	3360	3360	3360	3275	3275
Adj. R-squared	0.07	0.09	0.31	0.10	0.13	0.30	0.07	0.07

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 2001-2014. For this column standard errors are clustered at the individual level. 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. These ratios are calculated for each of 98 municipalities. Column 5 includes the value of the car stock. Dependent variable measured only for 2014. Column 6 includes both the value of the car stock and wealth held in pension accounts. In this column the dependent variable is measured only for 2014. In column 7 the dependent variable is based on average wealth, 2012-2014 (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. Parental wealth is measured as the average over the period when the respondent was 7-14 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 is slightly lower in columns 7-8 as some of the respondents do not have strictly positive income or liquid assets.

In column 6 wealth kept in pension accounts is also added. This addition also mutes the point estimate of the patience parameter a little, although it is not significantly different from the reference estimate in column 1. Even if the difference is not statistically different there are, in fact, good reasons why adding pension wealth would attenuate the result. 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 documented by Chetty et al. (2014a) 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 that we invited to participate in the experiment took up 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 that have been invited, and the propensity scores have been estimated using the variables included in Table 1. 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. Also in this case, do we not find any important deviation 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 variables included in Table 1. To the extent that this is a reasonable assumption, our results do not appear too specific to the sample that we have elicited patience measures for. In total, Table 4 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.

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. However, as described in section 4 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 6 we construct patience measures based on all possible combinations of the payment dates that we have exposed subjects to ("today", "in 8 weeks", and "in 16 weeks"). Column 1-3 show bivariate correlations between net wealth ranks and patience for all the combinations of payout days that subjects were asked to complete choice tasks for. Across all three combinations of payout days we observed a correlation of similar magnitude. In column 4-6 we add the full set of control variables as in

Table 2, column 8. Across all patience measures the estimated parameter on patience is stable and only slightly smaller than for the case where no control variables are included.[19]

5.6 Size of inter vivo wealth transfers

As a final robustness check, we provide an assessment of the potential size of inter vivo wealth transfers from parents to children. A reason for the observed strong positive association between time discounting and position in the wealth distribution could be that parents make significant transfers to their children during adulthood and that this is correlated with patience. To investigate whether there are significant inter vivo transfers from parent to children of a magnitude that significantly affects wealth accumulation of the respondents we link parents and children and exploit the longitudinal dimension of the data to examine whether adjustments of parents' wealth are correlated with adjustments to their children's wealth. Specifically, we regress the first-difference of the child's (log) liquid assets on the first difference of the parents' (log) liquid assets using annual data for the period 2001-2014. If monetary transfers from parents to children are widespread, we should expect to find a significant and negative coefficient reflecting that a relative decrease in parents' liquid assets is accompanied by a relative increase in the respondent's liquid assets. The results, reported in Appendix I, show no evidence of a significant relationship between changes in parental liquid asset holdings and changes in respondent liquid asset holdings. This finding is robust to the definition of parental and child wealth, including debt.

[19] In order to test for the existence of present-biased preferences we have constructed an index that compares near-present trade-offs with more remote trade-offs, i.e. choice situations which vary in their remoteness relative to the point in time the decision is made, holding all other things fixed. Specifically the index is $\phi_{\text{present bias}} = \text{median}\left(\frac{z[\text{choiceID=i}])-z[\text{choiceID=j}]}{10}\right)$, where the difference in the numerator is calculated for each choiceId-pair $(i, j) \in \{(1, 11), (2, 12), (3, 13), (4, 14), (5, 15)\}$ with i indexing the 0 vs. 8 weeks trade-offs and j indexing the 8 vs. 16 week trade-offs, cf Table A1. The distribution of $\phi_{\text{present bias}}$ is centered at and is symmetric around zero (not reported) and does hence not indicate that present-biased preferences are important in our data. There could be several reasons that we do not detect present bias. First, similar to the majority of previous studies on time discounting, our setting does not involve immediacy, but instead makes use of a short time delay prior to the earliest possible payment date. Present bias is generally found to be much less pronounced if such a delay is added (see Balakrishnan et al. 2015 for a setting using convex budget choices). Second, the payments were not carried out in cash, but instead transferred to participants' bank account. A general critique on intertemporal choice experiments is that elicited discount rates do not reflect the marginal propensity to consume earlier rather than later (see Frederick et al. 2002 for a discussion). This might have worked against detection of a significant present bias. Third, Andreoni and Sprenger (2012) discuss another point: "[*i*]f subjects have access to even modest amounts of liquidity, researchers should be surprised to measure any present bias in experiments with monetary rewards" (p. 3335). This idea is formalized in Epper (2015) which shows that present bias could indeed be a result of liquidity constraints together with positive income expectations.

Table 6: Patience and wealth inequality. Alternative patience measures

Dep. var.: Wealth percentile rank	(1)	(2)	(3)	(4)	(5)	(6)
Patience, 8 vs. 16 weeks	8.14***			6.07***		
	(1.44)			(1.51)		
Patience, 0 vs. 8 weeks		8.79***			6.72***	
		(1.48)			(1.55)	
Patience, 0 vs. 16 weeks			8.97***			6.98***
			(1.55)			(1.61)
Risk aversion				3.12	3.03	3.22
				(1.92)	(1.92)	(1.92)
Year dummies for educational attainment	No	No	No	Yes	Yes	Yes
Gross income decile dummies	No	No	No	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes
Wealth at age 18 decile dummies	No	No	No	Yes	Yes	Yes
Parental wealth decile dummies	No	No	No	Yes	Yes	Yes
Demographic controls	No	No	No	Yes	Yes	Yes
Constant	44.68***	44.16***	43.73***	34.17***	33.60***	33.18***
	(1.03)	(1.06)	(1.15)	(3.39)	(3.42)	(3.44)
Observations	3634	3634	3634	3360	3360	3360
Adj. R-squared	0.01	0.01	0.01	0.07	0.07	0.07

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. For each respondent, wealth and gross income are measured as averages over the period 2012-2014. Parental wealth is measured as the average over the period when the respondent was 7-14 years old. ‘Demographic controls’ include three variables: a gender dummy, a dummy for being single in 2013, and a dummy for having dependent children in 2013. The number of observations decreases in columns 4-6 due to some of the respondents not reporting school grades.

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. We test this proposition by analyzing a unique combination of data with information about subjective patience attitudes and real-world wealth levels 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. We find substantial heterogeneity in elicited patience across individuals, and that individuals with a relatively high level of patience are positioned relatively high in the wealth distribution consistently over the 15 year period. The correlation between patience and the position in the wealth distribution is significant and of the same magnitude as the correlation between education and wealth, and exists after controlling for education, income, initial wealth and parental wealth, suggesting that the savings mechanism is important. We also find that people with a relatively low level of patience are more likely to be persistently affected by credit constraints. This is consistent with models where impatient people run down their assets in order to keep current spending relatively high, implying they face a higher risk of becoming credit constrained (Krueger et al., 2016; Carroll et al., 2017). In this sense, credit constraints are to some extent self-imposed in these models.

Overall, our results point to the potential importance of incorporating heterogeneous time discounting in 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 show that the ordering of elicited patience predicts the position in the real-life wealth distribution. Making a direct link between experimentally elicited discounting behavior and discount rates entering models of aggregate savings behavior would 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), experiments involving relatively small stakes, i.e. much smaller than the stakes involved in most real-life settings, require the use of choice sets with relatively large gains from postponing payments. Consequently, estimated discount rates become much higher than what is 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 on the relationship between discounting behavior and wealth inequality. The normative consequences of the results are not obvious. Effects of preference heterogeneity may have important implications for the design of redistribution policies. Differences in wealth originating purely from the budget constraint, such as ability differences, income shocks, and transfers, reflect differences in lifetime consumption possibilities, but differences in patience generate wealth inequality for individuals even if they face similar lifetime consumption possibilities. If the goal of redistribution and social insurance policy is to reduce inequality in consumption possibilities then, viewed through the lens of a neoclassical model, policies targeting savings and wealth may not be ideal because such policies lead to differences in lifetime consumption of people having the same economic resources. On the other hand, a high degree of impatience may reflect present-bias or other behavioral biases, which might call for forced savings schemes that reduce wealth inequality (Chetty et al. 2014a).

Appendices

A Derivation of equation (3)

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

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

and the transversality condition $w\left(T\right)=0$.

By integrating the flow budget constraint (2), we obtain the following intertemporal budget constraint

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

showing that wealth at age a of an individual equals the discounted value of initial wealth plus the discounted value of income (excluding capital income) earned over the life up to age a and minus the discounted value of total consumption up to age a.

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

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

By integrating (5), we obtain

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

which is substituted into the above equation in order to get

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

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

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

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

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

Next, 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 $\gamma(a)$.

B 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

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

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 $k \neq 0$.[20] For $T > a$, this implies that $\frac{e^{kT}-1}{T} > \frac{e^{ka}-1}{a}$.

[20]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.

C Relationship between wealth and the intertemporal elasticity of substitution

Differentiating (3) with respect to θ gives:

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

where the last equality comes from equation (9). We know from Appendix B 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.

D Invitation letter

Figure A1: Invitation letter

ØKONOMISK INSTITUT
KØBENHAVNS UNIVERSITET

[redacted]

Kære [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

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

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

E 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

F The risk task and risk aversion measure

The risk task

We also elicited measures of risk aversion. To do so, we used investment games (IGs) similar to Gneezy and Potters (1997). 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 rate of returns across the choice situations. A typical choice situation is depicted in the figure below. The left panel shows the initial state of a choice situation. The subject was endowed with ten 100-points blocks positioned at the very left of the screen. He could then decide how many of these blocks he wished 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-points block. The bad outcome occurred with probability 40% and yielded 70 points for each invested 100-points block. The interface worked the same as in the time task.

Figure A2: Risk choice task. Initial screen (a) and selected option (b)

(a) (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.

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. What was paid out, was the sum of the sure account and the resolved outcome of the originally risky account. Payments were transferred directly to their NemKonto on the next banking day.

Risk aversion measure

Our risk aversion index is constructed as follows: We take all choice situations with zero skewness, i.e. with probability 0.5 (see Table A2). We then normalize and aggregate using the median.[21]

[21]Once again, taking the arithmetic mean does not change our results.

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

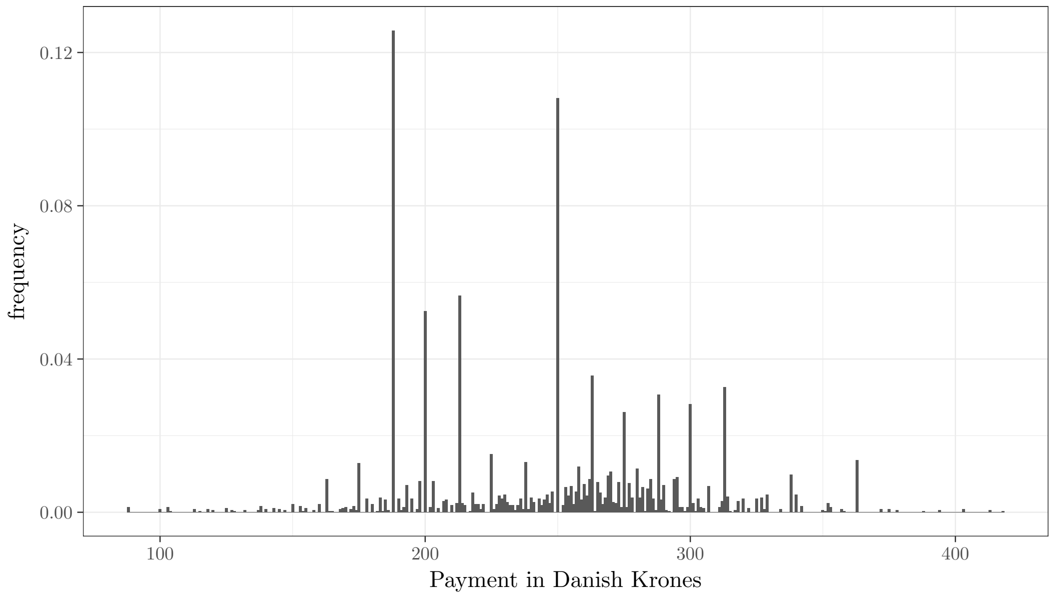
We define:

$$\phi_{\text{risk aversion}} = \text{median}\left(\frac{z}{10}\right),$$

where z denotes the number of blocks kept in the safe account in each choice situation. $\phi_{\text{risk aversion}}$ 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).

G Distribution of payments from the experiment

Figure A3: Distribution of payments from the experiment



H CRRA

Theoretically, the association between risk aversion and wealth is not clear. According to the theory presented in section 3, 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. The model predicts a positive effect of the CRRA parameter on wealth if the rate of time preference is greater than the real interest rate on savings and a negative effect if the rate of time preference is smaller than the real interest rate on savings. Here we perform an implicit test of this prediction: For each of the three patience groups, we regress the wealth percentile rank on the experimental measure of risk aversion. The results are presented in Table A3. Comparing the estimated coefficients on risk aversion in columns 1-3 it appears that the less patient the group is, the more positive is the effect of risk aversion on relative net wealth. This is consistent with the model prediction. Columns 4 and 5 control for the variation in the patience measure within the 'Low' and 'Medium' patience groups (recall from Figure 2 that there is no variation in the patience measure for the 'High' patience group). Controlling for the variation in patience within the patience groups increases the trend that the positive effect of risk aversion on relative net wealth is strongest for the least patient group.

Table A3: CRRA

Dep. var.: Wealth percentile rank	Low patience (1)	Medium patience (2)	High patience (3)	Low patience (4)	Medium patience (5)
Risk aversion	6.06+	5.00	0.46	6.45*	5.15
	(3.16)	(4.10)	(2.82)	(3.14)	(4.09)
Patience				8.54*	9.22
				(3.82)	(8.21)
Constant	43.58***	47.85***	52.62***	40.90***	41.14***
	(1.97)	(2.28)	(1.74)	(2.31)	(6.40)
Observations	1355	1044	1235	1355	1044
Adj. R-squared	0.00	0.00	-0.00	0.00	0.00

Notes: OLS regressions. Dep. var.: Within-cohort average wealth percentile rank, 2012-2014. Robust standard errors in parentheses. + p<0.10, * p<0.05, ** p<0.01, *** p<0.001. Columns 4 and 5 control for variation in the patience measure within the 'Low' and 'Medium' patience groups, respectively. In the 'High' patience group, there is no variation in the patience measure (=1 for all).

I Inter vivo transfers

Table A4 uses annual data for the period 2001-2014 to analyze whether adjustments of parents' wealth are correlated with adjustments of their children's wealth. The children comprise the respondents in the experiment. Columns 1-3 report results from regressing the first-difference of the child's (log) liquid assets on the first difference of the parents' (log) liquid assets and other covariates. Column 1 presents the bivariate relationship and shows a positive correlation between the changes in child and parental liquid assets. If monetary transfers from parents to children were widespread, this should be reflected in a negative coefficient indicating that a decrease in parents' liquid assets is accompanied by an increase in the child's liquid assets. Column 2 further controls for the first-difference of the child's (log) non-capital income, age of the child, educational attainment of the child, and year fixed effects. This makes the effect of changes in parental liquid assets insignificant. Column 3 adds the first difference of the parents' (log) bank debt to allow for parents incurring debt and passing on the money to the child. The results show no evidence of this.

Columns 4-6 present results from regressing the first-difference of the child's (log) bank debt on covariates similar to those in columns 1-3. If monetary transfers from parents to children were used to reduce the bank debt of children to a great extent, we would expect a positive relationship between changes in child bank debt and parental liquid assets (a decrease in parental liquid assets associated with a decrease in child bank debt) or a negative relationship between changes in child bank debt and parental bank debt (an increase in parental bank debt associated with a decrease in child bank debt). The results in columns 4-6 show that neither of those relationships are detectable. In sum, the results presented in Table A4 are not consistent with widespread inter vivo transfers from parents to respondents.

Table A4: Inter vivo transfers

Dep. var.:	Δln(Child liquid assets)			Δln(Child bank debt)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(Parent liquid assets)	0.024*	0.018	0.014	-0.010	-0.015*	-0.017**
	(0.010)	(0.010)	(0.011)	(0.006)	(0.006)	(0.007)
Δln(Child non-capital income)		0.481***	0.455***		-0.004	-0.006
		(0.033)	(0.039)		(0.020)	(0.022)
Age		0.087***	0.089***		-0.182***	-0.200***
		(0.013)	(0.016)		(0.017)	(0.020)
Age^2		-0.001***	-0.001***		0.003***	0.003***
		(0.000)	(0.000)		(0.000)	(0.000)
Years of education		-0.037*	-0.025		0.019	0.006
		(0.015)	(0.023)		(0.018)	(0.027)
(Years of education)^2		0.001*	0.001		-0.001	-0.000
		(0.001)	(0.001)		(0.001)	(0.001)
Δln(Parent bank debt)			-0.000			0.002
			(0.007)			(0.008)
Year dummies	No	Yes	Yes	No	Yes	Yes
Constant	0.094***	-1.153***	-1.255***	0.080***	3.022***	3.374***
	(0.004)	(0.238)	(0.297)	(0.005)	(0.285)	(0.342)
N	40793	40793	29786	33444	33444	25739
Adj. R-squared	0.000	0.017	0.014	0.000	0.015	0.017

Notes: OLS regressions. The table uses annual data for the period 2001-2014. Columns 1-3 show results from regressing Δln(Child liquid assets) on Δln(Parent liquid assets) and other covariates. Columns 4-6 show results from regressing Δln(Child bank debt) on Δln(Parent liquid assets) and other covariates. Cluster-adjusted standard errors at the child level in parentheses. * p<0.05, ** p<0.01, *** p<0.001. The number of observations decreases in columns 3 and 6 due to some of the parents not having bank debt.

J Top ten percent wealthiest

Table A5 shows regressions corresponding to those presented in Table 2. However, in Table A5 the dependent variable is a dummy variable indicating whether the respondent belongs to the ten percent wealthiest. 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 six 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 ten percent wealthiest

Dep. var.: Dummy for top 10 % of the wealth distribution	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	0.10***	0.07***	0.07***	0.07***	0.07***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
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
Wealth at age 18 decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Parental wealth 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	-0.03	-0.03	-0.04	-0.03
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Observations	3634	3634	3634	3360	3360	3360	3360	3360
Adj. R-squared	0.01	0.04	0.06	0.06	0.09	0.10	0.10	0.10

Notes: OLS regressions. Dep. var.: Dummy for top 10 % within-cohort wealth distribution, 2012-2014. 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 is measured for each respondent as the average over the period 2012-2014. Parental wealth is measured as the average over the period when the respondent was 7-14 years old. 'Demographic controls' include three variables: a gender dummy, a dummy for being single in 2013, and a dummy for having dependent children in 2013. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

K 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 that the denominator in the above equation is at least 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.

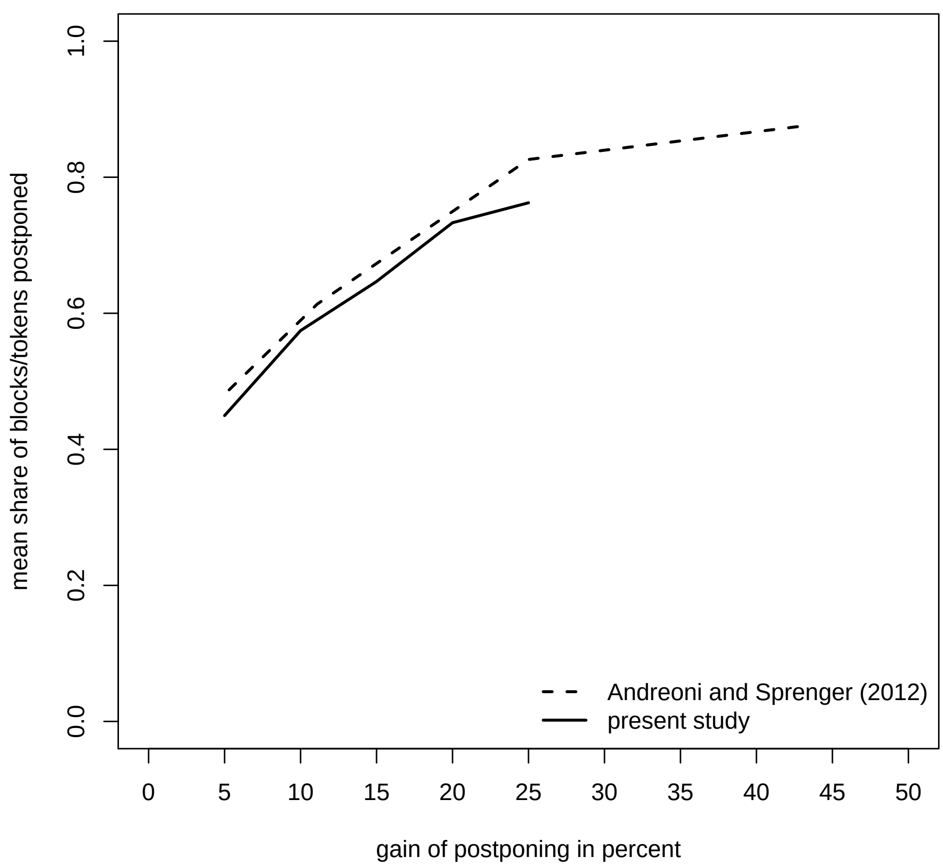
For respondents with loan accounts, we define the marginal interest rate as the highest calculated loan account-specific interest rate. If a respondent only has deposit accounts, we define the marginal interest rate as the smallest account-specific interest rate among the calculated account-specific 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 has only deposit accounts is determined by the account where the lowest return is earned.

L Comparing experimental results to previous work

In this appendix, we compare our experimentally generated choice data to similar choice data from a related study (Andreoni and Sprenger 2012). 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. In each of these budget choices they were asked to allocate 100 tokens between two different payment dates. For comparability, we pick the most similar delays in their experiment, namely 35 and 70 days. Besides 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 3,634 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, in our study, we displayed each allocation choice 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.

The figure below juxtaposes 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. 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 A4: 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 tolen in percent of the price of a sooner token.

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