Time Discounting and Wealth Inequality*

Thomas Epper[†‡¶]

Ernst Fehr[‡¶]

Helga Fehr-Duda[§¶]

Claus Thustrup Kreiner[¶]

David Dreyer Lassen[¶]

Søren Leth-Petersen[¶]

Gregers Nytoft Rasmussen[¶]

June 2019

Abstract

This paper documents a large association between individuals' time discounting in incentivized experiments and their positions in the real-life wealth distribution derived from Danish high-quality administrative data for a large sample of middle-aged individuals. The association is stable over time, exists throughout the wealth distribution and remains large after controlling for education, income profile, school grades, initial wealth, parental wealth, credit constraints, demographics, risk preferences and additional behavioral parameters. Our results suggest that savings behavior is a driver of the observed association between patience and wealth inequality as predicted by standard savings theory.

Keywords: Wealth inequality, savings behavior, time discounting, experimental methods, administrative data
JEL codes: C91, D15, D31, E21

*We thank Martin Browning, Christopher Carroll, Russell Cooper, Thomas Dohmen, Nir Jaimovich, Alexander Sebald, Erik Wengström and seminar participants at Harvard University, Institute for Fiscal Studies (IFS), European Central Bank (ECB), Aarhus University, University of Bologna, University of St.Gallen, University of Zurich, IFN Stockholm, Fourth European Workshop on Household Finance, CEPR Public Policy Symposium 2018, IIPF Annual Congress 2018 and AEA Annual Meeting 2019 for helpful comments and discussions. We are also grateful for comments by four referees, an anonymous coeditor and coeditor Stefano DellaVigna that have improved the paper considerably. Financial support from the European Research Council on the Foundations of Economic Preferences (#295642) and HHPolitics (#313673) and the Candys foundation is gratefully acknowledged. The activities of CEBI are financed by the Danish National Research Foundation.

†University of St.Gallen, School of Economics and Political Science, Varnbüelstrasse 19, CH-9000 St.Gallen, Switzerland.

‡University of Zurich, Department of Economics, Blümlisalpstrasse 10, CH-8006 Zurich, Switzerland.

§University of Zurich, Department of Banking and Finance, Plattenstrasse 32, CH-8032 Zurich, Switzerland.

¶Center for Economic Behavior and Inequality (CEBI), Department of Economics, University of Copenhagen, Øster Farimagsgade 5, DK-1353 Copenhagen, Denmark.

Why some people are rich while others are poor is of fundamental interest in social science. Standard savings theory predicts that people who place a larger weight on future payoffs will be more wealthy throughout the life cycle than more impatient people because of differences in savings behavior. Macroeconomic research suggests that this relationship between time discounting and wealth inequality, operating through the savings channel, can be quantitatively important and help explain why wealth inequality greatly exceeds income inequality (Krusell and Smith 1998; Quadrini and Ríos-Rull 2015; Carroll et al. 2017). In addition, heterogeneity in time discounting potentially plays an important role in the propagation of business cycles and the effects of stimulus policies because impatient individuals tend to run down wealth and, thereby, have limited opportunities to smooth consumption (Carroll et al. 2014; Krueger et al. 2016).

Rich experimental evidence – from the famous marshmallow experiments measuring delayed gratification in children in the 1960s to recent research on intertemporal choices to reveal discounting behavior of adults – points to pervasive heterogeneity in time discounting across individuals, but without linking this to wealth inequality (Mischel et al. 1989; Barsky et al. 1997; Frederick et al. 2002; Harrison et al. 2002; Abdellaoui et al. 2010; Attema et al. 2010; Epper et al. 2011; Andreoni and Sprenger 2012; Sutter et al. 2013; Augenblick et al. 2015; Attema et al. 2016; Carvalho et al. 2016; Falk et al. 2018).

Our first main contribution is to document a large association between time discounting of individuals and their positions in the wealth distribution. This relationship between patience and wealth inequality is precisely estimated, stable over time and exists throughout most of the wealth distribution. Secondly, we provide evidence suggesting that differences in savings behavior are a driver of the observed association as predicted by savings theory.

We obtain these results by combining data from preference-elicitation experiments with high-quality administrative data for a large sample of about 3,600 mid-life Danish individuals. We use established incentivized experimental elicitation methods to measure patience – defined as behaviorally revealed time discounting – and other behavioral parameters. The Danish administrative data provides longitudinal information about individuals' real-life wealth and income as well as detailed background information relevant for understanding wealth formation (Leth-Petersen 2010; Boserup et al. 2016).

We provide different types of evidence on the association between patience and wealth inequality. We start by dividing the subjects into three equally sized groups according to their level of patience and plot the group averages of their percentile rank positions in the within-cohort wealth distribution from

2001 to 2015.[1] Over this 15-year period, the group average of the most patient individuals is persistently 6-7 percentiles higher in the wealth distribution than the average of the least patient individuals, and the medium patient individuals are, on average, in between the two other groups in the wealth distribution. The stability of the relationship between patience and wealth inequality over such a long period is consistent with the notion that it is shaped by deep and persistent underlying forces rather than income or wealth shocks appearing around the time when patience is elicited.

To assess the importance of the relationship between patience and wealth inequality, we compare it to how much the position in the wealth distribution is correlated with educational attainment and parental wealth. Arguably, educational attainment is one of the most important predictors of lifetime inequality (Huggett et al. 2011), and parental wealth is known to be one of the strongest predictors of individual wealth (Charles and Hurst 2003). We find that patience is as powerful as education in predicting a person's position in the wealth distribution and half as powerful as parental wealth.

We find that the average wealth level of the most patient individuals is DKK 215,000 higher than the average wealth level of the most impatient individuals in middle age, corresponding to about half of the median wealth level in the sample. Quantile regressions show that the association between patience and wealth is close to zero at the bottom of the wealth distribution, consistent with the presence of credit constraints, and increases over the distribution such that the effect at percentile 95 is about three times as large as the average effect.

In the context of standard savings theory, we show that patient individuals are wealthier than impatient individuals at all points in the life cycle due to differences in savings behavior.[2] Theoretically, wealth is also determined by permanent income, the timing of income, wealth transfers, initial wealth and risk preferences. The association between patience and wealth can arise because patience is correlated with these wealth determinants. Identifying the impact of patience on wealth running through savings is a challenge because of the impossibility of randomly assigning preferences to people. We provide suggestive evidence on the role of the savings channel by collecting additional data to comprehensively control for the other wealth determinants. In the baseline specification, including 70 controls motivated by the theory, we find a strongly significant relationship between patience and wealth inequality with an association equal to 3/4 in magnitude of the bivariate relationship. This suggests that

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

[2] Note that this unambiguous effect of patience does not apply to the within-cohort variation in consumption, savings and wealth accumulation even in a basic life-cycle savings model. The reason is that patient individuals consume less than impatient individuals early in life, but consume more later in life.

the savings channel is a driver of the strong association between patience and wealth inequality.

We also include additional information about preferences and behavior from the experiment. This includes whether individuals are present biased or future biased, whether they make non-monotonic choices in the experiment and to what extent they are altruistic. The coefficients on these additional behavioral parameters are all small and insignificant at conventional levels in the wealth rank regressions.[3] The coefficient on patience becomes even larger and stands out when compared to the role of risk attitudes, altruism and other behavioral parameters.

Theory predicts that relatively impatient people wish to borrow more and that they, therefore, impose a higher risk of being credit constrained on themselves. This potential effect is important for the propagation of business cycle shocks and the efficacy of stimulus policy (Carroll et al. 2014; Krueger et al. 2016) and, more generally, for the association between patience and wealth inequality. The association between patience and wealth rank may be muted because constrained individuals with relatively low, yet different levels of, patience are unable to run down wealth further and, therefore, end up with the same low level of wealth. We assess the impact of credit constraints by considering whether individuals have low levels of liquid assets relative to disposable income (e.g. Zeldes 1989; Johnson et al. 2006; Leth-Petersen 2010). By splitting the sample into those likely and unlikely to be affected by credit constraints, we find the association between patience and wealth percentile rank to be small and insignificant for constrained individuals. In contrast, the association is large and highly significant for individuals unlikely to be affected by constraints. This evidence is consistent with the theoretical insight that the overall association between patience and wealth inequality is muted by credit constraints, and it explains why patience and wealth are unrelated at the bottom of the wealth distribution.

The credit constraint indicator is a crude measure. In reality, people can have differential access to credit and, therefore, effectively face constraints with varying intensity. The relevant slope of the intertemporal budget line is then the interest rate on marginal liquidity. To further account for credit constraints, we use account level data on debt, deposits and interest payments during the year to measure the interest rate on marginal liquidity faced by the individuals (Kreiner et al. 2019). The slope of the budget line may also vary across savers because some individuals are better at obtaining high returns on financial assets, as indicated by recent evidence (Fagereng et al. 2018). Therefore, we also control

[3] The insignificance of present bias may reflect that the experiment is not ideal to identify this type of behavior. Individuals are on average time consistent in our experiment. This is similar to the results in the related convex time budget experiments of Andreoni and Sprenger (2012) and Augenblick et al. (2015). The work by Augenblick et al. (2015) and Andreoni et al. (2018) suggests that present bias is more prevalent in experiments in which individuals make intertemporal choices on "bads" (such as effort).

for historical asset ownership and returns. After controlling for these additional financial variables, the association between patience and wealth inequality is still strong and precisely estimated.

We elicit the individuals' discounting behavior using state-of-the-art money-sooner-or-later choice experiments, which are well-suited for large-scale implementation on an internet platform. A potential concern is that the elicited variation in time discounting across individuals may simply reflect variation in market interest rates and credit constraints (Frederick et al. 2002; Cohen et al. 2019; Dean and Sautmann 2018) because of arbitrage or, more generally, that the patience-wealth rank association reflects wealth causing patience. Three pieces of evidence suggest that this concern is not critical. First, we find very stable relationships between patience and wealth inequality and between patience and the likelihood of being credit constrained over a 15-year period. This shows that the associations are not driven by short-term shocks or other temporary variation at business cycle frequency (Dean and Sautmann 2018). Second, the strong association between patience and wealth rank remains after we control for market interest rates and credit constraints. This result is consistent with evidence of "narrow bracketing" whereby subjects do not integrate their choices in an experiment into their broader choice set. Recent evidence of narrow bracketing in the context of our experimental task is provided by Andreoni et al. (2018). Third, we exploit survey information about time discounting for a sample of 2,548 subjects from the 1952-1955 cohorts, collected when they were 18-21 years old. When using the crude measure of time discounting in the survey collected 30 years *before* we examine the wealth of the individuals, we also find a quantitatively important and stable relationship between patience and wealth inequality over the period 2001-2015.

Our study relates to the literature in public finance and macroeconomics documenting substantial wealth inequality and trying to understand its causes and consequences. This literature shows that wealth inequality is persistent and considerably larger than income inequality (Piketty and Saez 2014). Work on understanding the driving forces behind wealth inequality has mainly focused on differences across people in income processes, earnings capacity, wealth transfers, capital returns and public policy (e.g. Heathcote et al. 2009; Piketty 2014; Hubmer et al. 2016; Boserup et al. 2016, 2018; De Nardi and Fella 2017; Benhabib et al. 2017, 2019; Fagereng et al. 2018). A smaller literature on wealth inequality has studied the impact of preference heterogeneity in macro models (e.g. Krusell and Smith 1998; Krueger et al. 2016; Carroll et al. 2017). These studies show that even a limited degree of heterogeneity in time discounting can potentially generate a significant increase in wealth inequality compared to the reference case with homogeneous preferences and that heterogeneous time discounting significantly improves the

models' abilities to match the empirically observed wealth distribution. Our contribution relative to this literature is that we measure the actual time discounting of individuals independently and link it to their positions in the real-life wealth distribution. The large association between patience and wealth inequality provides support for models that incorporate heterogeneity in time discounting to explain wealth inequality and, more generally, consumption behavior (e.g. Alan et al. 2018).

Our paper also contributes to the experimental literature showing that elicited discount rates predict real-life outcomes (Chabris et al. 2008; Meier and Sprenger 2010; Lawless et al. 2013; Sutter et al. 2013; Backes-Gellner et al. 2018). Our study has the advantage that it is the first to combine data from a fully incentivized experiment with detailed, longitudinal register data on real-life outcomes for a large sample of individuals. This enables us to provide the new, compelling evidence on the relationship between patience and wealth inequality.

The next section derives theoretically the association between patience and wealth inequality within the context of a basic savings model. Section 2 presents the sampling scheme, the experimental design and the register data. Section 3 presents the empirical results and Section 4 features different robustness checks. Section 5 concludes.

1 Association between time discounting and wealth inequality in theory

This section illustrates in a basic deterministic life-cycle savings model how heterogeneity in subjective discounting generates differences in savings behavior leading to permanent differences in wealth levels across individuals at all ages. It also points to other wealth determinants that might be correlated with individual discount rates. In the empirical analysis, we include controls for these other determinants in an attempt to isolate an effect operating through the savings channel.

Consider an individual choosing spending $c(a)$ over the life cycle $a \in (0, T)$ so as to maximize the discounted utility

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

where $u\left(\cdot\right)$ is instantaneous utility, θ is the coefficient of relative risk aversion (CRRA), and ρ is the rate of time preference. 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 $w(a)$ is wealth, $y(a)$ is income excluding capital income, and r is the market interest rate yielding capital income $rw(a)$. Utility (1) is maximized subject to the budget constraint (2), a given level of initial wealth $w(0)$ and the No Ponzi game condition, $w(T) \geq 0$. 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 wealth equation (see online Appendix A):

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

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

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

Wealth may both increase or decrease when going through the life cycle (higher a), and wealth may also be negative throughout the life cycle. The wealth equation (3) leads to the following prediction (see online Appendix A for a proof):

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 more wealth at all points in the life cycle* (a) *conditional on the other wealth determinants* $(Y, \gamma(a), T, \theta)$.

This shows that the savings channel generates a positive association between patience and wealth at *all ages*. Note that the effect of patience on consumption and savings is ambiguous because patient individuals consume less than impatient individuals early in life, but consume more later in life.[4]

Patience may also be correlated with the other wealth determinants. If, for example, patient individuals attain higher education levels and, therefore, higher permanent income Y, then this creates a positive relationship between patience and wealth beyond the savings mechanism. On the other hand, more education would normally also imply a steeper income profile, which in isolation reduces the level of wealth at all ages (due to lower values of $\gamma(a)$ in equation 3). In the empirical analysis, we include a large set of controls for other wealth determinants in an attempt to isolate the relationship between patience and wealth running through the savings channel.

[4]Note also that the CRRA parameter has ambiguous effects on wealth. 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.

In the simple model, individuals borrow and lend at the market interest rate r. In reality, the slope of the budget constraint may also vary with patience. For example, a large literature has theoretically and empirically examined the role of credit constraints for savings behavior (Zeldes 1989; Leth-Petersen 2010; Krueger et al. 2016). For illustration, consider the case where borrowing is possible only up to a certain limit. This credit constraint becomes binding for the most impatient individuals who wish to run down wealth further but, conditional on being constrained, wealth does not vary with patience. In the empirical analysis, we use different measures of credit constraints to examine whether impatient individuals are more likely to be constrained, and we analyze whether time discounting is associated with wealth inequality after controlling for credit constraints and other factors measuring the slope of the budget constraint.

2 Experimental design, sample and data

Our empirical analysis combines experimental data and administrative register data linked together using social security numbers. This section describes the sampling scheme, the design and implementation of the experiment and the register data.

2.1 Sample and recruitment for the experiment

Respondents were recruited by sampling individuals from the Danish population register satisfying the criteria that they were born in the period 1973-1983 and resided in the municipality of Copenhagen (which is the largest municipality in Denmark and includes the capital city) when they were seven years old. For people in mid-life, the timing of education and retirement should have the least influence on the wealth ranking compared to other phases of life and income is arguably a good proxy for permanent income (Haider and Solon 2006). A total of 27,613 individuals received a personal invitation letter in hard copy from the University of Copenhagen. The letter invites them to participate in the online experiment taking place in February 2015. The letter informs subjects about a unique username and password needed to log in to a web page, the expected time to complete the experiment, the possibility of earning money in the experiment and contact information for support (an English translation of the letter is available in online Appendix B.1). The analysis includes the 3,620 of the invitees, who successfully completed the experiment on the experimental platform and received a payment (13 percent of all invitees).[5] Participation rates at this level are common for similar experimental studies (e.g. Andersson et al. 2016

[5]We also excluded 97 respondents without the required register data information (typically immigrants) or stating gender and/or year of birth that did not match the register data.

report 11 percent). Sections 2.3 and 4 analyze selection into the experiment.

The online experiment includes three preference elicitation tasks to measure time, risk and social preferences. Each task is accompanied by short video instructions and comprehension questions. The three blocks appear in an individualized random order and, within each block, the set of choice situations is once again randomized. The elicitation tasks involve real monetary incentives. We use an experimental currency and inform the participants that 100 points correspond to DKK 25 in real money (USD 1 $\simeq$ DKK 6.5 at the time of the study). At the end of the experiment, the subject spins a wheel displayed on the screen in order to determine the choice situation relevant for payment. The random choice situation where the wheel stops is then displayed together with the subject's decision, and the points are exchanged into money. Payment is done via a direct bank transfer at the relevant date (details follow below). The possible payments considering all three tasks ranged from DKK 88 to 418. The average amount paid out was DKK 245.

2.2 Measurement of patience and other behavioral parameters

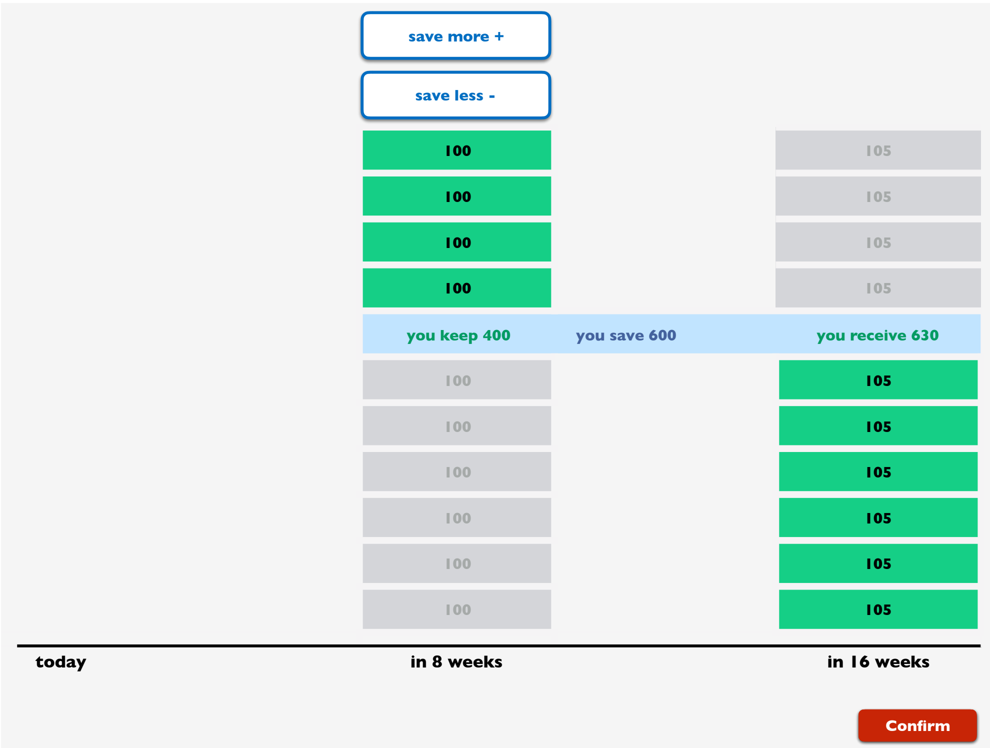
We use a state-of-the-art money-sooner-or-later experiment to elicit patience.[6] Our measurement of intertemporal choice behavior is based on convex time budgets (Andreoni and Sprenger 2012). We depict intertemporal choices graphically and present a single allocation choice per page. We use a total of 15 independent choice situations that differ in terms of payment dates and interest payments.

Figure 1 depicts a screenshot of a typical choice situation. At the beginning of each choice situation, each subject is endowed with ten 100-point blocks. These ten blocks are allocated to the earlier of the two payment dates (8 weeks in Figure 1). The subject then has the possibility to move some or all of the ten blocks to the later date (16 weeks in Figure 1). When shifting a block into the future, the subject is compensated by a (situation-specific) interest payment. That is, each 100-point block's value increases once it is deferred to the later point in time. In the example depicted in the figure, each block allocated at the later point in time has a value of 105 points. The subject thus has to decide how many of the ten blocks to keep for earlier receipt and how many of the blocks to postpone for later receipt. In this example, the subject chooses to allocate four 100-point blocks for receipt in 8 weeks, and to save the remaining six 100-point blocks for receipt in 16 weeks. Deferring the receipt of six blocks leads to a total

[6] We use money-sooner-or-later experiments because they are well-suited for large-scale implementation on an internet platform. The experimental literature has also used experiments with real effort to elicit discounting behavior because they appear better able to measure present bias compared to convex time budget experiments (Augenblick et al. 2015; Augenblick and Rabin 2019). More recently Andreoni et al. (2018) show that a sizeable present bias also occurs if subjects allocate "bads", i.e. payments to the experimenter, in a convex time budget task, which suggests that it is not the convex time budget method per se that makes the detection of present bias difficult, but the framing of the task.

interest payment of 6·5=30 points. Choices are made by clicking on the respective block, after which a horizontal bar appears that can be moved up and down, or by using the keyboard.

Figure 1: Example of a choice situation



Notes: The figure shows a screenshot of a typical choice situation. Each subject is endowed with ten colored 100-point blocks to be received in 8 weeks. The subject can move some or all of the ten blocks to be received in 16 weeks. Each block allocated at the later point in time has a value of 105 points. In the example, the subject chooses to allocate four 100-point blocks for receipt in 8 weeks, and save the remaining six 100-point blocks for receipt in 16 weeks. To avoid status quo bias, the user interface is designed such that the subject has to make an active choice. The subject is only able to confirm the decision and move on after actively choosing one of the allocations.

The choice situations involve three different payment dates, "today", "in 8 weeks", and "in 16 weeks", with combinations of all three payment dates (details are provided in online Appendix B.2). The compiled list of transactions are sent electronically to a bank for implementation of the payout. Subjects know that the payment is initiated either on the same day, or exactly 8 or 16 weeks later. Hence, the payment dates displayed on the screen refer to the points in time where the transactions are actually initiated. It takes 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 (using this account implies that participants do not have to provide account information).

The applied interest rates vary across choice situations. For example, the five choice situations asking subjects to choose between receiving payments in 8 weeks or 16 weeks have rates of return in the interval 5-25 percent (amounting to annualized interest rates in the range of 32-145 percent). This range

of offered interest rates is similar to those used in other studies. In online Appendix B.3, we show that the distribution of choices made by the participants in our internet experiment is very similar to the choice distribution in the original convex time budget study of Andreoni and Sprenger (2012) based on a lab experiment with students. We also display the distributions of structurally estimated individual discount rates based on four different specifications of a random utility model. The distributions and individual ordering of the discount rates are very similar, with an average annual discount rate in the range 39 to 51 percent across the different models. This is in line with the previous literature, surveyed by Frederick et al. (2002) and Cohen et al. (2019). In our analysis, we focus on the relationship between individuals' positions in the elicited patience distribution and their positions in the wealth distribution. This relationship is insensitive to the overall level of discounting and is robust to changes in the discount rates as long as the ordering of discount rates across individuals is unchanged.

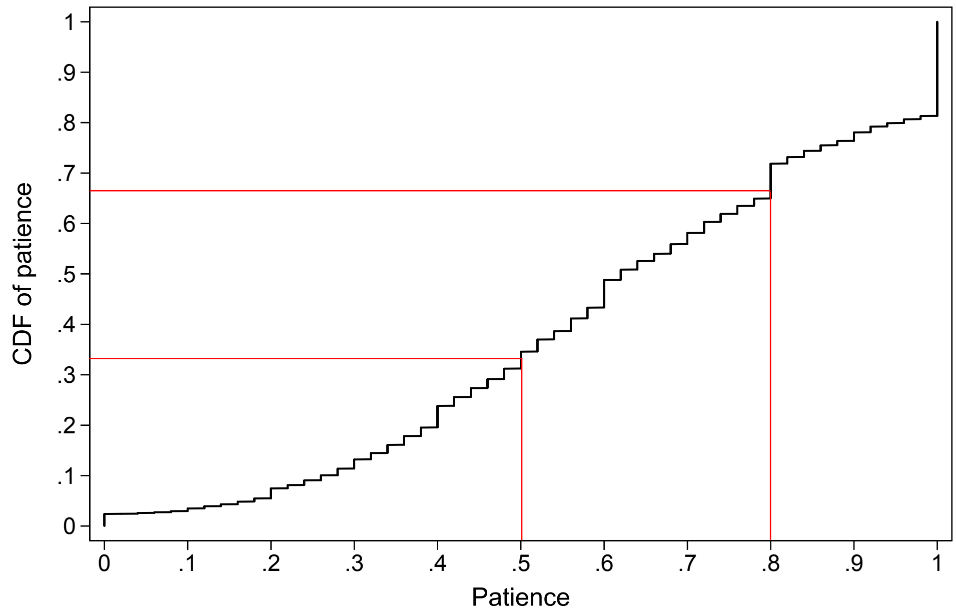
We use a simple patience index based on the arithmetic mean of blocks saved for later receipt to measure an individual's degree of patience. This index is based on the five intertemporal choice situations with allocations between $t_1 = 8$ weeks and $t_2 = 16$ weeks:

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

where z_i denotes the number of blocks saved in situation i, and where we divide each choice by the total number of blocks so that $\phi_{\text{patience}} \in [0, 1]$. We interpret this as an indicator of long-run discounting with higher values of ϕ_{patience} reflecting greater patience. Due to the discreteness of our measures (10 blocks to allocate in each of the 5 choice situations), our index can take values in steps of $1/50$.

For the patience measure defined in (4), censoring occurs at both ends of the scale by construction, making it impossible to detect lower and higher discount rates than those offered in the experiment. Figure 2 depicts the cumulative distribution of this patience index. It reveals substantial heterogeneity across the individuals in the sample with the exception of the top end of the distribution where 18 percent of the individuals saved all blocks in all five choice situations. Figure 2 also shows tertile cut-off points, which we use to split individuals into high, medium and low patience groups in order to be able to illustrate the differences in outcomes across these groups graphically. As discussed further in Section 4.2, our key results are robust to using other ways of measuring patience with the experimental data, e.g., using patience as measured by the allocations between $t_1 = 0$ weeks and $t_2 = 8$ or 16 weeks.

Figure 2: Distribution of the patience index



Notes: The figure shows the cumulative distribution of the patience index computed from expression (4) using the experimental data with allocations between $t_1 = 8$ weeks and $t_2 = 16$ weeks. The vertical lines indicate tertile cut-off points.

Individuals with the same long-run discount rate may accumulate different wealth levels because some individuals are present biased or have other non-constant discounting behavior (Angeletos et al. 2001). To analyze the role of non-constant discounting, we compute the difference in savings choices between 0-8 weeks (short run) and 8-16 weeks (long run) for each of the five interest rates offered in the experiment and take the average of these differences for each individual. According to this measure, individuals are on average time consistent. About 1/3 of the individuals display no bias, a little less than 1/3 save more in the long-run decisions than in the short-run decisions ("present biased"), and a little more than 1/3 save more in the short-run decisions than in the long-run decisions ("future biased").[7] We include this information in the empirical analysis.

The distribution of individuals' differences between short-run and long-run decisions is bell shaped around zero (see online Appendix B.4) suggesting that this measure could reflect choice errors in the experiment rather than systematic behavioral biases. Choi et al. (2014) document a correlation between choice inconsistencies and savings. In the empirical analysis, we therefore also include an indicator variable for individuals who violate monotonicity by saving more in a choice situation offering a low interest rate compared to a similar choice situation offering a high interest rate.

[7] Our finding of no systematic present bias based on the non-parametric measure is confirmed when we estimate structural β-δ models, cf. online Appendix B.3.

In some of the analyses, we include information about individuals' risk aversion and altruism elicited in the experiment. The types of tasks involved in the elicitation of these measures and the visualization on the screen were made as similar as possible to the ones used for elicitation of patience, resulting in a risk aversion index and an altruism index going from zero to one, as in the case of patience. Online Appendices B.5 and B.6 provide additional information about the elicitation of risk aversion and altruism.

2.3 Register data information on wealth and other characteristics

The choice data from the experiment is linked at the individual level with administrative register data at Statistics Denmark. The register data contain demographic characteristics and longitudinal information about annual income and values of assets and liabilities at the end of each year for each individual.[8] The income and wealth information is based on third-party reports to the Danish tax authorities who use them for tax assessment and selection for audit (Kleven et al. 2011). For instance, employers report earnings, government institutions report transfer payments and banks, mortgage institutions, mutual funds and insurance companies report values of assets and liabilities. The value of assets includes bank deposits, market value of listed stocks, bonds and mortgage deeds in deposit and value of property assessed by the tax authorities using land and real estate registries. The value of liabilities includes all debt except debt to private persons. The data contains information about adult individuals (age≥18) over the period 1980-2015. Wealth accumulated in pension accounts and estimated car values are available as of 2014. Our results are robust to the inclusion of these components, see the robustness analysis in Section 4.2.

The Danish wealth data have been used previously for research on wealth inequality (Boserup et al. 2016), retirement savings (Chetty et al. 2014a), impact of credit constraints (Leth-Petersen 2010; Kreiner et al. 2019), effects of wealth taxation (Jakobsen et al. 2018) and accuracy of survey responses (Browning and Leth-Petersen 2003; Kreiner et al. 2015). Wealth inequality has been reasonably stable in Denmark over the 35-year observation period, with the top 10 percent richest owning between 50 and 80 percent of wealth depending on the definition of wealth and the sample considered (Boserup et al. 2016; Jakobsen et al. 2018).

Table 1 provides summary statistics for our respondents (column a) and compares their characteristics to those of a 10 percent random sample of the full population of this age group (columns b-c).[9] The

[8]In online Appendix D.2, we show that results are unchanged when we consider household-level wealth.

[9]The differences in the table between the sample of respondents and the 10 percent random sample consist of differences between respondents and non-respondents as well as differences between the individuals invited for the experiment and the population. Respondents and non-respondents are compared in online Appendix B.7.

respondents' median wealth level is somewhat higher than the median of their annual gross income, while the variance of wealth is considerably higher. People in the bottom 10 percent of the distribution have negative net wealth. Percentile 95 of the wealth distribution is about five times the median. The corresponding ratio for the income distribution is less than two, showing that wealth is more unequally distributed than income. The respondents are slightly more likely to have children and are slightly more educated compared to the random sample. The distributions of income and wealth are statistically significantly different from the random sample, but the differences are not large. For example, the differences in the median levels of income and wealth are 6-7 percent. Income is slightly higher for the respondents throughout the income distribution, while the wealth distribution of respondents is somewhat more dispersed. Section 4 provides evidence suggesting that our main results are not very sensitive to the differences in sample composition shown in Table 1.

Table 1: Means of selected characteristics. Respondents vs. 10 percent of the population

	(a) Respondents	(b) Population	(c) (a)-(b)	
Age	37.32	37.31	0.01	(0.82)
Woman (=1)	0.50	0.50	-0.01	(0.44)
Single (=1)	0.28	0.28	-0.01	(0.23)
Dependent children (=1)	0.70	0.68	0.02	(0.00)
Years of education	14.90	14.70	0.20	(0.00)
Gross income distribution				
p5	135,745	113,992	21,753	
p25	287,472	263,532	23,941	
p50	382,997	355,896	27,101	(0.00)
p75	484,463	453,367	31,096	
p95	719,754	698,786	20,968	
Wealth distribution				
p5	-337,615	-234,125	-103,490	
p25	93,899	124,101	-30,202	
p50	486,006	458,345	27,661	(0.00)
p75	1,066,468	947,205	119,263	
p95	2,395,664	2,215,063	180,601	
Observations	3,620	70,756	74,376	

Notes: Variables are based on 2015 values. The random 10 percent sample of the Danish population is drawn from individuals born in the same period (1973-1983) and not included in the gross sample. P-values from unconditional t-tests of equality of means in parentheses. The reported p-values for the gross income distribution and the wealth distribution are from two-sample Kolmogorov-Smirnov tests for equality of distribution functions. (=1) indicates a dummy variable taking the value 1 for individuals who satisfy the description given by the variable name. Wealth denotes the value of real estate, deposits, stocks, bonds, mortgage deeds in deposit, cars and pension accounts minus all debt except debt to private persons. The tax assessed values of housing is adjusted by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. Gross income refers to annual income and excludes capital income. Wealth and income are measured in Danish kroner (DKK). The table includes individuals for whom a full set of register variables is available.

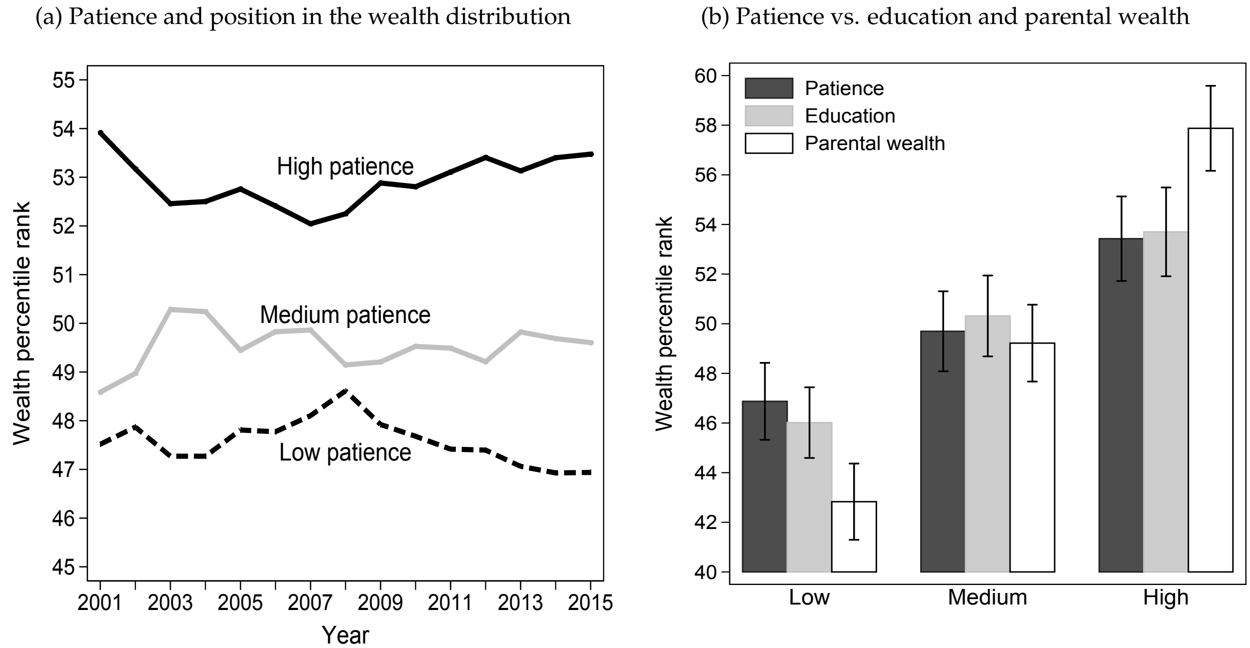
3 Empirical results

We start this section by presenting evidence on the overall association between time discounting and wealth inequality. Informed by basic savings theory, we then introduce a large number of control variables in an attempt to isolate an association between patience and wealth inequality operating through the savings channel. We also analyze the role of present bias, risk preferences and altruism elicited in the experiment. Finally, we analyze the role of credit constraints using administrative data with detailed financial information at the individual level.

3.1 Association between time discounting and wealth inequality

Figure 3 presents graphical evidence of the association between the elicited time discounting of the individuals and their positions in the wealth distribution, measured by the individual's percentile rank in the within cohort×time distribution of the sample (e.g. Chetty et al. 2014b). This measure has several advantages: by construction it controls for life-cycle and time trends in wealth; it works well with zero and negative values that are common in wealth data; and it is robust to outliers and unaffected by monotone transformations of the underlying data. In Figure 3a, we split the sample into three equally sized groups according to the degree of patience in the experiment and plot the average position in the wealth distribution of each group of individuals over the period 2001-2015. The group average of the most patient individuals is persistently 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. The difference between the most patient group and the most impatient group is about 6-7 wealth percentiles throughout the 15-year period spanned by the data. This stability of the association between patience and position in the wealth distribution shows that it is not driven by wealth shocks appearing around the same time as patience is elicited and that the relationship persists beyond temporary variations in wealth at business cycle frequencies.

Figure 3: Association between time discounting and wealth inequality



Notes: Panel a shows the association between elicited patience and the position in the wealth distribution in the period 2001-2015. The position in the distribution is computed as the within cohort×time percentile rank. The sample is split into three equally sized groups according to the tertiles of the patience measure such that "High patience" includes the 33 percent most patient individuals in the sample, "Low patience" the 33 percent most impatient individuals and "Medium patience" the group in between the "High patience" and "Low patience" groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. Panel b compares the patience-wealth association to the education-wealth association and to the parental wealth-wealth association. The subject's wealth and educational attainment are measured in 2015, where educational attainment equals years of completed education. Parental wealth is measured when the subject was 18 years old. The individuals in the sample are split into three equally sized groups according to patience, years of education and parents' position in their wealth distribution, respectively. Cut-offs for the education groups (years) are: Low [8, 14]; Medium [14, 16.5]; High [16.5, 21] where the numbers refer to years of completed education. Whiskers represent 95% confidence intervals.

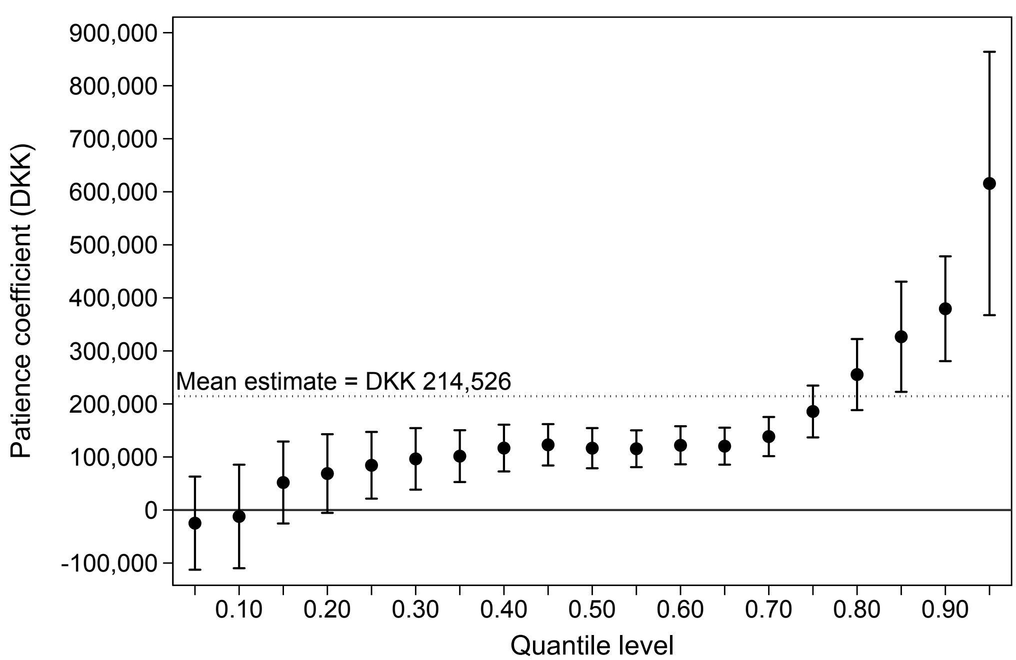
To assess the magnitude of the association between patience and wealth inequality, we compare it to the association between educational attainment levels and wealth inequality. Huggett et al. (2011) argue that educational attainment is one of the most important factors contributing to lifetime inequality. Figure 3b splits the sample into three equally sized groups according to educational attainment as measured by the number of years of completed education, which range from 8 to 21 years. As is clear from the graph, the differences between the most educated group and the least educated group and between the most patient group and the least patient group are almost the same and equal to 7-8 percentiles. We also compare the patience-wealth association to the relationship between parental wealth and child wealth. It is well-known from the intergenerational literature that parental wealth is a very strong predictor of child wealth (Charles and Hurst 2003; Clark and Cummins 2014; Adermon et al. 2018). Figure 3b shows that individuals with parents in the top 1/3 of the parental wealth distribution are positioned 15 percentiles higher in the child wealth distribution than individuals with parents in the lowest 1/3 of the

parental wealth distribution. In other words, heterogeneity in time discounting and in education are roughly equally important for individuals' position in the wealth distribution, whereas parental wealth is roughly twice as important.

A regression of wealth in amounts (DKK) on the patience index, including age dummy variables to control for life-cycle patterns, gives a coefficient of DKK 215,000. This coefficient measures the average effect of moving from the lowest to the highest level of patience in the sample. The increase in wealth corresponds to about half of the median wealth level reported in Table 1.

Figure 4 provides evidence on the association between patience and wealth measured throughout the wealth distribution. The graph shows coefficients from quantile regressions of wealth on patience and their 95 percent confidence intervals. The average effect of DKK 215,000 is illustrated by the horizontal dotted line. The association between patience and wealth is close to zero in the bottom 10 percent of the wealth distribution. This is consistent with the presence of credit constraints, as described theoretically in Section 1 and documented empirically in Section 3.4. The association between patience and wealth increases as we move up in the wealth distribution with a point estimate at percentile 95 of DKK 620,000, which is about three times as large as the average effect.

Figure 4: Relationship between patience and wealth throughout the wealth distribution



Notes: The figure plots patience coefficients from quantile regressions of wealth measured in DKK on the patience index and age indicators to account for life-cycle patterns. Whiskers represent 95 percent confidence intervals. The dotted line indicates the patience coefficient from an OLS regression with the same variables.

In summary, the overall association between patience and the position in the wealth distribution is strongly significant, quantitatively important, stable across 15 years and exists through the entire wealth distribution except at the very bottom.

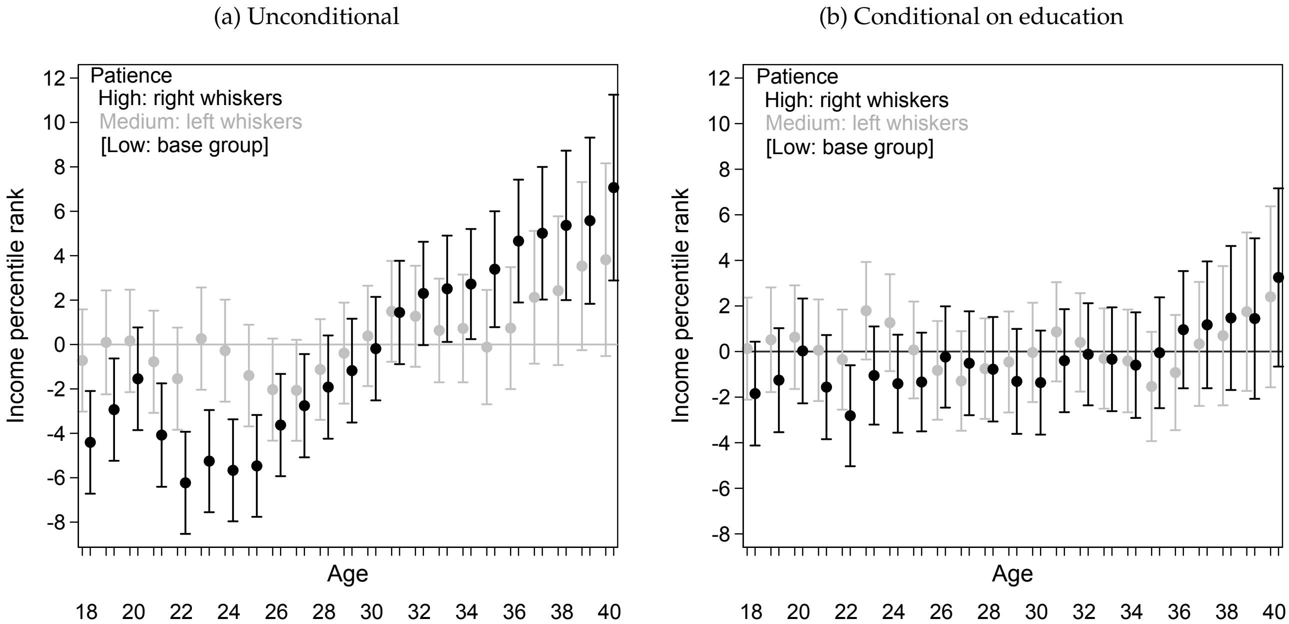
3.2 Evidence on the savings channel

The bivariate association between patience and wealth inequality in Figure 3 is potentially caused by higher savings propensities of patient individuals in accordance with standard savings theory, but it could also exist because of a correlation between patience and other wealth determinants as described theoretically in Section 1. Identifying the long-run impact of differences in preferences is a challenge because it is impossible in practice to randomly assign type characteristics to people. We provide suggestive evidence on the savings channel by employing a selection-on-observables strategy. We do this by measuring the strength of the association between patience and wealth in multivariate regressions with a large set of controls for other potential wealth determinants. Arguably, the identified association between patience and wealth inequality operates through the savings channel if the analysis is successful in controlling for all other channels.[10]

Theoretically, differences across individuals in the level of permanent income and in the time profiles of income are important for the cross-sectional variance in wealth. In addition, these wealth determinants are likely correlated with patience since patient individuals are more prone to make educational investments. Figure 5 shows how the position in the labor income distribution differs across the three patience groups defined in Figure 3. Figure 5a plots for each age of the individuals the coefficients from a regression of the percentile rank in the income distribution on the patience group indicators, where "Low patience" is the reference group. 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 lower in the income distribution than the less patient groups, but at age 40 they are positioned about seven percentiles higher than the low patience group, suggesting that individuals in the most patient group have higher levels of permanent income. It turns out that controls for educational attainment capture these income differences very well. Figure 5b plots the patience coefficients from the same regressions when we include 11 dummy indicators for years of completed education. The patience coefficients are now close to zero. This suggests that inclusion of educational attainment indicators in the wealth rank regressions adequately controls for differences in permanent income and in timing of income.

[10]We control comprehensively for variables motivated by theory but, recognizing that other covariates could matter and that variables may be measured with error, the evidence on the savings channel can only be suggestive. Section 4 reports results from a large number of sensitivity analyses.

Figure 5: Relationship between discounting behavior and income over the life cycle



Notes: Panel a plots coefficients from regressions of 'within-age-group-and-year labor income percentile rank' on two patience group indicators ("High patience" and "Middle patience"). The base group is "Low patience". The definition of the three groups is described in the note to Figure 3a. Panel b plots patience group coefficients from the same type of regressions, but this time including 11 dummy indicators for years of completed education. Panel b shows that the patience coefficients are insignificant, suggesting that educational attainment dummies adequately control for differences in permanent income and in timing of income. Whiskers represent 95 percent confidence intervals in both panels.

Table 2 shows the impact on the patience-wealth inequality association of including the 11 educational attainment controls. Column 1 reports the result from a bivariate regression of the wealth rank percentile in 2015 on the patience measure.[11] The estimate shows that moving from the lowest to the highest level of patience in the sample is associated with a difference of 11.4 wealth percentiles. The association is precisely estimated with a standard error of 1.73, corresponding to a p-value of significance equal to 0.00. When including the educational attainment indicators in column 2, the coefficient on patience decreases somewhat, but it is still large with a value of 9.6 percentiles.

In column 3, we include 59 additional control variables in the regression. We control for differences in income path by including decile indicator variables for the position in the within-cohort income distribution in 2015 (gross income excluding capital income), for the observed income growth from age 25-27 to age 30-32 and for the expected income growth from 2014 to 2016 obtained from survey information accompanying the experiment. We also include decile indicators for school grades motivated by the fact that cognitive ability is relevant for individuals' income potential and also correlated with time

[11]We focus on the wealth positions at the end of the observation period because at this point in the life cycle, individuals have completed their education and income is arguably a good proxy for permanent income (Haider and Solon 2006). Appendix D.2 shows that the results are robust to using a longer time period for measuring the position in the wealth distribution.

discounting (Dohmen et al. 2010).

We include decile dummies for the within-cohort wealth rank at age 18 to capture the potential role of differences in initial wealth across individuals when entering into adulthood. Wealth accumulation may also be influenced by transfer payments from parents during adulthood (De Nardi 2004, Boserup et al. 2016). Under the assumption that the variation in family transfer payments across individuals is a function of parental wealth, we control for this source of variation in wealth by including decile indicators for parental wealth measured when individuals are 18 years old.[12]

Additionally, we include risk aversion elicited in the experiment among the controls. It is well-known that risk aversion and patience are correlated (e.g. Leigh 1986; Anderhub et al. 2000; Eckel et al. 2005), and risk aversion is theoretically a potential wealth determinant, although its effect on wealth is ambiguous (see footnote 4). Finally, we also include demographic controls for gender, marital status and the presence of dependent children.

After including all 70 controls in column 3, the patience-wealth inequality association is 8.5 percentiles, which is equal to 3/4 of the bivariate association in column 1, and it is precisely estimated with a standard error of 1.75. We arrive at the same conclusion, when we look at wealth amounts in column 4. The estimated coefficient on patience indicates an about DKK 150,000 difference between the lowest and the highest level of patience, which is approximately 3/4 of the bivariate association reported in Figure 4. These results suggest that the savings channel is a driver behind the large observed association between patience and wealth inequality.

[12]We obtain the same result if we confine the sample to individuals where both parents are alive in 2015, see Table A8 online Appendix D.2. This rules out that wealth differences are driven by inheritance from parents.

Table 2: Patience and wealth inequality

Dep. var.: Wealth	(1) Rank	(2) Rank	(3) Rank	(4) DKK	(5) Rank	(6) Rank	(7) Rank	(8) Rank
Patience	11.37	9.59	8.45	146,915	9.45	-1.44	11.14	7.72
	(1.73)	(1.75)	(1.75)	(39,743)	(1.92)	(2.29)	(2.41)	(2.25)
Risk aversion			2.53	49,227	2.45	-2.81	5.31	3.18
			(2.04)	(56,821)	(2.04)	(2.84)	(2.70)	(2.54)
Altruism					-3.67			
					(2.16)			
Present bias (=1)					1.23			
					(1.33)			
Future bias (=1)					2.58			
					(1.32)			
Non-monotonic choices in time task (=1)					-1.99			
					(1.07)			
Interest rate on liquidity								-1.63
								(0.10)
Owned stocks, 2008-2014 (=1)								6.21
								(1.56)
Rate of return on stocks, 2008-2014								0.36
								(0.54)
Educational attainment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,620	3,620	3,552	3,552	3,552	1,353	2,157	2,157
Adj. R-squared	0.01	0.02	0.08	0.08	0.08	0.03	0.08	0.19

Notes: OLS regressions of wealth inequality on patience. Robust standard errors in parentheses. Ranks in the wealth distribution used as the dependent variable are computed within-cohort in 2015. In column 4, the outcome variable is wealth measured in amounts (DKK) in 2015. The measurement of patience is described in expression (4). The interest rate on liquidity and the rate of return on stocks are measured in percent. Column 6 reports estimation results on the subsample of respondents who are recorded holding liquid assets worth less than one month's disposable income in 2014. Columns 7 and 8 report estimation results on the subsample holding liquid assets worth more than one month's disposable income in 2014. The controls for educational attainment include indicator variables for 12 lengths of education measured in years in the Danish education system. The additional controls include income decile indicators based on the position in the within-cohort gross income (excluding capital income) distribution in 2015, decile indicators based on the observed income growth from age 25-27 to age 30-32, decile indicators for the expected income growth from 2014 to 2016 obtained from survey information accompanying the experiment, school performance decile indicators based on self-reported school grades, initial wealth decile indicators based on the position in the within-cohort wealth distribution at age 18, parental wealth decile indicators based on the position of parents in the parental wealth distribution measured within the cohort of the respondent when the respondent was 18 years old, a gender dummy, a dummy for being single, a dummy for having dependent children and a constant term. In addition, column 4 includes age indicators.

3.3 Present bias, choice inconsistency and altruism

In column 5 of Table 2, we include additional information from the experiment about preferences and behavior as described in Section 2.2. We include indicator variables for whether individuals display present-biased behavior or future-biased behavior and for making non-monotonic choices in the experiment. We also include the altruism index in the regression. When adding these variables, the patience coefficient increases from 8.5 percentiles to 9.5 percentiles. The additional behavioral coefficients are all small and insignificant at conventional levels. As discussed in Section 2.2, the fact that present bias is insignificant might reflect that the experimental design used in this study is not ideal for detecting such behavior. Nevertheless, the results show that the elicited long-run patience level strongly predicts wealth inequality, while risk preferences and social preferences elicited in the experiment play little or no role for wealth inequality.

3.4 The role of financial markets

Theory predicts that relatively impatient people wish to borrow more. As a consequence, they impose, on themselves, a higher risk of being credit constrained. This can be important for propagation of business cycle shocks and the efficacy of stimulus policy (Carroll et al. 2014; Krueger et al. 2016) and also for the association between patience and wealth inequality that we study. This association may be muted because constrained individuals with differing levels of patience are unable to run down wealth further and, therefore, end up with the same level of wealth, as is described theoretically in Section 1.

To measure credit constraints, we follow the previous literature and construct a dummy indicator for respondents holding liquid assets corresponding to less than one month of disposable income (e.g. Zeldes 1989; Johnson et al. 2006; Leth-Petersen 2010). Using this measure, we find a remarkably stable and quantitatively important association between the individuals' degrees of patience and their propensities to be credit constrained over the period 2001-2015 (see online Appendix C.1). The stable relationship over such a long period is consistent with the notion of self-imposed credit constraints.

In columns 6 and 7 of Table 2, we analyze the relationship between patience and wealth inequality for credit constrained individuals and unconstrained individuals, respectively. For this exercise, we split the sample based on the credit constraint indicator measured in 2014, i.e. the year before we measure the wealth rank, and estimate the baseline specification in column 3 for the two subsamples. The association between elicited patience and wealth percentile rank turns out to be small and insignificant at conventional levels for the credit constrained individuals (column 6). In contrast, the association for the

unconstrained individuals is 11.1 percentiles (column 7) and thus considerably larger than the 8.5 percentiles obtained for the full sample (column 3). This evidence is consistent with the theoretical insight that the overall association between patience and wealth inequality is muted by credit constraints and can explain why patience and wealth are unrelated in the bottom of the wealth distribution (cf. Figure 4).

The assumption underlying the credit constraint indicator is that some individuals may borrow at a fixed interest rate, while others cannot borrow at all. Arguably, this does not capture the entire effect of credit constraints as people can have different access to credit and, therefore, effectively face constraints with varying intensity. The relevant slope of the budget line is the interest rate on marginal liquidity, which may vary across individuals. To further account for credit constraints, we compute a measure of this "marginal interest rate" and include it among the controls in column 8 of Table 2. The marginal interest rate is derived from account-level data with information about debt, deposits and interest payments during the year. We impute the interest rate for each account of an individual from yearly interest payments and end-of-year balances. For people with debt accounts, we select the highest interest rate among debt accounts as the marginal interest rate. For people without debt, we select the lowest interest rate among their deposit accounts based on the logic that this is the cheapest source of liquidity. Kreiner et al. (2019) show that the computed interest rates match actual interest rates set by banks well and that this measure of credit constraint tightness improves the ability to predict spending responses to a stimulus policy. Details about the construction of the marginal interest rate, its distribution and validation of the imputation are presented in online Appendix C.2 and in Kreiner et al. (2019).

Recent evidence also suggests that some individuals are better at obtaining high returns on financial assets (Fagereng et al. 2018), which create variation in the slope of the budget line of savers. To account for this type of variation, we compute stock market returns for each individual by dividing the sum of dividend income and realized capital gains/losses during the year with the market value of stocks. As returns and ownership fluctuates somewhat from year to year, we calculate the average value over the period 2008-2014. Besides the stock market returns, we also include an indicator variable for owning stocks during the period.

In Table 2, column 8, we expand the specification of Table 2, column 7, for the subsample of individuals who are not likely to be affected by (hard) credit constraints and include the interest rate on marginal liquidity, the financial asset ownership indicator and the rate of return on financial assets. The coefficient on the marginal interest rate is precisely estimated and has the expected negative sign. People

who own stocks are, as expected, more likely to be placed higher in the wealth distribution. Given the other covariates, the return on assets turns out not to be important for the wealth rank. The inclusion of the financial variables mutes the association between patience and the wealth rank compared to column 7, but the association is still strong, precisely estimated and comparable in magnitude to the baseline specification in column 3. Since patient individuals are likely to face low interest rates on loans because they have accumulated a high level of wealth, the estimate in column 8 may be a lower bound for the relevant association between patience and wealth inequality.

The empirical findings in this section are also relevant for concerns about whether differences in elicited time discounting simply reflect variation in real-life market interest rates facing the individuals participating in the experiment rather than their time preferences (Frederick et al. 2002, Krupka and Stephens 2013, Dean and Sautmann 2018). For example, Dean and Sautmann (2018) suggest that shocks to income in a developing-country context can affect the intertemporal marginal rate of substitution elicited experimentally, implying that an experimental measure may not uncover differences in inherent discounting behavior of the participants. Our findings of stable relationships between patience and wealth inequality and patience and credit constraint propensity over a 15-year period are, however, hard to reconcile with explanations based on shocks or other temporary variation in income and wealth at business cycle frequency.

Likewise, the fact that patience significantly predicts the wealth percentile rank after controlling for market interest rates and asset returns suggests that the patience-wealth rank relationship is not simply driven by arbitrage. This finding is consistent with the view that experimentally elicited discount rates contain – due to narrow bracketing – relevant information about individuals' subjective time discounting. This complements other evidence about narrow bracketing in the experimental literature showing that subjects do not integrate their choices in the experiment into their broader choice sets. For example, recent evidence by Andreoni et al. (2018) shows that subjects do not arbitrage against market interest rates when making intertemporal allocations of cash in experiments.

4 Importance of reverse causality, selection and measurement

This section presents a series of robustness checks. First, we reproduce the association between patience and wealth inequality using survey information about time discounting for individuals surveyed in the 1970s. This addresses 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 for the wealth data obtained from the administrative registries. Second, we show that the results are robust to the measurement of patience and wealth and to selection into participating in the experiment.

4.1 Association between a survey measure of patience in early adulthood and wealth inequality three decades later

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 2,548 individuals from the 1952-1955 cohorts.[13] The survey data is merged with administrative records covering the same period as the core analysis. In this way, we examine whether an alternative measure of time discounting, collected when individuals in the survey are 18-21 years old, is predictive of future inequality in wealth when they are about 45-60 years old. The respondents in the 1973 survey were asked, among other things, the following question: *If given the offer between the three following jobs, which one would you choose?* (*i*) *A job with an average salary from the start.* (*ii*) *A job with low salary the first two years but high salary later.* (*iii*) *A job with very low salary the first four years but later very high salary.* We interpret this question about the preference over the timing of income streams as a proxy for time discounting, where respondents answering (*iii*) are the most patient and respondents answering (*i*) are the least patient. This aligns with the interpretation of the money-sooner-or-later experiments to elicit time discounting. We also asked this survey question to a subsample of the participants in the experiment. For this group, we observe a strong correlation between the survey-based measure of patience and patience elicited in the incentivized experiment (see online Appendix D.1).

Figure 6 replicates Figure 3 for the DLSY sample. Figure 6a shows the average position in the wealth distribution in the period 2001-2015 for each of the three patience groups defined by the three answers to the survey question in the DLSY sample in 1973. The most patient group of individuals is consistently at the highest position in the wealth distribution, followed by the group with medium patience and with the least patient individuals on average attaining the lowest position. The difference in the average wealth rank position of the most patient and the least patient is about 7-8 wealth percentiles. Figure 6b compares the predictive power of the early-adulthood survey measure of patience and the education level of the individuals observed in the register data.[14] It shows that the association between patience

[13]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.

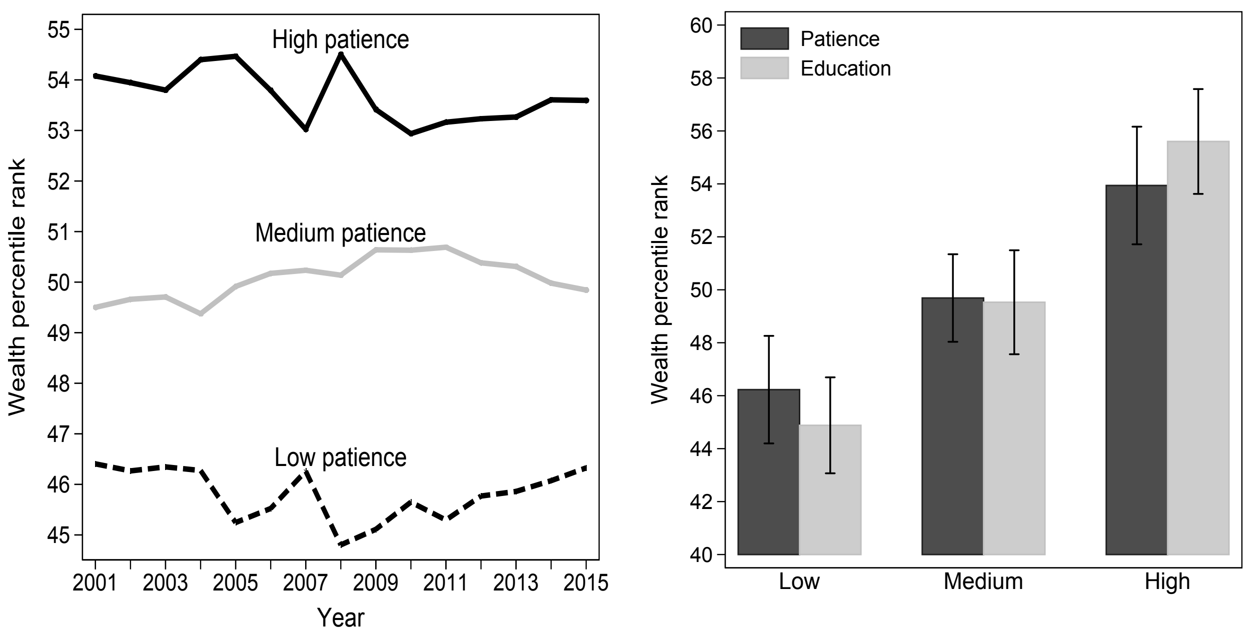
[14]We cannot compare the patience-wealth rank association to the association between parental wealth position and child wealth position as in Figure 3b for the DLSY survey sample because the respondents are born before 1960 when the identity of

and wealth inequality is about the same size as the association between education and wealth inequality. The persistence, magnitude and size relative to education resemble the pattern observed in Figure 3.

Figure 6: Patience in 1973, educational attainment and wealth inequality

(a) Patience in 1973 and position in the wealth distribution 2001-2015

(b) Patience in 1973 vs. education



Notes: Panel a shows the association between time discounting elicited in the Danish Longitudinal Survey of Youth (DLSY) in 1973 and the position in the wealth distribution in the period 2001-2015. The position in the wealth distribution is computed as the 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*. 664 respondents preferred a flat income profile "Low patience", 1,157 preferred a steeper profile "Medium patience", and 727 preferred the steepest profile "High patience". Panel b compares the patience-wealth association to the education-wealth association. The subject's wealth and educational attainment is measured in 2001. Educational attainment equals years of completed education. The individuals in the sample are split into three groups according to patience and years of education. The division by patience is the same as in panel a. For education, three equally sized groups are defined based on years of education. Cut-offs for the education groups (years): Low [8, 13]; Medium [13, 14.5]; High [14.5, 22] where the numbers refer to years of completed education. Whiskers represent 95% confidence intervals.

Table 3 presents regressions of wealth percentile ranks on dummy variables for the DLSY patience groups. Column 1 shows results from a regression without control variables included, corresponding to the association between patience and wealth inequality reported in Figure 6b. The standard errors of the regression estimates show that the differences between the low patience group and the medium and high patience groups are significant at the one percent level. Column 2 includes dummy indicators for the number of years of completed education, income decile indicators, decile indicators for initial wealth measured in 1983 (first occurrence of individual-level wealth data) and demographic controls.

most parents is missing in the register data. The link between parents and children exists for all cohorts born in 1960 and later.

Including the controls mutes the patience coefficients, but the high patience group parameter is still sizable and significant at a five percent level. Column 3 reports the result from running the same regression with the level of wealth in amounts as outcome variable. It shows that the most patient individuals in the survey have about DKK 110,000 more wealth than the impatient individuals conditional on all the control variables. This is about the same magnitude as the finding in column 4 of Table 2.

In summary, the results from using a measure of patience elicited early in the life cycle confirms the findings from the core analysis based on experimental elicitation of time discounting that relatively patient individuals are consistently positioned higher in the wealth distribution. This suggests that the patience-wealth rank association is not driven by a causal relationship going from wealth to patience or driven by shocks, affecting both patience and wealth, appearing around the time when patience is elicited.

Table 3: Patience in 1973 and position in the wealth distribution, 2001

	(1)	(2)	(3)
Dep. var.: Wealth	Rank	Rank	DKK
Patience, high	7.71	3.24	111,501
	(1.54)	(1.51)	(44,865)
Patience, medium	3.49	1.54	55,351
	(1.34)	(1.30)	(57,706)
Controls	No	Yes	Yes
Observations	2,546	2,546	2,546
Adj. R-squared	0.01	0.13	0.03

Notes: OLS regressions. Robust standard errors in parentheses. The regressions are based on 2001, which is the first year in Figure 6a. By then, the individuals in the DLSY sample (born 1952-1955) were in their mid-lifes such that it is comparable to the scenario in our core analysis. Dummies for medium and high patience are included in the regressions, low patience is the reference group. The patience groups are based on the time discounting question in DLSY, see notes to Figure 6. The controls include year indicators for educational attainment, income decile indicators based on the position in the gross income (excluding capital income) distribution, initial wealth decile indicators based on the position in the wealth distribution in 1983, a gender dummy, a dummy for being single, a dummy for having dependent children and a constant term. Two observations are dropped because of missing wealth data in 1983.

4.2 Measurement and selection

Appendix D.2 provides a large number of robustness analyses showing that the results are robust to different ways of measuring patience in the experiment, various ways of controlling for shocks and education, different specifications of wealth and selection into participating in the experiment. The results are described below.

Our patience measure is based on the subset of choice situations where the subjects are asked to choose between payouts 8 and 16 weeks from the experiment date. As described in Section 2, 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 (one day). It is possible from the experiment to construct patience measures based on all combinations of the payment dates that we exposed subjects to ("today", "in 8 weeks" and "in 16 weeks"). It turns out that the parameter estimates on patience are very similar across the different combinations of payment dates.

About 19 percent of the sample consistently postpone payments in the intertemporal choice situations, cf. Figure 2. In order to verify that individuals who always postpone payments do not drive our main result, we re-estimate the association between patience and wealth with and without controls on a subsample omitting these individuals. The association becomes somewhat smaller, but it is still quantitatively important and strongly significant. Finally, we estimate discount rates structurally using a random utility model. In order to make the scale comparable to our patience index, we rank the estimated discount rates and use the discount rate rank as a regressor. With this measure, moving from the least patient to the most patient individual in the sample is associated with an increase of close to 11 rank points in the wealth distribution, which is similar to the association reported in column 1 of Table 2.

The tax assessed values of houses used to compute individual wealth may be somewhat below market values. To account for this potential bias, we adjust the values by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range following Leth-Petersen (2010). The overall association between patience and wealth inequality is nearly unchanged after this adjustment. The wealth data including housing and financial wealth are consistently third-party reported for a long period of time. However, they lack two components of wealth that are potentially important for assessing wealth inequality, namely the value of cars and the value of wealth accumulated in pension accounts. Data documenting these two components have recently become available, but only from 2014 onwards. The inclusion of pension wealth slightly mutes the association between patience and wealth inequality, while the inclusion of car values has almost no effect.[15] Measuring wealth at the household level instead of at the individual level also leaves the association between patience and position in the wealth distribution almost unchanged. We also examine differences in financial wealth. For this narrower wealth concept, we find a larger association

[15]There are good reasons why adding pension wealth would attenuate the estimate. 90 percent of contributions to pension accounts are made to illiquid employer organized pension accounts (Kreiner et al. 2017), and the contributions are predominantly determined by collective labor market agreements. As Chetty et al. (2014a) document, the majority responds passively to these savings mandates, i.e. they do not adjust other types of savings in response to these savings mandates.

with patience compared to the broad wealth measure.

To explore the potential role of shocks and other transitory variations in the measurement of wealth and income, we compute three-, five- and seven-year averages for each of these variables and re-estimate the wealth rank regressions. The coefficient on patience is essentially identical across these cases. We obtain the same conclusion if we, as an alternative way to reduce the importance of shocks, consider subsamples of subjects who have lived in stable relationships (no spouse or same spouse) and not experienced unemployment shocks or health shocks for a long period before the elicitation of patience. We reach the same conclusion in another sensitivity analysis where we confine the sample to individuals where both parents are alive in 2015, thereby ruling out that wealth differences are driven by inheritance from parents.

In the control set, we include 11 dummy variables for years of educational attainment. To allow for the possibility of variation in returns across educations with the same length, for example comparative literature studies, economics and physics, we conduct sensitivity analyses where we include more detailed education controls. The expanded educational control set did not change the estimated effect of patience on wealth in any important way.

Only a fraction of the subjects whom we invited to participate in the experiment accepted the invitation, and this potentially implies that our sample is selected and not representative of the population at large. To address this issue, we re-estimate the key associations between patience and wealth inequality using propensity score weighting, where the propensity scores are estimated using register data information about participants and the population at large: year indicators for educational attainment, decile indicators for income, observed income growth, parental wealth and wealth at age 18 as well as age indicators, a gender dummy, a dummy for being single and a dummy for having dependent children. We find no important deviations from the baseline estimates.

5 Conclusion

According to standard savings theory, differences in how much people discount the future generate differences in savings behavior and thereby wealth inequality. We provide a direct empirical link between time discounting and wealth inequality by combining data on individuals' time discounting collected from a large-scale, incentivized experiment with administrative data revealing the positions of individuals in the real-world wealth distribution. We document a quantitatively important association between

patience and wealth inequality, which is of the same magnitude as the association between educational attainment and wealth inequality. The association is stable over time and exists throughout the wealth distribution except at the very bottom. We find that 3/4 of the association exists after controlling for a large number of variables capturing other wealth determinants. This suggests that the savings channel is a driver of the observed association between patience and wealth inequality, consistent with savings theory.

Taken together, our results suggest that differences in time discounting across individuals play a significant role for wealth differences and, more generally, point to the potential importance of incorporating heterogeneous time discounting into models of consumption and savings behavior as originally suggested by Krusell and Smith (1998) and recently applied by Cooper and Zhu (2016), Hubmer et al. (2016), Krueger et al. (2016), Carroll et al. (2017), De Nardi and Fella (2017) and Alan et al. (2018).

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

Our study also contributes to inequality research at a broader level. Most studies aiming at explaining inequality assume homogenous preferences/behavior and focus on differences across people in innate abilities, realization of income shocks, transfer payments and related components entering the budget constraint. Our finding that elicited time discounting predicts large, systematic differences in income profiles and wealth accumulation across people suggests that heterogeneity in preferences also has a role to play in the formation of inequality.

References

Abdellaoui, M., Attema, A. E., and Bleichrodt, H. (2010). Intertemporal tradeoffs for gains and losses: An experimental measurement of discounted utility. *Economic Journal*, 120(545):845–866.

Adermon, A., Lindahl, M., and Waldenström, D. (2018). Intergenerational wealth mobility and the role of inheritance: Evidence from multiple generations. *Economic Journal*, 128(612):482–513.

Alan, S., Browning, M., and Ejrnæs, M. (2018). Income and consumption: A micro semistructural analysis with pervasive heterogeneity. *Journal of Political Economy*, 126(5):1827–1864.

Anderhub, V., Gäuth, W., Mäuller, W., and Strobel, M. (2000). An experimental analysis of intertemporal allocation behavior. *Experimental Economics*, 3(2):137–152.

Andersson, O., Holm, H. J., Tyran, J.-R., and Wengström, E. (2016). Risk aversion relates to cognitive ability: Preferences or noise? *Journal of the European Economic Association*, 14(5):1129–1154.

Andreoni, J., Gravert, C., Kuhn, M. A., Saccardo, S., and Yang, Y. (2018). Arbitrage or narrow bracketing? On using money to measure intertemporal preferences. NBER Working Paper No. 25232.

Andreoni, J. and Sprenger, C. (2012). Estimating time preferences from convex budgets. *American Economic Review*, 102(7):3333–3356.

Angeletos, G.-M., Laibson, D., Repetto, A., Tobacman, J., and Weinberg, S. (2001). The hyperbolic consumption model: Calibration, simulation, and empirical evaluation. *Journal of Economic Perspectives*, 15(3):47–68.

Attema, A. E., Bleichrodt, H., Gao, Y., Huang, Z., and Wakker, P. P. (2016). Measuring discounting without measuring utility. *American Economic Review*, 106(6):1476–1494.

Attema, A. E., Bleichrodt, H., Rohde, K. I., and Wakker, P. P. (2010). Time-tradeoff sequences for analyzing discounting and time inconsistency. *Management Science*, 56(11):2015–2030.

Augenblick, N., Niederle, M., and Sprenger, C. (2015). Working over time: Dynamic inconsistency in real effort tasks. *Quarterly Journal of Economics*, 130(3):1067–115.

Augenblick, N. and Rabin, M. (2019). An experiment on time preference and misprediction in unpleasant tasks. *Review of Economic Studies*, 86(3):941–975.

Backes-Gellner, U., Herz, H., Kosfeld, M., and Oswald, Y. (2018). Do preferences and biases predict life outcomes? Evidence from education and labor market entry decisions. CESifo Working Paper No. 6863.

Barsky, R. B., Juster, F. T., Kimball, M. S., and Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *Quarterly Journal of Economics*, 112(2):537–579.

Benhabib, J., Bisin, A., and Luo, M. (2017). Earnings inequality and other determinants of wealth inequality. *American Economic Review*, 107(5):593–97.

Benhabib, J., Bisin, A., and Luo, M. (2019). Wealth distribution and social mobility in the US: A quantitative approach. *American Economic Review*, 109(5):1623–1647.

Boserup, S. H., Kopczuk, W., and Kreiner, C. T. (2016). The role of bequests in shaping wealth inequality: Evidence from Danish wealth records. *American Economic Review: Papers and Proceedings*, 106(5):656–61.

Boserup, S. H., Kopczuk, W., and Kreiner, C. T. (2018). Born with a silver spoon? Danish evidence on wealth inequality in childhood. *Economic Journal*, 128:F514–F544.

Browning, M. and Leth-Petersen, S. (2003). Imputing consumption from income and wealth information. *Economic Journal*, 113(488):F282–F301.

Carroll, C., Slacalek, J., Tokuoka, K., and White, M. N. (2017). The distribution of wealth and the marginal propensity to consume. *Quantitative Economics*, 8:977–1020.

Carroll, C. D., Slacalek, J., and Tokuoka, K. (2014). The distribution of wealth and the MPC: Implications of new European data. *American Economic Review: Papers and Proceedings*, 104(5):107–111.

Carvalho, L., Meier, S., and Wang, S. (2016). Poverty and economic decision-making: Evidence from changes in financial resources at payday. *American Economic Review*, 106(2):260–284.

Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., and Taubinsky, D. (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of Risk and Uncertainty*, 37(2-3):237–269.

Charles, K. K. and Hurst, E. (2003). The correlation of wealth across generations. *Journal of Political Economy*, 111(6):1155–1182.

Chetty, R., Friedman, J. N., Leth-Petersen, S., Nielsen, T. H., and Olsen, T. (2014a). Active vs. passive decisions and crowd-out in retirement savings accounts: Evidence from Denmark. *Quarterly Journal of Economics*, 129(3):1141–1219.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014b). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics*, 129(4):1553–1623.

Choi, S., Kariv, S., Müller, W., and Silverman, D. (2014). Who is (more) rational? *American Economic Review*, 104(6):1518–50.

Clark, G. and Cummins, N. (2014). Intergenerational wealth mobility in England, 1858-2012. Surnames and social mobility. *Economic Journal*, 125:61–85.

Cohen, J. D., Ericson, K. M., Laibson, D., and White, J. M. (2019). Measuring time preferences. *Journal of Economic Literature, forthcoming*.

Cooper, R. and Zhu, G. (2016). Household finance over the life-cycle: What does education contribute? *Review of Economic Dynamics*, 20:63–89.

De Nardi, M. (2004). Wealth inequality and intergenerational links. *Review of Economic Studies*, 71(3):743–768.

De Nardi, M. and Fella, G. (2017). Saving and wealth inequality. *Review of Economic Dynamics*, 26:280–300.

Dean, M. and Sautmann, A. (2018). Credit constraints and the measurement of time preferences. *Working paper*.

Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2010). Are risk aversion and impatience related to cognitive ability? *American Economic Review*, 100(3):1238–1260.

Eckel, C., Johnson, C., and Montmarquette, C. (2005). Saving decisions of the working poor: Short- and long-term horizons. In Harrison, G. W., Carpenter, J., and List, J. A., editors, *Field Experiments in Economics (Research in Experimental Economics, Volume 10)*, pages 219–260. Emerald Group Publishing Limited.

Epper, T., Fehr-Duda, H., and Bruhin, A. (2011). Viewing the future through a warped lens: Why uncertainty generates hyperbolic discounting. *Journal of Risk and Uncertainty*, 43(3):169–203.

Fagereng, A., Guiso, L., Malacrino, D., and Pistaferri, L. (2018). Heterogeneity and persistence in returns to wealth. NBER Working Paper No. 22822.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., and Sunde, U. (2018). Global evidence on economic preferences. *Quarterly Journal of Economics*, 133(4):1645–1692.

Frederick, S., Loewenstein, G., and O'Donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, 40(2):351–401.

Gneezy, U. and Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, 112(2):631–645.

Haider, S. and Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *American Economic Review*, 96(4):1308–1320.

Harrison, G. W., Lau, M. I., and Williams, M. B. (2002). Estimating individual discount rates in Denmark: A field experiment. *American Economic Review*, 92(5):1606–1617.

Heathcote, J., Storesletten, K., and Violante, G. L. (2009). Quantitative macroeconomics with heterogeneous households. *Annual Review of Economics*, 1(1):319–354.

Hubmer, J., Krusell, P., and Smith, Jr., A. A. (2016). The historical evolution of the wealth distribution: A quantitative-theoretic investigation. NBER Working Paper No. 23011.

Huggett, M., Ventura, G., and Yaron, A. (2011). Sources of lifetime inequality. *American Economic Review*, 101(7):2923–2954.

Jakobsen, K., Jakobsen, K., Kleven, H., and Zucman, G. (2018). Wealth taxation and wealth accumulation: Theory and evidence from Denmark. CEBI working paper 2018-04.

Johnson, D. S., Parker, J. A., and Souleles, N. S. (2006). Household expenditure and the income tax rebates of 2001. *American Economic Review*, 96(5):1589–1610.

Kleven, H. J., Knudsen, M. B., Kreiner, C. T., Pedersen, S., and Saez, E. (2011). Unwilling or unable to cheat? Evidence from a tax audit experiment in Denmark. *Econometrica*, 79(3):651–692.

Kreiner, C. T., Lassen, D. D., and Leth-Petersen, S. (2015). Measuring the accuracy of survey responses using administrative register data: Evidence from Denmark. In Carroll, C. D., Crosley, T. F., and

Sabelhaus, J., editors, *Improving the Measurement of Consumer Expenditures*, chapter 10. University of Chicago Press.

Kreiner, C. T., Lassen, D. D., and Leth-Petersen, S. (2019). Liquidity constraint tightness and consumer responses to fiscal stimulus policy. *American Economic Journal: Economic Policy*, 11(1):351–379.

Kreiner, C. T., Leth-Petersen, S., and Skov, P. (2017). Pension saving responses to anticipated tax changes: Evidence from monthly pension contribution records. *Economics Letters*, 150:104–107.

Krueger, D., Mitman, K., and Perri, F. (2016). Macroeconomics and household heterogeneity. In Taylor, J. B. and Uhlig, H., editors, *Handbook of Macroeconomics*, volume 2, chapter 11. Elsevier.

Krupka, E. L. and Stephens, M. (2013). The stability of measured time preferences. *Journal of Economic Behavior & Organization*, 85:11–19.

Krusell, P. and Smith, Jr., A. A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, 106(5):867–896.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112(2):443–478.

Lawless, L., Drichoutis, A. C., and Nayga, R. M. (2013). Time preferences and health behaviour: A review. *Agricultural and Food Economics*, 1(1):17.

Leigh, J. P. (1986). Accounting for tastes: Correlates of risk and time preferences. *Journal of Post Keynesian Economics*, 9(1):17–31.

Leth-Petersen, S. (2010). Intertemporal consumption and credit constraints: Does total expenditure respond to an exogenous shock to credit? *American Economic Review*, 100(3):1080–1103.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, 3(4):303–328.

McFadden, D. (1981). Econometric models of probabilistic choice. In Manski, C. F. and McFadden, D. L., editors, *Structural Analysis of Discrete Data with Econometric Applications*, chapter 5. MIT Press.

Meier, S. and Sprenger, C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, 2(1):193–210.

Mischel, W., Shoda, Y., and Rodriguez, M. L. (1989). Delay of gratification in children. *Science*, 244(4907):933–938.

Piketty, T. (2014). *Capital in the twenty-first century*. Harvard University Press.

Piketty, T. and Saez, E. (2014). Inequality in the long run. *Science*, 344(6186):838–843.

Quadrini, V. and Ríos-Rull, J.-V. (2015). Inequality in macroeconomics. In Atkinson, A. B. and Bourguignon, F., editors, *Handbook of Income Distribution*, volume 2B, chapter 14. Elsevier.

Sutter, M., Kocher, M. G., Glätzle-Rützler, D., and Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review*, 103(1):510–531.

Zeldes, S. P. (1989). Consumption and liquidity constraints: An empirical investigation. *Journal of Political Economy*, 97(2):305–346.

Online Appendices

A Theory

A.1 Derivation of equation (3)

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

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

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

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

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

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

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

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

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

A.2 Relationship between patience and wealth

Differentiating equation (3) with respect to ρ gives:

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

Higher patience (lower ρ) leads to higher wealth, $\frac{\partial w(a)}{\partial\rho}\leq 0$, iff

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

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

B Experiment

B.1 Invitation letter

Below is a copy of the invitation letter (in Danish) and an English translation.

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 your username and password to others. Please feel free to contact us if you are having trouble logging in or have any further questions. You can call project coordinator Gregers Nytoft Rasmussen at phone number 35 33 02 77 Monday-Thursday 2:00 p.m. – 5:30 p.m. or write to the address analyse@econ.ku.dk.

Sincerely yours,

Søren Leth-Petersen

Project manager, professor

B.2 Choice situations for time task

Table A1 presents a list of all choice situations in the time task. x_1 is the value of a block allocated at t_1. x_2 is the value of a block allocated at t_2. t_1 and t_2 are delays in weeks. 'delay' corresponds to the difference between t_2 and t_1. 'annual rate' is the annual rate of return imputed by the relative values of the blocks. It is defined as $\frac{1}{(t_1-t_2)/52} \ln\left(\frac{x_1}{x_2}\right)$. 'slope' denotes the slope of the budget line in (x_1, x_2)-space, i.e. $-\frac{x_2}{x_1}$.

Table A1: Intertemporal choice situations

choiceId	x_1	x_2	t_1	t_2	delay	annual rate	slope
1	100	105	0	8	8	0.317	-1.050
2	100	110	0	8	8	0.620	-1.100
3	100	115	0	8	8	0.908	-1.150
4	100	120	0	8	8	1.185	-1.200
5	100	125	0	8	8	1.450	-1.250
6	100	105	0	16	16	0.159	-1.050
7	100	115	0	16	16	0.454	-1.150
8	100	125	0	16	16	0.725	-1.250
9	100	135	0	16	16	0.975	-1.350
10	100	145	0	16	16	1.208	-1.450
11	100	105	8	16	8	0.317	-1.050
12	100	110	8	16	8	0.620	-1.100
13	100	115	8	16	8	0.908	-1.150
14	100	120	8	16	8	1.185	-1.200
15	100	125	8	16	8	1.450	-1.250

B.3 Comparing the experimental results to previous work

In this appendix, we compare our choice data from the time discounting experiment to similar choice data from a related study (Andreoni and Sprenger 2012 [AS]), and we show that estimated discount rates, using four different specifications of a random utility model, are within the range found by other studies.

Comparing to Andreoni and Sprenger (2012): Although there are some differences between the budget choice designs and the selected populations in our study and AS, we show that the overall behavior found in the two data sets appears to be both qualitatively and quantitatively similar. Our patience measure is constructed using five choice situations. In each of these five choice situations, subjects chose to allocate 10 blocks between an earlier point in time (8 weeks, i.e. 56 days in the future) and a later point

in time (16 weeks, i.e. 112 days in the future). Subjects in the AS study faced a series of related budget choices. They were asked to allocate 100 tokens between two different payment dates in each of these budget choices. For comparability, we pick the most similar delays in their experiment, namely 35 and 70 days. In addition to different delays and different numbers of blocks/tokens to allocate, the two studies vary with respect to the subject sample and the presentation format. Specifically, the AS sample consists of 97 San Diego undergraduates, whereas our study uses data from 3,620 middle-aged individuals from the general Danish population. In their experiment, subjects were presented an ordered list of allocation choices with fixed payment dates on each screen. In contrast, we displayed each allocation choice in our study separately on a new screen. The five allocation choices we use to construct our patience index were interleaved with other choices involving different payment dates, and they appeared in randomized order. Furthermore, we held the value of an earlier block fixed at 100 points, whereas AS fixed the price of a future token for each date configuration.

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

Estimating discount rates: Here, we describe the results of structural estimation of individual discount rates. Consider the decision problem from the subject's perspective. Define a choice situation S (see rows in Table A1) as a tuple of attributes (x_1, t_1, x_2, t_2), where x_1 and x_2 denote the value (points) of a block materializing at the earlier point in time t_1 and the later point in time t_2, respectively. Delays will be reported in calendar weeks.

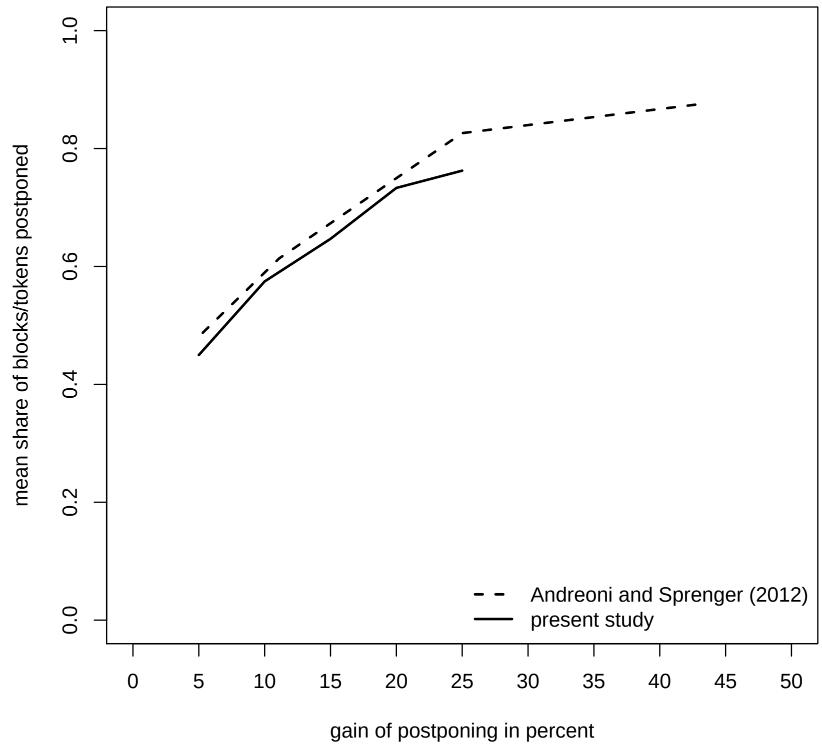
Assuming additively separable time discounting, a subject's choice z is the outcome of the maximization problem

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

subject to the budget constraint

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

Figure A2: Comparing choices in our experiment to existing work



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

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

In order to make the model operational, we have to assume specific functional forms for the discount function $d(t)$ and the utility function $u(w)$. We start with introducing our most general specification and then discuss variants of the model imposing restrictions on certain behavioral parameters. For the discount function $d\,(t)$, we use the quasi-hyperbolic form (Laibson 1997)

$$d(t) = \begin{cases} 1 & \text{if } t = 0 \\ \beta e^{-\rho \frac{t}{52}} & \text{if } t > 0 \end{cases},$$

where ρ denotes the annualized discount rate and $\beta < 1$ denotes present bias. The utility function $u(w)$ takes the iso-elastic form

$$u(w) = \begin{cases} w^{1-\theta} & \text{if } \theta < 1 \\ \ln(w) & \text{if } \theta = 1 \\ -w^{1-\theta} & \text{if } \theta > 1 \end{cases},$$

where θ denotes an Arrow-Pratt-type coefficient of relative aversion towards income fluctuations. We normalize such that $u(\min(w_2)) = 0$ and $u(\max(w_1)) = 1$. Note that a single choice situation S only informs us about whether an individual is more or less patient than a certain threshold (see the rates listed in Table A1). The fact that we observe multiple choices per subject and that these choice situations vary with respect to their implicit interest rates permit us to bound the discount rate to an interval.

We estimate four different models:

- **Model 1:** To be able to compare estimated discount rates with our non-parametric index of patience, we first restrict attention to choice situations with payment dates $t_1 = 8$ weeks and $t_2 = 16$ weeks. Based on the five choice situations satisfying this requirement, we estimate the discount rate ρ. As these situations involve tradeoffs between two future dates only, they do not permit identification of the present bias parameter β. Furthermore, for this specification we also restrict utility to be linear in outcomes, such that $\theta = 0$.

- **Model 2:** This model's specification is equivalent to the specification of Model 1, but we estimate it on all 15 choice situations in our time discounting experiment. Once again, we restrict $\beta = 1$ and $\theta = 0$.

- **Model 3:** Like Model 2, our third model is also estimated on all available time discounting data. However, the specification of Model 3 differs from Model 2 in that it allows for non-exponential discounting. The model thus requires estimation of the two behavioral discounting parameters ρ and β. As for the previous models, we assume utility to be linear in outcomes, such that $\theta = 0$.

- **Model 4:** Lastly, we estimate the most general model introduced above allowing for both non-linear utility and present bias.

Until now, we have considered a deterministic model. To incorporate the possibility of errors, we have to make an assumption about the stochastic nature of choices. To do this, we assume random utility with additively separable choice noise (McFadden 1974, 1981). Denoting S_z as the temporal points allocation

arising from choice z in a specific situation, the utility of S_z is given by $U(S_z) = d(t_1)u((10 - z)x_1) + d(t_2)u(z \cdot x_2)$. We presume that the utility of a temporal stream of outcomes equals $V(z) = U(S_z) + \varepsilon_z$, with ε_z being an i.i.d. random variable representing error in evaluating utility.

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

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

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

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

where η denotes the vector of parameters to be estimated. The first product multiplies over all m choice situations in $\mathcal{S}$, and the second product multiplies over all 11 possible allocations. Note that the stochastic specification of the model introduces an additional precision parameter λ, which is constrained to be positive. $\lambda = 0$ represents random choice. In this case, choice probabilities follow a uniform distribution over the 11 possible allocations. Large λ's, on the other hand, indicate higher precision.

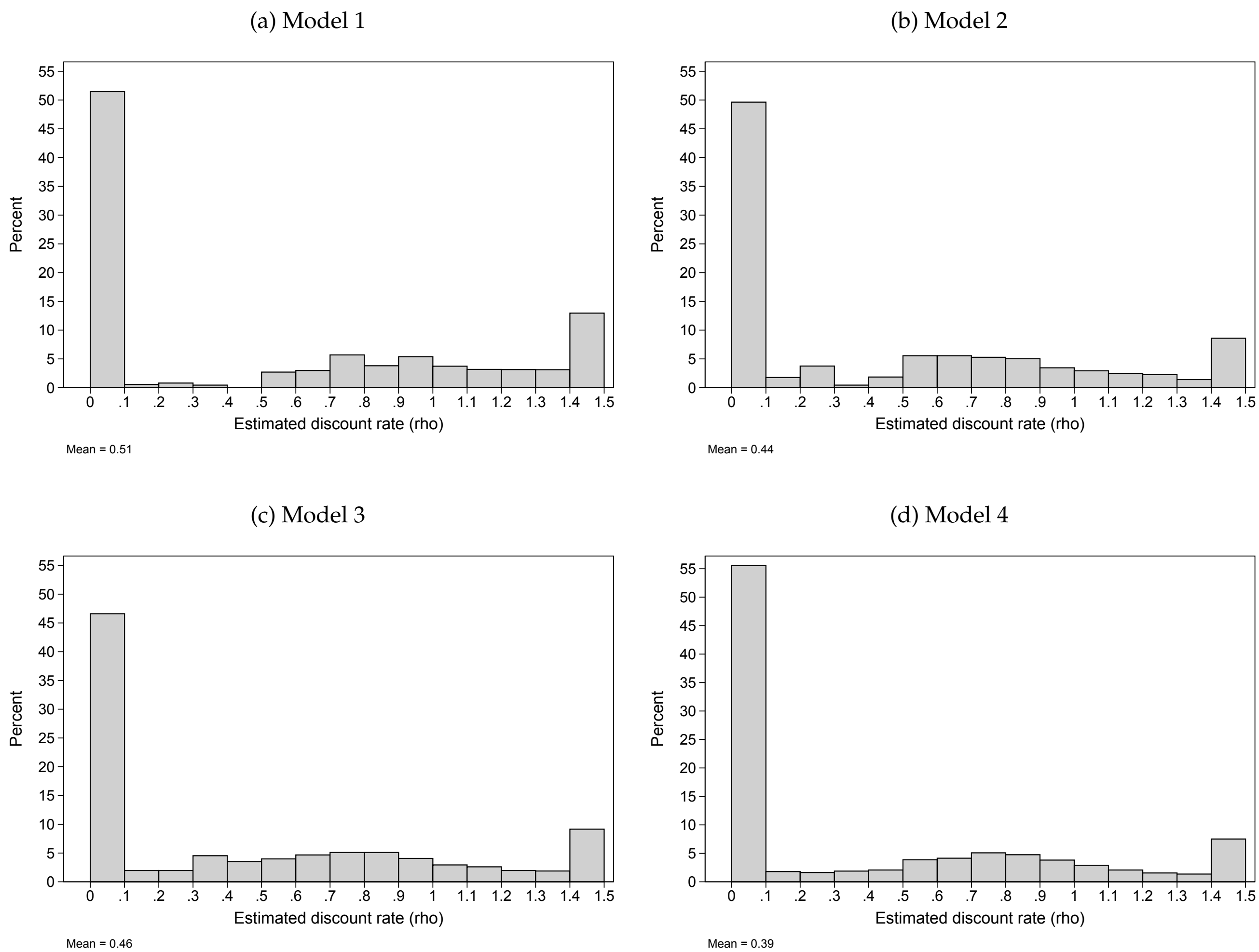
Figure A3 depicts the distribution of estimated annual discount rates for all individuals in our sample for the four different models. Subjects who always chose to save all blocks in all choice situations are included. For some subjects, the estimated annual discount rates exceed 1.45, which is the maximum discount rate offered in the experiment, cf. Table A1. We set the actual discount rate to 1.45 for these subjects. The distributions are very similar across the four models, with a mean discount rate ranging from 39 to 51 percent per annum. This is in line with the previous literature, for example surveyed by Frederick et al. (2002).

Models 3 and 4 allow for non-constant discounting. For these models, we find that 45-55 percent of the individuals seem reasonably unbiased, defined as $\beta \in (0.95, 1.05)$, while 15 percent display present-biased behavior and 30-40 percent display future-biased behavior, i.e. there is little evidence that present bias is important. This is broadly consistent with the findings from the non-parametric measure where slightly more individuals are future biased than present biased.

In Table A2, we show that the ordering of individuals according to level of patience across models

1-4 is very similar to the ordering according to our non-parametric patience index defined in equation (4). The table shows the results from rank-rank regressions where the dependent variable is based on the patience index while the explanatory variables are based on the estimated discount rate from each of the four models. Across the models, the rank-rank coefficient is in the range 0.84-0.97.

Figure A3: Distributions of structurally estimated discount rates



Notes: The panels show distributions of structurally estimated annual discount rates. The estimated discount rates are based on four different models:
Panel a: Exponential discounting. Linear utility. Uses the five money sooner-or-later tasks that involve payments at $t_1 = 8$ weeks and $t_2 = 16$ weeks.
Panel b: Exponential discounting. Linear utility. Uses all 15 experimental time choice situations.
Panel c: Allows for non-exponential discounting. Linear utility. Uses all 15 experimental time choice situations.
Panel d: Allows for non-exponential discounting. Allows for non-linear utility. Uses all 15 experimental time choice situations.
In all four panels, estimated discount rates are censored at 1.45, which is the maximum discount rate offered in the experiment.

Table A2: Relationship between the non-parametric patience measure and structurally estimated discount rates

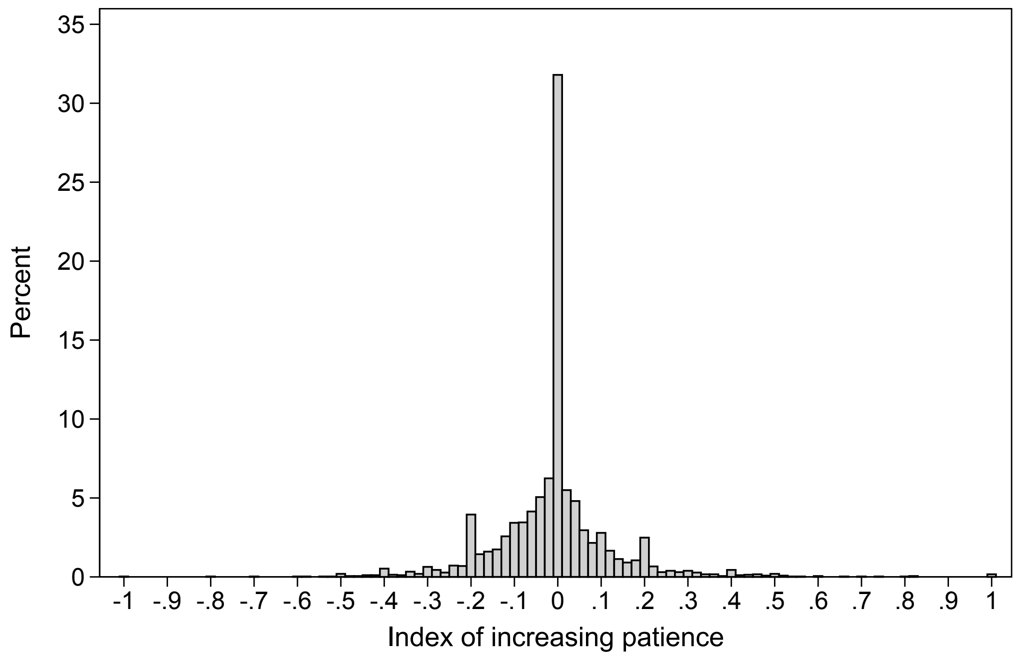
Dep. var.: Rank of non-parametric patience, 8 vs. 16 weeks	(1)	(2)	(3)	(4)
Rank of estimated discount rate, model 1	0.97			
	(0.00)			
Rank of estimated discount rate, model 2		0.89		
		(0.01)		
Rank of estimated discount rate, model 3			0.84	
			(0.01)	
Rank of estimated discount rate, model 4				0.85
				(0.01)
Constant	0.02	0.06	0.08	0.07
	(0.00)	(0.01)	(0.00)	(0.00)
Observations	3,620	3,620	3,620	3,620
Adj. R-squared	0.93	0.79	0.71	0.73

Notes: OLS regressions of the ranked non-parametric patience measure on ranked estimated discount rates from models 1-4. Robust standard errors in parentheses.

B.4 Distribution of the non-parametric measure of non-constant time discounting

We compute the difference in savings choices between 0-8 weeks (short run) and 8-16 weeks (long run) for each of the five interest rates offered in the experiment and take the arithmetic mean of these differences for each individual. The distribution across individuals of this difference between short-run and long-run decisions is bell shaped around zero as shown in the figure below. According to this measure, individuals are on average time consistent with about 1/3 exhibiting no bias, while a little less than 1/3 of the individuals save more in the long run decisions than in the short run decisions ("present biased") and close to 1/3 of the individuals save more in the short run decisions than in the long run decisions ("future biased").

Figure A4: Distribution of increasing patience, non-parametric measure



Notes: The figure shows the distribution of the index of increasing patience. The higher the index, the more the individual has chosen to save in the 8-16 weeks situations (long run) relative to the 0-8 weeks situations (short run).

B.5 Risk task and risk aversion measure

We use investment games similar to Gneezy and Potters (1997) to measure risk aversion. The main differences to their setup are: (*i*) that we used a graphical interface to present the investment choice and (*ii*) that we varied both probabilities of winning and rates of return across the choice situations. In addition, like for all other preference elicitation tasks, we carefully explained the task with the help of animated videos. A typical choice situation is depicted in Figure A5. The left panel shows the initial state of a choice situation. The subject was endowed with ten 100-point blocks positioned at the very left of the screen and could then decide how many of these blocks to invest in a risky asset. The (binary) risky asset, depicted on the right-hand side of the choice screen, resulted in either a good outcome or a bad outcome. In the example, the good outcome occurred with probability 60 percent (illustrated by the wheel on top of the risky asset) and yielded 130 points for each invested 100-point block. The bad outcome occurred with probability 40 percent and yielded 70 points for each invested 100-point block. The user interface worked in the same way as in the time task.

Figure A5: Risk choice task

(a) Initial screen (b) Selected option

A total of 15 choice situations are implemented. They vary in terms of probabilities and rates of return. Table A3 presents a list of all choice situations in the risk task. 'vb' is the value of a block. 'm1' is the multiplier in case the good state occurs, in which case the new value of a block is vb×m1. 'm2' is the multiplier in case the bad state occurs, in which case the new value of a block is vb×m2. 'p' is the probability of the good state. 'mev' is the expected multiplier, mev $= p \times m_1 + (1-p) \times m_2$. 'msd' standard deviation of the multiplier, msd $= \sqrt{p \times (m_1 - \text{mev})^2 + (1-p) \times (m_2 - \text{mev})^2}$. 'mskew' is the skewness of the multiplier, mskew $= \frac{p \times (m_1 - \text{mev})^3 + (1-p) \times (m_2 - \text{mev})^3}{\text{msd}^3}$. 'slope' is the slope of the budgets, i.e. the ratio of prices, $slope = \frac{m_2 - 1}{m_1 - 1}$.

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

We construct the risk aversion index as follows: We take all choice situations with zero skewness, i.e. with probability 0.5 (choiceId 1, 4, 7, 14 and 15 in Table A3). We then normalize and aggregate using the arithmetic mean:

Table A3: 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

$$\phi_{\text{risk aversion}} = \text{mean}\left(\frac{z_1}{10}, \frac{z_4}{10}, \frac{z_7}{10}, \frac{z_{14}}{10}, \frac{z_{15}}{10}\right),$$

where z_i denotes the number of blocks kept in the safe account in choice situation i. $\phi_{\text{risk aversion}}$ is an index of risk aversion with $\phi_{\text{risk aversion}} \in [0, 1]$. Higher values of $\phi_{\text{risk aversion}}$ indicate greater risk aversion, and a $\phi_{\text{risk aversion}}$ of zero indicates minimum risk aversion.

B.6 Social preference task and altruism measure

We use dictator games to measure altruism. In each choice situation, the subject (dictator) chose one out of eleven allocations of points between her-/himself and an anonymous person (the recipient). The recipient took part in another session of our study, but did not make choices as a dictator. Dictators and recipients were randomly matched, and they remained anonymous to each other at all points in time. Possible allocations were displayed using a graphical interface. The cost of increasing or decreasing the recipient's payoff varied across the different choice situations. Figure A6 depicts a typical choice situation as it was presented to dictators. The left panel illustrates the initial screen in that choice situation with no allocation yet selected. Once the dictator picked the preferred option, a blue bar appeared around the selected option. The right panel of the figure illustrates the situation in which allocation 5 was chosen.

Figure A6: Social preference task

(a) Initial screen (b) Selected option

12 choice situations were implemented. Table A4 presents the list of all choice situations in the social preference task. $(\text{own}_1, \text{other}_1)$ refers to the allocation on top of the choice screen, and $(\text{own}_2, \text{other}_2)$ refers to the allocation on the bottom of the choice screen. The budget lines for the choice situations have slope $= \frac{\text{other}_2 - \text{other}_1}{\text{own}_2 - \text{own}_1}$. The choice situation presented in Figure A6 corresponds to choiceId 4 in Table A4.

Table A4: Choice situations in social preference task

choiceId	own_1	other_1	own_2	other_2	slope
1	1,050	550	450	950	-0.667
2	1,000	500	500	1,000	-1.000
3	950	450	550	1,050	-1.500
4	900	450	600	1,050	-2.000
5	850	450	650	1,050	-3.000
6	850	400	650	1,100	-3.500
7	800	400	700	1,100	-7.000
8	750	400	750	1,100	∞
9	700	400	800	1,100	7.000
10	700	450	800	1,050	6.000
11	650	400	850	1,100	3.500
12	650	450	850	1,050	3.000

Like in the other tasks, choice situations in the social preference task appeared in individualized random order. If the random choice situation picked in the payment stage was from the set of social preference tasks, the subject was informed about her choice in that situation. The choice could not be reverted at this stage, however. The subject (dictator) and the other person (recipient) received the respective amounts in the chosen allocation. Payments were transferred directly to people's NemKonto.

We construct an altruism index as follows: We take all choice situations with negative slope (choiceId 1 to 7 in Table A4) and aggregate using the arithmetic mean. We define:

$$\phi_{\text{altruism}} = \text{mean}\,(z_1, ..., z_7)\ ,$$

where $z_i \in [0, 1]$ denotes the allocation $(\text{own}, \text{other})$ in choice situation i. $z_i = 0$ is the allocation on top of the choice screen, and $z_i = 1$ is the allocation on the bottom of the choice screen. Thus, higher values of z_i means giving more to the recipient.

Specifically, $(\text{own}, \text{other}) = ((1 - z_i)\text{own}_1 + z_i\text{own}_2, (1 - z_i)\text{other}_1 + z_i\text{other}_2)$. ϕ_{altruism} is an index of costly altruism with $\phi_{\text{altruism}} \in [0, 1]$. Higher values of ϕ_{altruism} indicate greater altruism, and a ϕ_{altruism} of zero indicates minimum altruism (maximum selfishness).

B.7 Respondents vs. non-respondents

Table A5 provides summary statistics for our respondents (column a) and non-respondents (column b) and their differences (column c). The respondents are slightly older, less likely to be single and slightly more educated compared to non-respondents. Wealth and income of the respondents are higher throughout the distributions.

Table A5: Means of selected characteristics. Respondents vs. non-respondents

	(a) Respondents	(b) Non-respondents	(c) (a)-(b)	
Age	37.32	36.46	0.86	(0.00)
Woman (=1)	0.50	0.49	0.00	(0.74)
Single (=1)	0.28	0.38	-0.10	(0.00)
Dependent children (=1)	0.70	0.64	0.06	(0.00)
Years of education	14.90	14.17	0.73	(0.00)
Gross income distribution				
p5	135,745	98,974	36,772	
p25	287,472	234,953	52,520	
p50	382,997	341,621	41,376	(0.00)
p75	484,463	434,679	49,784	
p95	719,754	655,002	64,752	
Wealth distribution				
p5	-337,615	-351,123	13,507	
p25	93,899	48,894	45,006	
p50	486,006	317,455	168,551	(0.00)
p75	1,066,468	800,084	266,385	
p95	2,395,664	2,024,448	371,216	
Observations	3,620	23,624	27,244	

Notes: Variables are based on 2015 values. P-values from unconditional t-tests of equality of means in parentheses. The reported p-values for the gross income distribution and the wealth distribution are from two-sample Kolmogorov-Smirnov tests for equality of distribution functions. (=1) indicates a dummy variable taking the value 1 for individuals who satisfy the description given by the variable name. Wealth denotes the value of real estate, deposits, stocks, bonds, mortgage deeds in deposit, cars and pension accounts minus all debt except debt to private persons. The tax assessed values of housing is adjusted by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. Gross income refers to annual income and excludes capital income. Wealth and income are measured in Danish kroner (DKK). The table includes individuals for whom a full set of register variables is available.

C Empirical results

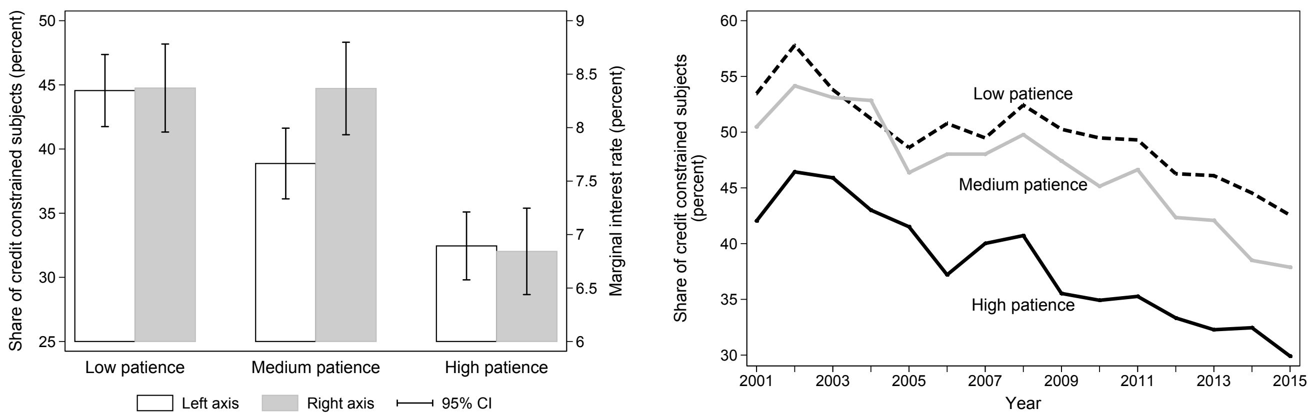
C.1 Association between patience and the propensity to be credit constrained

Figure A7 displays the association between patience and the two measures of credit constraints described in Section 3.4. Panel a shows that patient individuals tend to be less credit constrained than impatient individuals according to both measures. Panel b shows that the cross-sectional relationship between patience levels and the propensity to be credit constrained is stable over the period 2001-2015. The panel also shows that the propensity to be observed with low levels of liquid assets generally declines for all three patience 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.

Figure A7: Association between time discounting and propensity to be credit constrained

(a) Patience and the probability of being credit constrained

(b) Prevalence of credit constraints across levels of patience, 2001-2015



Notes: The figures show the association between elicited patience and different measures of credit constraints. The sample is split into three equally sized groups according to the tertiles of the patience measure such that "High patience" includes the 33 percent most patient individuals in the sample, "Low patience" the 33 percent most impatient individuals and "Medium patience" the group in between the "High patience" and "Low patience" groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. In panel a, the white bars show the association between elicited patience and the propensity to hold liquid assets worth less than one month's disposable income in 2014. The grey bars show the association between elicited patience and the marginal interest rate in 2014 for the three patience groups. Panel b shows the association between elicited patience and the share of individuals within each patience group who are observed with liquid assets corresponding to less than one month's disposable income in the period 2001-2015.

C.2 Marginal interest rates

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

For respondents with loan accounts, we define the marginal interest rate as the highest calculated loan account-specific interest rate. If a respondent only has deposit accounts, we define the marginal interest rate as the smallest account-specific interest rate among the calculated account-specific interest rates for that respondent. The rationale is that the cost of liquidity is given by the loan account with

the highest interest rate if a respondent has loan accounts, whereas the cost of liquidity for a respondent who only has deposit accounts is determined by the account where the lowest return is earned. Table A6 shows the distribution of the computed marginal interest rates.

Table A6: Distribution of marginal interest rates

Percentile	p5	p25	p50	p75	p95
Marginal interest rate	0.00	0.97	6.25	12.73	22.82

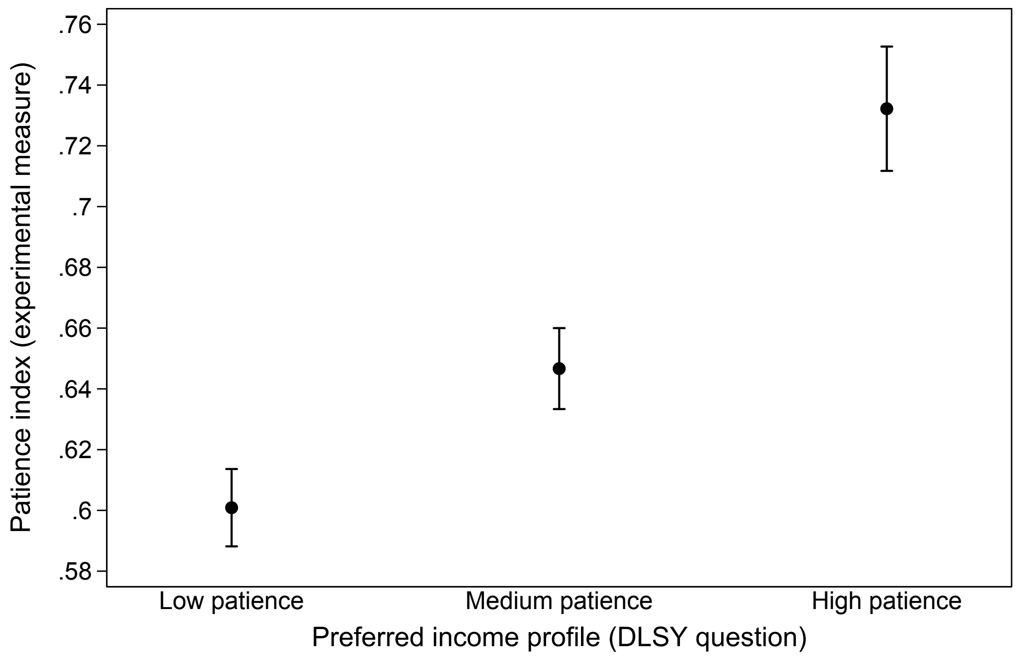
D Importance of reverse causality, selection and measurement

D.1 Comparing patience measured in the DLSY survey and in the experiment

In this appendix, we compare patience elicited with the DLSY survey questions to the patience elicited in the experiment. We do this with data from a large-scale online study conducted during the year 2018. 4,152 Danes of the cohorts with birth year 1967 to 1986 completed the study. In addition to the DLSY survey measure described in section 4.1, the study also included our intertemporal choice task with real monetary incentives. With the exception that there were 100 blocks instead of 10 to be allocated between two points in time in each of the choice situations, the intertemporal choice task was identical to that described in section 2. For comparability, we bin the 100 blocks into 10 and then construct our patience index based on the $t_1 = 8$ weeks vs. $t_2 = 16$ weeks allocations.

Figure A8 depicts the average (dots) of our patience index conditional on the three possible responses in the DLSY question and 95 percent confidence intervals (whiskers). It shows that responses in the DLSY question and choices in the incentivized, intertemporal choice task are highly and significantly correlated.

Figure A8: Comparison of DLSY and experimental measure

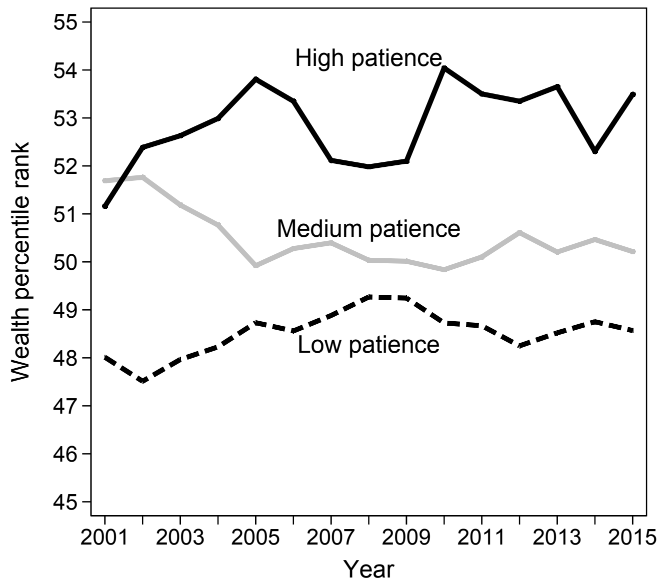


Notes: This figure presents a binned scatterplot displaying, for each category of the DLSY measure, the average of the patience index based on the experiment together with the 95 percent confidence interval.

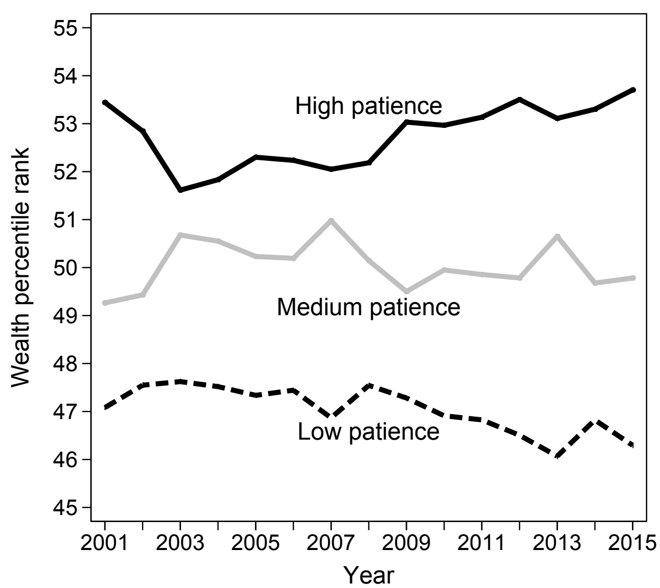
To further corroborate the evidence about the stable relationship between the two measures and wealth inequality, we have reproduced Figure 3a and the corresponding survey-based version, Figure 6a, for the 2,096 respondents from the 2015 experimental sample where we have both patience based on the experiment and based on the survey question that was used in the original 1973 DLSY. The result is displayed in the figure below. The top panel is based on the survey question and the bottom panel is based on the experimental measure. The two figures both show a very stable wealth rank ordering across the three patience groups. The levels are generally similar across the two panels, even though the impatient group according to the survey measure is perhaps ranked slightly higher than the impatient group according to the experimental measure.

Figure A9: Survey and experimental measures of patience and position in the wealth distribution 2001-2015 in the experimental sample

(a) Split by preferred income profile question (DLSY style)



(b) Split according to the experimental measure



Notes: In a follow-up study including 2,096 respondents from the main experiment, we aked the survey question on preferred income profile that was also used in the 1973 Danish Longitudinal Survey of Youth. Panel a shows the association between time discounting elicited as in the DLSY and the position in the wealth distribution in the period 2001-2015. 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.* ["Low patience"] *(ii) A job with low salary the first two years but high salary later.* ["Medium patience"] *(iii) A job with very low salary the first four years but later very high salary.* ["High patience"] Panel b shows the association between experimentally elicited patience and the position in the wealth distribution in the period 2001-2015. The sample is split into three patience groups according to the patience measure. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.5, 0.8]; High [0.8, 1.0]. In both panels, the position in the wealth distribution is computed as the within cohort×time percentile rank in the sample.

D.2 Robustness analysis related to measurement and selection effects

In the main analysis, our patience measure is based on the subset of choice tasks where the subjects were asked to choose between payouts 8 and 16 weeks from the experiment date. As described in section B.2, 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 A7, we construct patience measures based on all possible combinations of the payment dates that we exposed subjects to ("today", "in 8 weeks" and "in 16 weeks"). Row 1 reproduces Table 2, column 1 (without controls) and column 3 (with controls). Rows 2-3 in Table A7 present estimates based on regressions where the patience measure is based on alternative choice situation horizons. The parameter estimates on patience are stable across these regressions. Row 4 omits observations for individuals always postponing the payouts, and also here the parameter on patience is significant and not statistically distinguishable from the baseline specification in row 1. In the final row we use the rank of the structurally estimated discount rate, cf. Appendix B.3, as our patience measure. Also in this case are the estimates practically identical to the estimates for the baseline specification, cf. row 1.[16]

[16]Since the discount rate in this regression is estimated, the standard errors in the regression are potentially underestimated. Ideally, standard errors should be bootstrapped. However, the computational burden of estimating the discount rates is already immense. Bootstrapping with a reasonable number of replications is therefore not practically feasible.

Table A7: Patience and wealth inequality. Other patience measures

Dep. var.: Wealth percentile rank Patience measure:	(1) No controls	(2) With controls
1. Non-parametric, 8 vs. 16 weeks	11.37	8.45
	(1.73)	(1.75)
2. Non-parametric, 0 vs. 16 weeks	11.79	8.83
	(1.88)	(1.90)
3. Non-parametric, 0 vs. 8 weeks	11.80	8.88
	(1.78)	(1.81)
4. Non-parametric, 8 vs. 16 weeks, $\neq 1$	8.90	7.11
	(2.25)	(2.26)
5. Rank of estimated discount rate	10.52	7.85
	(1.66)	(1.67)

Notes: OLS regressions of within-cohort wealth percentile rank on patience measures and other covariates. The table shows estimated coefficients for various measures of patience. Robust standard errors in parentheses. The specification "With controls" includes the same control variables as column 3 in Table 2. "Non-parametric, 8 vs. 16 weeks" is the standard measure referred to as "Patience" in the other tables and figures. In row 4, "$\neq 1$" indicates that individuals who always postpone in the choice situations are omitted. The rank of estimated discount rates in row 5 ranges from 0 to 1 to be comparable to the non-parametric measures of patience. In this row, a higher rank means a lower estimated discount rate. The number of observations is 3,620 in the "No controls" spececification and 3,552 in the "With controls" specification. However, in the row "Non-parametric, 8 vs. 16 weeks, $\neq 1$", the number of observations is 2,943 and 2,895, respectively.

Table A8 provides a number of additional robustness checks. For convenience, row 1 displays the results from the baseline specification, cf. Table 2, column 1 (without controls) and column 3 (with controls). Row 2 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. This is done to account for the fact that the tax assessed values may be somewhat below market values (Leth-Petersen 2010). The estimate of the patience parameter attenuates slightly but the parameter is precisely estimated and is within one standard deviations from the reference estimate in row 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 from 2014 onwards. In row 3, we include the value of the car stock among assets and calculate the net wealth rank based on 2015 data. The patience parameter is close to the estimate in row 1. We further include wealth kept in pension accounts in row 4. This addition slightly mutes the point estimate of the patience parameter. There are

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

In the experiment we have collected information about patience for individuals and not all adult household members. Wealth is, however, arguable accumulated jointly in the household. In row 5, we have reproduced the baseline specification using housheold level wealth as the basis of the wealth rank. The results are practically unaffected by this change.

An important subcomponent of wealth is liquid financial wealth, including deposits, stocks and bonds. In row 6, we use liquid financial wealth as the basis for calculating the wealth rank. In this case the results indicate an even stronger association between patience and the wealth rank.

The theory posits that wealth transfers from parents can be a confounder. In the baseline specification, we control flexibly for parental wealth. However, we do not see actual transfers in the data. In order to assess whether this is likely to confound the results, we re-estimate the baseline specification for the subsample of individuals where both parents are alive. The most important transfer from parents to children is likely to take place when parents die and pass on bequest. If both parents are alive such transfers have not yet been materialized. The results in row 7 are practically identical to the baseline specification.

Only a fraction of the subjects whom we invited to participate in the experiment accepted the invitation, and this can potentially imply that our sample is selected and not representative of the population at large. In row 8, we re-estimate the reference specification from row 1 using propensity score weighting, where the propensity scores measure the propensity to participate in the experiment for all the subjects who were invited. The propensity scores are estimated using variables created from information available in the administrative registries accessible for both participants and non-participants: year dummies for educational attainment, decile dummies for income, observed income growth, parental wealth and wealth at age 18 as well as age dummies, a gender dummy, a dummy for being single and a dummy for having dependent children. The results are close to the estimate from the reference specification. In row 9, we construct propensity scores measuring the propensity to be in the experiment compared to the population at large. As with previous cases, we find no important deviations from the benchmark model. The propensity score weighting approach is based on the assumption that the selection into the

experiment can be adequately captured by the set of covariates on which the propensity score is estimated. To the extent that this is a reasonable assumption, our results do not appear too specific to the sample for which we elicit patience measures.

Table A8: Patience and wealth inequality. Robustness analyses

Dep. var.: Wealth percentile rank Specification of Wealth:	(1) No controls	(2) With controls
1. Wealth, 2015	11.37	8.45
	(1.73)	(1.75)
2. Wealth, adjusted housing value	11.24	7.05
	(1.72)	(1.69)
3. Wealth, adjusted housing value + car value	11.05	6.79
	(1.73)	(1.68)
4. Wealth, adjusted housing value + car value + pension wealth	9.93	5.24
	(1.74)	(1.51)
5. Wealth, household level	11.03	8.25
	(1.72)	(1.75)
6. Financial assets	16.82	9.91
	(1.70)	(1.55)
7. Wealth, both parents alive	11.03	8.60
	(2.18)	(2.21)
8. Wealth, IPW: respondents vs. non-respondents	9.69	7.05
	(1.76)	(1.78)
9. Wealth, IPW: respondents vs. population	10.00	7.17
	(1.86)	(1.85)

Notes: OLS regressions of within-cohort wealth percentile rank on the patience measure and other covariates. The table shows estimated coefficients for the patience measure. Robust standard errors in parentheses. The specification "With controls" includes the same control variables as column 3 in Table 2. Row 1 reproduces the regressions in columns 1 and 3 from Table 2. Row 2 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses of the same property class and in the same location and price range. Row 3 includes the value of the car stock. Row 4 includes both the value of the car stock and wealth held in pension accounts. In row 5, the dependent variable is constructed on the baseline wealth measure (as in row 1), but the within-cohort wealth percentile rank is computed at the household level instead of at the individual level. Row 6 considers only financial assets, ie. stocks, bonds and deposits. Row 7 uses the baseline wealth measure, but the estimations are based on the subset of observations where the respondents' parents are both still alive. In row 8, the dependent variable is constructed on the baseline wealth measure, but the equation is estimated using inverse probability weighting where probability weights are based on respondents vs. non-respondents. Row 9 presents results for the baseline wealth measure estimated using inverse probability weighting where the weights are based on respondents vs. population. The number of observations is 3,620 in the "No controls" column and 3,552 in the "With controls" column. However, in row 7, the sample is restricted to individuals with both parents alive, which reduces the number of observations to 2,365 and 2,333, respectively. Furthermore, in the "No controls" column in rows 8 and 9, the number of observations is 3,573, as the inverse probability weighting requires that all variables used to construct the weights are observable.

Table A9 presents a number of additional robustness checks. Again, row 1 displays the results from the baseline specification, cf. Table 2, column 1 (without controls) and column 3 (with controls). In

row 2, we allow for a categorization of educational attainment consisting of 59 categories representing educational subject areas (e.g. "comparative literature studies", "economics" and "physics"). In this way we allow, for example, for the possibility that a degree in literature has a different return than a degree in physics. This does not change the estimated parameter on patience.

In rows 3-5, we calculate the wealth rank and income deciles based on averages over 2013-2015, 2011-2015 and 2009-2015, respectively. Across all these cases, the estimated patience parameter is essentially identical. In row 6 we condition on being in the labor force every year in the period 2011-2015 and not experiencing unemployment in the period 2011-2015, with wealth rank and income deciles based on 2015. Again, the patience parameter is very close to the baseline specification. In row 7 we condition on having a stable relationship status (no spouse or same spouse) in the five-year period 2011-2015. The wealth rank and income deciles are based on 2015. The patience parameter is now slightly lower than in the other rows but is still precisely estimated and within one standard deviation from any of the patience estimates in the other rows. Finally, we restrict the sample to respondents whose socioeconomic status did not indicate poor health in the period 2008-2015, but this does not affect the estimated parameter in any important way either.

Table A9: Patience and wealth inequality. Robustness analyses

Dep. var.: Wealth percentile rank Specification:	(1) No controls	(2) With controls
1. Wealth 2015, income 2015	11.37	8.45
	(1.73)	(1.75)
2. Wealth 2015, income 2015, 59 educational groups	11.37	8.33
	(1.73)	(1.77)
3. Wealth 2013-2015, income 2013-2015	11.16	8.60
	(1.74)	(1.76)
4. Wealth 2011-2015, income 2011-2015	11.32	8.61
	(1.74)	(1.76)
5. Wealth 2009-2015, income 2009-2015	11.51	9.04
	(1.75)	(1.76)
6. Wealth 2015, income 2015, in the labor force every year 2011-2015,	11.64	8.61
no unemployment 2011-2015	(2.32)	(2.34)
7. Wealth 2015, income 2015, stable relationship status 2011-2015	9.73	7.17
	(1.95)	(1.97)
8. Wealth 2015, income 2015, good health 2008-2015	11.00	7.95
	(1.94)	(1.96)

Notes: OLS regressions of within-cohort wealth percentile rank on the patience measure and other covariates. The table shows estimated coefficients for the patience measure. Robust standard errors in parentheses. The specification "With controls" includes the same control variables as column 3 in Table 2. Row 1 reproduces the regressions in columns 1 and 3 from Table 2. Row 2 controls flexibly for education by including indicators for 59 general educational groups instead of indicators for years of schooling. "Comparative literature studies", "economics" and "physics" are examples of general educational groups. Row 3 includes wealth rank (dependent variable) and income deciles computed within cohorts based on averages over 2013-2015, row 4 is similar, but wealth rank and income deciles are based on averages over 2011-2015 and in row 5, the two variables are based on averages over 2009-2015. Row 6 uses the baseline specification, but the estimations are based on the subset of respondents who were in the labor force every year in the period 2011-2015, and who were never unemployed in the period 2011-2015. Row 7 uses the baseline specification, but restricts the sample to respondents who had a stable relationship status (i.e. no spouse or the same spouse) in the period 2011-2015. Row 8 also uses the baseline specification, but restricts the sample to respondents whose socioeconomic status did not indicate poor health in the period 2008-2015. The number of observations is 3,620 in the "No controls" column and 3,552 in the "With controls" column. However, in row 6, that conditions on labor force participation and no unemployment, the number of observations is 2,265 and 2,243, respectively. In row 7 that conditions on stable relationship status, the number of observations is 2,704 and 2,651, respectively. Furthermore, row 8 that conditions on good health has 3,030 and 2,987 observations, respectively.