FACULTY OF SOCIAL SCIENCES
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PhD Thesis

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Patience, Risk Aversion, and Economic Behavior:

Combining Experimental Data with Administrative Register Data

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Acknowledgments

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Gregers Nytoft Rasmussen

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Summary

In models of economic behavior, assumptions about preferences are essential. Empirical knowledge about preferences is therefore important in explaining the behavior of individuals. This PhD thesis studies relationships between preferences and economic decision-making at the individual level. The work presented here is based on large-scale online experiments with more than 5,000 Danish respondents. The experiments involved incentivized intertemporal choices and investment choices designed to elicit measures of individual-level patience and risk aversion. The experimental preference measures are linked at the individual level to Danish third-party reported administrative register data. The work in this thesis distinguishes itself by facilitating a comparison between experimentally elicited preferences and long-term real-life economic behavior observed in the registers, while earlier studies have primarily evaluated the relationships between preferences and economic decision-making in short-term laboratory settings.

The thesis consists of three self-contained chapters, which all contribute to the understanding of how heterogeneity in preferences relates to actual economic decision-making at the individual level. In chapter 1, I document that time and risk preferences are important for behavior on the loan market in terms of several outcomes: loan to income ratios, the timing of first debt incurrence, interest rates paid on debt, the choice of mortgage loan, and delinquencies on loans. Chapter 2 investigates the relationship between time discounting and wealth inequality. We find a strong positive correlation between measured patience levels and the respondents' positions in the wealth distribution. In chapter 3, I study the association between preference heterogeneity and insurance demand and find positive relationships between insurance purchases and levels of risk aversion as well as patience.

The thesis establishes empirical evidence that experimentally elicited time and risk preferences are meaningfully correlated with observed real-life economic behavior. This suggests that experimental preference measures can be generalized to non-laboratory settings. Thus, the work presented here supports the external validity of such experimental preference measures.

Chapter 1: Patience, risk aversion, and debt behavior

This paper tests whether time and risk preferences are related to behavior on the loan market. Measures of patience and risk aversion are elicited for about 5,000 Danish participants in an incentivized online experiment. The experimental preference measures are matched to individual-level debt behavior in the field as observed in detailed administrative register data. I find that patient individuals have lower ratios of non-mortgage loan to income, postpone the incurrence of their first

non-mortgage debt further, pay lower average interest rates on their non-mortgage debt, are less likely to choose mortgages with deferred amortization (interest-only mortgages), and are less likely to be delinquent on loans. Furthermore, the results indicate that risk averse mortgage holders are less likely to choose adjustable-rate mortgages.

Chapter 2: Heterogeneous discounting behaviour and wealth inequality[1]

with Thomas Epper, Ernst Fehr, Helga Fehr-Duda, Claus Thustrup Kreiner, David Dreyer Lassen, and Søren Leth-Petersen

According to standard economic theory, differences in how much people discount the future generate differences in savings behaviour and thereby wealth inequality. To test this prediction, we use state-of-the-art experimental methods to elicit discounting behavior for a large sample of middle-aged individuals in Denmark and link these experimental data to administrative register data holding information about their real-life wealth over a period of 15 years. We find that individuals with relatively low discount rates are consistently positioned higher in the wealth distribution. The correlation between heterogeneity in discounting behaviour and the position in the wealth distribution is significant and of the same magnitude as the correlation between education and wealth, and it exists after controlling for education, income, initial wealth and parental wealth, suggesting that the savings mechanism is important. Finally, we show that the least patient individuals are more likely to be affected by liquidity constraints, consistent with models where liquidity constraints are self-imposed.

Chapter 3: Preference heterogeneity and insurance demand: Combining experimentally elicited time and risk preferences with data on insurance coverage at the individual level

This paper investigates the relationship between preference heterogeneity and insurance demand by combining Danish administrative register data with data from an incentivized large-scale experiment. The experiment was conducted on the Internet with about 5,000 Danish participants and included intertemporal choices and investment choices designed to elicit time and risk preferences of the respondents. Models of insurance demand predict a positive relationship between an individual's degree of risk aversion and the optimal level of insurance coverage, ceteris paribus, but are less clear-cut on the effect of time preferences on insurance demand. I study insurance demand in two separate domains: unemployment insurance and health insurance. The results indicate positive effects of

[1] A small part of this chapter builds on ideas first presented in my master's thesis. However, based on the collaboration with the co-authors of the chapter presented here, it has been completely rewritten and includes substantial new research results.

patience on the probability of having insurance coverage in both of the insurance domains and a positive effect of risk aversion on purchasing unemployment insurance.

Resumé (Danish summary)

Antagelser omkring præferencer er afgørende i modeller for økonomisk adfærd. Derfor er empirisk viden om præferencer vigtig for at forklare individers adfærd. Denne ph.d.-afhandling undersøger sammenhænge mellem præferencer og økonomisk beslutningstagen på individniveau. Afhandlingen er baseret på online-eksperimenter med over 5.000 danske deltagere. Eksperimenterne omfattede incitamentsbaserede intertemporale beslutninger og investeringsbeslutninger designet til at frembringe mål for tålmodighed og risikoaversion på individniveau. De eksperimentalle præferencemål sammenkædes med danske tredjepartsindberettede registerdata på individniveau. Denne afhandling skiller sig ud ved at muliggøre en sammenligning mellem eksperimentelt frembragte præferencer og længerevarende virkelig økonomisk adfærd observeret i registrene, mens tidligere studier hovedsageligt har evalueret sammenhænge mellem præferencer og økonomisk beslutningstagen i kortvarige laboratorieomgivelser.

Afhandlingen består af tre selvstændige kapitler, der alle bidrager til forståelsen af, hvordan heterogenitet i præferencer relaterer sig til virkelig økonomisk beslutningstagen på individniveau. I kapitel 1 dokumenterer jeg, at tids- og risikopræferencer har betydning for adfærd på lånemarkedet med hensyn til flere variable: Gæld relativt til indkomst, tidspunkt for første gældsstiftelse, renter betalt på gæld, valg af realkreditlån og misligholdelse af lån. Kapitel 2 undersøger sammenhængen mellem tidsdiskontering og formueulighed. Vi finder en stærk positiv korrelation mellem målte tålmodighedsniveauer og deltagernes placering i formuefordelingen. I kapitel 3 undersøger jeg sammenhængen mellem præferenceheterogenitet og efterspørgslen efter forsikring og finder positive sammenhænge mellem forsikringskøb og niveauer af risikoaversion samt tålmodighed.

Afhandlingen klarlægger empirisk evidens for, at eksperimentelt fremkaldte tids- og risikopræferencer er meningsfyldt korreleret med observeret økonomisk adfærd i virkelighedens verden. Dette tyder på, at eksperimentelle præferencemål kan generaliseres til omgivelser uden for laboratoriet. Dermed støtter afhandlingen den eksterne validitet af sådanne eksperimentelle præferencemål.

Chapter 1

Patience, risk aversion, and debt behavior

Gregers Nytoft Rasmussen, University of Copenhagen and CEBI[*]

September 2017

Abstract

This paper tests whether time and risk preferences are related to behavior on the loan market. Measures of patience and risk aversion are elicited for about 5,000 Danish participants in an incentivized online experiment. The experimental preference measures are matched to individual-level debt behavior in the field as observed in detailed administrative register data. I find that patient individuals have lower ratios of non-mortgage loan to income, postpone the incurrence of their first non-mortgage debt further, pay lower average interest rates on their non-mortgage debt, are less likely to choose mortgages with deferred amortization (interest-only mortgages), and are less likely to be delinquent on loans. Furthermore, the results indicate that risk averse mortgage holders are less likely to choose adjustable-rate mortgages.

[*] Department of Economics, University of Copenhagen, Øster Farimagsgade 5, building 26, DK-1353 Copenhagen K, Denmark (e-mail: gregers.nytoft.rasmussen@econ.ku.dk). The experiment referred to in this paper was organized by the following research group: Claus Thustrup Kreiner, David Dreyer Lassen, Søren Leth-Petersen, and Gregers Nytoft Rasmussen (University of Copenhagen), Ernst Fehr and Helga Fehr-Duda (University of Zurich), and Thomas Epper (University of St.Gallen). I would like to thank David Dreyer Lassen and audiences at the Spring School in Behavioral Economics - University of California San Diego, University of Zurich, and the Summer School on Socioeconomic Inequality – University of Bonn for helpful comments. I am grateful to FinanceDenmark for providing data on mortgage loans and to the Danish tax authority for providing data on loan delinquencies. The activities of Center for Economic Behavior and Inequality (CEBI) are financed by a grant from the Danish National Research Foundation. Financial support from the ERC Advanced Grant (Foundations of Economic Preferences, Project ID: 295642) is gratefully acknowledged.

1. Introduction

Access to the loan market is an important factor for many individuals in achieving goals such as smoothing consumption over time or purchasing a home. However, what drives individual debt behavior? The main contribution of this paper is to show empirically how time and risk preferences relate to behavior on the loan market. I measure levels of patience and risk aversion for approximately 5,000 Danish respondents. They participated in an incentivized Internet-based experiment involving intertemporal choices and investment choices designed to elicit time and risk preferences. The resulting preference measures are linked at the individual level with real-world debt behavior observable in Danish administrative register data. I study aspects of debt behavior in both the mortgage and the non-mortgage domains to embrace the loan market broadly. Debt outcomes that I consider are 1) non-mortgage loan to income ratio, 2) age at first incurrence of non-mortgage debt, 3) average interest rate paid on non-mortgage debt, 4) the chosen type of mortgage loan, and 5) delinquencies on loans. The register data are third-party reported which implies that potential biases of self-reported outcomes are avoided.[1]

My results show that heterogeneity in individual-level patience and risk aversion is important for debt behavior. Patient individuals have lower ratios of non-mortgage loan to income, postpone the incurrence of their first non-mortgage debt further, and pay a lower average interest rate on their non-mortgage debt once incurred. Apart from the timing of first non-mortgage debt, these relationships are maintained when controlling flexibly for socio-demographic variables. Regarding the choice of mortgage loan, I find a negative relationship between a mortgage holder's level of patience and the probability that he holds an Interest-Only Mortgage (IOM). Similarly, more risk averse mortgage holders are less likely to have chosen an Adjustable-Rate Mortgage (ARM). My finding that patience reduces the propensity to choose mortgages with deferred amortization coincides with the result that risk aversion reduces the probability of choosing mortgages with adjustable interest rates by being robust to controlling for a rich set of demographic, economic, and loan specific characteristics. I further show that individuals who are more patient are less likely to be delinquent on a loan. Again, this relationship is maintained when controlling for socio-demographic variables.

[1] For example, Zinman (2009) finds that survey respondents in the US Survey of Consumer Finances undercounted their credit card debt by at least 50 percent relative to industry data. Bucks & Pence (2008) use the same survey and compare self-reported information on mortgage terms with lender-reported data. They find that respondents tend to have imperfect recollection of mortgage contracts.

Given that I study aspects of debt behavior belonging to separate strands of literature, it is appropriate to describe how the paper relates to and contributes to existing works. This is the topic of the next section.

Relationship to literature

Several studies on debt-related outcomes have focused on the effect of financial literacy. For example, previous work finds that less financially literate individuals a) tend to use high-cost borrowing (Disney & Gathergood, 2013; Lusardi & de Bassa Scheresberg, 2013; Lusardi & Tufano, 2015; Stango & Zinman, 2009), b) are more likely to default on mortgages (Gerardi, Goette, & Meier, 2013), c) get less favorable terms on credit contracts (Levinger, Benton, & Meier, 2011), and d) are more likely to exhibit irresponsible credit card behavior (Robb, 2011). However, in spite of the standard theory of intertemporal choice highlighting that debt holding is related to time preferences (Fisher, 1930), there is little empirical evidence on how preferences affect debt behavior. Likely, this is because preferences are normally unobservable. Notable exceptions include the work of Stephan Meier and Charles Sprenger. They match experimental time preference measures to individual credit reports and annual tax returns. Meier & Sprenger (2010) find that present-biased individuals are more likely to have credit card debt, and – conditional on borrowing – present-biased individuals have higher amounts of credit card debt. Meier & Sprenger (2012) discover a positive relationship between an experimental measure of individual-level patience and creditworthiness as measured by the Fair Isaac Corporation (FICO) credit score.

It is conceivable that individual-level financial literacy is related to time preferences. The acquisition of financial knowledge can be seen as an investment in human capital in which the acquisition is costly in the present and is expected to give a positive return in the future. Given this intertemporal trade-off, heterogeneity in individual-level time preferences should play a role in determining how much an individual has invested in financial knowledge. Ceteris paribus, individuals who are more patient should be willing to invest more in acquiring financial knowledge. This is supported by Jappelli & Padula (2013). Meier & Sprenger (2013) provide evidence on this hypothesis. They conduct a field study in which individuals are offered the possibility to participate in a free, short financial education program. Time preferences are measured for individuals who choose to participate in the financial education program as well as for those who choose not to. The study finds that a) more patient individuals have higher levels of financial knowledge, and b) that more patient individuals are more likely to participate in the offered financial education program and acquire financial knowledge. The latter correlation is maintained when controlling for socio-demographic characteristics and prior financial knowledge.

In sum, previous literature informs that financial literacy is related to behavior on the credit market, but also that financial literacy is associated with deep preferences. In this paper, I investigate further the roles of time and risk preferences in debt behavior at the individual level.

A growing body of research focuses on the choice of mortgage type. Campbell & Cocco (2003) focus on how households choose between a Fixed-Rate Mortgage (FRM) and an Adjustable-Rate Mortgage (ARM) in the context of a life-cycle model. Among other things, they study how risk and time preferences affect the optimal mortgage choice. The main disadvantage of ARMs is that payments may rise suddenly as the interest rate varies in relation to market conditions. If income does not increase accordingly, the buffer-stock savings of a household could be exhausted and force a reduction in consumption (cash-flow risk). With an FRM, the borrower pays a fixed interest rate each period. The disadvantage of an FRM is that the interest rate is usually higher than the interest rate on an ARM because the lender requires a term premium and a prepayment risk premium on the FRM. Furthermore, if inflation and nominal interest rates fall, the interest rate on an FRM will remain constant (inflation risk) whereas it will fall for an ARM. In Campbell & Cocco's model, more risk averse households place higher importance on the cash-flow risk of ARMs (potential for higher interest payments) and thus ARMs are less beneficial to risk averse households. The effect of time preferences on the choice between an FRM and an ARM is ambiguous in Campbell & Cocco's model. A more impatient household will accumulate a smaller buffer-stock of liquid financial assets. On the one hand, impatient households are therefore more exposed to the cash-flow risk of ARMs (have to reduce consumption more in case of an increase in the interest rate) which makes ARMs less beneficial. On the other hand, impatient households are also more exposed to the inflation risk of FRMs, as they have less money to pay refinancing/prepayment fees in the event of decreasing interest rates. This makes FRMs less beneficial.

The determinants of mortgage choices have also been analyzed empirically. Some studies have focused on the repayment type (repayment mortgage vs. alternative mortgage product/IOM) (e.g. Cocco, 2013; Cox, Brounen, & Neuteboom, 2015; Gathergood & Weber, 2017; LaCour-Little & Yang, 2010), while others have studied the interest rate type (FRM vs. ARM) (e.g. Gathergood & Weber, 2017; Koijen, van Hemert, & van Nieuwerburgh, 2009). I contribute to this research by analyzing how time and risk preferences affect people's mortgage choices with respect to the repayment type as well as the interest rate type. The present paper is believed to be the first to combine incentivized, experimental preference measures with field data on mortgage choices.

I also contribute to the literature on the determinants of credit default. Examples of prior papers that use household-level data to study defaulting behavior are Fay, Hurst, & White (2002) who find that households are more likely to default when the associated financial benefit is higher, and Gross & Souleles (2002) who conclude that lower costs of defaulting may increase the propensity to default. Thus, these studies support the idea that defaulting is a strategic decision. However, from an intuitive perspective, defaulting behavior can also be viewed as an intertemporal choice. The benefit of defaulting (not servicing one's debt) is realized in the immediate future, while the costs of defaulting (future exclusion from the loan market and social stigma) must also be endured in the more distant future. Therefore, patient individuals, who assign a higher value to future costs, are expected to default less. Meier & Sprenger (2012) provide indirect support for this. They find that higher individual-level patience is associated with higher creditworthiness as measured by the FICO credit score. By combining in the present paper an experimental patience measure with administrative data on loan delinquencies reported by financial institutions, I further substantiate the hypothesis that individual time preferences are predictive for the repayment of borrowed money.

The remainder of the paper is organized as follows: Section 2 describes the design of the Internet-based experiment and introduces the experimental preferences measures as well as the administrative data, section 3 presents and discusses the results, and section 4 concludes.

2. Experimental design and data[2]

The Internet-based experiment was conducted in two waves in February 2015 and June 2016. The main part of the experiment consisted of interactive saving and investment choice situations designed to elicit time and risk preferences of respondents. Besides choice tasks, respondents filled out an online questionnaire.[3] We recruited respondents who satisfied the following two criteria: 1) born in the period 1973-1986, and 2) resided in Copenhagen Municipality (Københavns Kommune) when they were seven years old.[4] Statistics Denmark, the central authority on Danish statistics, provided a dataset of all of the 36,047 individuals who met the sample criteria. The dataset contained names,

[2] The descriptions of the experimental design and the measures of patience and risk aversion are abbreviated versions of those found in Rasmussen (2017).

[3] For example, the online questionnaire asked the respondents to state their most recent math grade obtained in school and to self-report their level of risk aversion.

[4] This geographical screening was chosen to be able to merge the experimental data with the Copenhagen School Health Records Register for another research project.

current addresses, and civil registration numbers. We invited everyone in the gross sample to participate by sending personal invitation letters in hard copy. Each letter contained a unique username and password combination needed to log in.

After logging in to the web page, respondents were presented with thorough instructions. Decisions in the choice tasks were incentivized such that respondents were motivated to reveal their preferences truthfully by making considered decisions. At the end of the experiment, one of the choice situations was drawn at random, and payoffs were paid out according to the choice of the respondent in the drawn situation. The payouts were transferred directly to the personal bank accounts of the respondents. The average payout was 251 DKK.[5] See Rasmussen (2017) for further details on the experimental setup.

Additional discussion on the saving choices in the experiment is given below.

Measuring patience

All respondents were presented with 5 saving choices to elicit their levels of patience.[6] In each saving situation, we asked the respondents to distribute 10 blocks of points between two accounts. One account promised a smaller but sooner payout and the other promised a larger but later payout. Specifically, the sooner payout account would be paid out 8 weeks and two days after participation and the later payout account would be paid out 16 weeks and two days after participation. This front-end delay was incorporated in the saving situations to elicit a longer-run patience measure. If the sooner payout account would have been paid out immediately after participation, hyperbolic discounting (present bias/decreasing impatience) might induce a bias in the longer-run patience measure (Frederick, Loewenstein, & O'Donoghue, 2002).

Appendix 5.1 shows a screenshot of one of the saving situations. In this example, the respondent has allocated five blocks to the 8 weeks' account and five blocks to the 16 weeks' account. Each block allocated to the 8 weeks' account was worth 100 points and each block allocated to the 16 weeks' account was worth 105 points. 100 points corresponded to 25 DKK. If this saving choice was selected randomly at the end of the experiment, the respondent would receive 125 DKK 8 weeks and two days after participation and 131.25 DKK 16 weeks and two days after participation.

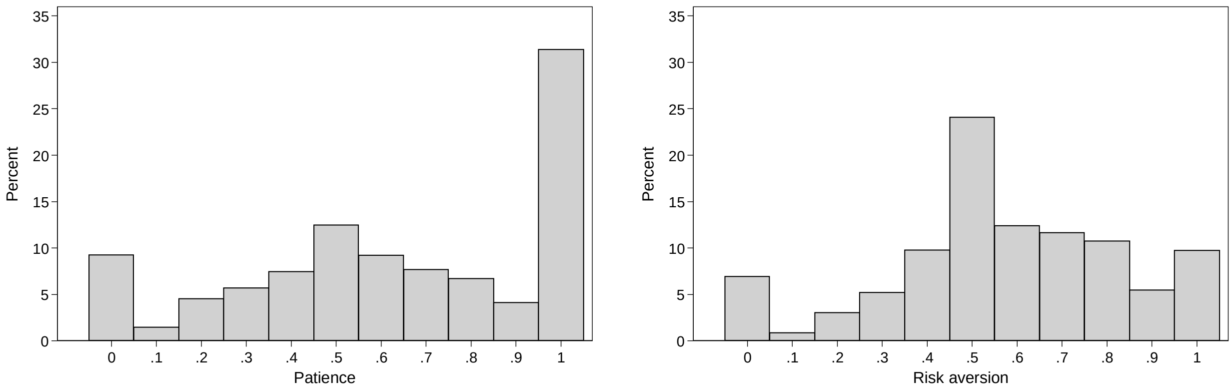
The value of the blocks on the 8 weeks' account was kept constant at 100 points throughout the five 8 vs. 16 weeks' choices. The value of the blocks on the 16 weeks' account varied between 105,

[5] 1 USD ≈ 6.5 DKK during both experimental waves.
[6] The saving choices are inspired by Andreoni & Sprenger (2012). However, we used a graphical interface to present the saving choices and showed only one choice per page.

110, 115, 120, and 125 points. The order of the saving situations was randomized. The starting point for the five choice situation was that all 10 blocks were placed on the 8 weeks' account. We then asked the respondents to choose a distribution of the 10 blocks between the two accounts.[7] We deliberately framed the choice situation as a saving decision in order to make it less abstract. The instructions explained that you would get an *interest income* if you chose to *save* the blocks, i.e. place them on the 16 weeks' account. See the last section of the thesis for an English transcript of the instructions.

I measure the patience level for each respondent by computing the median number of saved blocks across the five 8 vs. 16 weeks saving situations and normalizing by 10.[8] The research question of the present paper requires a reliable measure of the heterogeneity in patience *between* respondents while accurate estimates of the level of patience are not necessary. I will study between-respondent variation in patience levels and its relation to debt behavior directly in terms of how many blocks the respondents chose to save in the saving situations rather than estimating a discounting model for time preferences based on the choices. The advantage of this model-free approach is that I avoid introducing assumptions about parameter values. The left panel in figure 2.1 shows the distribution of the constructed non-parametric patience measure.

Figure 2.1: Distributions of the patience and risk aversion measures.



Notes: 5,082 respondents. Only respondents for whom a full set of register variables is available are included.
Left-hand panel: Distribution of the patience measure. $Patience = median\left(\frac{\#\ of\ blocks\ saved}{10}\right)$.
Right-hand panel: Distribution of the risk aversion measure.
$Risk\ aversion = median\left(\frac{\#\ of\ blocks\ kept\ at\ risk{-}free\ account}{10}\right)$.

[7] To avoid status quo bias, we designed the user interface such that the respondent had to make an active choice. Specifically, as the respondent moused over one of the accounts vertically, a blue saving bar summarized the outcomes of each allocation (see appendix 5.1). The respondent was only able to confirm his decision and move on after actively choosing one of the allocations.

[8] The results presented in the paper do not change if I use the arithmetic mean to aggregate the five saving situations instead.

Measuring risk aversion

The respondents were also given 5 separate investment situations in which they had to allocate 10 blocks of points between a risky investment project and a risk-free account where the payout was certain.[9] In each investment situation, there was a 50-50 probability that the investment project would turn out to be favorable or unfavorable (zero skewness).[10] The order of investment situations was randomized. Appendix 5.2 shows a screenshot of a sample investment situation. In this example, the respondent has allocated five blocks to the risk-free account and five blocks to the risky investment project. The value of blocks on the risk-free account was kept constant at 100 points throughout the five investment situations, whereas the value of blocks in the risky investment project differed across the five situations. The expected value of the investment project as well as the spread between the point value in the favorable and the unfavorable outcome varied. The point values were 121 vs. 81, 131 vs. 71, 135 vs. 75, 151 vs. 50, and 161 vs. 60 such that the expected value of a block allocated to the investment project was greater than the 100 points in the risk-free alternative in all five situations.

Similar to the patience measure, I compute the level of risk aversion for each respondent by taking the median number of blocks allocated to the risk-free account across the five investment situations and normalizing by 10.[11] The right panel in figure 2.1 shows the distribution of this non-parametric risk aversion measure.

Administrative register data

The experimental sample consists of 5,207 respondents. The choice data from the experiment are linked with Danish administrative register data at the individual level.[12] The register data can be

[9] Our procedure is inspired by Gneezy & Potters (1997), but we depict the investment situations graphically.

[10] The favorable vs. unfavorable outcome of an investment situation would only be determined if it was drawn at random to be the choice situation relevant for payout at the end of the experiment.

[11] Again, the results presented in the paper do not change if I use the arithmetic mean to aggregate the five investment situations instead.

[12] The participants were not informed that the data from the experiment would be linked with the administrative register data, and they were therefore not asked to give their consent to this. The Danish Data Protection Agency has approved the research project and this procedure. To merge the experimental data with the register data, the usernames provided in the invitation letters were translated into anonymized civil registration numbers. It is important for the linkage between experimental and register data that the respondents in the experiment are identical to the people who were actually invited. Since the experiment was executed online, one cannot be certain that the respondents in the experiment exclusively consist of people who were invited to participate. Though the invitation letter requested that the log in details were not passed on to others, it is possible that some of the invited subjects let e.g. a colleague or another member of the household participate instead. This is problematic in the sense that the experimental choices of individual x would be linked with register data for individual y. To reduce this source of error, the respondents were asked to state their gender and year of birth first thing after logging in to the experiment. 79 respondents for whom the stated gender and/or year of birth is not identical to the information in the register data are excluded from the analysis. The fact that the payouts from the experiment were transferred directly to the personal bank accounts of the invited individuals might have reduced the prevalence of such spurious respondents.

categorized into three different types. First, I apply data on mortgage loans provided by FinanceDenmark, the trade association for banks and mortgage institutions in Denmark. The mortgage institutions in Denmark lend both ARMs and FRMs with a maximum maturity of 30 years. Danish FRMs are similar to those known from the US with a fixed interest rate for the full term of the mortgage. Since 2003, the mortgage institutions have also offered IOMs with up to 10 years of interest-only payments allowing the lender to reduce the mortgage payments in the beginning of the mortgage period. When the period of deferred amortization expires, the principal is to be repaid over the remaining maturity unless the loan is refinanced. IOMs can be established as either ARMs or FRMs. The loans are secured on real property, and the legal lending limit is a loan to value (LTV) ratio of 80 percent for private residential property. Mortgage institutions are not allowed to charge individual-specific interest rates or fees.

The dataset holds detailed loan information about every mortgage contract held by the experimental respondents at the end of year 2014, and it allows me to identify the repayment type (repayment mortgage vs. IOM) and the interest rate type (FRM vs. ARM) of respondents' mortgages. These will be the dependent variables in the following analysis of mortgage choices. Furthermore, the data includes the year of mortgage origination and the mortgage institutions' valuations of loan specific LTV ratios. The LTV ratio is defined as the mortgage institution's assessment of the size of the remaining debt relative to the sales value of the property provided as collateral for the loan. In the analysis of mortgage choices, I will only consider mortgage holders whose mortgage loans are based on owner-occupied homes. This leaves 1,514 mortgage holders among the respondents.[13] In Denmark, all mortgage loans are recourse, which implies that it is not possible to strategically default on a mortgage by walking away from the property. The debt follows the borrower, and he remains liable to repay the potential deficiency after a foreclosure auction. This makes it unattractive to default on mortgages. In fact, only one of 1,514 mortgage holders in the sample was delinquent on a mortgage by the end of 2014.

The second type of register data is provided by the Danish tax authority and includes administrative register data containing information on any delinquencies on both non-mortgage and mortgage loans held by respondents at the end of year 2014.[14] The dataset defines a loan to be delinquent if a payment obligation is more than 60 days overdue.

[13] 24 of the 1,514 respondents with mortgage loans held mortgages on two owner-occupied homes. For these respondents, I use the highest LTV ratio over their two homes.

[14] Kreiner, Leth-Petersen, & Willerslev-Olsen (2017) have used the same data set to study the intergenerational correlation in financial trouble.

The third type of data includes demographic characteristics from public administrative registers and individual-level information from the income tax register. The income tax register holds information on annual income as well as values of assets and liabilities at the end of each year going back to 1987. Data are available up to and including 2014.

A common feature of all the register data is that it is third-party reported. For example, employers report earnings, government institutions report transfer payments, and information on assets, liabilities, mortgage contract details, and loan delinquencies is reported by financial institutions. This is an advantage compared to related empirical literature that relies on self-reported survey measures, which makes the accuracy of such responses difficult to assess.

I also have access to register data for any potential partners of the respondents. In the analyses of the relationships between preferences and mortgage choices, I will include several control variables at the household level to account for the fact that the financing of a home is often decided together with a partner.

Table 2.1 reports means of the above-mentioned variables. I focus on the 5,082 respondents for whom a full set of register variables is available. Column (1) shows mean values for the full sample. Column (2) compares the subsample of mortgage holders with the subsample of non-mortgage holders. Mortgage holders make up about 30 percent of the full sample (1,514 respondents). The reported p-values refer to unconditional t-tests of equality of means. Compared to non-mortgage holders, mortgage holders are, on average, older, more likely to have a partner, and more likely to have children. Furthermore, mortgage holders have higher educational attainment, higher income (both at individual and household levels), and have more debt relative to income on average.

Columns (3) and (4) focus on mortgage holders and divide them by mortgage repayment type and mortgage interest rate type, respectively. These divisions are relevant for the analysis of mortgage choice. 55 percent of the mortgage holders have at least one IOM, while 45 percent hold repayment mortgages exclusively. 68 percent hold at least one ARM and 32 percent hold FRMs exclusively. It is noted that column (3) shows that IOM holders, on average, have less liquid assets relative to their disposable income, pay higher average interest rates on their non-mortgage debt, and have higher mortgage loan to value ratios compared to the holders of repayment mortgages. In conclusion, this suggests that IOMs and the lower payments that they provide appeal more to households who are short of liquidity. Turning to the interest rate type, column (4) shows that holders of FRMs have refinanced their mortgage more recently than ARM holders. Across all mortgage holders, the average time since the most recent mortgage refinance is 2.5 years.

The lower part of table 2.1 presents means of relevant variables from the online experiment. Column (3) shows that holders of IOMs are, on average, less patient, and column (4) displays that holders of ARMs are less risk averse on average. In the results section, I use regression analysis to study the roles of patience and risk aversion in mortgage choices.

Table 2.1: Summary statistics – comparison of means.

	(1)	(2) Mortgage vs. non-mortgage holders			(3) Mortgage repayment type			(4) Mortgage interest rate type		
	Full sample	Mortgage holders	Non-mortgage holders	p-value	Repayment mortgage	Interest-only mortgage	p-value	Fixed-rate mortgage	Adjustable-rate mortgage	p-value
Administrative data										
Age	34.175	35.784	33.492	0.000	36.192	35.445	0.000	35.288	36.020	0.000
Woman (=1)	0.504	0.480	0.515	0.025	0.480	0.480	0.991	0.458	0.491	0.235
Single (=1)	0.335	0.116	0.429	0.000	0.127	0.108	0.251	0.090	0.129	0.028
Dependent children (=1)	0.486	0.708	0.392	0.000	0.693	0.721	0.236	0.669	0.727	0.020
Years of education	14.408	15.188	14.077	0.000	15.319	15.079	0.043	15.197	15.184	0.916
Ln(total income)	12.633	12.916	12.513	0.000	12.943	12.894	0.083	12.899	12.925	0.392
Non-mortgage loan to income ratio	1.016	1.244	0.919	0.404	0.448	1.906	0.215	0.705	1.502	0.525
Ln(total household income)	13.090	13.538	12.900	0.000	13.555	13.525	0.257	13.533	13.541	0.787
Liquid assets to disp. income ratio, household level	0.530	0.426	0.574	0.116	0.531	0.339	0.000	0.437	0.421	0.754
Loan to income ratio, household level	1.935	4.345	0.912	0.000	3.264	5.243	0.350	2.616	5.170	0.258
Age at first incurrence of non-mortgage debt	21.095	21.336	20.990	0.000	21.534	21.181	0.014	21.534	21.245	0.059
Average interest rate, non-mortgage debt (%)	4.053	4.513	3.858	0.000	3.797	5.107	0.000	4.306	4.611	0.124
Household average interest rate, non-mortgage debt (%)	4.129	4.590	3.934	0.000	3.978	5.098	0.000	4.450	4.657	0.273
Mortgage loan to value ratio		0.753			0.699	0.799	0.000	0.756	0.752	0.742
Years since latest mortgage refinance		2.507			2.560	2.463	0.458	1.650	2.916	0.000
Loan delinquency	0.086	0.017	0.116	0.000	0.007	0.024	0.010	0.012	0.019	0.371
Experimental data										
Patience	0.633	0.655	0.624	0.003	0.689	0.626	0.000	0.661	0.652	0.602
Risk aversion	0.571	0.557	0.577	0.010	0.563	0.551	0.352	0.579	0.546	0.019
Self-reported risk aversion	4.208	4.211	4.207	0.942	4.338	4.105	0.002	4.481	4.082	0.000
Self-reported math grade	8.764	8.944	8.686	0.000	9.044	8.861	0.066	8.906	8.961	0.604
Observations	5082	1514	3568	5082	687	827	1514	489	1025	1514

Notes: The p-values are from unconditional t-tests of equality of means. Register variables are based on 2014 values. (=1) indicates a dummy variable which takes the value 1 for respondents who satisfy the description given by the variable name. Liquid assets include bank deposits and market values of stocks and bonds. Income ratios are based on annual income. When determining the age at first incurrence of non-mortgage debt, I use age 28 as a cutoff to balance the sample. The youngest birth cohort in the sample (1986) is 28 years old in year 2014, which is the last year of observable non-mortgage debt. 91.4 percent of the sample was 28 years of age or younger at their first incurrence of non-mortgage debt. For the remaining respondents, I set the age at first non-mortgage debt incurrence to missing. In this table, the interest rate paid on non-mortgage debt is set equal to zero for individuals/households who do not hold non-mortgage debt. The table includes both the experimental measure of risk aversion and a self-reported risk aversion measure. The self-reported measure will be introduced in the results section. Only 4,640 of the 5,082 respondents reported a math grade.

Having access to anonymized civil registration numbers of all individuals in the gross sample, I can compare the register-based characteristics of the respondents and the non-respondents. Column (1) in appendix 5.3 tests the significance of the differences in means across respondents and non-respondents for everyone in the gross sample with a full set of register data available (t-tests). On average, respondents are less likely to be singles, more likely to be homeowners, have higher educational attainment, have higher income, and hold more liquid assets. To take into account the selection into the experiment, I have estimated the probability that an individual from the gross sample chose to participate based on the characteristics included in appendix 5.3. All regressions presented in the paper have been repeated weighting each observation with the inverse of the probability that the individual participated. This is done to inflate the weight for respondents who are underrepresented in terms of observable characteristics. If the observable characteristics predict the decision to participate sufficiently, the selection can be ignored when weighting with the inverse of the participation probability. The estimated effects presented in the paper are robust to this sensitivity analysis (not reported).

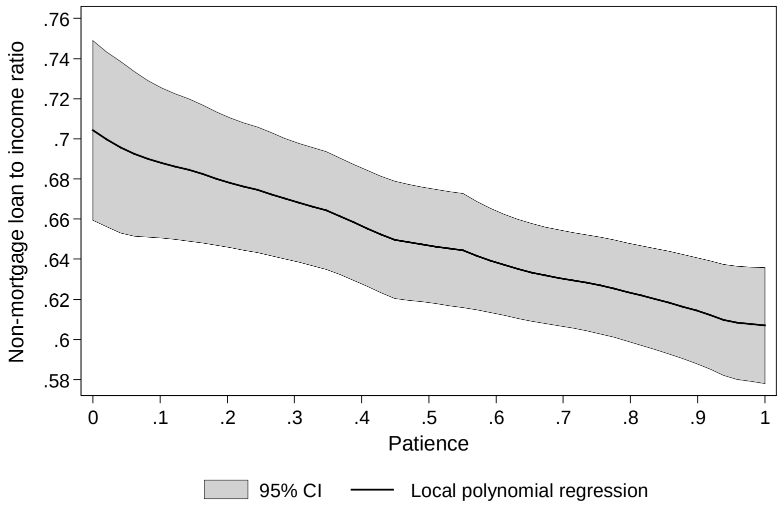
The gross sample includes everyone who lived in Copenhagen Municipality when they were seven years old. Therefore, it is relevant to test whether the average characteristics of the gross sample differ from those of the rest of the population. Column 2 in appendix 5.3 compares the gross sample with a 10 percent random sample of the Danish population who are not in the gross sample (i.e., did not live in Copenhagen Municipality when they were seven years old), but who were born in the same period (1973-1986). Most notably, the table shows that the share of singles is larger, and the share of homeowners is smaller in the gross sample relative to the 10 percent sample. To allow for the differences between the 10 percent sample and the respondents in terms of the observable characteristics in appendix 5.3, I have also run the regressions in the paper using inverse probability weights to adjust for this (not reported). Again, the results do not deviate noticeably from what is presented in the paper.

3. Results and discussion

Patience and non-mortgage loan to income ratio

The first and broadest debt outcome that I consider is the ratio of non-mortgage loan to annual income**.** Intertemporal choice theory (e.g. Fisher, 1930) predicts that patience is negatively related to debt accumulation. To test this prediction, figure 3.1 plots a local polynomial regression curve of the non-mortgage loan to income ratio against the patience measure. The figure confirms the negative correlation predicted by the theory.

Figure 3.1: Non-mortgage loan to income ratio plotted against patience.



Notes: 5,082 observations. Local polynomial regression of non-mortgage loan to income ratio on the patience measure. Non-mortgage loan to income ratio is censored at p95.

Next, I examine whether the negative correlation found in figure 3.1 is maintained when controlling for covariates. Table 3.1 presents results from OLS regressions of the non-mortgage loan to income ratio on the measure of patience and other covariates. Column (1) shows output from a regression that only includes the experimental preference measures. Column (2) extends the analysis by adding income, educational attainment, and other demographic characteristics. The negative effect of patience remains significant at the 1 percent level in column (2). Going from minimum to maximum patience (0 to 1) is associated with a reduction in the non-mortgage loan to income ratio of about 0.09 on average.

A potential confounding factor in the analysis is financial literacy/cognitive ability. It is conceivable that debt accumulation as well as measures of risk aversion and patience are correlated with cognitive ability. This might not be a problem in the present analysis, as I include income and educational attainment in the regressions, which are likely to serve as proxies for cognitive ability. However, Dohmen, Falk, Huffman, & Sunde (2010) studied a representative sample of the adult German population and found that people with higher cognitive ability are significantly more risk willing and significantly more patient. The correlations in their study remain significant when controlling for personal characteristics, income, and educational attainment.[15] Column (3) in table 3.1 adds flexible dummies for the most recent math grade obtained in school to further control for financial literacy and cognitive ability.[16] The inclusion of math grade dummies does not affect the estimate of the impact of the patience measure.

Table 3.1: Non-mortgage loan to income ratio regressed on covariates (OLS).

	(1)	(2)	(3)
Patience	-0.127 ***	-0.088 **	-0.090 **
	(0.033)	(0.033)	(0.035)
Risk aversion	-0.041	-0.073	-0.047
	(0.042)	(0.041)	(0.043)
Income decile dummies	No	Yes	Yes
Year dummies for educational attainment	No	Yes	Yes
Demographic characteristics	No	Yes	Yes
Math grade dummies	No	No	Yes
Constant	0.746 ***	-1.683 *	-1.413
	(0.036)	(0.823)	(0.921)
Observations	5082	5082	4640

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. The number of observations decreases in column (3) due to some of the respondents not reporting a math grade. Non-mortgage loan to income ratio is censored at p95.

17.6 percent of the respondents do not have any non-mortgage debt. To take these corner solution responses into account, appendix 5.4 reproduces the results in table 3.1 using tobit regressions. The results in appendix 5.4 show that the estimated negative effect of patience on the non-mortgage loan to income ratio is robust to this exercise.

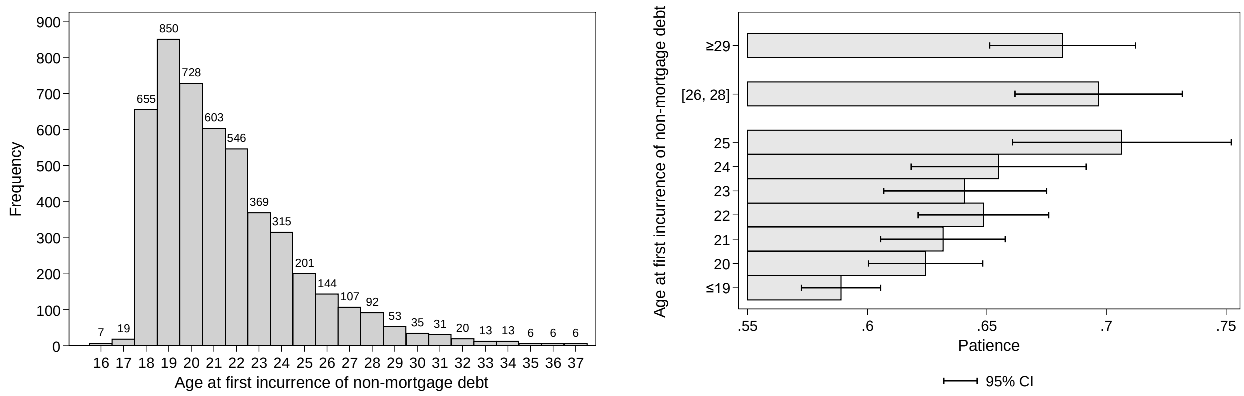
[15] Nevertheless, a recent experimental study suggests that cognitive ability is correlated with random decision making rather than with risk preferences (Andersson, Holm, Tyran, & Wengström, 2016).

[16] Agarwal & Mazumder (2013) find specifically that math scores are important for household financial decision-making. In their study, individuals with higher math scores are less likely to make well-defined financial mistakes. Additionally, a recent publication by PISA reports a strong correlation between students' financial literacy and mathematics performance (OECD, 2017).

Patience and timing of first non-mortgage debt

Economic intuition suggests that time discounting and timing of first debt incurrence are related. One would expect individuals who are less patient to incur their first debt sooner in order to enjoy a higher current consumption. The longitudinal dimension of the administrative data enables tracking at which age respondents incurred their first non-mortgage debt. I only include loan amounts greater than 1,000 DKK (≈ 154 USD). In this study, non-mortgage debt includes, e.g., credit cards, consumer loans, car loans, and regular bank loans, but excludes State education loans. The left panel in figure 3.2 shows the distribution of age at first incurrence of non-mortgage debt. The histogram shows a jump in first debt incurrence at age 18 when respondents become of legal age. The distribution peaks at age 19 and decreases with age afterward. The fact that the peak is at 19 and not 18 years of age is explained by both age and non-mortgage debt being measured at the end of each calendar year. Hence, respondents born late in the year have had little time as 18-year-olds to borrow legally until the balance sheet date. The year in which the respondents turn 19 is the first year where they have been able to borrow legally during the entire year.

Figure 3.2: Age at first incurrence of non-mortgage debt.



Notes: Non-mortgage debt observed in the period 1987-2014. 4,646 out of 5,082 respondents (91.4 percent) were of age 28 or younger when incurring their first non-mortgage debt.
Left-hand panel: Distribution of age at first incurrence of non-mortgage debt. Truncated at age 16 and 37.
Right-hand panel: Average value of the patience measure by age at first non-mortgage debt incurrence. Patience and age at first incurrence of non-mortgage debt are positively correlated: Spearman's rho = 0.105; p-value = 0.000 (using data from 4,646 respondents).

The right panel in figure 3.2 shows the relationship between age at first incurrence of non-mortgage debt and the experimental patience measure. The panel plots the average value of the patience measure for each age group. The youngest birth cohort in the sample (1986) is 28 years old in year 2014, which is the last year of observable non-mortgage debt. Consequently, I use age 28 as the cutoff in the figure. 91.4 percent of the sample had incurred their first non-mortgage debt by age 28.[17] The right panel shows a positive correlation: The longer the respondents postponed the incurrence of their first non-mortgage debt, the more patient they are on average (Spearman's rho = 0.105; p-value = 0.000). This confirms the above-mentioned intuition. In addition, the association between the experimental patience measure and the timing of the respondents' first debt incurrence observed several years prior suggests that the patience measure reflects fundamental and stable time preferences.

Patience and interest rates paid on non-mortgage debt

Empirical work by Disney & Gathergood (2013); Lusardi & de Bassa Scheresberg (2013); Lusardi & Tufano (2015); Stango & Zinman (2009) finds that less financially literate individuals are more likely to use high-cost borrowing. However, as documented by Meier & Sprenger (2013), the acquisition of financial literacy is related to time preferences. In this section, I explore whether individuals who are less patient tend to use high-cost borrowing. To do this, I consider the average interest rate paid on non-mortgage debt by each respondent, conditional on having non-mortgage debt. I approximate the average interest rate paid by each individual as $r_i = \frac{R_i^{14} * 100}{\frac{1}{2}(D_i^{13} + D_i^{14})}$, where R_i^{14} is the total non-mortgage interest payments for individual i during 2014, D_i^{13} is individual i's amount of outstanding non-mortgage debt at the end of 2013, and D_i^{14} is the amount of outstanding non-mortgage debt held by individual i at the end of 2014. I compute the average interest rates for those 3,958 respondents for whom the denominator is greater than 1,000 DKK ($\approx$ 154 USD). The resulting interest rates are censored at the 5th and the 95th percentiles.[18] The left panel in appendix 5.5 shows the distribution of the computed interest rates.

Table 3.2 shows results from OLS regressions of the computed average interest rate on the measures of patience and risk aversion and other covariates. Column (1) shows a negative relationship between patience and the paid average interest rate. Column (2) includes income decile dummies and

[17] The administrative information on non-mortgage debt is missing in the dataset for year 1994. This means that the analysis overvalues the age of first non-mortgage debt incurrence for respondents who took out their first non-mortgage debt in 1994. As a result, I have run a robustness check including only respondents who were born in the period 1977-1986. These respondents were maximum 18 years old in 1995, which is the first year after the break in the time series. Consequently, this subsample became of legal age after the data break. The result is convincingly robust and shows a positive correlation between patience and age at first incurrence of non-mortgage debt (Spearman's rho = 0.098; p-value = 0.000).

[18] This approximation of the average interest rate is exact if the debt evolves linearly between 2013 and 2014. If it does not, the computation of the average interest rate may introduce a measurement error.

flexible dummies for educational attainment along with other demographic characteristics. The negative effect of patience remains significant at the 1 percent level. Going from minimum to maximum patience (0 to 1) is associated with a reduction in the paid interest rate of about 0.5 percentage points on average.

Column (3) adds self-reported math grades obtained in school as a supplementary proxy for cognitive ability. The inclusion of math grade dummies does not affect the estimated effect of patience on paid interest rates.

Table 3.2: Average interest rate paid on non-mortgage debt (%) regressed on covariates (OLS).

	(1)	(2)	(3)
Patience	-0.689 ***	-0.526 **	-0.553 **
	(0.179)	(0.175)	(0.182)
Risk aversion	-0.567 *	-0.189	-0.217
	(0.236)	(0.232)	(0.241)
Income decile dummies	No	Yes	Yes
Year dummies for educational attainment	No	Yes	Yes
Demographic characteristics	No	Yes	Yes
Math grade dummies	No	No	Yes
Constant	5.954 ***	-8.427	-8.111
	(0.194)	(4.748)	(5.205)
Observations	3958	3958	3636

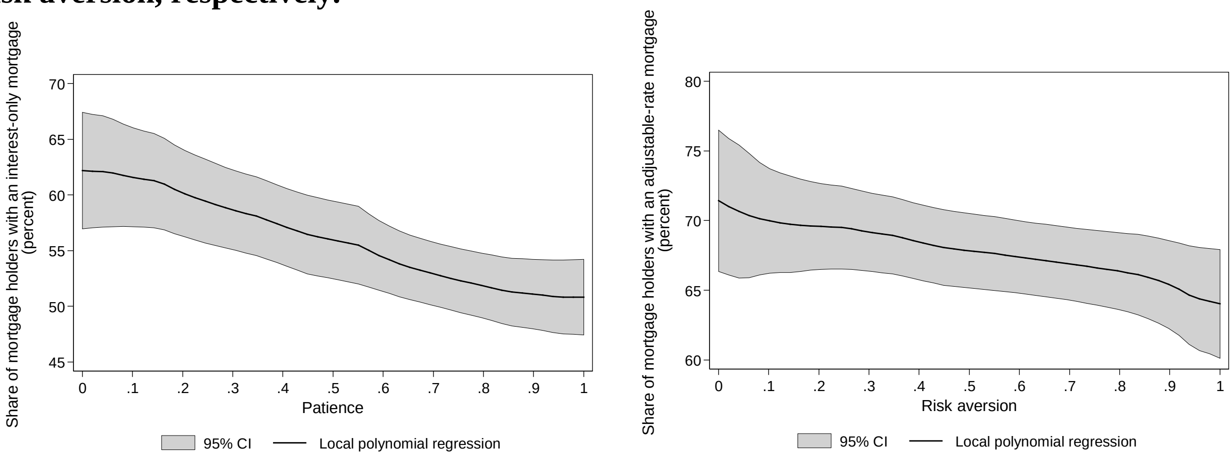
Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. The number of observations decreases in column (3) due to some of the respondents not reporting a math grade.

The documented negative relationship between patience and paid interest rates is interesting in itself as it suggests that behavior on the loan market relates to time preferences. People borrow money to increase current consumption at the expense of future consumption. Therefore, the interest rate on debt can be viewed as the price paid for being impatient, where individuals who are more patient pay a lower price on average. Furthermore, the relationship between patience and interest rates will be taken into account in the following section on mortgage choice.

Preferences and mortgage choice

The above analyses have shown that patient individuals have lower ratios of non-mortgage loan to income, postpone the incurrence of their first non-mortgage debt further, and that they pay a lower average interest rate on their debt once incurred. This section studies relationships between the experimental preference measures and mortgage choices in the field. The left panel in figure 3.3 plots a local polynomial regression curve of the share of mortgage holders holding IOMs against the patience measure. The right panel plots the share of mortgage holders holding ARMs against the measure of risk aversion. The plots indicate a negative relationship between patience and the probability of holding an IOM and a negative (but less significant) relationship between risk aversion and ARM holding.

Figure 3.3: Interest-only mortgage and adjustable-rate mortgage plotted against patience and risk aversion, respectively.



Notes: 1,514 observations. Mortgage type identified based on detailed loan information from Danish mortgage institutions on every mortgage contract held by the experimental respondents at the end of year 2014.
Left-hand panel: Local polynomial regression of the share of mortgage holders holding IOMs on the patience measure.
Right-hand panel: Local polynomial regression of the share of mortgage holders holding ARMs on the risk aversion measure.

Next, I estimate probit regressions to substantiate the relationships between the experimental preference measures and mortgage choices. The dependent variable is a dummy variable for the type of mortgage (IOM vs. repayment mortgage and ARM vs. FRM, respectively). The independent variables will include the experimental preference measures and household-level control variables on income, liquid asset holdings, loan to income ratio (mortgage and non-mortgage loans combined), and the average interest rate paid on non-mortgage debt.[19] These four control variables are included to attenuate potential bias stemming from affordability and liquidity constraints influencing mortgage choices as well as being correlated with patience.[20] To maximize the number of observations, I set

[19] I follow earlier studies, including Zeldes (1989) and Leth-Petersen (2010), which have used the ratio of liquid assets to disposable income as a proxy for liquidity constraints.
[20] For example, Epper et al. (2017) find that more patient individuals are less likely to be liquidity constrained.

the interest rate paid on non-mortgage debt equal to zero for mortgage holders not holding non-mortgage debt.[21] The right panel in appendix 5.5 shows the distribution of the resulting interest rates. While patience and risk aversion are measured at the individual level, the above-mentioned control variables are constructed at the household level to reflect that the purchase of a home and the associated choice of mortgage are typically decisions made at the household level rather than at the individual level. When I run similar regressions (not reported here) replacing the household-level controls with their individual-level counterparts, the results are not affected. Furthermore, I control for the ratio of mortgage loan to property value and demographic characteristics. Finally, I include year of mortgage origination fixed effects and control for the mortgage interest rate type in the repayment type regression and vice versa.[22]

Earlier studies have found that risk preferences are domain-specific (e.g., Weber, Blais, & Betz, 2002). In the present paper, the experimental measure of risk aversion is based on respondents' willingness to invest in a risky investment project, which is potentially distinct from a mortgage choice. Dohmen et al. (2011) find that the general risk question used in the German Socio-Economic Panel is a favorable all-around predictor of risky behavior in the field. The online questionnaire that respondents in the present study filled out included a version of this general question on risk-taking.[23] Thus, the following estimations will also include specifications where said more general survey-based risk question replaces the experimental measure of risk aversion. The two measures of risk aversion are positively correlated: Spearman's rho = 0.173; p-value = 0.000.

Determinants of mortgage repayment choice

Table 3.3 shows estimation results from probit regressions of mortgage repayment type on the measures of patience and risk aversion and other covariates. The reported coefficients are marginal

[21] As a robustness test, I have repeated the mortgage choice regressions shown below in tables 3.2 and 3.3 excluding those 189 mortgage holders (12.5 percent) not having any non-mortgage debt. The results from this exercise (not reported) do not change the relationships between preferences and mortgage choices presented here.

[22] Koijen et al. (2009) introduced a theoretical model in which the long-term bond risk premium (difference between current nominal long interest rate and the average expected future nominal short interest rate) is the key determinant of mortgage choice. Households trade off the lower expected payments on ARMs against the higher variability/uncertainty of the payments. The higher the long-term bond risk premium, the more attractive is an ARM relative to an FRM. They find empirical evidence that a simple proxy for the long-term bond risk premium is a strong predictor for the probability of choosing an ARM over an FRM. In the present study, I include year of mortgage origination fixed effects in the regressions to control for the variation in the long-term bond risk premium.

[23] Survey question on risk aversion: *Are you generally willing to take risks or do you try to avoid risks?*
1 = very willing to take risks
…
7 = not at all willing to take risks

effects. The dependent variable is a dummy variable taking the value of 1 if the respondent holds an IOM and 0 if the respondent only holds repayment mortgages. Column (1) shows output from a parsimonious specification that only includes the experimental preference measures and year of mortgage origination fixed effects. The results show no effect of the risk aversion measure but a negative effect of patience, which is statistically significant at the 0.1 percent level. The marginal effect of -0.148 implies that moving from minimum to maximum patience (0 to 1) is associated with a reduction in the probability of having an IOM of about 15 percentage points on average.

Column (2) shows results from adding income, liquid asset holdings, loan to income ratio (mortgage and non-mortgage loans combined), the average interest rate paid on non-mortgage debt, mortgage LTV, a dummy for whether the mortgage holder has an ARM, flexible dummies for educational attainment, and demographic characteristics. In the previous section, I documented that individuals who are less patient tend to use higher-cost non-mortgage borrowing, which points out that non-mortgage interest rates should be included in the current regression. It is noted that when the household's average interest rate paid on non-mortgage debt is included in table 3.3, a positive relationship with the likelihood of choosing an IOM is seen. The more expensive a mortgage-holding household's non-mortgage debt is, the more likely the household is to have an IOM. The marginal effect implies that a 1 percentage point increase in the average non-mortgage interest rate increases the probability of holding an IOM by 1.4 percentage points on average. From a personal financial point of view, this makes perfect sense: The lower initial mortgage payments associated with the choice of an IOM over a repayment mortgage implies that the household will have more cash available for paying down the more expensive non-mortgage debt or reducing the necessity to incur new non-mortgage debt to finance current consumption. It further appears that an increase in the mortgage LTV ratio is associated with an increased probability of choosing an IOM. As is also evident from table 2.1, column (3), IOMs are primarily used to borrow larger amounts relative to house value. Moreover, the results in table 3.3, column (2) show a positive relationship between holding an ARM and an IOM.

Cognitive ability is a potential confounding factor in the analysis. It could be that both mortgage choices and the measures of risk aversion and patience are correlated with cognitive ability.[24] In order to address this concern, column (3) controls for the self-reported most recent math grade obtained in school as an additional proxy for cognitive ability besides educational attainment and income. Adding

[24] For example, van Ooijen & van Rooij (2016) find that homeowners with higher levels of debt literacy are more likely to hold riskier mortgages.

self-reported math grades has a negligible effect on the estimated relationship between patience and the probability of having an IOM.

Column (4) substitutes the experimental measure of risk aversion with the more general survey-based question on risk aversion. Because of few observations in some of the answer categories, the survey measure of risk aversion is aggregated into two dummy variables indicating whether a respondent stated a risk aversion below or above the medium value, 1-3 and 5-7, respectively. As the experimental measure, the survey-based risk aversion measure is insignificant in explaining the mortgage repayment choice.

The estimated negative effect of the patience measure on the probability of having an IOM is remarkably stable across the four specifications. The negative relationship is intuitively appealing: Patient individuals, who discount the future less relative to the present, are to a lesser extent attracted to lower initial mortgage payments followed by larger future outstanding loan balances offered by IOMs. Put differently, patient individuals are more willing to sacrifice present consumption to repay a mortgage loan.[25]

[25] The negative effect of patience on the probability of having an IOM is consistent with the finding in Rasmussen (2017). That paper uses the same sample and the same experimental patience measure and relates differences in individual-level patience to the demand for insurance. Across two different insurance domains, the paper finds that individuals who are more patient are more willing to pay an insurance premium in the present in order to be covered by insurance that might benefit them in the future.

Table 3.3: Probit regressions of interest-only mortgage dummy regressed on covariates (marginal effects at means).

	(1)	(2)	(3)	(4)
Self-reported risk aversion, 1-3 (=1)				0.047
				(0.041)
Self-reported risk aversion, 5-7 (=1)				-0.030
				(0.040)
Risk aversion	-0.063	-0.024	-0.038	
	(0.050)	(0.053)	(0.055)	
Patience	-0.148 ***	-0.135 **	-0.148 ***	-0.145 **
	(0.039)	(0.043)	(0.045)	(0.045)
Ln(total household income)		0.004	0.034	0.029
		(0.042)	(0.045)	(0.045)
Liquid assets to disp. income ratio, household level		-0.032	-0.028	-0.029
		(0.022)	(0.021)	(0.021)
Loan to income ratio, household level		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Household average interest rate, non-mortgage debt (%)		0.014 **	0.016 ***	0.015 ***
		(0.004)	(0.005)	(0.005)
Mortgage loan to value ratio		0.645 ***	0.634 ***	0.636 ***
		(0.084)	(0.086)	(0.087)
Adjustable-rate mortgage (=1)		0.349 ***	0.341 ***	0.335 ***
		(0.029)	(0.030)	(0.031)
Year of mortgage origination fixed effects	Yes	Yes	Yes	Yes
Year dummies for educational attainment	No	Yes	Yes	Yes
Demographic characteristics	No	Yes	Yes	Yes
Math grade dummies	No	No	Yes	Yes
Observations	1514	1514	1400	1400

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. (=1) indicates a dummy variable which takes the value 1 for respondents who satisfy the description given by the variable name. Income ratios are based on annual income. Demographic characteristics include age, age^2, gender, marital status, and dependent children. The number of observations decreases in columns (3) and (4) due to some of the respondents not reporting a math grade.

Determinants of mortgage interest rate choice

Table 3.4 shows estimated marginal effects from probit regressions in which mortgage interest rate type is the dependent variable. The control variables correspond to those in table 3.3, while the dependent variable is a dummy variable taking the value of 1 if a respondent holds an ARM and 0 if a respondent only holds FRMs. Column (1) in table 3.4 shows a negative relationship between risk aversion and the probability of holding an ARM. Going from minimum to maximum risk aversion (0 to 1) is associated with a reduction in the probability of having an ARM of about 10 percentage points on average. This supports the model prediction of Campbell & Cocco (2003) that ARMs are less attractive to risk averse individuals because such individuals are more concerned with the cash-flow risk of ARMs (i.e., the potential for higher future interest payments). There is no significant effect of the patience measure on ARM holding. Again, this is consistent with Campbell & Cocco’s model, where the effect of time preferences on the choice between an FRM and an ARM is ambiguous.

However, after adding further covariates in columns (2) and (3) of table 3.4, the estimated effect of the risk aversion measure decreases and is no longer statistically significant. Instead, the results show that higher income households are more likely to choose ARMs. Additionally, there is a negative relationship between the mortgage LTV ratio and the probability of holding an ARM. This is in keeping with higher income households and households with smaller mortgage LTV ratios being less vulnerable to the potentially higher future interest payments of ARMs. Nevertheless, the likelihood of holding an ARM is increasing in the loan to income ratio (mortgage and non-mortgage loans combined) – possibly because households with high loan to income ratios who are financially hard up are willing to accept the cash-flow risk of ARMs to attain the lower debt service. In agreement with the result in table 3.3, homeowners with an IOM are more likely to hold an ARM.

In column (4) of table 3.4, the more general survey-based question on risk aversion replaces the experimental measure. I do this to accommodate the conjecture that the experimental risk aversion measure is too domain-specific to have explanatory power on mortgage interest rate choices. Supporting Campbell & Cocco’s model, the results show that more risk averse respondents (those who stated a level of risk aversion above 4 on the 7-point scale) are less likely to have ARMs. In this specification with all control variables included, more risk averse respondents have 9 percentage points lower probability of holding an ARM relative to the respondents who self-reported the medium value of risk aversion (significant at the 1 percent level).

Table 3.4: Probit regressions of adjustable-rate mortgage dummy regressed on covariates (marginal effects at means).

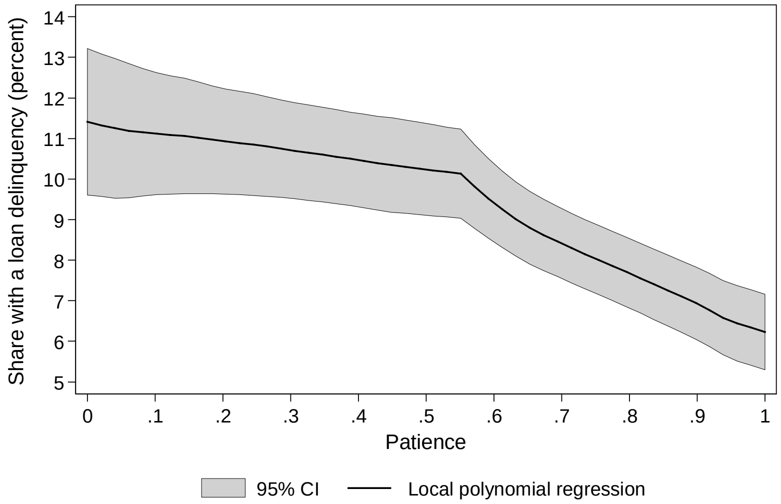
	(1)	(2)	(3)	(4)
Self-reported risk aversion, 1-3 (=1)				-0.010
				(0.032)
Self-reported risk aversion, 5-7 (=1)				-0.087 **
				(0.031)
Risk aversion	-0.102 *	-0.062	-0.051	
	(0.048)	(0.040)	(0.041)	
Patience	-0.003	0.023	0.021	0.027
	(0.037)	(0.032)	(0.033)	(0.033)
Ln(total household income)		0.190 ***	0.189 ***	0.179 ***
		(0.036)	(0.038)	(0.038)
Liquid assets to disp. income ratio, household level		0.006	0.026	0.026
		(0.012)	(0.015)	(0.016)
Loan to income ratio, household level		0.044 ***	0.043 ***	0.042 ***
		(0.010)	(0.010)	(0.010)
Household average interest rate, non-mortgage debt (%)		0.001	0.002	0.002
		(0.003)	(0.004)	(0.004)
Mortgage loan to value ratio		-0.217 ***	-0.198 ***	-0.201 ***
		(0.058)	(0.057)	(0.058)
Interest-only mortgage (=1)		0.223 ***	0.214 ***	0.210 ***
		(0.029)	(0.031)	(0.031)
Year of mortgage origination fixed effects	Yes	Yes	Yes	Yes
Year dummies for educational attainment	No	Yes	Yes	Yes
Demographic characteristics	No	Yes	Yes	Yes
Math grade dummies	No	No	Yes	Yes
Observations	1514	1514	1400	1400

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. (=1) indicates a dummy variable which takes the value 1 for respondents who satisfy the description given by the variable name. Income ratios are based on annual income. Demographic characteristics include age, age^2, gender, marital status, and dependent children. The number of observations decreases in columns (3) and (4) due to some of the respondents not reporting a math grade.

Patience and loan delinquencies

As mentioned above, only one of the 1,514 mortgage holders in the sample was delinquent on a mortgage loan by the end of 2014. Considering delinquencies on all loans (mortgage and non-mortgage) registered by the Danish tax authority, table 2.1 shows that the delinquency rate in the full sample is 8.6 percent, whereas it reduces to 1.7 percent for mortgage holders. Interestingly, when dividing mortgage holders into two groups according to the repayment type of their mortgages, table 2.1 shows that IOM holders are significantly more likely to have a loan delinquency relative to the group with repayment mortgages (p-value = 0.01). It is therefore relevant to test whether patience, having been shown to affect the choice between repayment mortgages and IOMs, is also a driver of loan delinquencies. Figure 3.4 plots a local polynomial regression curve of the share of respondents with loan delinquencies against the patience measure. The figure shows a negative relationship between patience and loan delinquency.

Figure 3.4: Loan delinquency plotted against patience.



Notes: 5,082 observations. Local polynomial regression of the share of respondents with loan delinquencies on the patience measure.

Table 3.5 examines whether the negative correlation found in figure 3.4 is robust to controlling for covariates. The table shows estimation results from probit regressions of loan delinquency on the measures of patience and risk aversion and other covariates. The reported coefficients are marginal effects. The dependent variable is a dummy variable taking the value of 1 if the respondent is delinquent on a loan at the end of 2014 and 0 if the respondent does not have a loan delinquency. Column (1) shows output from a regression that only includes the experimental preference measures. The results show negative effects of both the patience and the risk aversion measures. Column (2) extends the analysis by adding income, educational attainment, and other demographic characteristics. Income and educational attainment serve in part as proxies for cognitive ability to control for the possibility that patience and repayment behavior are both affected by cognitive ability. The marginal effects of the preference measures decrease, but patience remains statistically significant at the 0.1 percent level. The marginal effect of -0.025 implies that going from minimum to maximum patience (0 to 1) is associated with a reduction in the probability of having a loan delinquency of 2.5 percentage points on average, which is economically significant compared to the baseline probability of being delinquent on a loan of 8.6 percent in the sample. To further control for cognitive ability, column (3) controls for the self-reported math grade obtained in school. The estimated marginal effect of the patience measure is largely unaffected. In sum, the empirical results support the hypothesis outlined in the introductory section that there is an intertemporal aspect of repayment behavior. Individuals who are more patient are less likely to have loan delinquencies.

Table 3.5: Probit regressions of loan delinquency dummy regressed on covariates (marginal effects at means).

	(1)	(2)	(3)
Patience	-0.076 ***	-0.025 ***	-0.022 **
	(0.011)	(0.007)	(0.008)
Risk aversion	-0.050 ***	-0.015	-0.019 *
	(0.015)	(0.009)	(0.009)
Income decile dummies	No	Yes	Yes
Year dummies for educational attainment	No	Yes	Yes
Demographic characteristics	No	Yes	Yes
Math grade dummies	No	No	Yes
Observations	5082	5082	4640

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. The number of observations decreases in column (3) due to some of the respondents not reporting a math grade.

4. Conclusion

This paper presents evidence that time and risk preference are closely related to debt behavior. Methodologically, I link individual-level preferences elicited in an incentivized online experiment to objectively measured heterogeneity in real-world debt behavior. I show that individuals who are more patient have lower ratios of non-mortgage loan to income, postpone the incurrence of their first non-mortgage debt further, pay lower average interest rates on their non-mortgage debt, are less likely to choose mortgages with deferred amortization (interest-only mortgages), and are less likely to be delinquent on loans. Similarly, more risk averse mortgage holders are less likely to choose adjustable-rate mortgages. Apart from the timing of first non-mortgage debt, I find that these relationships are maintained when controlling for socio-demographic variables.

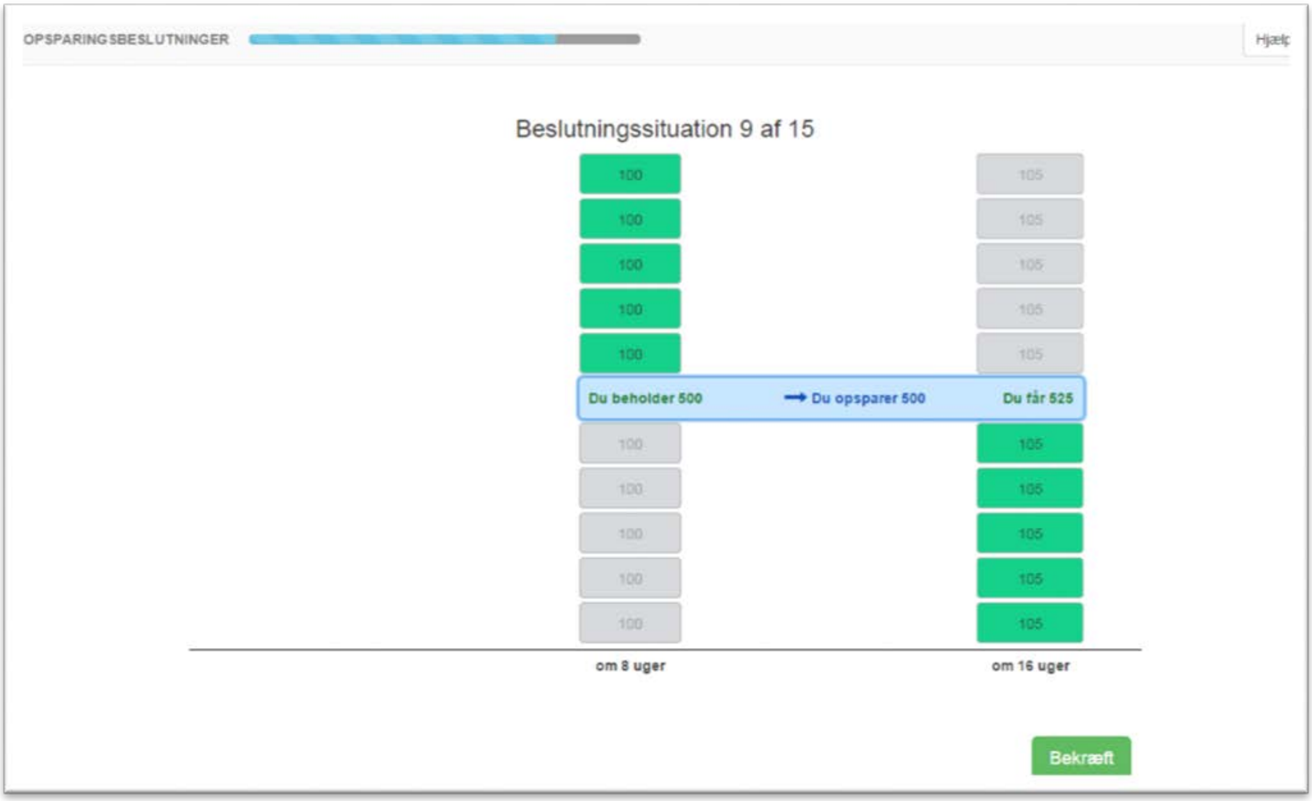
Since the onset of the global financial crises in 2008, macroprudential regulators have focused on the systemic risk imbedded in the mortgage market. On the one hand, households with ARMs or IOMs are – ceteris paribus – more exposed to situations with increasing interest rates and decreasing house prices potentially leading to low disposable income and technical insolvency. This would appear to warrant regulation to limit the penetration of these mortgage types in order to mitigate the risk to the financial system as a whole. On the other hand, this paper has shown that borrowers choose mortgages to match their preferences. IOMs are chosen to a greater extent by impatient individuals who are less willing to sacrifice present consumption to repay the mortgage. Choosing an IOM can be used as a means to smooth consumption over the life-cycle. Thus, IOMs can enhance the welfare of individuals who expect their future income to be higher. Another benefit of the lower initial mortgage payments associated with choosing an IOM over a repayment mortgage is that the household will have more cash available for paying down more expensive non-mortgage debt. Alternatively, the extra available cash can reduce the necessity to incur new non-mortgage debt to finance current consumption. The paper provides evidence that households who pay higher interest rates on non-mortgage debt are more likely to have an IOM. Furthermore, lower initial mortgage payments can enable IOM holders to invest more in financial assets other than real estate and thus benefit from portfolio diversification. ARMs can also enhance welfare by providing a lower current interest rate to individuals who are willing to accept the risk of potentially higher future interest payments.

The desire to limit ARMs or IOMs due to the consideration for systemic risk should be balanced with welfare costs associated with such a limitation, as the scope of choosing mortgage contracts to match preferences would be reduced. However, although individuals can benefit from being able to choose mortgages that match their preferences, the present study also finds that IOM holders are more likely to have non-mortgage loan delinquencies relative to a group holding repayment mortgages. If it is conceivable that the reported negative relationship between patience and loan defaults would also apply to mortgage defaults in the event of a recession, then this could call for more regulation to limit the latitude with which borrowers are able to choose mortgage types to match their time preferences. As an example, the Danish government recently urged mortgage institutions to limit new ARM and IOM lending to borrowers with the highest loan to income ratios in areas where house prices have increased most rapidly. This action was based on a recommendation from the Danish Systemic Risk Council (2017). This approach was intended to reduce the available mortgage products for those borrowers who are most vulnerable to increasing interest rates and decreasing house prices, while others can still benefit from a complete selection of mortgage products.

As a concluding remark, this paper supports the external validity of experimental preference measures. Few studies have been in a position to link experimental data to objectively measured financial behavior in the field. The finding in the present work that experimentally elicited preferences can be used to explore the relationship between preferences and real-world financial behavior is, therefore, promising from an experimental perspective.

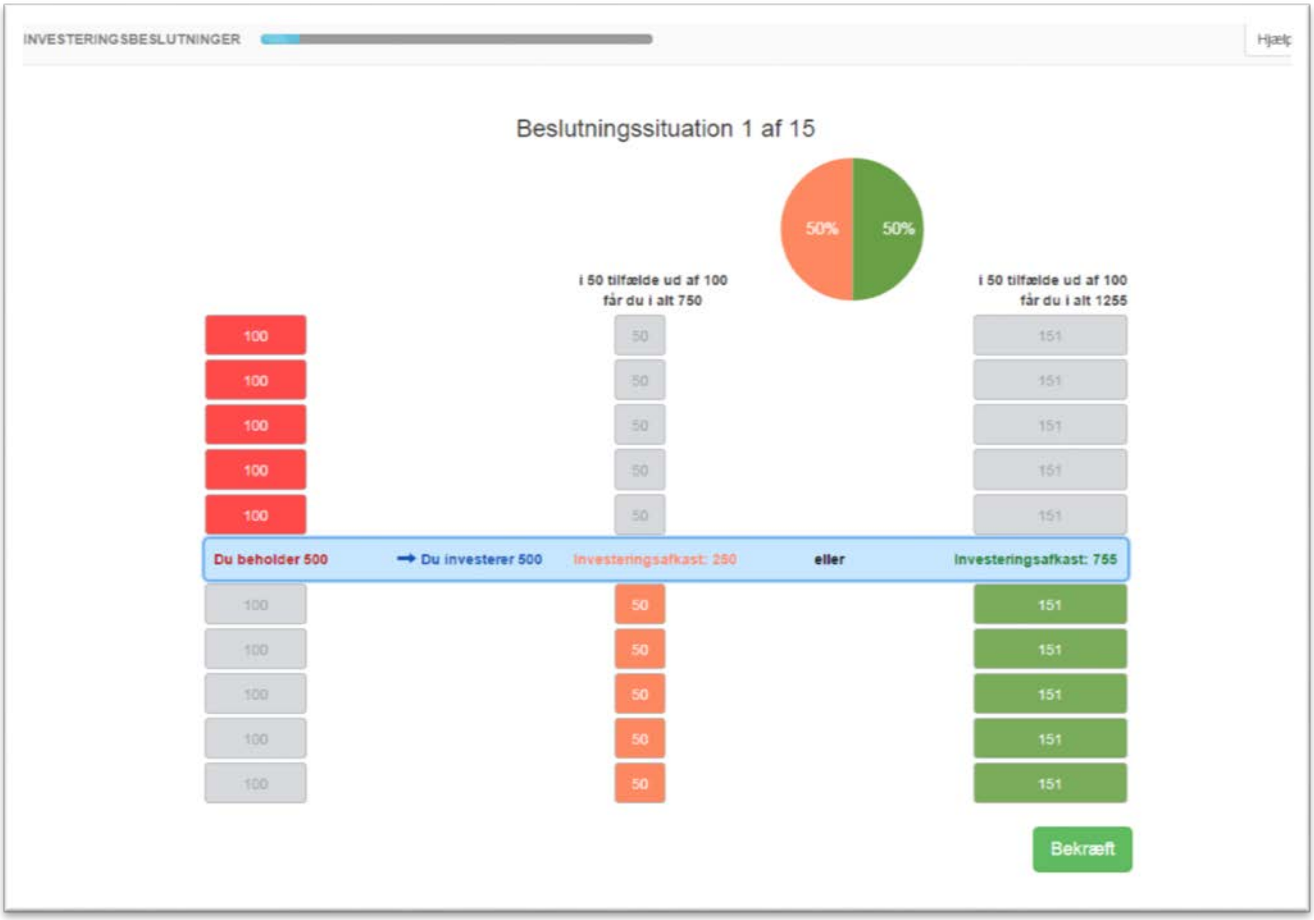
5. Appendix

Appendix 5.1: Screenshot of a saving choice. 8 vs. 16 weeks.



Notes: The blue saving bar summarizes the outcome of the allocation. In this case, the respondent chose to keep 500 points in the 8 weeks account (left) and save 500 points (right) such that he would get 525 points in 16 weeks.

Appendix 5.2: Screenshot of an investment choice.



Notes: The blue investment bar summarizes the outcome of the allocation. In this case, the respondent chose to keep 500 points on the risk-free account (left) and invest 500 points in the risky investment project (right) such that he would get 750 or 1255 points in total depending on the outcome of the investment project.

Appendix 5.3: Means of selected characteristics.

	(1) Respondents vs. non-respondents			(2) Gross sample vs. 10 % of population		
	Respondents	Non-respondents	p-value	Gross sample	Population	p-value
Age	34.17	34.03	0.011	34.05	34.97	0.000
Woman (=1)	0.50	0.49	0.058	0.49	0.50	0.001
Single (=1)	0.34	0.41	0.000	0.40	0.31	0.000
Dependent children (=1)	0.49	0.48	0.377	0.48	0.55	0.000
Homeowner (=1)	0.33	0.29	0.000	0.29	0.51	0.000
Years of education	14.41	13.79	0.000	13.88	14.33	0.000
Ln(Total income)	12.63	12.51	0.000	12.52	12.63	0.000
Ln(Liquid assets)	10.35	10.03	0.000	10.07	10.24	0.000
Observations	5082	30611	35693	35693	83464	119157

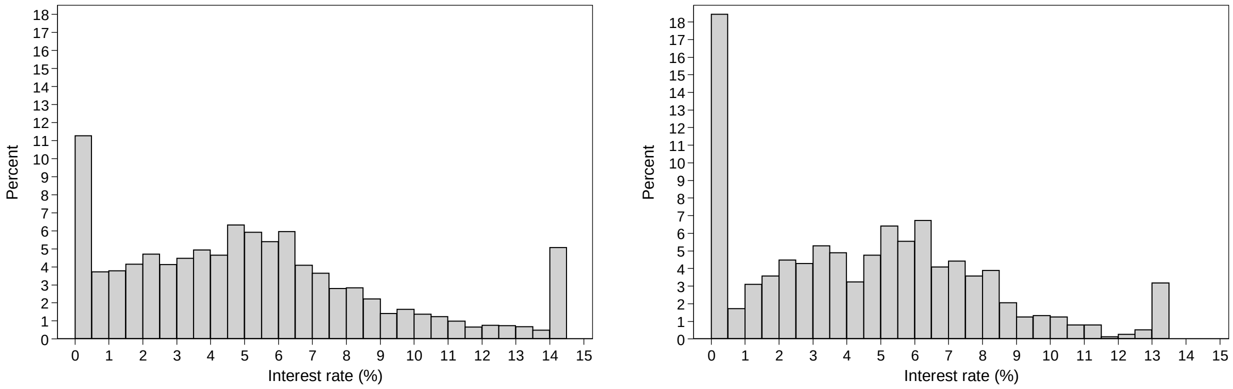
Notes: The p-values are from unconditional t-tests of equality of means. Variables are based on 2014 values. The random 10 percent sample of the Danish population is drawn among those who are not in the gross sample (i.e., did not live in Copenhagen Municipality when they were seven years old), but who were born in the same period (1973-1986). (=1) indicates a dummy variable which takes the value 1 for individuals who satisfy the description given by the variable name. Liquid assets include bank deposits and market values of stocks and bonds. The table includes individuals for whom a full set of register variables is available.

Appendix 5.4: Non-mortgage loan to income ratio regressed on covariates (tobit, lower limit = 0).

	(1)	(2)	(3)
Patience	-0.173 ***	-0.128 ***	-0.132 **
	(0.039)	(0.039)	(0.040)
Risk aversion	-0.062	-0.086	-0.053
	(0.051)	(0.049)	(0.052)
Income decile dummies	No	Yes	Yes
Year dummies for educational attainment	No	Yes	Yes
Demographic characteristics	No	Yes	Yes
Math grade dummies	No	No	Yes
Constant	0.692 ***	-2.434 *	-2.093
	(0.042)	(0.984)	(1.100)
Observations	5082	5082	4640

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. The number of observations decreases in column (3) due to some of the respondents not reporting a math grade. Non-mortgage loan to income ratio is censored at p95.

Appendix 5.5: Distributions of computed interest rates paid on non-mortgage debt.



Notes: Average interest rates are computed based on non-mortgage interest payments during 2014 and amounts of outstanding non-mortgage debt at the end of 2013 and 2014. The computed interest rates are censored at the 5th and the 95th percentiles. Bin width: 0.5 percentage points.
Left-hand panel: 3,958 individual-level observations. Average computed interest rate: 5.2 percent.
Right-hand panel: 1,514 household-level observations for mortgage holders. The interest rate paid on non-mortgage debt is set to zero for those 189 mortgage holders not holding non-mortgage debt. Average computed interest rate: 4.6 percent.

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Chapter 2

Heterogeneous Discounting Behaviour and Wealth Inequality*

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Abstract

According to standard economic theory, differences in how much people discount the future generate differences in savings behaviour and thereby wealth inequality. To test this prediction, we use state-of-the-art experimental methods to elicit time preferences for a large sample of middle-aged individuals in Denmark and link these experimental data to administrative register data holding information about their real-life wealth over a period of 15 years. We find that individuals with relatively low discount rates are consistently positioned higher in the wealth distribution. The correlation between heterogeneity in discounting behaviour and the position in the wealth distribution is significant and of the same magnitude as the correlation between education and wealth, and it exists after controlling for education, income, initial wealth and parental wealth, suggesting that the savings mechanism is important. Finally, we show that the least patient individuals are more likely to be affected by liquidity constraints, consistent with models where liquidity constraints are self-imposed.

Keywords: Wealth inequality, preference heterogeneity, preference elicitation, experimental methods, register data

JEL codes: C91, D15, D31, E21

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1 Introduction

Wealth inequality is significant. The share of total wealth owned by the 10 percent wealthiest is in the range of 60-90 percent over the last 150 years in both the US and in Europe (Piketty and Saez 2014), and wealth inequality is the focus of much public and academic debate (see e.g. the symposium on wealth and inequality in the 2015 winter volume of the Journal of Economic Perspectives). Work on understanding the driving forces behind wealth inequality has focused on differences across people in income processes, wealth transfers, saving propensities, capital returns and public policy (e.g. Heathcote et al. 2009; Piketty 2014; Hubmer et al. 2016; Boserup et al. 2016, 2017; Fagereng et al. 2016; De Nardi and Fella 2017). Yet, knowledge is still limited. Standard textbook theory predicts that differences in how much people discount future consumption/utility generate wealth inequality. Patient individuals have lower discount rates, save more, and therefore become more wealthy. This paper is the first to test this hypothesis directly by relating discounting behaviour of individuals to their actual position in the wealth distribution. Experimental evidence points to pervasive heterogeneity in discounting behaviour (e.g. Mischel et al. 1989; Barsky et al. 1997; Andreoni and Sprenger 2012; Toubia et al. 2013), but without relating it to wealth inequality. Macro models suggest that heterogeneity in discounting behaviour may have significant effects on wealth inequality (Krusell and Smith 1998; Carroll et al. 2017), as well as having consequences for the propagation of business cycle shocks and the effects of stimulus policy (Carroll et al. 2014; Krueger et al. 2016), but without measuring discounting behaviour directly.

To test whether differences across people in subjective discounting can explain observed wealth inequality, we combine experimentally generated data providing information about preferences of individuals and administrative data providing detailed information about their wealth in real life. The analysis is carried out in Denmark where this data collection strategy is possible. People born during 1973-1983 in the capital city of Copenhagen were invited to participate in online, incentivized experiments in February 2015, giving information about preferences for about 3,600 individuals, which is a large sample in an experimental context. We select cohorts who are in mid-life at the time where we elicit discounting behaviour. This is at a point in the life-cycle where we suspect the ranking of wealth to be less influenced by the timing of education and retirement and where observed income is arguably a good proxy for permanent income (Haider and Solon 2006). We elicit time and risk preference parameters using state-of-the-art experimental methods similar to Andreoni and Sprenger (2012) and Gneezy and Potters (1997). In the time preference experiments, subjects choose between receiving a sum of money paid out in eight or in sixteen weeks, and the money is paid out automatically to their bank accounts. The data collected in the experiment are merged at the individual level to longitudinal income and wealth records as well as other administrative registers covering the period 2000-2014. The income and wealth components are third-party reported directly from employers, banks, financial intermediaries etc. to the tax authorities who use them for tax assessment and selection for audit, and they are therefore of a high quality (Card et al. 2010; Kleven et al. 2011).

Our results reveal a strong correlation between experimentally elicited patience and the individuals' positions in the wealth distribution, measured by the percentile rank of the individual in the time-conditional within-cohort distribution (e.g. Chetty et al. 2014b). The 1/3 of the subjects who are most patient lie on average six percentiles higher up in the wealth distribution than the 1/3 of the subjects who are least patient, and the 1/3 of the subjects in the middle group lie, on average, in between the two other groups in the wealth distribution.

A standard assumption in economic theory is that individual preferences are fixed (Stigler and Becker 1977). Consistent with this assumption we show that the relationship between our elicited patience measure and the position in the wealth distribution is stable over the 15 year period where we measure wealth.

To assess the magnitude of this relationship, we compare with the association between wealth inequality and educational attainment, which Huggett et al. (2011) argue to be one of the most important factors contributing to life time inequality. When comparing the 1/3 of the subjects with the lowest education level (compulsory schooling level or only slightly more) to the 1/3 with the highest education level (college degree or more), we find a difference of seven percentiles in the wealth distribution. This suggests that preferences are roughly as important as education in determining a person's position in the wealth distribution. Taken at face value this could simply reflect that discounting and educational attainment are correlated, but we show in a multivariate analysis that the relationship between discounting and position in the wealth distribution is only slightly smaller when controlling for education. This is also the case when holding other factors such as school grades, income, initial wealth and parental wealth fixed thereby controlling for other mechanisms that might confound the correlation between discounting and wealth. This indicates that there exists a significant relationship between discounting and wealth operating through the savings channel as predicted by theory.

Our sample is large in an experimental context, but too small to study the dynamics in the very top of the wealth distribution. However, we do find a significant relationship between patience and the propensity to be in the top 10% of the wealth distribution, and we also show that patience is correlated with different sub-components of net wealth.

Net wealth may be constrained from below by borrowing limits. The presence of credit constraints is a leading theoretical and empirical explanation of why fiscal stimulus policy may be effective (Zeldes 1989; Johnson et al. 2006). Individuals may become credit constrained because of income shocks, but as pointed out by recent research credit constraints may also be self-imposed because relatively impatient individuals have less savings and are more likely to be affected by credit constraints (Carroll et al. 2014, 2017). More generally, the propagation of shocks is typically stronger in an environment where discount factors are heterogeneous because more people are affected by credit constraints (Krueger et al. 2016). Consistent with these hypotheses, we find that individuals who are relatively impatient are more likely to be affected by credit constraints. This is documented using two tests for being affected by constraints. In one test we follow the previous empirical literature (e.g. Leth-Petersen 2010) and consider people as being affected by constraints if they are observed holding liquid funds worth less than one month of disposable income (hard credit constraint), and in the other we consider people as being affected by constraints if they face a high interest rate on borrowing (soft credit constraint).

The next section provides a more detailed description of the relationship to existing literature. Section 3 illustrates within a basic life-cycle savings model why we should expect heterogeneity across individuals in subjective discounting to generate differences in their wealth levels at all ages, and the key potential confounders when testing this hypothesis. Section 4 presents the empirical setup, including the sampling scheme, the experimental design, and the register data on wealth and characteristics of the participants. Section 5 goes through the main results and presents additional analyses and robustness checks. Section 6 concludes.

2 Relationship to literature

Our work is related to at least three different strands of literature, the experimental literature concerned with eliciting subjective preference parameters, the macro economic literature on inequality and its causing factors, and a literature attempting to quantify the intergenerational transmission of savings behaviour. In this section we go through each of them in turn.

Experimental literature: An early experimental result revealing differences in the degree of patience is the famous marshmallow test conducted with young children (Mischel et al. 1989). The experimental literature has made much progress on quantifying preferences at the individual level through experimental methods, e.g. Epper et al. (2011); Attema et al. (2016), and several studies using experimental methods to elicit preference parameters have found evidence suggesting that there is pervasive cross sectional heterogeneity in preferences. Andreoni and Sprenger (2012), whose basic elicitation methods we apply, find vast individual-level heterogeneity in their data, as do Abdellaoui et al. (2009); Epper et al. (2011); Abdellaoui et al. (2013); Bleichrodt et al. (2016), albeit the focus in these studies is not on relating preferences to the wealth distribution. A standard concern about extrapolating the result from experimental studies to real-life is that experimental studies are often based on relatively small samples, often consisting of students (see e.g. the discussion in Exadaktylos et al. 2013). Another concern is that experimentally elicited measures of preferences are potentially context-specific and the result of the specific laboratory setting applied. Frederick et al. (2002) summarize the early experimental literature measuring subjective discount rates and go through a number of challenges associated with the measurement of preferences. To alleviate these concerns, some studies confront elicited preferences with real-life data. However, these studies typically do not focus on savings behaviour,[1] and very few studies have been able to confront elicited subjective discount factors with data on real-life wealth. Exceptions are Meier and Sprenger (2010) who find that (present biased) time preferences correlate with credit card borrowing, and Meier and Sprenger (2012) who find that the degree of time discounting predicts repayment of credit as measured by FICO credit scores.

[1] For example, Chabris et al. (2008) show that individual discount rates predict inter-individual variation in health-related field behaviours, for example exercise, BMI, and smoking. Lawless et al. (2013) find that elicited time preferences for money predicts smoking cessation and obesity. Backes-Gellner et al. (2017) confront elicited patience with real-life data on student outcomes such as program completion and find that elicited patience predicts real-life outcomes.

Macro models of inequality: Traditional macro-economic models of consumption and savings with heterogeneous agents assume agents are homogeneous in terms of preferences and the stochastic properties of the income process (Heathcote et al. 2009; De Nardi and Fella 2017). A common feature of this class of models is that individuals face different shock sequences and thereby realizations of income, which lead them to make different consumption-savings decisions. Initial conditions may vary across individuals, for example by allowing for heterogeneity in initial wealth or innate productivity, which add additional potential for heterogeneity in consumption and savings choices. As relatively good data on earnings are widely available, this has been the preferred way to introduce heterogeneity. An alternative way to introduce heterogeneous "initial conditions" is to let preferences vary across individuals, keeping the assumption that preferences of each individual is fixed. Krusell and Smith (1998) present one of the earliest examples of models featuring heterogeneous discount factors, and they show that a limited degree of discount heterogeneity can generate a significant increase in wealth inequality compared to the reference case with homogeneous preferences. More recently, Carroll et al. (2017) present a model where discount heterogeneity is needed for fitting the wealth distribution. Economists have historically been treating preferences as stable over time and as similar among people, see for example Stigler and Becker (1977), and have been reluctant to introduce preference heterogeneity in order to make models fit the data better. The background for this position is that it is difficult to discipline such an exercise when no direct information about preferences is available (Heathcote et al. 2009).

Intergenerational literature: Our study is also related to two recent papers examining the correlation across generations in wealth and savings behaviour. Black et al. (2015) and Fagereng et al. (2016), using Swedish and Norwegian adoption data, find that children are persistently influenced by the savings behaviour of their adoption parents suggesting that economic behaviour is different among people and that it plays an important role for the accumulation of wealth later in life and hence for wealth inequality.

3 Theory

This section first illustrates within a simple neoclassical, deterministic life-cycle savings model why we should expect heterogeneity across individuals in subjective discounting to generate differences in their wealth levels at all ages, and shows some key potential confounders when testing this hypothesis. Afterwards, we discuss various extensions of the simple framework.

3.1 A basic neoclassical model of individual life-cycle savings

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

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

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

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

where $y(a)$ is income excluding capital income, $w(a)$ is wealth, r is the real 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 relationship between the wealth level of an individual at age a in the life-cycle and the different wealth determinants (see 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:

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

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

From expression (3) follows the main prediction (see Appendix B):

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

This shows that subjective discounting and wealth is related through the savings channel, and that when measuring this correlation empirically the potential confounders are differences across people in permanent income Y, time profile of income $\gamma(a)$, (expected) lifetime T, real interest rate r on savings, and the CRRA parameter θ reflecting the degree of intertemporal substitution in consumption.

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 (lower values of $\gamma(a)$), which in isolation reduce the level of wealth at a given age.

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

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

3.2 Extensions

Income shocks: The model allows only for deterministic variation in income over the life-cycle. This is in contrast to standard macro models of wealth inequality where income develops stochastically and is uninsurable (De Nardi and Fella 2017). This gives variation in wealth beyond the income determinants in the above model (Y,$\gamma(a)$). Krusell and Smith (1998) show that heterogeneity in discounting behaviour may improve the ability of the basic macro model to explain wealth inequality and, as described in the introduction, many other papers have afterwards included heterogeneous discounting in macro models of wealth inequality.

Borrowing constraints: The model has a perfect capital market with the same real interest rate r for all borrowing and savings. A large literature has examined theoretically and empirically the role of borrowing constraints to explain the persistent effects of business cycle shocks and the effectiveness of stimulus policy (Zeldes 1989; Leth-Petersen 2010; Krueger et al. 2016).

To see the implications of including (hard) borrowing constraints, consider in our simple model the special case where consumers can never have negative wealth, i.e. $w(a) \geq 0$ for all $a \in (0, T)$. Assume initial wealth $w(0)$ is zero and income is constant, $y(a) = y$ for all a. For patient individuals with $\rho < r$, the constraint is not binding, because they would wish to have an increasing consumption profile, implying that the wealth equation (3) still applies.

For impatient individuals with $\rho > r$, wealth becomes zero at all points in the life-cycle, $w(a) = 0$ for all a. These individuals would prefer a decreasing consumption profile over the life-cycle implying borrowing over the life-cycle. However, since this is not possible because of the borrowing constraint they will end up consuming their current income. All individuals with $\rho > r$, but different degrees of impatience ρ, will then end up having the same wealth at all points in time (zero in this case). Thus, borrowing constraints may imply that impatient individuals (ρ above some threshold) are constrained from borrowing, and this implies that wealth is uncorrelated with impatience for this group.

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

In the empirical analysis, we use measures of both hard and soft borrowing constraints to examine whether there exists correlation between subjective discount factors and the propensity to be borrowing constrained.

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

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

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

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

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

Wealth transfers: Inter vivo transfers and bequest influence wealth inequality (De Nardi 2004; Boserup et al.2016; 2017). The model does not explicitly include wealth transfers, but wealth transfers received may be included in $y(a)$, in which case the wealth expression (3) is unchanged. In a similar vein, we may interpret $c(a)$ as spending including transfers. From an empirical point of view, transfers only matter if they are correlated with subjective discounting (after controlling for income and the other wealth determinants described above). If, for example, more patient individuals are also more prone to save in order to leave bequests then this creates a positive relationship between patience and wealth running through savings. Thus, the main prediction is the same. The only difference is that the savings are motivated by giving consumption possibilities to others in the future rather than own future consumption.

4 Data, experimental design and empirical approach

Our overall approach is to measure preferences using experimental techniques for a stratified sample drawn from the population and linking this information at the individual level to administrative records with third-party reported longitudinal information about wealth, income and demographic characteristics covering the period 2000-2014 in order to explore whether differences in elicited patience are predictive of differences in observed wealth. Combining experimental data with administrative register data is made possible by the unique Danish research infrastructure, whereby data can be linked across modes of data collection using social security numbers.

In order to test the hypothesis that preference heterogeneity is related to the position in the wealth distribution, we maintain the assumption that preferences are stable across time and (potentially) only vary across individuals. Inherent to the basic theory is that discount factors impact savings decisions, and the theory consequently predicts that preference heterogeneity, i.e. variation in patience across individuals, will be related to wealth inequality. The theory also suggests that the association between preferences and the accumulation of wealth may be confounded by factors such as the individual earnings path, initial conditions, e.g. ability and initial wealth, and transfers. Our approach is to document that elicited patience predicts the position in the wealth distribution over an extended period, 15 years, and to investigate whether this relationship is confounded by any of these factors. An important aspect of the empirical approach is to confront the experimental measures with real-life data in order to ensure that experimentally elicited preference measures are relevant for describing real-life decisions. Before turning to the results the remainder of this section describes the sampling scheme, the experimental design and its implementation. Also, a description of the register data with longitudinal information about wealth, income and a host of characteristics of the individuals in our sample is provided.

4.1 Sample and recruitment for the experiment

We recruited respondents by sampling from the Danish population register individuals satisfying the following two criteria: (*i*) born in the period 1973-1983, and (*ii*) residing in the municipality of Copenhagen (Københavns Kommune) when they were seven years old, i.e. we sent out invitations to the complete birth cohorts meeting the sampling requirements. Statistics Denmark, the central authority on Danish statistics, provided a data set of all individuals who met the sample criteria. The data set contained names, current addresses, and civil registration numbers. We invited everyone in the gross sample to participate by sending personal invitation letters in hard copy. Each letter contained a unique username and password combination needed to log in to a web page through which the experiments was conducted. Upon receiving the invitation letter invitees could decide to participate by logging in to the web page.

We invited a total of 27,613 subjects for participation in our online experiment taking place in February 2015.[2]

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

4,190 (15.17 percent) of all invitees logged in to our experimental platform. The vast majority (3,717 or 88.71 percent) of subjects who did so successfully completed the experiment and received a payment. Our analyses include a total of 3,634 subjects. 83 subjects had to be dropped from our data because of data protection issues and mismatches of socioeconomic characteristics with register data.[3]

We employed the following recruiting procedure: Subjects received an official invitation from the University of Copenhagen by letter mail.[4] It informed subjects about the login details, the expected time to complete the experiment and contact information for support.[5] Subjects were informed that the payment for participating in the study would depend on their choices, and that the final payment would, on average, correspond to a decent hourly wage.[6]

Subjects who followed the web link in the invitation letter arrived at a login page. Upon successful login, a single page with introductory instructions appeared. These instructions described the outline of the experiment and payment modalities. Subjects were also presented with a graphical depiction of a wheel they had to spin at the end of the experiment. They were told that the spin of the wheel at the end determines the choice situation that counts for payment, and, hence, that all choices they make during the course of the experiment could be picked and were relevant. There were three elicitation tasks, a time task, a risk task and a social task. Each task was accompanied by short video instructions and comprehension questions.[7] The three blocks appeared in individualized random order. Within each block, the set of choice situations was once again randomized. Our main focus in this paper is the time task, which is described in detail in the next subsection. A description of the risk task can be found in Appendix F. The present study does not use data from the social task.

The average completion time was 46.85 minutes. It took the fastest subject 21.25 minutes to complete the experiment. The distribution of completion times has positive skew. We did not prevent subjects from taking breaks during the experiment session. However, once they logged in for the first time, they were required to finish the experiment within a two week time frame. Our elicitation tasks involved real monetary incentives. During the study, we used an experimental currency. 100 points corresponded to 25 Danish kroner (DKK).[8] This provided us more flexibility for calibration of the choice situations. To determine the choice situation relevant for payment, subjects spun a wheel containing all the choice situations they were confronted with. The random choice situation at which the wheel stopped was then displayed together with the subject's decision. Then, the points were exchanged into money. Payment was done via direct bank transfer at the relevant date (details follow below). When converting from points to DKK, we rounded the amount up to the next unit. Possible payments considering all three tasks ranged from 88 to 418 DKK. The average amount paid out was 245.23 DKK. A distribution of

[3]For checking whether the person participating corresponded to the person who was invited we initially asked check questions about the age and gender of the person participating.

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

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

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

[7]An English transcript of the relevant parts of the video instructions can be found in the last section of the thesis.

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

payments can be found in Appendix G.

4.2 Measuring patience

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

4.2.1 Time task

To elicit intertemporal choice behaviour, we use convex time budgets (CTBs for short; Andreoni and Sprenger 2012). Our presentation format differs from what has been originally proposed in Andreoni and Sprenger (2012). Specifically, we depict intertemporal choices graphically and present only a single allocation choice per page.[9] We used a total of 15 independent choice situations that differed in terms of payment dates and interest payments.

Figure 1 depicts screenshots of a typical choice situation. The left panel shows a typical choice screen in its initial state. The right panel presents the same situation after selection of an allocation.

Figure 1: Example of choice situation

(a) Initial screen (b) Selected option

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

At the beginning of each choice situation, each subject was endowed with ten colored 100-points blocks. These ten blocks were allocated at the earlier of the two payment dates (in Figure 1a: "in 8 weeks"). The subject then had the possibility to move some (or all) of these ten blocks at the later date (in Figure 1a: "in 16 weeks"). When shifting a block into the future, the subject was compensated by a (situation-specific) interest payment. That is, each 100-points block's value increased once it was deferred to the later point in time. In the example depicted in Figure 1, each block allocated at the later point in time has a value of 105 points. The subject thus had to decide how many of the ten blocks he wanted to keep for earlier receipt, and how many of the blocks he wanted to

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

postpone for later receipt. Figure 1b presents an example selection. In this example, the subject chose to allocate four 100-points blocks in 8 weeks, and save the remaining six 100-points blocks for receipt in 16 weeks. Deferring the receipt of the latter six blocks led a total interest payment of 30 points. Choices were made by clicking (or touching) the respective block, and then moving around the horizontal savings bar. Alternatively, it was possible to use the keyboard or the buttons at the very top. Once a definitive choice was made, the subject clicked on the "Confirm" button at the bottom right. The decision was then stored in the database and it was no longer possible to revert the choice. The next (randomly selected) choice situation was presented thereafter. Once all 15 choice situations were presented, the experiment continued with the next task or the end-of-experiment questionnaire.

Choice situations involved three different payment dates: "today", "in 8 weeks", and "in 16 weeks". Combinations of all three payment dates were used in the experiment. We decided to state delays in terms of weeks (instead of months) to prevent possible weekday effects. The interest rates applied varied across choice tasks. For example, for the five choice tasks asking subjects to choose between receiving payments in 8 weeks or 16 weeks we applied interest rates in the interval 5-25 percent.[10] The payments were consolidated on a per-day basis. The compiled list of transactions were then sent electronically to the bank for implementation of the payout. Subjects knew that the payment was initiated either at the same day, or exactly 8 or 16 weeks later. Hence, the payment dates shown on screen refer to the point in time where the transaction was actually initiated. It took one day to transfer the money to the subjects "NemKonto", which is a publicly registered bank account that every Danish citizen possesses. Exceptions were non-banking days, such as weekends or holidays. In this case, the transaction occurred at the subsequent banking day.

4.2.2 The patience measure

The collected choice task data enable us to calculate a non-parametric measure of patience.[11] That is, we construct a measure that is specific to each individual in our sample, and this measure is based on choice data only and does not involve auxiliary assumptions on the structure of individual preferences. Our patience index is constructed by taking the choice variable z, i.e. the number of blocks saved for late receipt. We then normalize and aggregate the measure across the various choice situations. Aggregation is performed using the median, and it ensures that our measure is robust to single outliers in choice.[12] For constructing our *patience* measure, we take the five choice situations that involve allocations between $t_1 = 8$ weeks and $t_2 = 16$ weeks.[13] We do this to remove any potential confound caused by including the present. In the robustness section we show that our results are robust to using indices based on trade-offs between "today" and "in 8 weeks", or "today" and "in 16 weeks".

[10] These rates amount to annualized interest rates in the range of 16-282%. The population discount rate, estimated using a random parameter model, equals to 36.1% per annum. The rates we find therefore lie in a similar range as those reported in the original paper introducing CTBs (Andreoni and Sprenger (2012)) and other studies reviewed in the literature section. It can be expected that discount rates for larger stake sizes are considerably lower. This "magnitude effect" (see Frederick et al. (2002)) would change the size of the discount rates, but not the relative position of subjects in the distribution. The latter is what we are interested in.

[11] We explicitly refer to our index as "patience" and not "time preferences" (see e.g. Andreoni and Sprenger 2012) to make clear that many other factors than deep preferences affect revealed discount rates (see e.g. the discussions in Frederick et al. 2002 and *Epper 2015*).

[12] As we deal with an ordinal index, the median is the proper aggregator. Our results, however, do not change if we take the arithmetic mean instead.

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

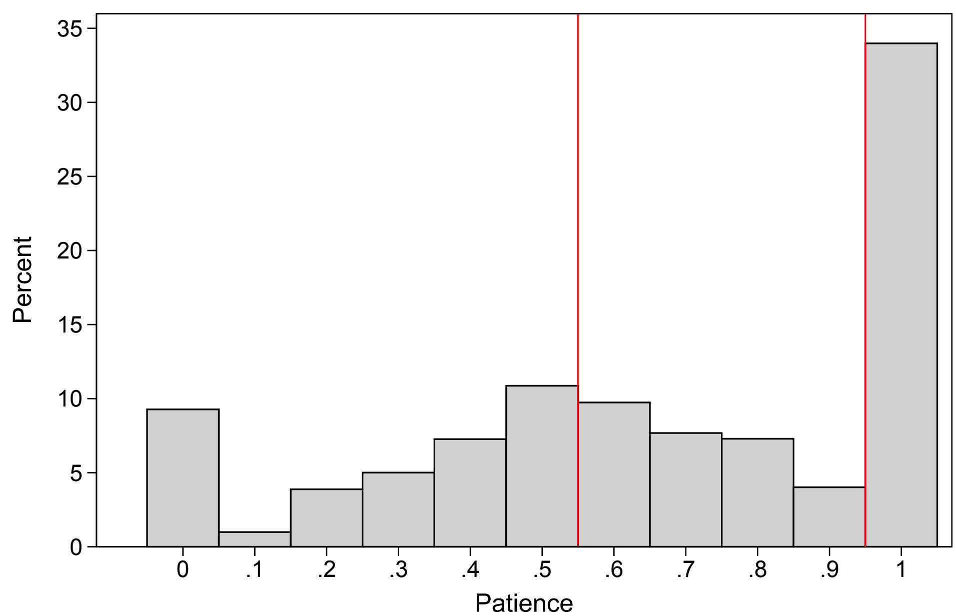
Our patience index is defined as follows:

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

where z denotes the number of blocks allocated at the later point in time, i.e. in 16 weeks.

ϕ_{patience} is an index of (longer-run) patience with $\phi_{\text{patience}} \in [0, 1]$. Due to the discreteness of our measures (10 blocks were allocated), our index can take values in 1/10th steps. Higher values of ϕ_{patience} indicate greater patience and a ϕ_{patience} of one indicates timing indifference. As a consequence of the way ϕ_{patience} is constructed censoring occurs at both ends of the scale, i.e. it is not possible to detect negative values or values larger than what the experimental scenarios span. Our non-parametric measure displays substantial heterogeneity. The histogram in Figure 2 depicts the distribution of our patience index. The vertical lines indicate tertile cut-off points. In many of our empirical analyses we split the patience index in tertiles of high, medium and low patience in order to facilitate visualization. Importantly, we find substantial individual-level variation in our sample, and it is this variation which we expect will be able to predict wealth inequality.

Figure 2: Histogram of patience index



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

4.3 Register data and the measurement of wealth and other characteristics

The choice data from the experiment are linked with Danish administrative register data at the individual level.[14]

[14]The participants were not informed that the data from the experiment would be linked with the administrative register data. The Danish Data Protection Agency has approved the research project and this procedure. To merge the experimental data with the register data, the usernames provided in the invitation letters were translated into anonymized civil registration numbers. It is important for the linkage between experimental and register data that the people who participated in the experiment are identical to the people who were invited. To check that the correct person participated in the experiment, the respondents were asked to state their gender and year of birth as the first thing after logging in to the experiment. 38 respondents for whom the stated gender and/or year of birth is not identical to the information in the register

The register data contain demographic characteristics and information from the income tax register. The income tax register includes information on annual income as well as the values of assets and liabilities at the end of each year. The value of assets includes assessed property value, market value of stocks, bonds and mortgage deeds in deposit and bank deposits. The value of liabilities includes all debt except debt to private persons. All the register data are third-party reported. For instance, employers report earnings, government institutions report transfer payments, and information on assets and liabilities is reported by financial institutions. The data in the registers are organized as a panel data set so that it is possible to observe income, assets, and liabilities back in time for the respondents in the experiment. The data are available for the period 2000-2014. There are two components of wealth that the data described so far does not include. One is wealth accumulated in pension accounts and the other is wealth kept in cars. These two components have become available as of 2014, and in the robustness section we examine if the inclusion of these two components affect our findings when we confine the analysis to be based only on wealth observed in 2014.

In total, we sent out 27,613 invitations and reached 3,634 participants giving a gross participation rate of 13%. Participation rates at this level are common for similar experimental studies (e.g. Andersson et al. 2016 report 11%). The sample selected to receive invitations to participate in the experiment was sampled from the population register. We therefore know the identity of participants as well as invitees who did not respond to the invitation. As a result, we are able to compare the characteristics of the participants and non-participants. Results from doing this are presented in Table 1, panel 1. Compared to non-participants, participants are slightly older, less likely to be single, more likely to be homeowners and have slightly longer education. The magnitude of the differences appear to be relatively small. Participants, however, have a significantly higher level of income, net wealth and liquid assets than non-participants. In Table 1, column d we list the corresponding statistics for a 10 percent random sample from the Danish population in order to assess how representative our sample is of the Danish population at large. Compared to the random sample from the population, the sample of respondents is on average slightly younger and less likely to have children staying at home. They have slightly longer education, are less likely to be home owners, have higher income, but less net wealth. However, the magnitude of these differences are relatively small, and, incidentally, the respondents appear to be more similar, on average, to the random sample from the population than the gross sample. In section 5.4, we will investigate whether our results are sensitive to the differences in sample composition documented in Table 1.

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data are excluded from the analysis.

Table 1: Summary of selected characteristics

	(1) Respondents vs. non-respondents			(2) Respondents vs. 10 % of population	
	(a) Respondents	(b) Non-respondents	(c) Difference, (a)-(b)	(d) Population	(e) Difference, (a)-(d)
Means					
Age	36.32	35.45	0.87	36.38	-0.06
Woman (=1)	0.50	0.49	0.01	0.50	0.00
Single (=1)	0.29	0.39	-0.10	0.29	0.00
Dependent children (=1)	0.57	0.52	0.05	0.60	-0.03
Homeowner (=1)	0.40	0.33	0.07	0.56	-0.16
Years of education	14.65	13.93	0.72	14.46	0.19
Medians					
Wealth	386146.00	251551.40	134594.60	397204.50	-11058.50
Non-capital income	369923.40	331215.30	38708.10	350046.80	19876.60
Liquid assets	29898.90	21641.40	8257.50	26940.20	2958.70
Observations	3634	23823	27457	67588	71222

Notes: Variables are based on 2014 values. The random 10 percent sample of the Danish population is drawn among those who are not in the gross sample (i.e., did not live in Copenhagen Municipality when they were seven years old), but who were born in the same period (1973-1983). (=1) indicates a dummy variable which takes the value 1 for individuals who satisfy the description given by the variable name. The value of the car stock and wealth held in pension accounts are included in the measure of wealth. Furthermore, the tax assessed values of housing is adjusted by the average ratio of market prices to tax assessed values among traded houses. These ratios are calculated for each of 98 municipalities. Non-capital income refers to annual income. Liquid assets include bank deposits and market values of stocks and bonds. The table includes individuals for whom a full set of register variables is available.

5 Results

5.1 Basic association between discounting behaviour and wealth inequality

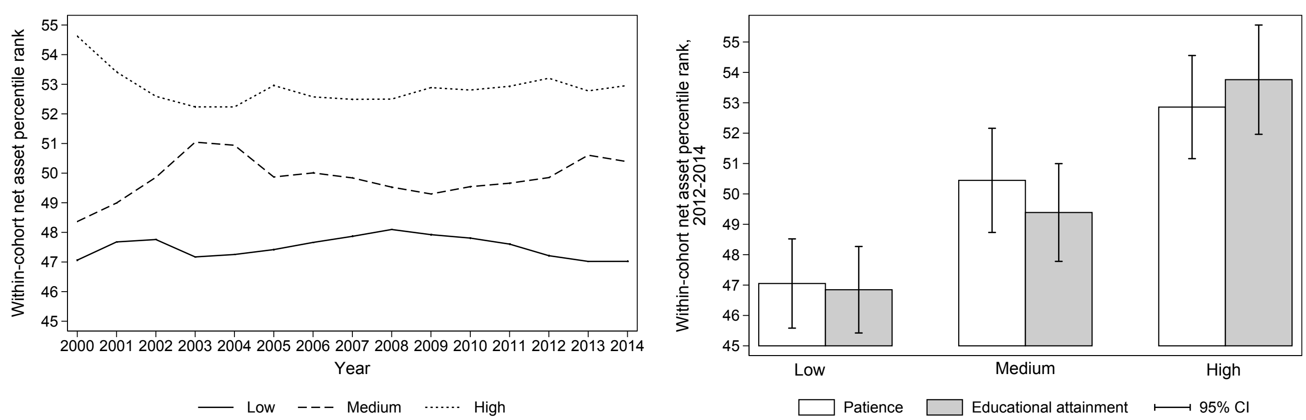
The basic neoclassical model of individual life-cycle savings presented in section 3, predicts that differences in discounting behaviour across individuals generate differences in savings behaviour which, in turn, generate differences in wealth. A basic premise of this proposition is that preferences are stable across time but can vary among individuals. In this section, we present the basic set of results where we investigate whether the experimentally elicited patience measure is predictive of the individual position in the wealth distribution. Wealth data are notoriously noisy and in order to construct the cleanest evidence we calculate the position in the net wealth distribution within the sample, measured by the percentile rank of the individual in the within cohort×time distribution (e.g. Chetty et al. 2014b). Figure 3a presents graphical evidence of the association between the elicited patience measure and the position in the real-life net wealth distribution of the individuals in the sample for each year in the period 2000-2014. In the figure, the sample is split into three equally sized groups according to the size of the patience measure such that the 'High' group includes the most patient individuals in the sample, 'Low' the least patient individuals and 'Medium' includes individuals with patience measures between the 'High' and 'Low' groups. The figure shows that the patience ordering of the individuals predicts the position in the net wealth distribution, so that the group consisting of the most patient individuals are at a higher position in the net wealth distribution on average, followed by the group with medium patience, and the group consisting of the most impatient individuals on average attain the lowest position in the net wealth distribution.

An important and standard assumption in economic theory (Stigler and Becker 1977), also underlying the basic model presented in section 2, is that preferences are reasonably stable across time. The stable relationship between elicited patience measures and the position in the wealth distribution is consistent with this assumption. One important caveat to mention is that patience is measured after the wealth data. This implies that we cannot rule out that historical savings and spending decisions have actually influenced our measurement of patience. However, the fact that the relationship between patience and the position in the wealth distribution is so stable over the period 2000-2014 suggests that this is not the case, at least within this 15-year period.[15]

Figure 3: Discounting behaviour, educational attainment and wealth inequality

(a) Patience and position in the wealth distribution 2000-14

(b) Patience vs. education



Notes: Panel a shows the association between elicited subjective discount factors and the position in the wealth distribution. The position in the wealth distribution is computed as the percentile. The sample has been split into three approximately equally sized groups according to the tertiles of the subjective discount factor such that 'High' includes the 33 percent most patient individuals in the sample, 'Low' the 33 percent most impatient individuals and 'Medium' the group in between the 'High' and 'Low' groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.6, 0.9]; High [1.0]. Panel b shows the association between the position in the wealth distribution and educational attainment, where the individuals in the sample have been split into three equally sized groups according to how many years of education they have completed. Cut-offs for the education groups (years): Low [8, 14); Medium [14, 16]; High (16, 21] where the numbers refer to years of completed education.

The basic theory suggests that heterogeneity in the degree of patience generates differences in savings behaviour that lead to wealth inequality. The theory is, however, simplistic and omits many realistic features, such as uncertainty, and including these would arguably mute the relationship between subjective discount factors and the position in the wealth distribution. Comparing the percentile rank position among the most patient with the rank position among the least patient in Figure 3a reveals a difference of about five to six rank points.

In order to assess whether this is a substantial magnitude we compare with the difference in wealth rank position between subjects with different educational attainment levels. Huggett et al. (2011) argue that educational attainment is one of the most important factors contributing to life time inequality, and we therefore think of

[15]Krupka and Stephens (2013) find, using a survey-elicited measure of time preferences, that measured discount rates reflect market interest rates faced by the individuals at the time of the survey rather than their pure rate of time preference. Eliciting discounting behaviour using experimental methods, as is done in the current study, arguably results in measures of patience that are robust to this and hence more closely related to the underlying theoretical concept. The stability of the relationship between elicited patience and the position in the wealth distribution shown in Figure 3a is consistent with this.

educational attainment as a useful comparison. In Figure 3b, we have split the sample into three equally sized groups according to educational attainment as measured by the number of years of completed education. The groups with least education has completed 8-14 years of education while the group with most education has completed 16-21 years of education. Comparing the groups with the lowest and the highest level of educational attainment shows a difference in the wealth rank position of six to seven rank points, which is quite similar to the difference in wealth rank positions between the most and the least patient groups. This finding suggests that the magnitude of the differences in wealth ranks between the most and the least patient groups is first order.

Figure 3 presents bivariate relationships and these can potentially be confounded by omitted factors. We therefore now turn to regression techniques and sequentially add potential confounders as control variables to the regressions in order to learn whether the relationship shown in Figure 3 is robust to these potential confounders. In the regressions, we focus on the wealth rank positions during the period 2012-2014. We do this because we would like to characterize the association between the elicited patience measure and wealth for individuals who have reached into a life stage where their current income is as close to its 'permanent level' as possible and where economic affairs are not dominated by early life decisions such as undertaking education and entering the labour market.[16] The results are presented in Table 2.

[16]We have also run the regression presented in Table 2 using the wealth data covering the period 2000-2014. The results are presented in section 5.4, and they confirm the results presented in Table 2.

Table 2: Patience and wealth inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	8.14***	6.62***	6.45***	6.88***	6.46***	5.89***	6.09***	6.35***
	(1.44)	(1.46)	(1.47)	(1.54)	(1.51)	(1.50)	(1.51)	(1.49)
Risk aversion							2.99	3.13
							(1.92)	(1.91)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-cohort non-capital income decile dummies, 2012-2014	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
Within-cohort net assets at age 18 decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Within-cohort parental net asset decile dummies	No	No	No	No	No	Yes	Yes	Yes
Additional controls	No	No	No	No	No	No	No	Yes
Constant	44.68***	42.86***	43.93***	43.09***	37.26***	35.31***	33.70***	33.07***
	(1.03)	(1.67)	(1.97)	(2.47)	(2.66)	(3.09)	(3.26)	(3.37)
Observations	3634	3634	3634	3360	3360	3360	3360	3360
Adj. R-squared	0.01	0.02	0.03	0.02	0.05	0.07	0.07	0.09

Notes: OLS regressions. Dep. var.: Within-cohort average net asset percentile rank, 2012-2014. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. The measurement of patience is described in expression (4). Parental net assets are measured when the respondents were 7-14 years old. 'Additional controls' include four variables: a gender dummy and share of the period (2012-2014) as single, with dependent children, and as homeowner. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

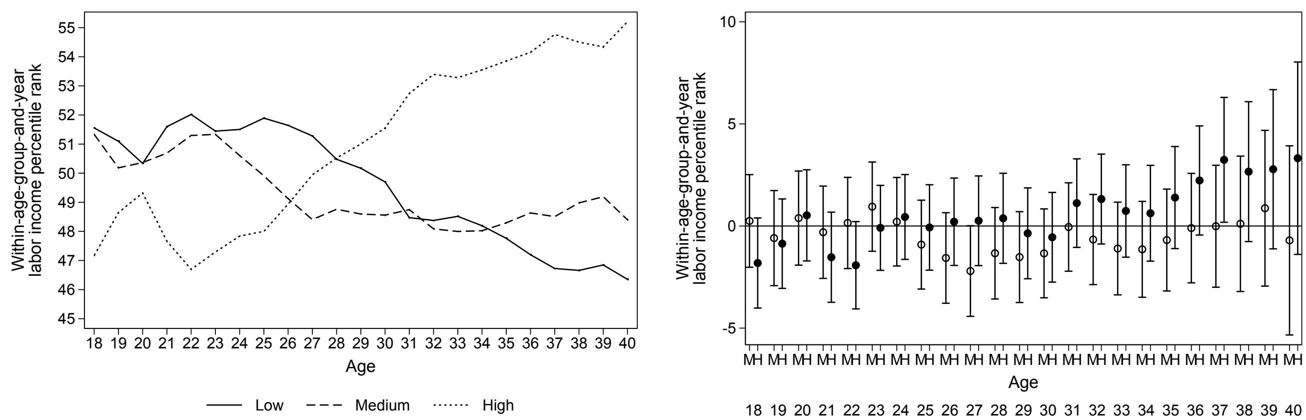
We start out in Column 1 presenting the results from a simple bivariate regression of the net wealth rank position on patience. Consistent with the graphical evidence, we find that moving from the lowest to the highest level of patience in the sample is associated with a difference of eight wealth rank points, and this relationship is highly statistically significant. In Figure 3b, we compared the magnitude of the association between patience and the position in the wealth distribution with the magnitude of the association between schooling and the position in the wealth distribution. However, as discussed in the theory section the most patient individuals might be more prone to delay income by choosing more education. In fact, the data show a statistically significant positive correlation between educational attainment and patience. The average years of education for the low patience group is 14.3, while it is 15.3 years for the high patience group. In this way, education would simply be another marker for patience as suggested by Lawrance (1991).

In column 2, flexible dummies for educational attainment are included as control variables. The coefficient on the patience measure decreases a bit, but remains highly significant and not statistically different from the coefficient in column 1. Thus, the relationship between patience and wealth exists beyond education. According to the basic theory, the cross-sectional variance in wealth potentially also depends on permanent income and the profile of income over time. In Figure 4a, we plot the position in the within-cohort income distribution for the respondents across different ages and separately for the three patience groups that were defined in Figure 3. The panel shows that the most patient group on average has a steeper income profile over the age interval 18-40. They start out being ranked lower in the income distribution than the less patient groups, but they pick up and by age 40 they are positioned about 6 rank points higher, indicating that their permanent level of income is higher. Such a pattern, where patient individuals choose relatively steep income profiles while less patient individuals choose relatively flat income profiles, is consistent with the theoretical conjecture that preferences are associated with the choice of education. The fact that more patient individuals have higher permanent income potentially implies that a correlation between wealth and patience can exist beyond the pure savings channel, i.e. without these individuals saving more relative to their permanent income. Arguably, we control for the effect of income timing and differences in permanent income by including flexibly for educational attainment in regressions reported in Table 2. To motivate this, consider Figure 4b which is analogous to Figure 4a except that we have now controlled for a set of fully flexible dummies for educational attainment. The figure shows that the differences across the three patience groups in level and slope of income are washed out by controlling for educational attainment. This suggests that including a detailed set of dummies for educational attainment in Table 2, column 2, adequately controls for differences in permanent income and for differences in the timing of income that are observed in the raw data.

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

(a) Unconditional

(b) Conditional on education



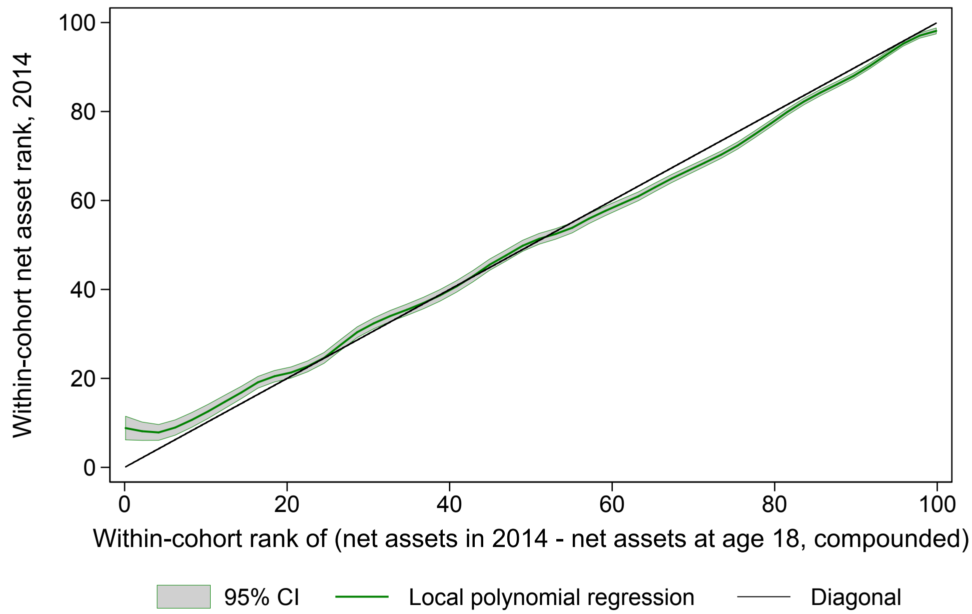
Notes: Panel a shows the position in the within-age-group-and-year labor income distribution for the respondents over the life-cycle separately for three patience groups. The sample has been split into three approximately equally sized groups according to the tertiles of the subjective discount factor such that 'High' includes the 33 percent most patient individuals in the sample, 'Low' the 33 percent most impatient individuals and 'Medium' the group in between the 'High' and 'Low' groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.6, 0.9]; High [1.0]. Panel b plots coefficients from regressions of 'within-age-group-and-year labor income percentile rank' on the patience groups and fully flexible 'years of education' dummies. 'M' and 'H' indicate the 'Medium' and 'High' patience groups, respectively. 'Low' patience is the base group. Capped spikes represent 95% CI. The panel shows that the income paths for the three patience groups are leveled out when controlling for education.

In column 3 of Table 2 we include decile dummies controlling for the average position in the (non-capital) income distribution among people belonging to the same cohort across the period 2012-2014. This can be considered as an additional way to control for permanent income. The parameter on our measure of patience is, however, hardly affected by the inclusion of these dummies.[17] The theory points towards initial conditions being important potential confounders. Ability constitutes one such important 'initial condition'. Recent evidence has suggested that cognitive ability correlates with preferences, both risk aversion and impatience (Dohmen et al. 2010).[18] In order to control for cognitive ability we include decile dummies for school grades in column 4, but this does not change the estimate of our parameter of interest. Initial wealth is another potential confounding factor according to the basic theory. Figure 5 plots the net asset percentile rank in year 2014 (last year of available data) against the percentile rank of net assets in year 2014 *less* net assets held at age 18, the age of majority. In constructing this figure, we have compounded net assets at age 18 with a considerable real interest rate (5 percent) to make sure that we do not underestimate the potential effect of initial wealth. The figure shows that the compounded wealth level at age 18 has a negligible effect on the relative wealth distribution in year 2014.

[17]We have also tried to construct a figure corresponding to Figure 3, but where net wealth is normalized by average income 2012-2014 before calculating the position in the net wealth distribution. This graph also showed that the most patient individuals are persistently located higher in the net wealth distribution than the less patient.

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

Figure 5: Importance of initial wealth at age 18



Notes: Local polynomial regression of net asset percentile rank (2014) on the percentile rank of net assets in 2014 less net assets held at age 18. Net assets at age 18 have been compounded by a real interest rate of 5 percent.

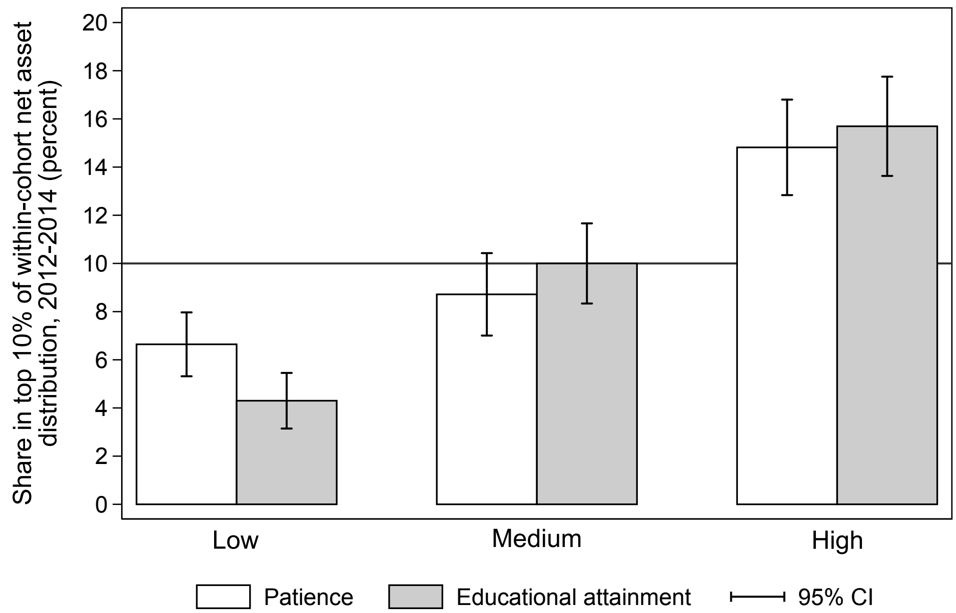
In Table 2, column 5 we include decile dummies for the within-cohort net asset rank at age 18. Consistent with the graphical evidence presented in Figure 5, the inclusion of these controls does not affect the parameter on patience in any important way. Wealth accumulation can, of course, also be influenced by transfers from parents. We do not directly observe bequests and inter vivo transfers in the data. However, such transfers are probably correlated with initial wealth and parental wealth. In column 6 we add decile dummies for the within-cohort parental net wealth, but this does not affect the parameter estimate associated with our patience measure significantly. While we do not directly observe transfers from parents to children we are able to exploit the longitudinal aspect of our administrative data. If parents make transfers to their children then that should create a negative correlation between adjustments in parental wealth and child wealth (Kolodziejczyk and Leth-Petersen 2013). This test is reported in Appendix I, and it does not show evidence of transfers from parents to children. As part of the experimental procedure we have also elicited risk preferences. Theoretically, the association between risk aversion on wealth is not clear. According to the theory presented in section 3, the CRRA parameter has ambiguous effects on wealth depending on the relative size of the rate of time preference and the real interest rate on savings. The model predicts a positive effect of the CRRA parameter on wealth if the rate of time preference is greater than the real interest rate on savings and a negative effect if the rate of time preference is smaller than the real interest rate on savings. In Appendix H we perform an implicit test of this prediction: For each patience group, we regress the net wealth percentile rank on the experimental measure of risk aversion. Consistent with the model prediction, the less patient the group is, the more positive the effect of risk aversion on relative wealth is. Irrespective of the theoretical association between risk aversion and wealth, previous studies have shown evidence that risk aversion and patience are correlated (e.g. Leigh 1986; Anderhub et al. 2000; Eckel et al. 2005). In our data elicited risk aversion is also correlated with elicited patience, and risk aversion could therefore potentially confound the association between wealth and patience. In column 7 we include our experimental measure of risk aversion among the control variables. Again, our parameter of interest is left virtually unchanged and remains strongly significant.

Finally, in column 8 we include a set of additional controls for gender, single status, dependent children and homeowner status, but the inclusion of the variables does not impact the parameter estimate on our patience measure either. In summary, we find that the pattern depicted in Figure 3 is statistically significant and that the relationship between patience and the position in the wealth distribution is robust to the inclusion of a number of important potential confounders. We find that there is a positive relationship between the position in the net wealth distribution such that comparing the bottom third with the top third in the patience distribution is associated with an difference in the position of the net wealth distribution of about 6 rank points.

5.2 Top 10 percent wealthiest

A sizable literature has studied the concentration of wealth at the top of the distribution. For example, Piketty and Saez (2014) find that the share of total wealth owned by the 10 percent wealthiest have been in the range 60-90 percent over the last 150 years in the US and Europe. In order to examine whether there is an association between our patience measure and the propensity to be in the top end of the wealth distribution we display in Figure 6 the fraction of respondents who belong to the ten percent wealthiest within the three patience groups defined in the previous section. The figure shows that in the least patient group about six percent belong to the ten percent wealthiest in the sample whereas 15 percent of the individuals categorized to be among the most patient individuals belong to the wealthiest ten percent in the sample. Again, we compare the association with that for education, and while the association between patience and the propensity to be among the ten percent wealthiest is not quite as stark, it is of the same order of magnitude and significant in economic terms. In Appendix J, we show regressions corresponding to the regressions presented in Table 2, but where the dependent variable is a dummy variable indicating whether the respondent belongs to the ten percent wealthiest. The results indicate that patience is statistically significant, even when we control for the most comprehensive set of control variables as in Table 2, column 8, and the parameter of interest attains a value that is close to what we see in the main analysis. Due to the limited sample size, it is impossible to credibly examine how patience is related to the propensity to belong to the group of very wealthy, say, top 0.1%.

Figure 6: Relationship between patience and being among the top 10% wealthiest



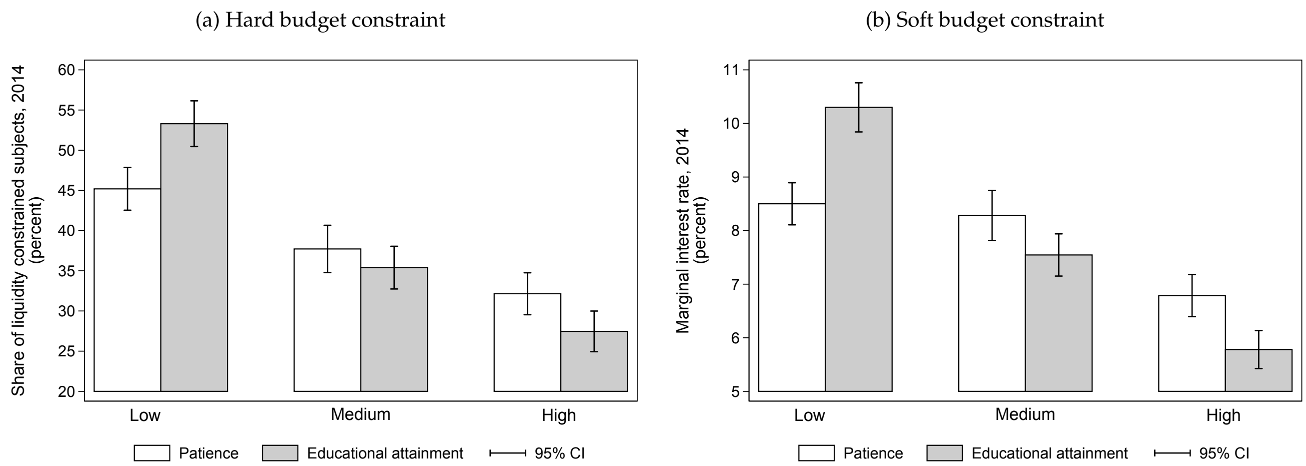
Notes: The white bars show the association between elicited patience and the propensity to be among the ten percent wealthiest in the sample. The sample has been split into three approximately equally sized groups according to the tertiles of the patience index such that 'High' includes the 33 percent most patient individuals in the sample, 'Low' the 33 percent most impatient individuals and 'Medium' the group in between the 'High' and 'Low' groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.6, 0.9]; High [1.0]. The grey bars show the association between the propensity to be among the ten percent wealthiest in the sample and educational attainment, where the individuals in the sample have been split into three equally sized groups according how many years of education they have completed. Cut-offs for the education groups (years): Low [8, 14); Medium [14, 16]; High (16, 21] where the numbers refer to years of completed education.

5.3 Heterogeneous discounting and liquidity constraints

Theory informs that people who are relatively patient will save relatively more and will therefore face a smaller risk of being liquidity constrained, or, conversely, that people who are relatively impatient are more likely to be affected by liquidity constraints. In this section, we explore the relationship between our measure of patience and two proxies for liquidity constraints. Liquidity constraints are inherently difficult to measure as they are defined by the shadow value of liquidity, which is not observed. We follow the previous literature and explore two different proxies for liquidity constraints. Our first measure is a dummy variable for the respondent holding liquid financial assets corresponding to less than one month's worth of disposable income. This measure has routinely been applied in the literature (e.g. Zeldes 1989; Johnson et al. 2006; Leth-Petersen 2010). However, it is not necessarily a good measure of the shadow value of liquidity as people can have different access to credit, which we do not observe, and therefore effectively face constraints that affect them with different intensity even if they are otherwise observationally equivalent. We therefore also construct a measure of the marginal interest rate, which is arguably a better proxy for the marginal price of liquidity. To construct a measure of the marginal interest rate we exploit that we have access to account level data with information about outstanding debt and interest payments during the year. We use this to calculate an average interest rate for each account that we observe for the individual. For people with debt accounts we pick the highest interest rate among debt accounts as the marginal interest rate. For people who do not have debt we pick the lowest interest rate among their deposit accounts based on the logic that this is the cheapest source of liquidity. This measure has been proposed by Kreiner et al. (2016) who document that it is able to match the interest rate on accounts where banks report nominal interest rates and to predict spending responses to a stimulus policy. In Appendix K we present more details about the construction of the marginal interest rate.

In order to illustrate the association between patience and the indicators for being affected by constraints, we do as before and split the sample into three equally sized groups depending on the magnitude of the experimental patience measure and calculate the fraction who are observed with liquid assets worth less than one month of disposable income, Figure 7a, and the average marginal interest rate, Figure 7b. Panel a shows that 33 percent of the individuals in the most patient group are observed with a low level of liquid assets in real-life while 45 percent are observed with a low level of liquid assets in the least patient group. This is consistent with the theoretically motivated proposition that impatient people save less and hence are more likely to end up in a situation where they are affected by liquidity constraints. In order to gauge the magnitude of this association we compare with education. To do this we split the sample into three equally sized groups (as we did in Figure 3b) depending on educational attainment. For each educational attainment group we have calculated the fraction observed with a low level of liquid assets. As is seen from Figure 7a, the low liquid asset gradient observed by moving from the highest to the lowest patience groups is about 12 rank points where as it is about 25 rank points when moving from the group with the highest level of educational attainment to the group with the lowest level of educational attainment. Turning to the association between the patience measure and the marginal interest rate, Figure 7b, the overall pattern is confirmed. The most patient group faces, on average, a marginal interest rate of about 7 percent while the least patent group faces a marginal interest rate of about 8.5 percent. Comparing with educational attainment, the group with the highest level of educational attainment faces, on average, a marginal interest of 6 percent while the group with the lowest level of educational attainment faces a marginal interest of about 10 percent on average. So, also for this measure is the schooling gradient stronger than the patience gradient, but the magnitude of the association between patience and the prevalence of people affected by liquidity constraints still appears to be substantial when measured with two different variables approximating for the importance of liquidity constraints.

Figure 7: Discounting behaviour and the probability of being credit constrained



Notes: Panel a: The white bars show the association between elicited patience and the propensity to hold liquid assets worth less than one month of disposable income. The sample has been split into three approximately equally sized groups according to the tertiles of the patience index such that 'High' includes the 33 percent most patient individuals in the sample, 'Low' the 33 percent most impatient individuals and 'Medium' the group in between the 'High' and 'Low' groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.6, 0.9]; High [1.0]. The grey bars show the association between the propensity to hold liquid assets worth less than one month of disposable income and educational attainment, where the individuals in the sample have been split into three equally sized groups according how many years of education they have completed. Cut-offs for the education groups (years): Low [8, 14); Medium [14, 16]; High (16, 21] where the numbers refer to years of completed education. Panel b: The white bars show the association between elicited patience and the marginal interest rate for the three patience groups defined in panel a. The grey bars show the association between the marginal interest rate and educational attainment, where groups are defined like in Panel a.

Figure 7 presents bivariate evidence. In Table 3 we show results from regressions where the dependent variable is the measure for holding low levels of liquid assets and the explanatory variables include patience as well as the same sets of control variables that we applied in the regressions presented in Table 2. Irrespective of the control set applied, the estimations suggest that patience is significantly associated with the propensity to be observed with low levels of liquid assets, and the magnitude suggest that the fraction with low liquid assets is ten percentage points lower for the group with the highest level of patience in the sample than for the group with the lowest level of patience in the sample. The analysis in Appendix K shows that the association between patience and marginal interest rates is also robust to controlling for covariates. In summary, we find clear evidence that elicited patience is correlated with the propensity to be affected by liquidity constraints, or more generally with the intensity of such constraints.

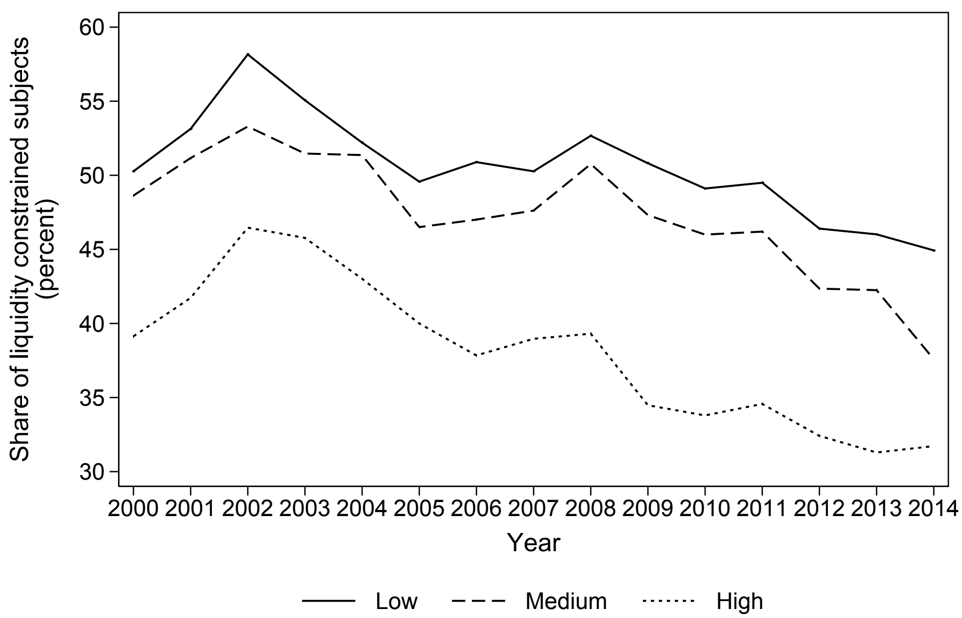
Table 3: Patience and liquidity constraints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	-0.16***	-0.12***	-0.11***	-0.11***	-0.11***	-0.10***	-0.10***	-0.10***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Risk aversion							0.01	0.01
							(0.03)	(0.03)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-cohort non-capital income decile dummies, 2012-2014	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
Within-cohort net assets at age 18 decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Within-cohort parental net asset decile dummies	No	No	No	No	No	Yes	Yes	Yes
Additional controls	No	No	No	No	No	No	No	Yes
Constant	0.49***	0.75***	0.74***	0.73***	0.81***	0.83***	0.82***	2.26
	(0.02)	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)	(1.19)
Observations	3626	3626	3626	3353	3353	3353	3353	3353
Adj. R-squared	0.01	0.07	0.09	0.09	0.10	0.11	0.11	0.13

Notes: OLS regressions. Dep. var.: Dummy for holding liquid assets worth less than one month of disposable income, 2014. Robust standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Parental net assets are measured when the respondents were 7-14 years old. 'Additional controls' include six variables: age, age^2, and dummies for gender, marital status, dependent children, and homeowner status. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

The theoretical description of preference heterogeneity is that preferences can vary among people but are relatively stable across time for each individual. However, when it comes to the measurement of the relationship between the indicators for being affected by liquidity constraints and elicited patience one important caveat applies: Patience is measured after the data used for constructing the indicator for holding low levels of liquid assets has been collected. This opens for the possibility that elicited patience is, in fact, a response to an adverse shock which has lead the individual to drive down his liquid assets and, consequently, transitorily behave as if he is not relatively patient even if he actually is. Figure 8 shows the fraction of people who are recorded with liquid assets worth less than one month of disposable income for the period 2000-2014 for each of the three patience groups. The graph shows that the propensity to be observed is generally declining for all three groups over time. This reflects the fact that people in the sample are in the early stages of their life-cycle and accumulate more assets as they get older. However, the figure shows a compelling pattern, where people who are classified as relatively patient are persistently, i.e. over a period of 15 years, recorded as being less likely to be affected by constraints. Such persistence is difficult to rationalize with short term shocks having appeared shortly before the point in time where patience has been elicited. We cannot rule out that very persistent shocks having appeared earlier than 2000 have affected the financial position of our respondents and that this could have affected elicited patience.

Figure 8: Prevalence of liquidity constraints across levels of patience, 2000-2014



Notes: The figure shows the association between elicited patience and the frequency of individuals within each patience group who are observed with liquid assets corresponding to less than one month of disposable income. The sample has been split into three approximately equally sized groups according to the tertiles of the patience index such that 'High' includes the 33 percent most patient individuals in the sample, 'Low' the 33 percent most impatient individuals and 'Medium' the group in between the 'High' and 'Low' groups. Cut-offs for the patience groups are: Low [0.0, 0.5]; Medium [0.6, 0.9]; High [1.0].

5.4 Additional analyses and robustness checks

The results presented so far are potentially sensitive to a number of choices made in order to operationalize the empirical analysis. In this section, we present a series of robustness checks to corroborate our findings, and the results from these are presented in Table 4. The first column in Table 4 reproduces column 8 from Table 2, i.e. the specification with the richest set of control variables included. The dependent variable in this specification is based on net wealth ranks calculated over the period 2012-2014. In that analysis, we focus on the latest years in the sample, because we want to characterize the association between elicited patience and wealth for individuals who have reached into a life stage where their current income is as close to its 'permanent level' as possible and where their financial position is not dominated by early life decisions such as undertaking education and entering the labour market. However, Figure 3a showed evidence that the bivariate association between patience and wealth is stable over a much longer period, 2000-2014. In Table 4, column 2, we re-estimate the reference model reported in column 1 using annual observations for the entire data period 2000-2014. Consistent with the impression provided by Figure 3a, the multivariate results are robust to this change. The association between the position in the asset distribution and patience is highly statistically significant and of the same magnitude as the corresponding estimate in Table 2.

Table 4: Patience and wealth inequality. Robustness analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	6.35***	4.76***	6.82***	5.93***	5.79***	4.61***	5.63***	5.68***
	(1.49)	(1.00)	(1.28)	(1.40)	(1.37)	(1.25)	(1.52)	(1.66)
Risk aversion	3.13	0.35	1.16	3.06	2.31	2.60	3.75	4.17*
	(1.91)	(1.27)	(1.64)	(1.81)	(1.74)	(1.57)	(1.96)	(2.11)
Year dummies for educational attainment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-cohort non-capital income decile dummies, 2012-2014	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-cohort net assets at age 18 decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-cohort parental net asset decile dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	No	Yes	No	No	No	No	No	No
Within-cohort non-capital income decile dummies	No	Yes	No	No	No	No	No	No
Constant	33.07***	44.86***	12.04***	29.15***	27.42***	15.83***	33.75***	32.25***
	(3.37)	(3.06)	(2.95)	(3.20)	(3.14)	(2.85)	(3.56)	(4.01)
Observations	3360	49473	3360	3360	3360	3360	3275	3275
Adj. R-squared	0.09	0.13	0.31	0.20	0.24	0.39	0.08	0.09

Notes: OLS regressions. Column 1 reproduces column 8 form Table 4.1. Column 2 includes annual data on net assets for the period 2000-2014. For this column standard errors are clustered at the individual level. Column 3 considers only financial assets, ie. stocks, bonds, and deposits. Column 4 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses. These ratios are calculated for each of 98 municipalities. Column 5 includes value of the the car stock. Dependent variable measured only for 2014. Column 6 includes both the value of the car stock and wealth held in pension accounts. In this column the dependent variable is measured only for 2014. In column 7 the dependent variable is based on average net assets, 2012-2014 (as in column 1), but the equation is estimated using inverse probability weighting where probability weights are based on respondents vs. non-respondents. In Column 8 results from estimating using inverse probability weighting where the weights are based on respondents vs. population. The number of observations is slightly lower in columns 7-8 as some of the respondents do not have strictly positive non-capital income or liquid assets.

The theory presented in section 2 characterizes wealth as being held in just one asset. A natural interpretation is that it reflects net wealth, which is the wealth concept we have used in the analysis so far. An alternative interpretation is that it reflects financial assets. In column 3 the reference specification is re-estimated using financial assets, consisting of stocks, bonds and deposits, as the basis for constructing the position in the wealth distribution. Also for this outcome we find that the positive relationship between patience and the ranking in the financial asset distribution is similar to the result obtained in the reference specification based on net wealth.[19] Column 4 adjusts tax assessed values of housing by the average ratio of market prices to tax assessed values among traded houses. These ratios are calculated for each of 98 municipalities. The estimate of the patience parameter is largely unaffected relative to the reference estimate in column 1. The wealth data, including housing and financial wealth, are consistently third-party reported for an exceptionally long period. However, they lack two components of wealth that are potentially important for assessing wealth inequality, wealth kept in the car stock and wealth accumulated in pension accounts. Data documenting these two components has recently become available, but only for 2014. In column 5, we include the value of the car stock among assets and calculate the net wealth rank based only on 2014 data. The patience parameter is slightly smaller than the reference estimate presented in column 1 but not significantly different from it. In column 6 also wealth kept in pension accounts is added. This addition mutes the point estimate of the patience parameter additionally, although it is not significantly different from the reference estimate in column 1. Even if the difference is not statistically different there are, in fact, good reasons why adding pension wealth would attenuate the result. 90 percent of contributions to pension accounts are made to illiquid employer organized pension accounts (Kreiner et al. 2017), and the contributions are predominantly determined by collective labour market agreements. As documented by Chetty et al. (2014a) the majority responds passively to these savings mandates, i.e. they do not adjust other types of savings in response to these savings mandates.

Only a fraction of the subjects that we invited to participate in the experiment took up the invitation, and this can potentially imply that our sample is selected and not representative of the population at large. In column 7 we re-estimate the reference specification from column 1 using propensity score weighting, where the propensity scores measure the propensity to participate in the experiment for all the subjects that have been invited, and the propensity scores have been estimated using the variables included in Table 1. The results presented in column 7 are close to the estimate from the reference specification. In Column 8 we construct propensity scores measuring the propensity to be in the experiment compared to the population at large. Also in this case, do we not find any important deviation from the benchmark model. The propensity score weighting approach is based on the assumption that the selection into the experiment can be adequately captured by the variables included Table 1. To the extent that this is a reasonable assumption, our results do not appear too specific to the sample that we have elicited patience measures for. In total, Table 4 presents a series of alternative estimates designed in order to check the validity of our main finding showing that elicited patience is associated with wealth inequality and that the

[19] In agreement with the results presented in Figure 3, the more patient respondents are persistently ranked higher in the financial asset distribution relative to their less patient peers over the period 2000-2014 (not reported).

magnitude of the association is non-trivial.

Our patience measure is based on the subset of choice tasks where the subjects where asked to choose between payouts 8 and 16 weeks from the experiment date. However, as described in section 4 we also confronted subjects with trade-offs that involved payouts made as soon as possible after the experiment, where the delay only pertained to the time required to administer the transfer to the participant's account. In table 5 we construct patience measures based on all possible combinations of the payment dates that we have exposed subjects to ("today", "in 8 weeks", and "in 16 weeks"). Column 1-3 show bivariate correlations between net wealth ranks and patience for all the combinations of payout days that subjects were asked to complete choice tasks for. Across all three combinations of payout days we observed a correlation of similar magnitude. In column 4-6 we add the full set of control variables as in Table 2, column 8. Across all patience measures the estimated parameter on patience is stable and only slightly smaller than for the case where no control variables are included.[20]

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

Table 5: Patience and wealth inequality. Alternative patience measures

	(1)	(2)	(3)	(4)	(5)	(6)
Patience, 8 vs. 16 weeks	8.14***			6.35***		
	(1.44)			(1.49)		
Patience, 0 vs. 8 weeks		8.79***			6.74***	
		(1.48)			(1.53)	
Patience, 0 vs. 16 weeks			8.97***			7.03***
			(1.55)			(1.59)
Risk aversion				3.13	3.01	3.20
				(1.91)	(1.90)	(1.91)
Year dummies for educational attainment	No	No	No	Yes	Yes	Yes
Within-cohort non-capital income decile dummies, 2012-2014	No	No	No	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes
Within-cohort net assets at age 18 decile dummies	No	No	No	Yes	Yes	Yes
Within-cohort parental net asset decile dummies	No	No	No	Yes	Yes	Yes
Additional controls	No	No	No	Yes	Yes	Yes
Constant	44.68***	44.16***	43.73***	33.07***	32.66***	32.21***
	(1.03)	(1.06)	(1.15)	(3.37)	(3.38)	(3.42)
Observations	3634	3634	3634	3360	3360	3360
Adj. R-squared	0.01	0.01	0.01	0.09	0.09	0.09

Notes: OLS regressions. Dep. var.: Within-cohort average net asset percentile rank, 2012-2014. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. "Patience, 8 vs. 16 weeks" is the standard measure referred to as "Patience" in the other tables and figures. Parental net assets are measured when the respondents were 7-14 years old. 'Additional controls' include four variables: a gender dummy and share of the period (2012-2014) as single, with dependent children, and as homeowner. The number of observations decreases in columns 4-6 due to some of the respondents not reporting school grades.

As a final robustness check we assess the degree of inter vivo wealth transfers from parents to children. A reason for the wealth inequality that we see in the data could be that parents make transfers to their children during adulthood. To investigate whether there is significant inter vivo transfers from parent to children of a magnitude that significantly affects wealth accumulation of the respondents we link parents and children and exploit the longitudinal dimension of the data to examine whether adjustments of parents' wealth are correlated with adjustments to their children's wealth. Specifically, we regress the first-difference of the child's (log) liquid assets on the first difference of the parents' (log) liquid assets using annual data for the period 2000-2014. If monetary transfers from parents to children are widespread, we should expect to find a significant and negative coefficient reflecting that a relative decrease in parents' liquid assets is accompanied by a relative increase in the respondent's liquid assets. The results, reported in Appendix I, show no evidence of a significant relationship between changes in parental liquid asset holdings and changes in respondent liquid asset holdings. This finding is robust to the definition of parental and child wealth, including debt.

6 Concluding remarks

According to standard economic theory, differences in how much people discount the future generate differences in savings behaviour and thereby wealth inequality. We test this proposition by analyzing a unique combination of data with information about subjective patience attitudes and real-world wealth levels for a large sample of middle-aged individuals in Denmark. Subjective measures of patience are elicited using state-of-the-art experimental methods and linked to longitudinal administrative wealth records for a period covering 15 years. We find substantial heterogeneity in elicited patience across individuals, and that individuals with a relatively high level of patience are positioned relatively high in the wealth distribution consistently over the 15 year period. The correlation between patience and the position in the wealth distribution is significant and of the same magnitude as the correlation between education and wealth, and exists after controlling for education, income, initial wealth and parental wealth, suggesting that the savings mechanism is important. We also find that people with a relatively low level of patience are more likely to be persistently affected by credit constraints. This is consistent with models where impatient people run down their assets in order to keep current spending relatively high, implying they face a higher risk of becoming credit constrained (Krueger et al., 2016; Carroll et al., 2017). In this sense, credit constraints are to some extent self-imposed in these models.

Overall, our results point to the importance of incorporating heterogeneous time discounting in models of consumption and savings behaviour as originally suggested by Krusell and Smith (1998) and recently applied by Hubmer et al. (2016), Krueger et al. (2016), Carroll et al. (2017), De Nardi and Fella (2017) and Alan et al. (2017). In this paper we have shown that the ordering of elicited patience predicts the position in the real-life wealth distribution. To make a direct link between experimentally elicited discounting behaviour and discount rates entering models of aggregate savings behaviour would be a natural next step. Converting choice task data of the type collected in this study into discount rates can be done by imposing structure on the shape of the utility function. However, taking this step is likely to be a challenge in practice. Andreoni and Sprenger (2012) elicit discounting behaviour on a sample of college students using similar techniques as applied in this paper, but highlight that experiments involving relatively small stakes, i.e. much smaller than the stakes involved in most real-life settings, require the use of very high interest rates in the context of the experiment. Consequently, estimated discount rates become much higher than what is implied by aggregate models of discounting. However, insofar as the ordering of patience derived from small stake choice tasks is the same as it would be in a setting with large stakes, the experiments can credibly elicit the ordering of individuals in terms of their discounting behaviour. Our results suggest that this is the case.

Preference heterogeneity may also have important implications for the design of redistribution policies. Differences in wealth originating purely from the budget constraint, such as ability differences, income shocks, and transfers, reflect differences in lifetime consumption possibilities, but differences in patience generate wealth inequality for individuals even if they face similar lifetime consumption possibilities. If the goal of redistribution and social insurance policy is to reduce inequality in consumption possibilities then, viewed through the lens of a neoclassical model, policies targeting savings and wealth may not be ideal because such policies lead to differences in lifetime consumption of people having the same economic resources. On the other hand, a high degree of impatience may reflect present-bias or other behavioural biases, which might call for forced savings schemes that reduce wealth inequality (Chetty et al. 2014a). We do not find evidence suggesting present-biased behaviour, but cannot rule it out.

The relationship between patience and wealth documented in this paper also has other implications. It is standard practice to assume that preferences are stable, at least through adult life. However, recent evidence point towards the idea that preferences are potentially malleable in childhood. A recent field experiment in Turkey by Alan and Ertac (2017) finds that teaching to make children understand the long-term consequences of decision-making has persistent effects on the degree of patience in future intertemporal decisions of the children. Combined with our results, this suggests that school curriculum and education policy may have important long term implications for consumption behaviour and wealth inequality.

A Derivation of (3)

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

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

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

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

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

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

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

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

By integrating (5), we obtain

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

which is substituted into the above equation in order to get

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

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

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

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

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

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

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

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

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

B Relationship between wealth and impatience

Differentiating (3) with respect to ρ gives:

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

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

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

where $k \equiv \frac{\rho-r(1-\theta)}{\theta}$. The function $\frac{e^{ka}-1}{a}$ equals k when $a \to 0$ (which may be seen by applying l'Hôpital's rule) and is increasing in a for all values of $k \neq 0$.[21] For $T > a$, this implies that $\frac{e^{kT}-1}{T} > \frac{e^{ka}-1}{a}$.

C Relationship between wealth and the intertemporal elasticity of substitution

Differentiating (3) with respect to θ gives:

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

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

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

D Invitation letter

Figure A1: Invitation letter

ØKONOMISK INSTITUT
KØBENHAVNS UNIVERSITET

[redacted]

Kære [redacted],

FEBRUAR 2015

ØKONOMISK INSTITUT

ØSTER FARIMAGSGADE 5,
BYGNING 26
1353 KØBENHAVN K

TLF 35 33 02 77

analyse@econ.ku.dk

Dataansvarlig: Søren Leth-Petersen,
Professor

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

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

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

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

Brugernavn: deltager5795   Password: n4mw9!uay

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

Med venlig hilsen

Søren Leth-Petersen
Søren Leth-Petersen
Projektleder, professor

English translation of the invitation letter:

Dear «name»,

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

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

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

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

Username: «username» Password: «password»

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

Sincerely yours,

Søren Leth-Petersen
Project manager, professor

E Choice situations for time task

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

Table A1: Time choice situations

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

F The risk task and risk aversion measure

The risk task

We also elicited measures of risk aversion. To do so, we used investment games (IGs) similar to Gneezy and Potters (1997). The main differences to their setup is (i) that we used a graphical interface to present the investment choice, and (ii) that we varied both probabilities of winning and rate of returns across the choice situations. A typical choice situation is depicted in the figure below. The left panel shows the initial state of a choice situation. The subject was endowed with ten 100-points blocks positioned at the very left of the screen. He could then decide how many of these blocks he wished to invest in a risky asset. The (binary) risky asset, depicted on the right-hand side of the choice screen resulted in either a good outcome or a bad outcome. In the example, the good outcome occurred with probability 60% (illustrated by the wheel on top of the risky asset) and yielded 130 points for each invested 100-points block. The bad outcome occurred with probability 40% and yielded 70 points for each invested

100-points block. The interface worked the same as in the time task.

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

(a) (b)

A total of 15 choice situations were implemented. They varied in terms of probabilities and rates of return. Table A2 presents a list of all choice situations in the risk task.

Table A2: Risk choice situations

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

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

Risk aversion measure

Our risk aversion index is constructed as follows: We take all choice situations with zero skewness, i.e. with probability 0.5 (see Table A2). We then normalize and aggregate using the median.[22]

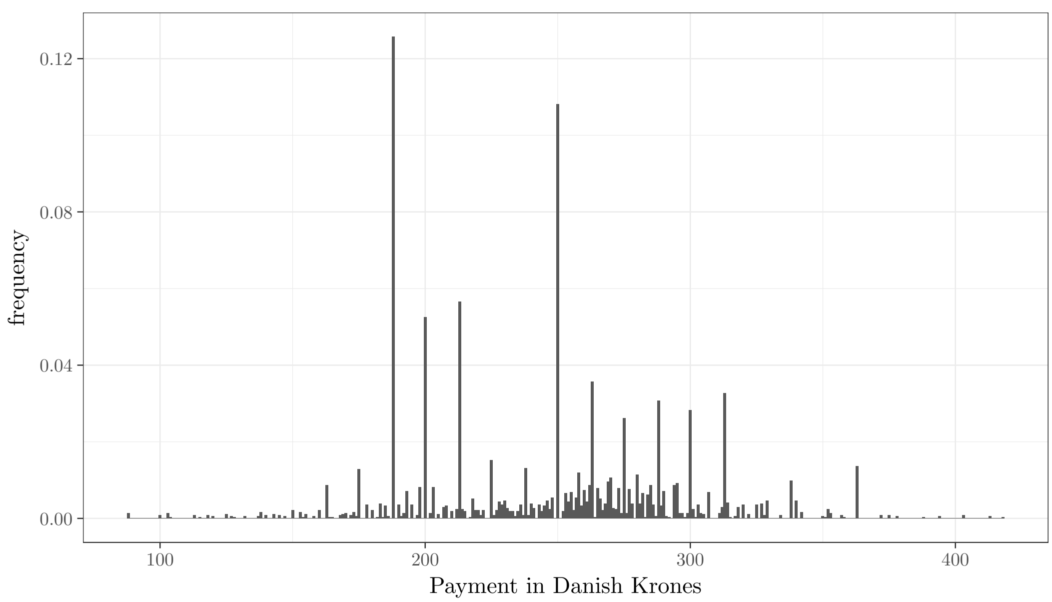
We define:

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

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

G Distribution of payments from the experiment

Figure A3: Distribution of payments from the experiment



H CRRA

Theoretically, the association between risk aversion and wealth is not clear. According to the theory presented in section 3, the CRRA parameter has ambiguous effects on wealth depending on the relative size of the rate of

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

time preference and the real interest rate on savings. The model predicts a positive effect of the CRRA parameter on wealth if the rate of time preference is greater than the real interest rate on savings and a negative effect if the rate of time preference is smaller than the real interest rate on savings. Here we perform an implicit test of this prediction: For each of the three patience groups, we regress the net asset percentile rank on the experimental measure of risk aversion. The results are presented in Table A3. Comparing the estimated coefficients on risk aversion in columns 1-3 it appears that the less patient the group is, the more positive is the effect of risk aversion on relative net wealth. This is consistent with the model prediction. Columns 4 and 5 control for the variation in the patience measure within the 'Low' and 'Medium' patience groups (recall from Figure 2 that there is no variation in the patience measure for the 'High' patience group). Controlling for the variation in patience within the patience groups increases the trend that the positive effect of risk aversion on relative net wealth is strongest for the least patient group.

Table A3: CRRA

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

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

I Inter vivo transfers

Table A4 uses annual data for the period 2000-2014 to analyze whether adjustments of parents' wealth are correlated with adjustments of their children's wealth. The children comprise the respondents in the experiment. Columns 1-3 report results from regressing the first-difference of the child's (log) liquid assets on the first difference of the parents' (log) liquid assets and other covariates. Column 1 presents the bivariate relationship and shows a positive correlation between the changes in child and parental liquid assets. If monetary transfers from parents to children were widespread, this should be reflected in a negative coefficient indicating that a decrease in parents' liquid assets is accompanied by an increase in the child's liquid assets. Column 2 further controls for the first-difference of the child's (log) non-capital income, age of the child, educational attainment of the child, and year fixed effects. This makes the effect of changes in parental liquid assets insignificant. Column 3 adds the first difference of the parents' (log) bank debt to allow for parents incurring debt and passing on the money to the child. The results show no evidence of this.

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

Table A4: Inter vivo transfers

	Δln(Child liquid assets)			Δln(Child bank debt)		
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(Parent liquid assets)	0.019*	0.013	0.010	-0.010	-0.014*	-0.014*
	(0.009)	(0.009)	(0.010)	(0.006)	(0.006)	(0.006)
Δln(Child non-capital income)		0.484***	0.461***		0.012	0.012
		(0.032)	(0.038)		(0.019)	(0.022)
Age		0.086***	0.089***		-0.219***	-0.235***
		(0.012)	(0.015)		(0.017)	(0.020)
Age^2		-0.001***	-0.001***		0.003***	0.003***
		(0.000)	(0.000)		(0.000)	(0.000)
Years of education		-0.044**	-0.038		0.016	0.008
		(0.014)	(0.021)		(0.017)	(0.023)
(Years of education)^2		0.002**	0.001		-0.001	-0.000
		(0.001)	(0.001)		(0.001)	(0.001)
Δln(Parent bank debt)			-0.000			0.001
			(0.007)			(0.008)
Year dummies	No	Yes	Yes	No	Yes	Yes
Constant	0.091***	-1.025***	-1.091***	0.096***	3.730***	3.992***
	(0.004)	(0.209)	(0.262)	(0.005)	(0.283)	(0.331)
N	43845	43845	32110	35303	35303	27263
Adj. R-squared	0.000	0.017	0.015	0.000	0.020	0.022

Notes: OLS regressions. The table uses annual data for the period 2000-2014. Columns 1-3 show results from regressing Δln(Child liquid assets) on Δln(Parent liquid assets) and other covariates. Columns 4-6 show results from regressing Δln(Child bank debt) on Δln(Parent liquid assets) and other covariates. Cluster-adjusted standard errors at the child level in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. The number of observations decreases in columns 3 and 6 due to some of the parents not having bank debt.

J Top ten percent wealthiest

Table A5 shows regressions corresponding to those presented in Table 2. However, in Table A5 the dependent variable is a dummy variable indicating whether the respondent belongs to the ten percent wealthiest in the period 2012-2014. Even after controlling for the full set of covariates in column 8, the results show that going from minimum to maximum patience (0 to 1) is associated with an increase of six percentage points in the probability of belonging to the wealthiest ten percent in a birth cohort. The effect of patience is significant at the 0.1 percent level.

Table A5: Top ten percent wealthiest

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	0.10***	0.07***	0.07***	0.07***	0.07***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Risk aversion							0.01	0.01
							(0.02)	(0.02)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-cohort non-capital income decile dummies, 2012-2014	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
Within-cohort net assets at age 18 decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Within-cohort parental net asset decile dummies	No	No	No	No	No	Yes	Yes	Yes
Additional controls	No	No	No	No	No	No	No	Yes
Constant	0.04***	-0.02	-0.02	0.01	-0.03	-0.03	-0.04	-0.05
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Observations	3634	3634	3634	3360	3360	3360	3360	3360
Adj. R-squared	0.01	0.04	0.06	0.06	0.09	0.10	0.10	0.12

Notes: OLS regressions. Dep. var.: Dummy for top 10 % within-cohort net asset distribution, 2012-2014. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Parental net assets are measured when the respondents were 7-14 years old. 'Additional controls' include four variables: a gender dummy and share of the period (2012-2014) as single, with dependent children, and as homeowner. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

K Marginal interest rates

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

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

Table A6 presents results from regressions of the computed marginal interest rate on covariates similar to those in Table 2. Across the specifications, the results in Table A6 show a negative and significant correlation between the measure of patience and the marginal interest rate. Column 8 shows that after controlling for the full set of control variables, going from minimum to maximum patience (0 to 1) is associated with a 0.9 percentage point decrease in the marginal interest rate.

Table A6: Marginal interest rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Patience	-1.95***	-1.02**	-1.02**	-1.17**	-1.02**	-0.88*	-0.92*	-0.93*
	(0.37)	(0.36)	(0.36)	(0.38)	(0.37)	(0.37)	(0.37)	(0.37)
Risk aversion							-0.65	-0.70
							(0.45)	(0.45)
Year dummies for educational attainment	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within-cohort non-capital income decile dummies, 2012-2014	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Self-reported school grades decile dummies	No	No	No	Yes	Yes	Yes	Yes	Yes
Within-cohort net assets at age 18 decile dummies	No	No	No	No	Yes	Yes	Yes	Yes
Within-cohort parental net asset decile dummies	No	No	No	No	No	Yes	Yes	Yes
Additional controls	No	No	No	No	No	No	No	Yes
Constant	9.13***	11.78***	12.17***	11.93***	13.87***	13.77***	14.12***	-17.75
	(0.27)	(0.56)	(0.66)	(0.78)	(0.83)	(0.90)	(0.93)	(18.03)
Observations	3598	3598	3598	3327	3327	3327	3327	3327
Adj. R-squared	0.01	0.09	0.10	0.09	0.12	0.13	0.13	0.14

Notes: OLS regressions. Dep. var.: Marginal interest rate, 2014 (%). Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Parental net assets are measured when the respondents were 7-14 years old. 'Additional controls' include six variables: age, age^2, and dummies for gender, marital status, dependent children, and homeowner status. The number of observations decreases in columns 4-8 due to some of the respondents not reporting school grades.

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Chapter 3

Preference heterogeneity and insurance demand:
Combining experimentally elicited time and risk preferences with data on insurance coverage at the individual level

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Abstract

This paper investigates the relationship between preference heterogeneity and insurance demand by combining Danish administrative register data with data from an incentivized large-scale experiment. The experiment was conducted on the Internet with about 5,000 Danish participants and included intertemporal choices and investment choices designed to elicit time and risk preferences of the respondents. Models of insurance demand predict a positive relationship between an individual's degree of risk aversion and the optimal level of insurance coverage, ceteris paribus, but are less clear-cut on the effect of time preferences on insurance demand. I study insurance demand in two separate domains: unemployment insurance and health insurance. The results indicate positive effects of patience on the probability of having insurance coverage in both of the insurance domains and a positive effect of risk aversion on purchasing unemployment insurance.

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1. Introduction

Research has shown that experimental measures of time preferences can predict real-world behavior such as smoking (Harrison, Lau, & Rutström, 2010), behavior on the loan market (Meier & Sprenger, 2010; Rasmussen, 2017), body mass index and physical exercise (Chabris, Laibson, Morris, Schuldt, & Taubinsky, 2008), and saving behavior (Epper et al., 2017). In this paper, I analyze whether heterogeneity in time preferences is correlated with insurance purchasing behavior.

A typical insurance product involves a premium to be paid in the present in order to benefit from insurance coverage in the future. When analyzing the demand for insurance at the individual level, it is intuitive to expect both risk and time preferences to play a role: Risk preferences because an insurance product hedges against uncertainty by promising an indemnity for future losses in exchange for a certain premium. Time preferences because the costs of an insurance product are up front while the benefits are in the future.

It is a well-established prediction from theoretical papers on insurance demand that an increase in an individual's degree of risk aversion will lead to an increase in the optimal level of insurance coverage, ceteris paribus (e.g. Schlesinger (2013)). However, the literature is less developed when it comes to the possible relationship between patience and insurance demand. One paper that considers this relationship is Gollier (2003). He studies a dynamic model in which consumers can self-insure by accumulating buffer-stock wealth. According to Gollier's model, an increase in the consumer's rate of patience will increase his willingness to accumulate buffer-stock wealth and thus decrease his insurance demand in the long run. Put differently, Gollier's model predicts that patient individuals will substitute self-insurance for market insurance.

The main purpose of this paper is to test whether heterogeneity in individual time and risk preferences can predict insurance coverage in the field – focusing on voluntary unemployment insurance and health insurance. I measure the levels of patience and risk aversion for about 5,000 Danish respondents in a large-scale Internet-based experiment involving intertemporal choices and investment choices. The experimental choices were incentivized with monetary rewards paid directly to the personal bank accounts of the respondents according to decisions made in the experiment. The resulting preference measures are linked at the individual level to Danish third-party reported administrative register data.

I find a positive relationship between risk aversion and the probability of having unemployment insurance. This is in accordance with the theoretical prediction. However, contrary to the prediction in Gollier (2003), I find that the measure of patience has a positive effect on the probability of having unemployment insurance and health insurance. Individuals who are more patient are more likely to be insured. This result is consistent with the following intuition: Individuals who are more patient discount the future less. Therefore, individuals who are more patient will be more willing to sacrifice current consumption and pay an insurance premium in the present in order to be covered by insurance in the future. The relationships between the preference measures and insurance coverage hold when controlling flexibly for income, wealth, educational attainment, and demographic characteristics.

The paper is related to Greene (1963, 1964) which are the first studies to combine measured attitudes toward risk with real-life insurance buying behavior. Greene (1963) measures risk attitudes for undergraduate students using a non-incentivized questionnaire. The author finds that the measured risk attitudes are not significantly correlated with insurance buying behavior. He recognizes that undergraduates are not ideal subjects as their insurance coverage might have been paid for by their parents, thus reducing the relationship between the subjects' risk attitudes and their insurance buying behavior. He further argues that some of the undergraduate students might have been liquidity constrained and that this can have affected their insurance purchasing behavior, which again would dilute the relationship between risk attitudes and insurance buying behavior. Greene (1964) performs a follow-up study to address the shortcomings of the previous subject pool. He repeats the analysis with a group of adult teachers, but the result remains unchanged: The study finds no evidence that attitudes toward risk predict real-life insurance purchasing behavior. Most subsequent empirical studies on insurance demand have used demographic and socioeconomic variables to proxy for risk aversion. See Outreville (2014) for a review of the literature. Cutler, Finkelstein, & McGarry (2008) take a different approach and study how behavioral proxies for individual risk aversion relate to insurance purchases.[1] I contribute to this research by analyzing directly how time and risk preferences elicited experimentally affect people's insurance buying behavior in the field.[2]

The finding that patience seems to be an important driver of insurance coverage at the individual level challenges the validity of empirical studies, which attempt to deduce risk preferences from observed insurance choices. For example, Cicchetti & Dubin (1994) use purchasing of insurance against the risk of home telephone line failure to estimate consumers' degrees of risk aversion. With the result

[1] The behavioral risk aversion proxies used in Cutler et al. (2008) include smoking, drinking, job-based mortality risk, receipt of preventive health care, and use of seat belts.

[2] Hansen, Jacobsen, & Lau (2016) combine claims data from an insurance company, administrative data on income and wealth, and experimental measures of risk and time preferences to estimate the willingness to pay for auto, home, and house insurance. However, contrary to the present study, they cannot link the experimental data with the insurance data. Thus, their analysis is based on broad population categories to which they extrapolate experimental preference measures.

of the present paper in mind, it might be inappropriate to infer risk preferences from whether individuals have chosen to insure or not without controlling for time preferences. Other studies have used observed deductible choices in auto insurance and/or home insurance to estimate risk preferences (Barseghyan, Molinari, O'Donoghue, & Teitelbaum, 2013; Barseghyan, Prince, & Teitelbaum, 2011; Cohen & Einav, 2007; Sydnor, 2010). The choice of deductible also has an intertemporal element: The insurance premium concerns the present, but the size of the deductible concerns the future. However, among the estimation strategies to infer risk preferences from observed insurance choices, inference based on deductible choices is arguably more appropriate than inference based on whether individuals have chosen to purchase insurance or not. Deductible choices are only made by individuals who are sufficiently patient to demand insurance in the first place. This suggests that deductible choices are less susceptible to the intertemporal aspect of insurance and more in accordance with a choice among lotteries over monetary outcomes determined by risk preferences.

Einav, Finkelstein, Pascu, & Cullen (2012) use data on employees' option choices regarding five employer-provided insurance plans to investigate whether individuals display a stable ranking in their risk preferences across different insurance contexts. The option choices correspond to different exposures to financial risk. As is the case with the above-mentioned papers deducing risk preferences from deductible choices, the fact that (Einav et al., 2012) only consider option choices for employees who have chosen to insure means that the scope for time preferences to blur the inference of risk preferences is reduced.

The remainder of the paper is structured as follows: Section 2 describes the experimental design and the elicitation of the measures of patience and risk aversion. Section 3 introduces the register data including details of unemployment insurance in Denmark. Section 4 presents and discusses the results, and section 5 concludes.

2. Experimental design[3]

The Internet-based experiment was conducted in two waves in February 2015 and June 2016. The main part of the experiment consisted of interactive saving and investment choice situations designed to elicit time and risk preferences of respondents. The order of the choice tasks was randomized. Besides choice tasks, respondents filled out an online questionnaire.[4]

[3] The descriptions of the experimental design and the measure of patience builds on and potentially repeats text from my master's thesis (Department of Economics, University of Copenhagen, 2015).

[4] For example, the online questionnaire asked the respondents to state their most recent math grade obtained in school and to self-report their levels of risk aversion and self-control.

We recruited respondents who satisfied the following two criteria: 1) born in the period 1973-1986, and 2) resided in Copenhagen Municipality (Københavns Kommune) when they were seven years old.[5] Statistics Denmark, the central authority on Danish statistics, provided a dataset of all of the 36,047 individuals who met the sample criteria. The dataset contained names, current addresses, and civil registration numbers. We invited everyone in the gross sample to participate by sending personal invitation letters in hard copy. The letters were printed on official University of Copenhagen letterhead. 560 of the 36,047 letters bounced back. Appendix 6.1 shows an example of the invitation letter along with an English translation.

The letter invited the selected persons to participate in an Internet-based study carried out by the University of Copenhagen and described what to do in order to participate. The letter explained that respondents would receive an amount of money after completing the experiment and that the amount would be automatically transferred to their personal bank accounts. It was pointed out that the size of the payout depended on the choices which the respondent made in the study. Each letter contained a unique username and password combination needed to log in. The letter also informed about a helpline (phone and email) that people could contact if they had problems logging in or had questions about the study.

After logging in to the webpage, the respondents were presented with thorough instructions. To facilitate the comprehension, the instructions for the choice tasks were given by voice-over in animated videos. See the last section of the thesis for an English transcript of the instructions. We considered it worthwhile to implement instruction videos, as our pilot studies had demonstrated that people found it tedious to read the instructions by themselves. In order to proceed to each of the choice tasks, the respondents had to answer control questions and go through a practice trial. The respondents received immediate feedback on the correctness of their answers to the control questions. During the course of the experiment, the respondents could review the relevant instructions. The respondents were free to leave the experiment and re-enter at the point they had reached. Appendix 6.2 shows the distribution of completion time.

Decisions in the choice tasks were incentivized such that respondents were motivated to reveal their preferences truthfully by making considered decisions. At the end of the experiment, one of the choice situations was drawn at random, and payoffs were paid out according to the choice of the

[5] This geographical screening was chosen to be able to merge the experimental data with the Copenhagen School Health Records Register for another research project.

respondent in the drawn situation.[6] The average payout was 251 DKK.[7] The payouts were handled through a platform for electronic bank transfers. Danish citizens are required to have a bank account (NemKonto) associated with their civil registration number. Payments from employers and public institutions are transferred to this account. This means that the system is well known in Denmark. Because we had information about the civil registration numbers of all individuals in the sample, we could use this platform to transfer the payouts directly to the personal bank accounts of the respondents. We believe that our approach to handling the payouts is advantageous compared to previous Internet-based experiments. In some earlier studies, respondents needed to state their bank account details online during the experiment. It is conceivable that some individuals would be reluctant to do so, and that this might increase self-selection bias.

Additional discussion on the saving choices in the experiment is given below.

Measuring patience

All respondents were presented with 5 saving choices to elicit their levels of patience.[8] In each saving situation, we asked the respondents to distribute 10 blocks of points between two accounts. One account promised a smaller but sooner payout and the other promised a larger but later payout. Specifically, the sooner payout account would be paid out 8 weeks and two days after participation and the later payout account would be paid out 16 weeks and two days after participation. This front-end delay was incorporated in the saving situations to elicit a longer-run patience measure. If the sooner payout account would have been paid out immediately after participation, hyperbolic discounting (present bias/decreasing impatience) might induce a bias in the longer-run patience measure (Frederick, Loewenstein, & O'Donoghue, 2002).

Appendix 6.3 shows a screenshot of one of the saving situations. In this example, the respondent has allocated five blocks to the 8 weeks' account and five blocks to the 16 weeks' account. Each block allocated to the 8 weeks' account was worth 100 points and each block allocated to the 16 weeks' account was worth 105 points. 100 points corresponded to 25 DKK. If this saving choice was selected randomly at the end of the experiment, the respondent would receive 125 DKK 8 weeks and two days after participation and 131.25 DKK 16 weeks and two days after participation.

[6] We adopted this random incentive mechanism to avoid portfolio effects (arising when all choices are paid at the end of the experiment) and wealth effects (arising if paying all choices sequentially during the experiment).

[7] 1 USD ≈ 6.5 DKK during both experimental waves.

[8] The saving choices are inspired by Andreoni & Sprenger (2012). However, we used a graphical interface to present the saving choices and showed only one choice per page.

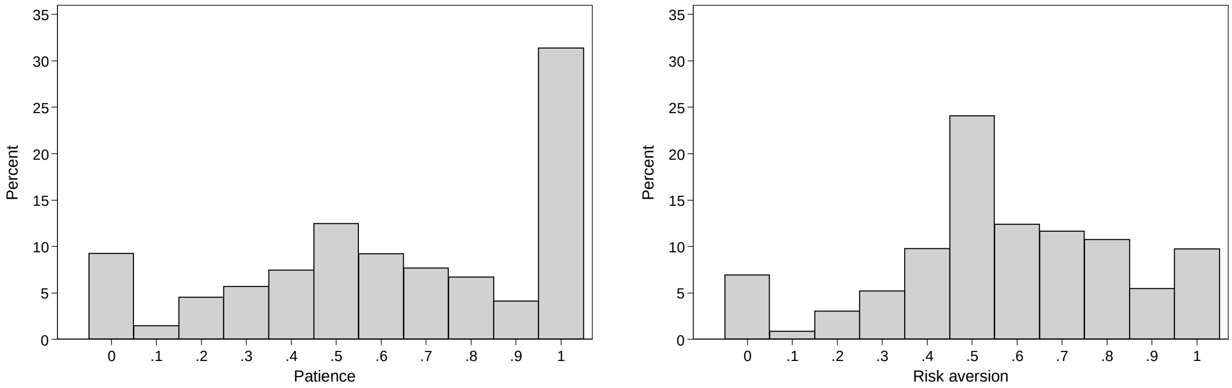
The value of the blocks on the 8 weeks' account was kept constant at 100 points throughout the five 8 vs. 16 weeks' choices. The value of the blocks on the 16 weeks' account varied between 105, 110, 115, 120, and 125 points. The order of the saving situations was randomized. The starting point for the five choice situation was that all 10 blocks were placed on the 8 weeks' account. We then asked the respondents to choose a distribution of the 10 blocks between the two accounts.[9] We deliberately framed the choice situation as a saving decision in order to make it less abstract. The instructions explained that you would get an *interest income* if you chose to *save* the blocks, i.e. place them on the 16 weeks' account.

I measure the patience level for each respondent by computing the median number of saved blocks across the five 8 vs. 16 weeks saving situations and normalizing by 10.[10] The research question of the present paper requires a reliable measure of the heterogeneity in patience *between* respondents while accurate estimates of the levels of patience are not necessary. I will study between-respondent variation in patience levels and its relation to insurance purchasing behavior directly in terms of how many blocks the respondents chose to save in the saving situations rather than estimating a discounting model for time preferences based on the choices. The advantage of this model-free approach is that I avoid introducing assumptions about parameter values. The left panel in figure 2.1 shows the distribution of the constructed non-parametric patience measure.

[9] To avoid status quo bias, we designed the user interface such that the respondent had to make an active choice. Specifically, as the respondent moused over one of the accounts vertically, a blue saving bar summarized the outcomes of each allocation (see appendix 6.3). The respondent was only able to confirm his decision and move on after actively choosing one of the allocations.

[10] The results presented in the paper do not change if I use the arithmetic mean to aggregate the five saving situations instead.

Figure 2.1: Distributions of the patience and risk aversion measures.



Notes: 5,084 respondents. Only respondents for whom a full set of register variables is available are included. Left-hand panel: Distribution of the patience measure. $Patience = median\left(\frac{\#\ of\ blocks\ saved}{10}\right)$.
Right-hand panel: Distribution of the risk aversion measure.
$Risk\ aversion = median\left(\frac{\#\ of\ blocks\ kept\ at\ risk-free\ account}{10}\right)$.

Measuring risk aversion

The respondents were also given 5 separate investment situations in which they had to allocate 10 blocks of points between a risky investment project and a risk-free account where the payout was certain.[11] In each investment situation, there was a 50-50 probability that the investment project would turn out to be favorable or unfavorable (zero skewness).[12] The order of investment situations was randomized. Appendix 6.4 shows a screenshot of a sample investment situation. In this example, the respondent has allocated five blocks to the risk-free account and five blocks to the risky investment project. The value of blocks on the risk-free account was kept constant at 100 points throughout the five investment situations, whereas the value of blocks in the risky investment project differed across the five situations. The expected value of the investment project as well as the spread between the point value in the favorable and the unfavorable outcome varied. The point values were 121 vs. 81, 131 vs. 71, 135 vs. 75, 151 vs. 50, and 161 vs. 60 such that the expected value of a block allocated to the investment project was greater than the 100 points in the risk-free alternative in all five situations.

[11] Our procedure is inspired by Gneezy & Potters (1997), but we depict the investment situations graphically.
[12] The favorable vs. unfavorable outcome of an investment situation would only be determined if it was drawn at random to be the choice situation relevant for payout at the end of the experiment.

Similar to the patience measure, I compute the level of risk aversion for each respondent by taking the median number of blocks allocated to the risk-free account across the five investment situations and normalizing by 10.[13] The right panel in figure 2.1 shows the distribution of this non-parametric risk aversion measure.

3. The data

The experimental sample consists of 5,207 respondents. The choice data from the experiment are linked with Danish administrative register data at the individual level. The participants were not informed that the data from the experiment would be linked with the administrative register data, and they were therefore not asked to give their consent to this. The Danish Data Protection Agency has approved the research project and this procedure. To merge the experimental data with the register data, the usernames provided in the invitation letters were translated into anonymized civil registration numbers. It is important for the linkage between experimental and register data that the respondents in the experiment are identical to the people who were actually invited. Since the experiment was executed online, one cannot be certain that the respondents in the experiment exclusively consist of people who were invited to participate. Though the invitation letter requested that the log in details were not passed on to others, it is possible that some of the invited subjects let e.g. a colleague or another member of the household participate instead. This is problematic in the sense that the experimental choices of individual x would be linked with register data for individual y. To reduce this source of error, the respondents were asked to state their gender and year of birth first thing after logging in to the experiment. 79 respondents for whom the stated gender and/or year of birth is not identical to the information in the register data are excluded from the analysis. The fact that the payouts from the experiment were transferred directly to the personal bank accounts of the invited individuals might have reduced the prevalence of such spurious respondents.

The following analyses will focus on the 5,084 respondents for whom a full set of register variables is available. The register data contain, i.a., demographic characteristics from public administrative registers and individual-level information from the income tax register. The income tax register includes information on annual income as well as values of assets and liabilities at the end of each year. The value of assets includes assessed property value, market values of stocks, bonds, and mortgage deeds in deposit, and bank deposits. The value of liabilities includes all debt except debt to

[13] Again, the results presented in the paper do not change if I use the arithmetic mean to aggregate the five investment situations instead.

private persons. The data in the registers are organized as a panel dataset so that it is possible to observe income, assets, and liabilities back in time for the respondents in the experiment. These data are available up to and including year 2014.

All register data are third-party reported. For instance, employers report earnings, government institutions report transfer payments, and information on assets and liabilities is reported by financial institutions. This feature of the data is an advantage compared to related literature that relies on self-reported survey measures, which makes the accuracy of such responses difficult to assess.

Furthermore, the registers contain information on how long time each individual has been unemployed during the year. Crucial to this paper, I can also observe in the registers whether an individual is a member of an unemployment insurance fund by the end of each year. This information is available up to and including year 2013. The Danish unemployment insurance system is organized around unemployment insurance funds, which are private non-profit institutions that are subsidized by the government. In order to be eligible for unemployment benefits in case of unemployment, the typical worker must 1) have been a member of an unemployment insurance fund for at least one year, 2) have had at least 52 weeks of work within the three years preceding the unemployment spell, and 3) be able to take work with one day's notice. Membership of an unemployment insurance fund and with it unemployment insurance is voluntary. The unemployment benefits amount to 90 percent of the unemployed worker's prior wage – though no more than 4,245 DKK (≈ 653 USD) per week as of 2017. The maximum unemployment benefit duration is two years.

Besides the unemployment insurance coverage, there is an additional motive for being a member of an unemployment insurance fund: If you have been a member of an unemployment insurance fund and have contributed to the so-called early retirement scheme (efterløn) for at least 30 years beginning no later than age 30, you are eligible to receive early retirement benefits. The birth cohorts in the sample considered in this paper will be able to receive early retirement benefits 3 years before the regular retirement age. In the subsequent analysis of the relationships between risk/time preferences and unemployment insurance coverage, I perform a robustness test excluding people who have contributed to the early retirement scheme, such that I can rule out that the remaining respondents are members of an unemployment insurance fund because of the early retirement motive.

As I know the anonymized civil registration numbers of all individuals in the gross sample, I can compare the register-based characteristics of the respondents and the non-respondents. Column (1) in table 3.1 reports the differences in means across respondents and non-respondents for everyone in the gross sample with a full set of register data available. Compared with non-respondents, respondents are, on average, less likely to be singles, more likely to be homeowners, have higher educational attainment, have higher income, and hold more liquid assets. Most of these differences are statistically significant but qualitatively small.

The gross sample includes everyone who lived in Copenhagen Municipality when they were seven years old. Column 2 in table 3.1 compares the gross sample with a 10 percent random sample of the Danish population who are not in the gross sample (i.e., did not live in Copenhagen Municipality when they were seven years old), but who were born in the same period (1973-1986). When comparing with the 10 percent sample, it appears that individuals in the gross sample are, on average, younger, more likely to be singles, less likely to have dependent children, less likely to be homeowners, have slightly shorter education, have lower income and hold less liquid assets. Again, most of these differences are small in economic magnitude but are statistically significant because of the large number of observations. In section 4, I show that my results are not sensitive to the differences in sample composition reported in table 3.1.

Table 3.1: Means of selected characteristics from register data.

	(1) Respondents vs. non-respondents			(2) Gross sample vs. 10 % of population		
	(a) Respondents	(b) Non-respondents	(c) Difference, (a)-(b)	(d) Gross sample	(e) Population	(f) Difference, (d)-(e)
Age	34.17	34.03	0,14	34.05	34.97	-0,92
Woman (=1)	0.50	0.49	0,01	0.49	0.50	-0,01
Single (=1)	0.34	0.41	-0,07	0.40	0.31	0,09
Dependent children (=1)	0.49	0.48	0,01	0.48	0.55	-0,07
Homeowner (=1)	0.33	0.29	0,04	0.29	0.51	-0,22
Years of education	14.41	13.79	0,62	13.88	14.33	-0,45
Ln(Total income)	12.63	12.51	0,12	12.52	12.63	-0,11
Ln(Liquid assets)	10.35	10.03	0,32	10.07	10.24	-0,17
Observations	5084	30611		35695	83464	

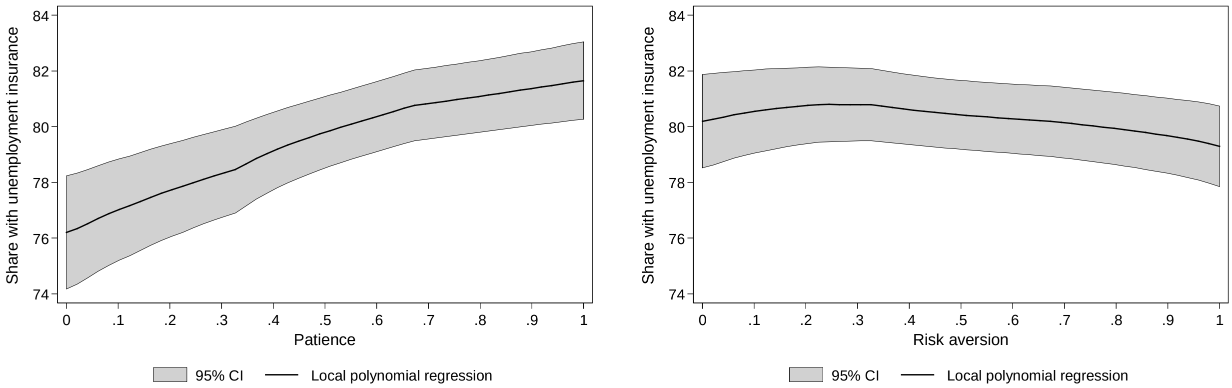
Notes: Variables are based on 2014 values. The random 10 percent sample of the Danish population is drawn among those who are not in the gross sample (i.e., did not live in Copenhagen Municipality when they were seven years old), but who were born in the same period (1973-1986). (=1) indicates a dummy variable which takes the value 1 for individuals who satisfy the description given by the variable name. Liquid assets include bank deposits and market values of stocks and bonds. The table includes individuals for whom a full set of register variables is available. The number of observations is slightly lower than reported in the table for the two variables income and liquid assets as some of the respondents do not have strictly positive income or liquid assets.

4. Results and discussion

Patience, risk aversion, and unemployment insurance

This section investigates how preferences relate to unemployment insurance take-up. To do so, I consider a subsample consisting of 4,172 respondents who were in the labor force in all years in the period 2011-2013. 3,330 (79.8 percent) of these respondents were covered by unemployment insurance in 2013. Figure 4.1 plots the local polynomial regression curves of the share of the sample with unemployment insurance against the patience measure and the measure of risk aversion, respectively. The figure shows a positive relationship between patience and the probability of having unemployment insurance, but no significant relationship between risk aversion and unemployment insurance take-up.

Figure 4.1: Unemployment insurance plotted against patience and risk aversion, respectively.



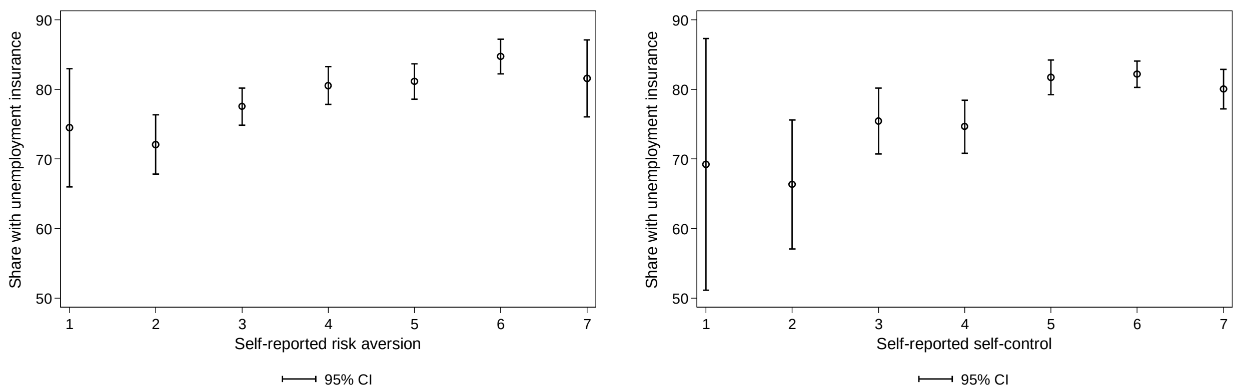
Notes: 4,172 observations. Unemployment insurance coverage is identified for each experimental respondent based on register information on membership of unemployment insurance funds at the end of 2013.
Left-hand panel: Local polynomial regression of the share of respondents with unemployment insurance on the patience measure.
Right-hand panel: Local polynomial regression of the share of respondents with unemployment insurance on the risk aversion measure.

At first, it may seem surprising that the experimental measure of risk aversion is not correlated with the probability of having unemployment insurance. One reason for the lack of correlation could be that individuals are able to self-protect against unemployment risk to some extent by their educational and occupational choices.[14] Even a risk averse respondent might not demand unemployment insurance if he has self-selected into a job with a low risk of becoming unemployed.

[14] Ehrlich & Becker (1972) define self-protection as activities that reduces the probability of a loss, while self-insurance affects the cost of a potential loss.

Another reason for the lack of correlation has to do with the measure of risk aversion. Weber, Blais, & Betz (2002) find that risk preferences are domain-specific. In the present paper, the experimental measure of risk aversion is based on the respondents' willingness to invest in a risky investment project, which is quite distinct from the decision to hedge against unemployment risk by taking out unemployment insurance. Dohmen et al. (2011) find that the general risk question used in the German Socio-Economic Panel is the best all-around predictor of risky behavior in the field. A version of this general question on risk-taking was also implemented in the online questionnaire that the respondents filled out.[15] The left panel in figure 4.2 plots the relationship between the probability of having unemployment insurance and self-reported risk aversion. The panel shows that the probability of having unemployment insurance is higher for respondents who state that they are more risk averse.

Figure 4.2: Unemployment insurance plotted against self-reported measures of risk aversion and self-control.



Notes: 4,172 observations.
Left-hand panel: Average share of respondents with unemployment insurance by self-reported values of risk aversion. Contrary to Dohmen et al. (2011), higher values represent higher levels of risk aversion.
Right-hand panel: Average share of respondents with unemployment insurance by self-reported values of self-control.

Table 4.1 substantiates the relationships between the probability of having unemployment insurance and the measures of patience and risk aversion. The table shows results from probit regressions of unemployment insurance coverage on the preference measures and other covariates. The reported coefficients are marginal effects. The dependent variable is a dummy variable that indicates whether

[15] Survey question on risk aversion: *Are you generally willing to take risks or do you try to avoid risks?*
1 = very willing to take risks
…
7 = not at all willing to take risks
The general survey-based question on risk aversion and the experimental measure of risk aversion are positively correlated: Spearman's rho = 0.173; p-value = 0.000.

a respondent had unemployment insurance by the end of 2013. Column (1) shows output from a parsimonious specification that only includes the experimental preference measures. In column (2), I exchange the experimental measure of risk aversion which is prone to be domain-specific with the more general survey-based question on risk aversion introduced in the left panel in figure 4.2. Because of few observations in some of the answer categories, the self-reported measure of risk aversion is aggregated into two dummy variables indicating whether the respondent stated a risk aversion below or above the medium value, 1-3 and 5-7, respectively. The results show that moving from minimum to maximum patience (0 to 1) is associated with an increase in the probability of being covered by unemployment insurance of about 8 percentage points on average. Similarly, the group of respondents reporting below medium risk aversion are about 5 percentage points less likely to have taken out unemployment insurance.

Table 4.1: Probit regressions of unemployment insurance dummy regressed on covariates (marginal effects at means).

	(1)	(2)	(3)	(4)
Risk aversion	-0.025			
	(0.025)			
Patience	0.083 ***	0.084 ***	0.037 *	0.036 *
	(0.019)	(0.019)	(0.018)	(0.018)
Self-reported risk aversion, 1-3 (=1)		-0.047 **	-0.036 *	-0.037 *
		(0.018)	(0.017)	(0.018)
Self-reported risk aversion, 5-7 (=1)		0.022	0.002	-0.005
		(0.017)	(0.016)	(0.017)
Unemployment rate within own educational group			0.027 ***	0.027 ***
			(0.005)	(0.005)
Has experienced unemployment, 2011-2013 (=1)			0.211 ***	0.208 ***
			(0.012)	(0.013)
Public employee (=1)			0.033 *	0.028
			(0.014)	(0.015)
Self-reported self-control, 1-3 (=1)				0.009
				(0.024)
Self-reported self-control, 5-7 (=1)				0.045 *
				(0.021)
Income decile dummies	No	No	Yes	Yes
Net asset decile dummies	No	No	Yes	Yes
Year dummies for educational attainment	No	No	Yes	Yes
Demographic characteristics	No	No	Yes	Yes
Math grade dummies	No	No	No	Yes
Observations	4172	4172	4172	3809

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2013 values unless otherwise stated. (=1) indicates a dummy variable which takes the value 1 for respondents who satisfy the description given by the variable name. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. The number of observations decreases in column (4) due to some of the respondents not reporting a math grade. The interaction between risk aversion and patience is insignificant.

In column (3), I add decile dummies for income and net asset holdings, flexible dummies for educational attainment, demographic characteristics, and other register based variables likely to correlate with the decision to take out unemployment insurance. I control for the unemployment rate within each respondent's own educational group to take differences in unemployment risk into account. The sample is split into 60 educational groups, and the computed unemployment rate ranges from 0.0 to 19.1 percent. These unemployment rates are computed based on all the people who were invited to participate in the experiment (the gross sample). As expected, the results show a positive relationship between the unemployment rate within own educational group and the probability of having unemployment insurance. An increase in the unemployment rate of one percentage point is associated with an increase of about 3 percentage points in the probability of having unemployment insurance on average. This could suggest that respondents are aware of the unemployment risk in their own educational group and respond to it. Furthermore, I include a dummy variable, which indicates whether the respondent has experienced unemployment within the three years leading up to the time when I observe unemployment insurance coverage.[16] The estimated marginal effect shows that respondents who have experienced unemployment in the past are, on average, 21 percentage points more likely to have unemployment insurance coverage. Again, this is consistent with those who are more likely to become unemployed having a higher incentive to buy unemployment insurance. Finally, I control for whether the respondents work in the public sector to control for different propensities to join an unemployment insurance fund across the private and the public sector. As Parsons, Tranæs, & Lilleør (2015) point out, there could be varying degrees of social pressure to join an unemployment insurance fund across sectors – e.g. as a way of expressing solidarity with other workers. The results imply that public employees are about 3 percentage points more likely to be covered by unemployment insurance. The estimate of the relationship between the probability of having unemployment insurance and the patience measure reduces after adding the additional control variables in column (3), but it remains statistically significant at the 5 percent level.

Financial literacy or cognitive ability are potential confounding factors. It is conceivable that both the decision on whether to have unemployment insurance and the measures of patience and risk aversion are correlated with cognitive ability. One could argue that this is less of a problem in the present analysis, as I include educational attainment and income in the regressions, both of which are likely to proxy for cognitive ability. However, Dohmen, Falk, Huffman, & Sunde (2010) study a representative sample of the adult German population and find that people with higher cognitive ability (measured by submodules of an IQ test) are significantly more patient and significantly more risk willing (measured by incentivized choice tasks). The correlations in their study remain significant when controlling for personal characteristics, educational attainment, and income.[17] To address this concern, column (4) in table 4.1 adds flexible dummies for the most recent math grade obtained in

[16] 22.1 percent of respondents have experienced unemployment in the period 2011-2013.
[17] Nevertheless, an experimental study suggests that cognitive ability is associated with random decision making rather than with risk preferences (Andersson, Holm, Tyran, & Wengström, 2016).

school (self-reported by the respondents in the online questionnaire) as an additional proxy for cognitive ability and financial literacy.[18]

Self-control is another potential concern. One could imagine that the observed positive relationship between the patience measure and the probability of having unemployment insurance is driven by heterogeneity in self-control. It could be that an individual with self-control problems is less likely to pay an insurance premium to be covered by unemployment insurance. Similarly, as Sutter, Kocher, Glätzle-Rützler, & Trautmann (2013) argue, an experimental patience measure as the one used in the present paper is likely related to self-control. The right panel in figure 4.2 plots the relationship between the probability of having unemployment insurance and a self-reported measure of self-control from the online questionnaire.[19] The panel shows that the probability of having unemployment insurance is higher for respondents who self-report that they are better at exercising self-control. As with the self-reported risk aversion, I aggregate the self-control categories into two dummy variables indicating whether the respondent stated a degree of self-control below or above the medium value, 1-3 and 5-7, respectively. The results in column (4) in table 4.1 show that the group of respondents who state that they are better at exercising self-control are about 5 percentage points more likely to have unemployment insurance coverage. However, the estimates of the relationships between the probability of having unemployment insurance and the measures of patience and risk aversion are robust to including self-reported math grades and ability to exercise self-control.

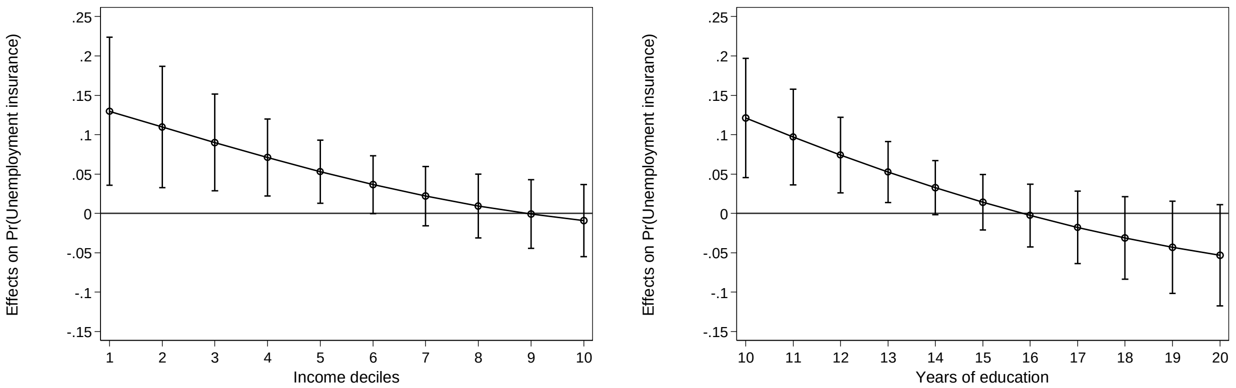
The results in table 4.1 show that the patience measure is both statistically and economically significant in explaining the probability of having unemployment insurance. Figure 4.3 investigates how the effect of patience depends on heterogeneity in income and education. The left panel in figure 4.3 is based on the same regression as that in table 4.1, column (4) but replaces the income decile dummies with income deciles and income interacted with the patience measure. The panel plots the average marginal effect of patience on the probability of having unemployment insurance for each income decile. The right panel in figure 4.3 is also based on the regression in column (4) but replaces the dummies for educational attainment with years of education and education interacted with the patience measure. The panel plots the average marginal effect of patience on the probability of having

[18] Agarwal & Mazumder (2013) find that math scores are important for household financial decision-making. In their study, individuals with higher math scores are less likely to make financial mistakes. Additionally, a recent publication by PISA documents a strong correlation between students' mathematics performance and financial literacy (OECD, 2017).

[19] Survey question on self-control: *I am good at exercising self-control in my actions and decisions.*
1 = strongly disagree
…
7 = strongly agree

unemployment insurance for different levels of educational attainment. Generally, the figure shows that the positive relationship between patience and unemployment insurance coverage is most pronounced for respondents with lower income and lower educational attainment. This is consistent with a larger share of less patient respondents not having unemployment insurance in the part of the sample with low income and low education. Possibly, respondents with fewer years of schooling are less aware of the need and purpose of unemployment insurance and find it harder to evaluate its costs and benefits, thus amplifying the effect of patience on unemployment insurance coverage for this group.

Figure 4.3: Average marginal effects of patience on Pr(Unemployment insurance).



Notes: 4,172 observations. Capped spikes represent 95% CI.
Left-hand panel: Based on the regression in table 4.1, column (4) but replaces the income decile dummies with income deciles and income interacted with the patience measure.
Right-hand panel: Based on the regression in table 4.1, column (4) but replaces the dummies for educational attainment with years of education and education interacted with the patience measure. Years of education is censored at 10 and 20 years.

Robustness tests

As mentioned in section 3, membership of a Danish unemployment insurance fund combined with paying contributions to the so-called early retirement scheme renders a person eligible to receive early retirement benefits. It is, therefore, possible that some people are more motivated to become members of unemployment insurance funds by the possibility to retire early than by the unemployment insurance coverage. This poses a problem for the analysis as it suggests that there is no one-to-one connection between observed membership of an unemployment insurance fund and demand for unemployment insurance. Appendix 6.5 addresses this concern. Column (1) reproduces the main regression from column (4), table 4.1 for comparison. Column (2) in appendix 6.5 re-estimates the reference model reported in column (1) but excludes respondents who contributed to the early retirement scheme in 2013. Hence, for the remaining respondents in column (2), I can rule out that memberships of unemployment insurance funds are because of the early retirement motive. The estimated marginal effects in column (2) show that the positive effects of patience and risk aversion on unemployment insurance fund membership are robust to this exercise. In sum, this shows that the reported effects of patience and risk aversion remain for this subsample where the unemployment insurance purchasing behavior is measured with less noise.

Column (3) in appendix 6.5 takes into account the selection into the experiment. Based on the characteristics included in table 3.1, I have estimated the probability that an individual in the gross sample chose to participate. Column (3) re-estimates the reference model weighting each observation with the inverse of the probability that the individual participated. The idea is to inflate the weight for respondents who are underrepresented in terms of observable characteristics. If the observable characteristics predict the decision to participate adequately, the selection can be ignored after weighting with the inverse of the participation probability. The estimated marginal effects in column (3) show that the results presented in table 4.1 are not sensitive to this inverse probability weighting.

To allow for differences between the 10 percent population sample and the respondents in terms of the observable characteristics in table 3.1, column (4) in appendix 6.5 re-estimates the reference model using inverse probability weights to adjust for this. Again, the results do not deviate from what is presented in table 4.1.

Patience, risk aversion, and health insurance

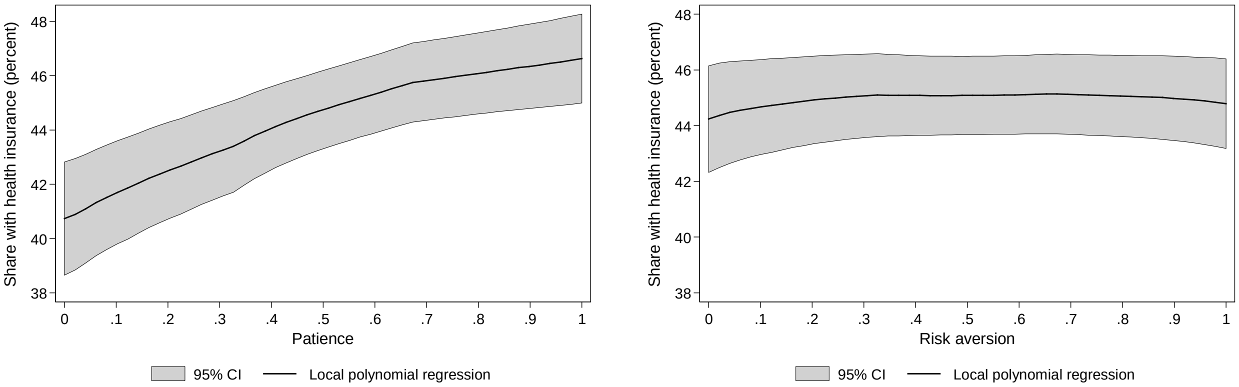
The Danish public health care system is predominantly financed through income tax, and treatments from general practitioners and treatments in the hospital sector are available free of charge. Other health-related expenses such as medicine and dental care involve user charges. Additionally, a market-dominating mutual insurance company called Sygeforsikringen “danmark” exists, which specializes in health insurance. The association will support its members financially if they fall ill by contributing to health-related expenses. In order to become a member of Sygeforsikringen “danmark”, you have to be healthy and no more than 59 years old at the time of applying.[20]

In the following, I analyze the determinants of the decision to be covered by health insurance. In the online questionnaire, the respondents were asked the following question: *Are you a member of*

[20] Further details about Sygeforsikringen “danmark” can be found on http://www.sygeforsikring.dk/Default.aspx?ID=33.

Sygeforsikringen ”danmark” (incl. “resting” members)?[21] 2,270 out of 5,084 respondents (44.6 percent) stated that they are members and thus covered by the health insurance.[22] Figure 4.4 plots the local polynomial regression curves of the share of the sample with health insurance against the experimental measures of patience and risk aversion, respectively. As was the case for unemployment insurance, the figure shows a positive relationship between patience and the probability of having health insurance, but no significant relationship between risk aversion and health insurance coverage.

Figure 4.4: Health insurance plotted against patience and risk aversion, respectively.



Notes: 5,084 observations.
Left-hand panel: Local polynomial regression of the share of respondents with health insurance on the patience measure. Right-hand panel: Local polynomial regression of the share of respondents with health insurance on the risk aversion measure.

Table 4.2 extends the analysis by showing estimated marginal effects from probit regressions in which health insurance coverage is the dependent variable. The control variables are similar to those used in the unemployment insurance analysis, while the dependent variable is a dummy variable taking the value of 1 if a respondent has health insurance and 0 if not.

[21] The insurance premium for “resting” members is lower than that for regular members. A “resting” membership means that the member is not currently covered by the health insurance, but that he can choose to pay the regular insurance premium at some later point in time to get the coverage, even if he does not meet the requirements about age and health then.
[22] About 42 percent of the Danish population are members of Sygeforsikringen *”danmark”*. Thus, the survey responses seem plausible.

Table 4.2: Probit regressions of health insurance dummy regressed on covariates (marginal effects at means).

	(1)	(2)	(3)	(4)
Risk aversion	0.022			
	(0.027)			
Patience	0.093 ***	0.090 ***	0.079 ***	0.082 ***
	(0.021)	(0.021)	(0.022)	(0.023)
Self-reported risk aversion, 1-3 (=1)		-0.016	-0.009	-0.006
		(0.020)	(0.020)	(0.021)
Self-reported risk aversion, 5-7 (=1)		0.018	-0.003	0.004
		(0.019)	(0.019)	(0.021)
Self-reported self-control, 1-3 (=1)				-0.053
				(0.030)
Self-reported self-control, 5-7 (=1)				-0.036
				(0.023)
Income decile dummies	No	No	Yes	Yes
Net asset decile dummies	No	No	Yes	Yes
Year dummies for educational attainment	No	No	Yes	Yes
Demographic characteristics	No	No	Yes	Yes
Math grade dummies	No	No	No	Yes
Observations	5084	5084	5084	4642

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. (=1) indicates a dummy variable which takes the value 1 for respondents who satisfy the description given by the variable name. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. The number of observations decreases in column (4) due to some of the respondents not reporting a math grade. The interaction between risk aversion and patience is insignificant.

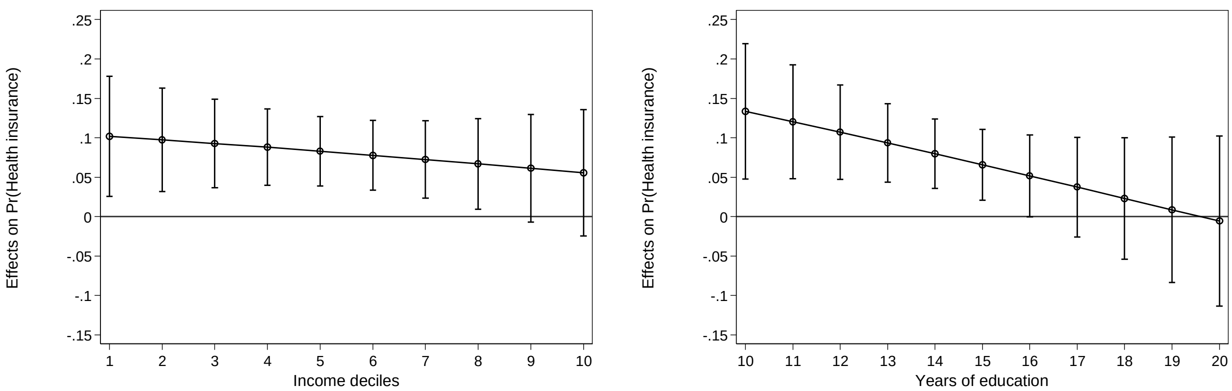
Fang, Keane, & Silverman (2008) find empirical evidence that cognitive ability is positively related to the demand for health insurance. The authors argue that individuals with high cognitive ability may be more knowledgeable about potential health risks, which could increase their demand for health insurance. If patience and risk aversion are also correlated with cognitive ability as documented in Dohmen et al. (2010), it is important to try to control for heterogeneity in cognitive ability in the regressions. I do this in columns (3) and (4) of table 4.2 by including income, educational attainment, and self-reported math grades. The table shows a positive and remarkably stable relationship between the patience measure and health insurance coverage across the four specifications. Going from minimum to maximum patience (0 to 1) is associated with an increase in the probability of having health insurance of 8-9 percentage points on average. The relationship is significant at the 0.1 percent level.

The estimated marginal effect is also economically significant compared to the baseline probability of having health insurance of 44.6 percent in the sample.

The marginal effects of the experimental and the self-reported measures of risk aversion have the expected signs but are not significant at the 5 percent level. When interpreting this result, it is important to keep in mind that all the respondents are covered by the free Danish health care system. The health insurance provided by Sygeforsikringen ”danmark” should be regarded as an additional layer of insurance coverage.

Figure 4.5 analyzes how the effect of patience on the propensity to buy health insurance depends on income and education. Both panels are based on the regression in table 4.2, column (4). In the regression underlying the left panel, income decile dummies are replaced by income deciles and income interacted with the patience measure. In the regression underlying the right panel, dummies for educational attainment are replaced by years of education and education interacted with the patience measure. The left panel shows that the positive effect of patience on health insurance coverage exists across the income distribution, whereas the right panel displays that the positive relationship between patience and health insurance coverage is most pronounced for respondents with lower educational attainment. This could be due to less educated respondents being less aware of the purpose of this additional health insurance and finding it harder to evaluate its costs and benefits, thus leading their health insurance purchasing behavior to be more influenced by their preferences for consumption possibilities in the present vs. in the future.

Figure 4.5: Average marginal effects of patience on Pr(Health insurance).



Notes: 5,084 observations. Capped spikes represent 95% CI.
Left-hand panel: Based on the regression in table 4.2, column (4) but replaces the income decile dummies with income deciles and income interacted with the patience measure.
Right-hand panel: Based on the regression in table 4.2, column (4) but replaces the dummies for educational attainment with years of education and education interacted with the patience measure. Years of education is censored at 10 and 20 years.

Appendix 6.6 tests whether the health insurance results are sensitive to the selection into the experiment. Column (1) replicates the main regression from column (4), table 4.2. Column (2) re-estimates the reference model weighting each observation with the inverse of the probability that an individual in the gross sample chose to participate. The participation probabilities are based on the characteristics included in table 3.1. Column (3) repeats this exercise based on the observable differences between the 10 percent population sample and the respondents. The results in appendix 6.6 show that the marginal effect of patience on the probability of having health insurance is robust to these adjustments.

5. Conclusion

This paper investigates relationships between experimental preference measures and choice of insurance coverage in the field at the individual level. I combine evidence from a large-scale incentivized choice experiment with objective third-party reported data from administrative registers. Based on intertemporal choices and investment choices in the experiment, I construct measures of patience and risk aversion for about 5,000 Danish respondents. In accordance with theoretical predictions, I find a positive relationship between risk aversion and the probability of having unemployment insurance. However, contrary to the prediction in Gollier (2003), I find that patience has a positive effect on the probability of having unemployment insurance and health insurance. The positive empirical association between patience and insurance coverage is intuitively appealing: The more patient an individual is, the less he discounts the future relative to the present. Therefore, a more patient individual will be more willing to pay an insurance premium in the present in order to be covered by insurance that might benefit him in the future. Relationships between the preference measures and insurance coverage are maintained when controlling for objectively reported income, wealth, educational attainment, and demographic characteristics.

The result that patience seems to be an important driver of insurance coverage at the individual level suggests that it is worthwhile to incorporate time preferences into models of insurance demand. Furthermore, the observed intertemporal aspect of insurance purchasing behavior challenges the validity of empirical studies, which attempt to infer individual-level risk preferences from observed insurance choices without taking heterogeneity in time preferences into account.

6. Appendix

Appendix 6.1: Invitation letter.

ØKONOMISK INSTITUT
KØBENHAVNS UNIVERSITET

[redacted]

Kære [redacted],

FEBRUAR 2015

ØKONOMISK INSTITUT

ØSTER FARIMAGSGADE 5,
BYGNING 26
1353 KØBENHAVN K

TLF 35 33 02 77

analyse@econ.ku.dk

Dataansvarlig: Søren Leth-Petersen,
Professor

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

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

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

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

Brugernavn: deltager5795 Password: n4mw9!uay

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

Med venlig hilsen

Søren Leth-Petersen

Søren Leth-Petersen
Projektleder, professor

English translation of the invitation letter.

Dear «name»,

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

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

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

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

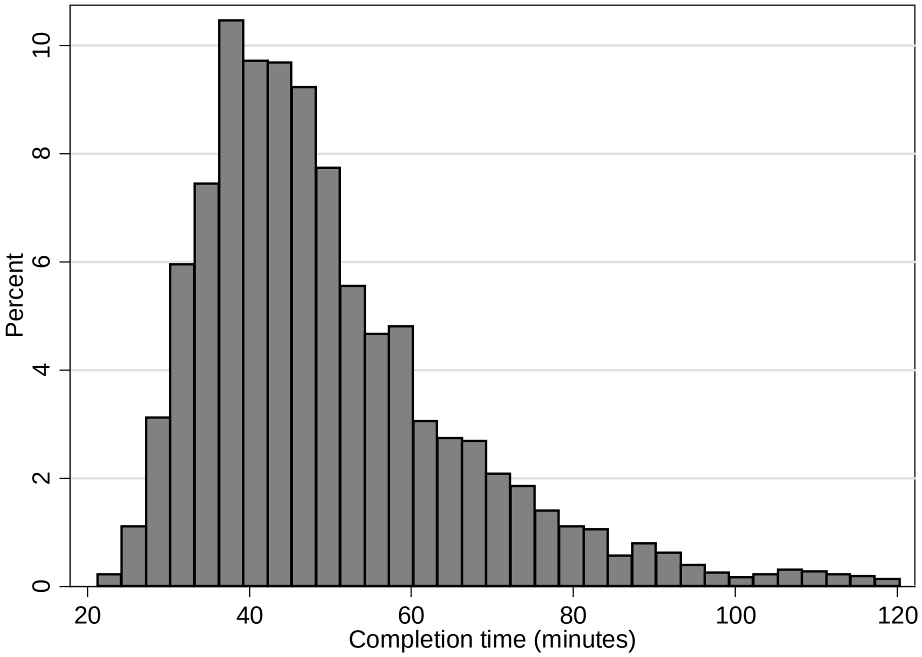
Username: «username»   Password: «password»

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

Sincerely yours,

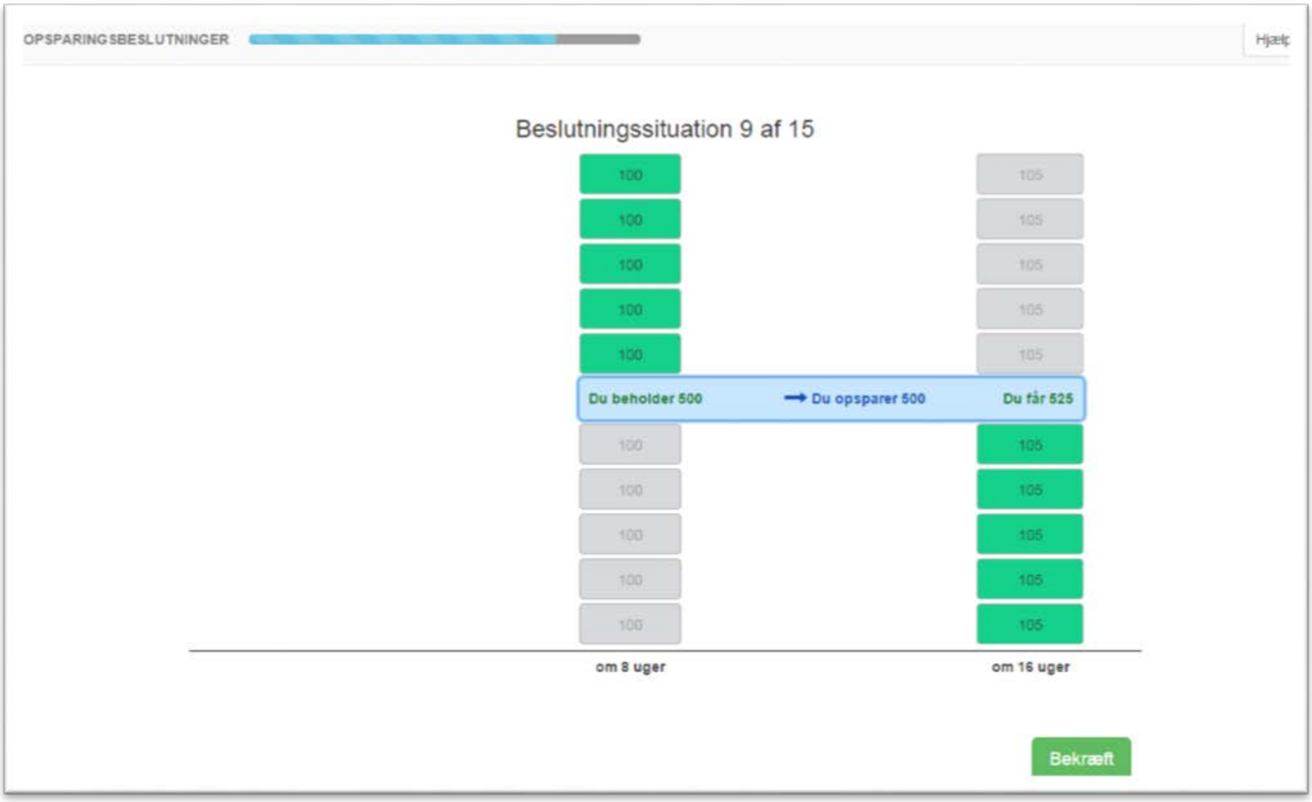
Søren Leth-Petersen
Project manager, professor

Appendix 6.2: Distribution of completion time.



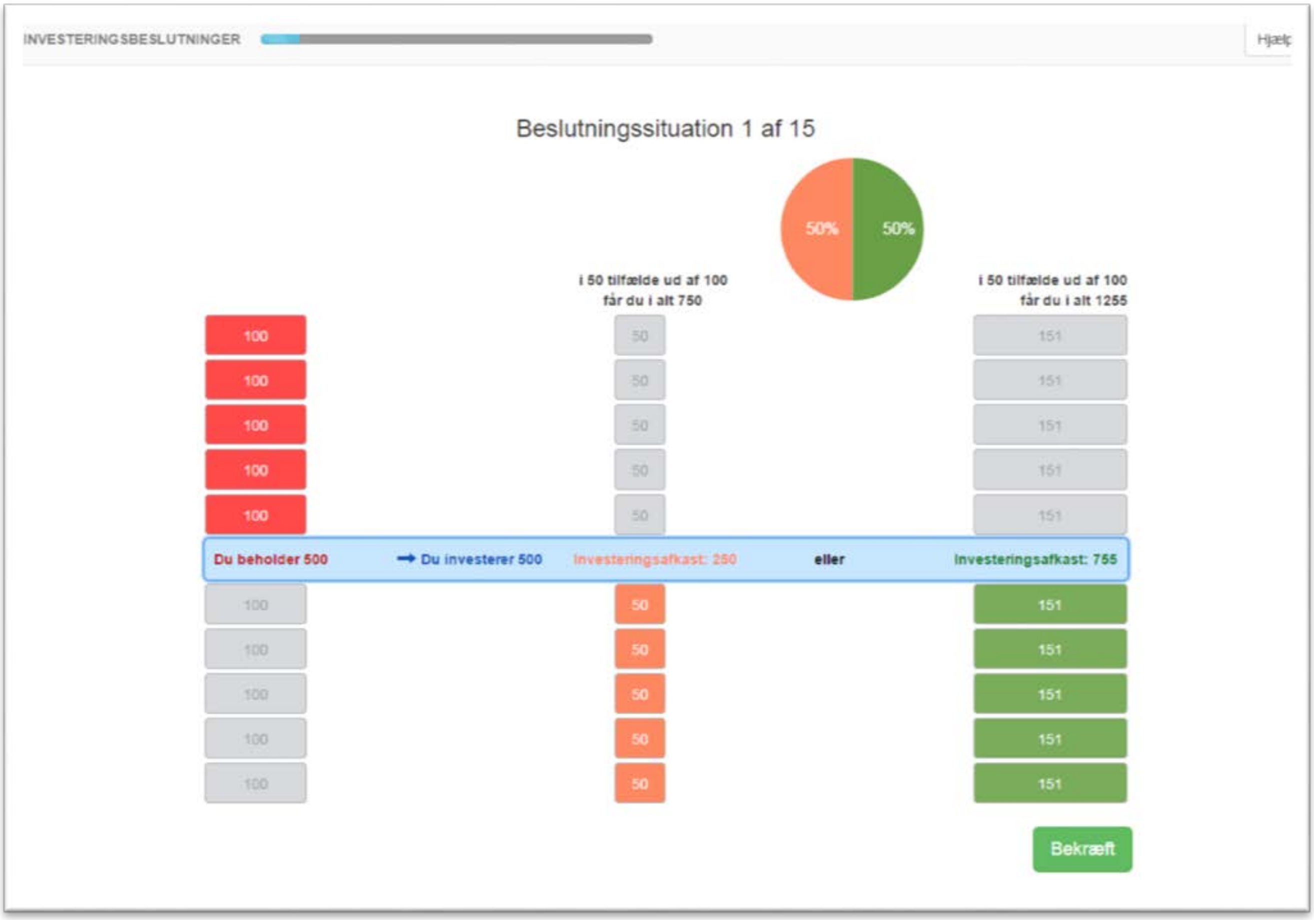
Notes: The histogram is truncated at 120 minutes. Some respondents spent considerably more time as it was possible to exit the experiment and re-enter later on. The median completion time was about 47 minutes.

Appendix 6.3: Screenshot of a saving choice. 8 vs. 16 weeks.



Notes: The blue saving bar summarizes the outcome of the allocation. In this case, the respondent chose to keep 500 points in the 8 weeks account (left) and save 500 points (right) such that he would get 525 points in 16 weeks.

Appendix 6.4: Screenshot of an investment choice.



Notes: The blue investment bar summarizes the outcome of the allocation. In this case, the respondent chose to keep 500 points on the risk-free account (left) and invest 500 points in the risky investment project (right) such that he would get 750 or 1255 points in total depending on the outcome of the investment project.

Appendix 6.5: Probit regressions of unemployment insurance dummy regressed on covariates (marginal effects at means).

	(1)	(2)	(3)	(4)
Patience	0.036 *	0.042 *	0.045 *	0.047 *
	(0.018)	(0.020)	(0.021)	(0.019)
Self-reported risk aversion, 1-3 (=1)	-0.037 *	-0.041 *	-0.048 *	-0.045 *
	(0.018)	(0.020)	(0.021)	(0.019)
Self-reported risk aversion, 5-7 (=1)	-0.005	-0.011	-0.017	-0.013
	(0.017)	(0.019)	(0.020)	(0.017)
Unemployment rate within own educational group	0.027 ***	0.029 ***	0.030 ***	0.028 ***
	(0.005)	(0.006)	(0.006)	(0.005)
Has experienced unemployment, 2011-2013 (=1)	0.208 ***	0.230 ***	0.232 ***	0.189 ***
	(0.013)	(0.014)	(0.014)	(0.012)
Public employee (=1)	0.028	0.025	0.037 *	0.029 *
	(0.015)	(0.016)	(0.016)	(0.015)
Self-reported self-control, 1-3 (=1)	0.009	0.010	0.008	0.011
	(0.024)	(0.026)	(0.027)	(0.025)
Self-reported self-control, 5-7 (=1)	0.045 *	0.048 *	0.040	0.055 *
	(0.021)	(0.023)	(0.023)	(0.022)
Income decile dummies	Yes	Yes	Yes	Yes
Net asset decile dummies	Yes	Yes	Yes	Yes
Year dummies for educational attainment	Yes	Yes	Yes	Yes
Demographic characteristics	Yes	Yes	Yes	Yes
Math grade dummies	Yes	Yes	Yes	Yes
Observations	3809	3543	3721	3721

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2013 values unless otherwise stated. (=1) indicates a dummy variable which takes the value 1 for respondents who satisfy the description given by the variable name. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. Column (1) reproduces the main specification in column (4), table 4.1. Column (2) restricts the sample to respondents who did not contribute to the early retirement scheme in 2013. Column (3) estimates the main specification using inverse probability weighting where probability weights are based on respondents vs. non-respondents. Column (4) presents results from estimating the main specification using inverse probability weighting where probability weights are based on respondents vs. population. The number of observations is slightly lower in columns (3)-(4) as some of the respondents do not have strictly positive income or liquid assets.

Appendix 6.6: Probit regressions of health insurance dummy regressed on covariates (marginal effects at means).

	(1)	(2)	(3)
Patience	0.081 ***	0.084 ***	0.089 ***
	(0.023)	(0.024)	(0.026)
Self-reported risk aversion, 1-3 (=1)	-0.006	-0.001	-0.018
	(0.021)	(0.022)	(0.023)
Self-reported risk aversion, 5-7 (=1)	0.004	0.004	-0.012
	(0.021)	(0.021)	(0.023)
Self-reported self-control, 1-3 (=1)	-0.054	-0.045	-0.046
	(0.030)	(0.032)	(0.034)
Self-reported self-control, 5-7 (=1)	-0.037	-0.046	-0.049
	(0.023)	(0.024)	(0.026)
Income decile dummies	Yes	Yes	Yes
Net asset decile dummies	Yes	Yes	Yes
Year dummies for educational attainment	Yes	Yes	Yes
Demographic characteristics	Yes	Yes	Yes
Math grade dummies	Yes	Yes	Yes
Observations	4642	4517	4517

Notes: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Register variables are based on 2014 values. (=1) indicates a dummy variable which takes the value 1 for respondents who satisfy the description given by the variable name. Demographic characteristics include age, age^2, gender, marital status, dependent children, and homeownership. Column (1) reproduces the main specification in column (4), table 4.2. Column (2) estimates the main specification using inverse probability weighting where probability weights are based on respondents vs. non-respondents. Column (3) presents results from estimating the main specification using inverse probability weighting where probability weights are based on respondents vs. population. The number of observations is slightly lower in columns (2)-(3) as some of the respondents do not have strictly positive income or liquid assets.

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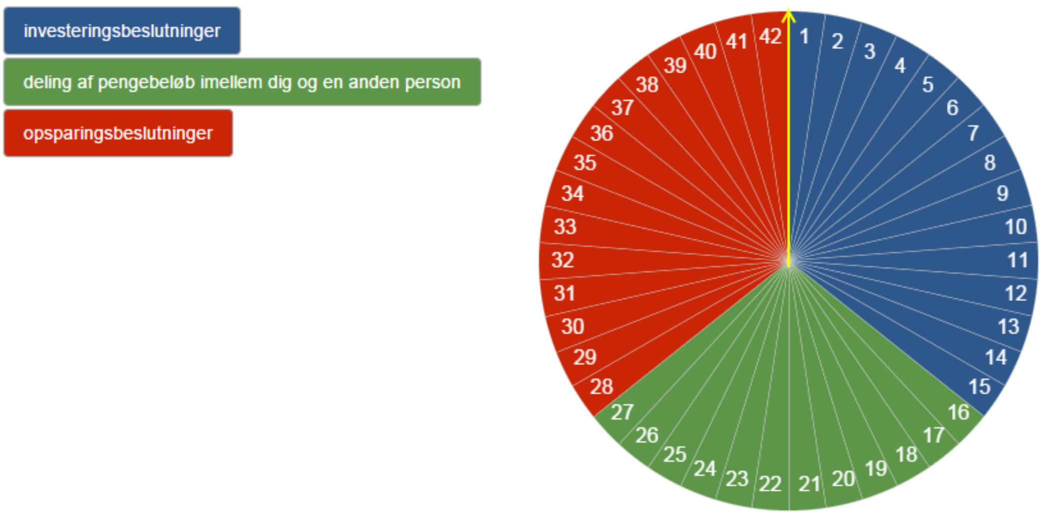
English transcript of introductory instructions

Welcome!
This survey is being conducted by the University of Copenhagen and will be used for research into how people make financial decisions.
When you have completed the survey, you will receive a sum of money in your NemKonto. The size of the amount will depend on your decisions during the survey and will, on average, be the equivalent of a decent hourly wage.
The survey revolves around three types of decisions:

1. INVESTMENT DECISIONS
2. SAVING DECISIONS
3. DIVIDING SUMS OF MONEY BETWEEN YOURSELF AND ANOTHER PERSON

Your task is to make decisions. Within each of the three decision-making areas you will be making 12-15 decisions.

In each decision situation, you will make a decision about a particular amount of points.
100 points is the equivalent of DKK 25.
One of the decision-making situations will be chosen for payout at the conclusion of the survey. The points you earned in this situation will be converted into DKK and transferred to your NemKonto. You will not have to pay tax on the amount. The University of Copenhagen has already settled this issue with the Danish Customs and Tax Administration (SKAT). Accordingly you will not have to declare it to SKAT.
At the conclusion of the survey you must spin the pointer on the wheel shown below. The place where the pointer stops will determine the decision-making situation, for which you will be paid. So you should be careful about each decision you make.



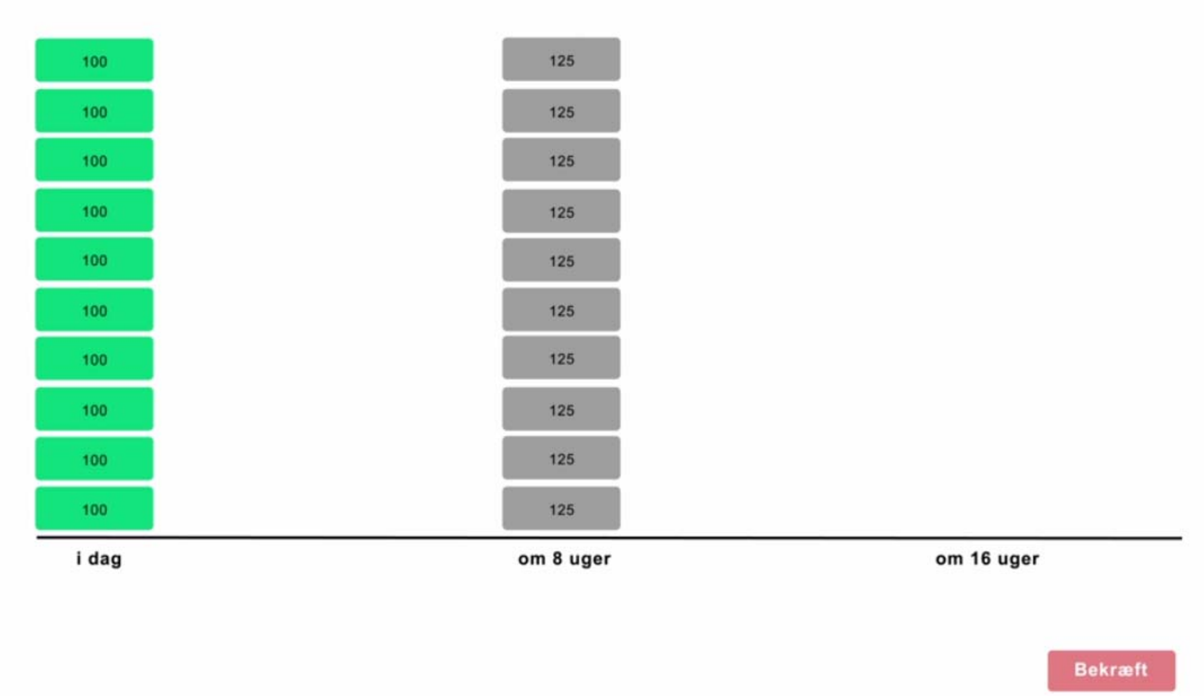
Please note that there are no right or wrong decisions. It is important to base the investment, saving, and distribution decisions you make on your own assessments and preferences.
All data will be stored anonymously.
The survey consists of four steps:

1. Questionnaire 1
2. Decisions within the three decision-making areas
3. Questionnaire 2
4. Selection of the decision-making situation you will be paid for, and determination of your prize in this situation.

Prior to each part of the survey you will be given detailed explanations.
The grey bar at the top of the window shows you where you have got to in the survey at any given time.
Click on 'Next'.

English transcript of instruction video regarding saving decisions

[001] Now we have reached the next part of the survey. [002] It is about saving. You need to make 15 saving decisions.
[003] At the start of each saving decision you have 1000 points. [004] These 1000 points are divided into 10 blocks of 100 points.
[005] You can hold on to each and every block in your account or save it.

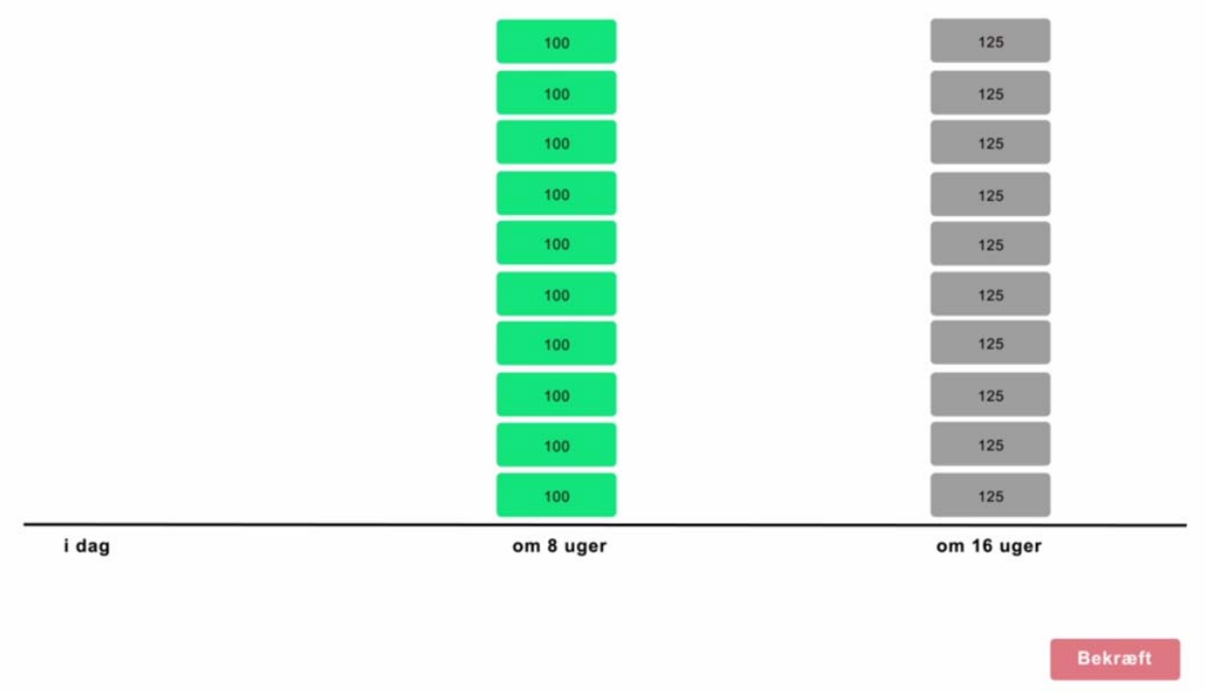


[006] There are three types of accounts:

1. [007] A day account. The points in this account will be credited on the next banking day.
2. [008] A short-term savings account. The points in the short-term savings account will be credited on the next banking day at the end of an 8-week period.
3. [009] A medium term savings account. The points in the medium term savings account will be credited on the next banking day at the end of a 16-week period.

[010] In each saving situation you will be presented with two accounts. We will ask you to divide the green blocks between the two accounts.
[011] In the following example, you can divide the points between the day account and the short-term savings account. [012] At the start, there are 1000 points in your day account. [013] You can save a number of blocks by transferring them to the short-term savings account. [014] By doing this you will get an interest payment. [015] In the example, you get 125 points in an 8-week period for every 100 points you save.
[016] You make your saving decision by positioning the light blue saving bar, which appears on one of the blocks after the first click. [017] You can move this bar as many times as you want before you continue with ‘Confirm’.
[018] Once you have clicked on ‘Confirm’, you can no longer change your decision.

[019] If this saving decision were selected for payment at the end of the survey, you would have 700 points credited on the next banking day and 375 points credited in 8 weeks.
[020] The points will be converted into DKK on the day in question, and the respective amount will be transferred to your NemKonto.
[021] One final remark: You will also be presented with saving situations, in which your points are initially placed in the short-term savings account. Then you need to divide the points between this account and the medium term savings account. [022] In this case, these points will be credited either after an 8-week period or after a 16-week period.

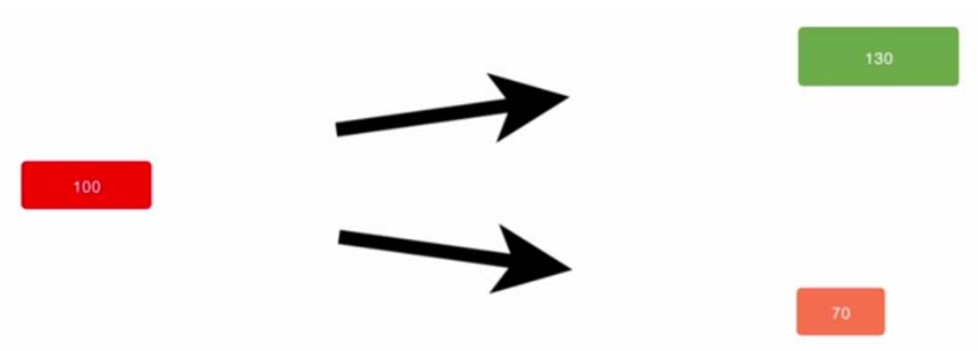


[023] Now we will show you some examples of situations. [024] It is important to acquaint yourself with how they work prior to making your actual saving decisions. [025] You can watch this video again at any time by clicking on the ‘Help’ button at the top right of the screen.

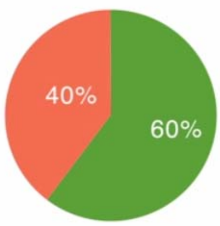
English transcript of instruction video regarding investment decisions

[001] Now we come to the next part of the survey. [002] It is about investment. [003] You need to make 15 investment decisions.
[004] At the start of each investment decision you have 1000 points in your account.
[005] These 1000 points are divided into 10 blocks of 100 points.

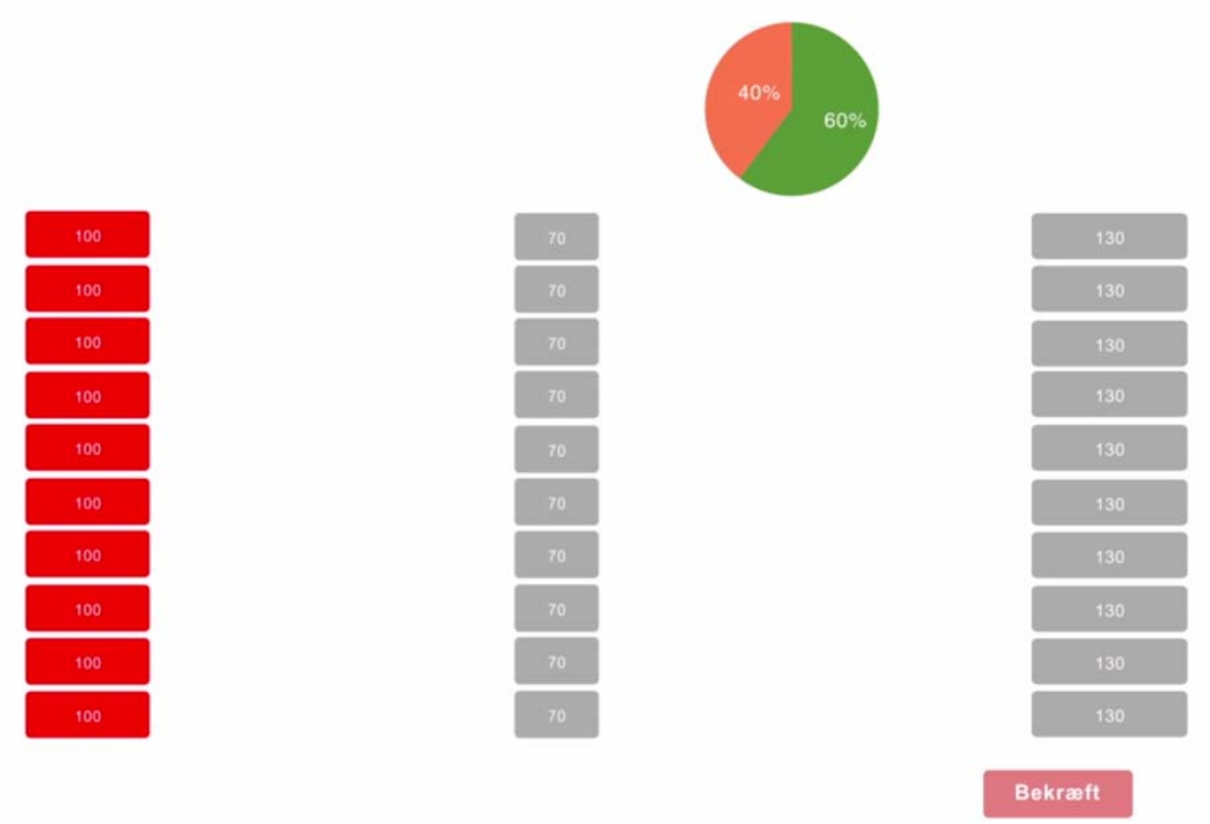
[006] You can hold on to each and every block or invest it in a project. [007] This project may turn out favorably or unfavorably.
[008] In the following example, if you invest 100 points you will earn 130 points in the event of a favorable, green outcome, or 70 points in the event of an unfavorable, orange outcome.



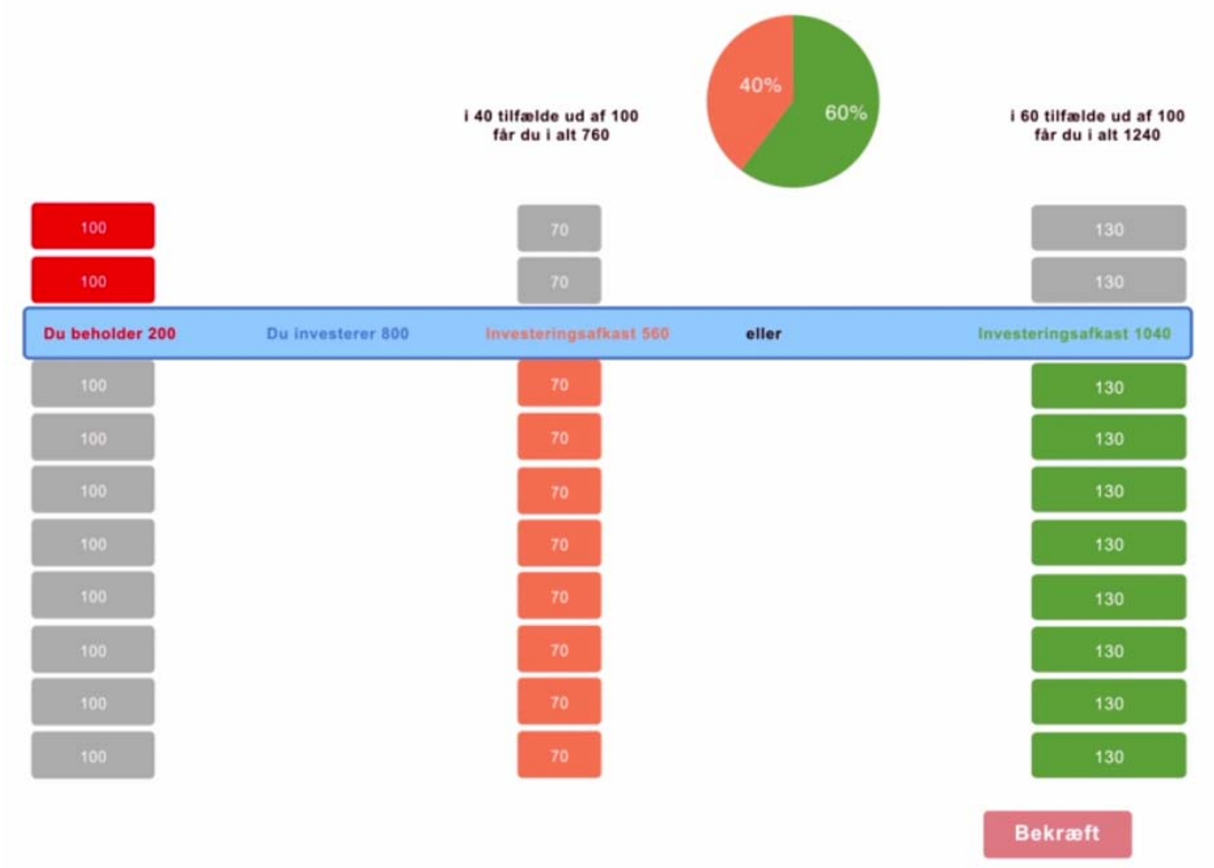
[009] The wheel shows the probability of the investment project turning out favorably or unfavorably. [010] The green area indicates the likelihood of the project turning out favorably, and the orange area indicates the likelihood of the project turning out unfavorably.



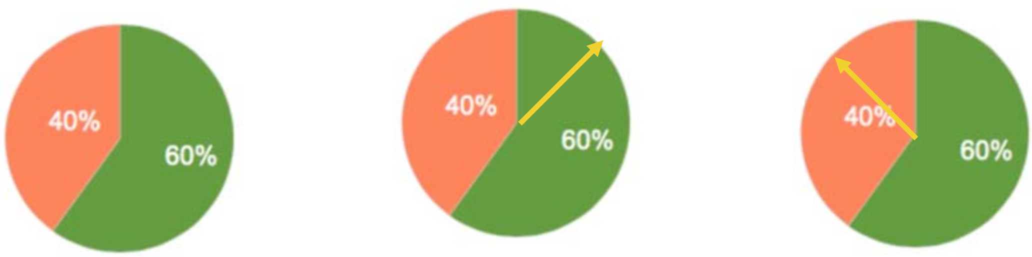
[011] In this example an average of 60 % of all investment projects turn out favorably, and 40 % of all investment projects turn out unfavorably.
[012] Now you can choose how many of the ten red blocks you want to hold on to in your account, and how many you would like to invest in this project.
[013] At the start of each investment decision you can see all the red blocks in your account.



[014] You make your investment decision by placing the light blue investment bar, which appears on one of the blocks after the first click. You can move this bar as many times as you want before you continue with ‘Confirm’. [015] Once you have clicked on ‘Confirm’, you can no longer change your decision.



[016] In this example you are investing eight blocks.
[017] If this investment decision were selected for payment at the end of the survey, either way you would hold on to the uninvested 200 points: in other words, regardless of whether the project turned out favorably or unfavorably. [018] You would also get a return that depended on the project's outcome. [019] In the best-case scenario the return would be 8 x 130 points: i.e. 1040 points. [020] In the worst-case scenario the return would be 8 x 70 points: i.e. 560 points. [021] These amounts are indicated in the light blue bar. [022] The points will be converted into DKK, and the amount will be transferred to your NemKonto.
[023] The outcome of the project will be determined by the place, at which the pointer happens to stop in the wheel. [024]. You can spin the pointer yourself by [025] clicking on the wheel. [026] If the pointer happens to stop in the green area, the project has turned out favorably. [027] If the pointer happens to stop in the orange area, the project has turned out unfavorably.



[028] In this example, the pointer stops in the orange area. [029] In other words, you earn 200 points from the uninvested amount PLUS 560 points in investment return. That makes 760 points in total.

[030] Now we will show you some examples of situations. [031] It is important to acquaint yourself with how they work prior to making your actual investment decisions. [032] You can watch this video again at any time by clicking on the ‘Help’ button at the top right of the screen.