More than Money: The Role of Preferences on Wealth Mobility*

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Abstract

We estimate the preferences of individuals from different wealth backgrounds to explain intergenerational wealth mobility. We use rich micro-level data on the balance sheets, consumption, and risky investments of Swedish residents, together with family wealth background measured during the offspring's early adulthood. We find that patience and risk-tolerance are strongly correlated with wealth background. Counterfactual analyses reveal that background-dependent preferences can explain at least 75 percent of the wealth gap between adults of non-rich backgrounds (90 percent of the population) and very-rich backgrounds (2.5 percent of the population). In contrast, early-adulthood heterogeneity in wealth, gifts and inheritances, and intergenerational transmission of human capital are not dominant determinants of wealth mobility.

Keywords: Household Finance, Personal Income, Wealth, Consumption, Savings.
JEL Classifications: D14, D31, E21, H24

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1 Introduction

From the popularized idea of the "American Dream" (Adams, 1931) to Rawls's theory of social justice (Rawls, 2005), social mobility is considered one of the cornerstones of democratic societies. Investigating its determinants is essential to understand the root causes of evolving social disparities and to design policies aimed at promoting both social and economic equality.

Economists have employed the concept of intergenerational elasticity of economic status to quantify the degree of social mobility. While a substantial and established body of research has utilized income as a proxy for economic status, a more recent and smaller literature has focused on wealth instead. Regardless of whether income or wealth is used as the metric, empirical evidence consistently demonstrates a significant correlation in economic status across generations (Black and Devereux, 2011; Charles and Hurst, 2003; Fagereng, Mogstad and Rønning, 2021). Additionally, many countries have experienced an increase in wealth and income inequality in the past decades (Chancel, Piketty, Saez and Zucman, 2022). Overall, this suggests a limited capacity for Western economies to promote upward mobility and underscores the importance of understanding its underpinning to guide the policy debate. While both income and wealth are important aspects of social status, large fortunes —unlike human capital— can be tied up in inherited assets and directly transferred across generations, potentially distorting the efficient allocation of capital in the economy. From a political economy perspective, persistent concentration of ownership can lead to a disproportionate influence of wealthy dynasties in politics and policymaking (Piketty, 2014).

The academic focus on income is partly due to data limitations and partly because wealth accumulation is a much more encompassing and complex phenomenon. It depends not only on income prospects, but also on consumption, saving, and investment decisions over the life-cycle. In other words, the study of intergenerational persistence in wealth requires not only understanding why income is correlated across parents and children, but also how children's wealth accumulation is influenced by their parents directly, through wealth transfers, and indirectly, through shared familial attitudes and preferences towards saving and investing.

To explain intergenerational mobility in income (and education or occupation, for that matter), economists have designed models in which parents care for their children's well-being and are thus willing to invest in their children's human capital.[1] In addition to parents' investment, the persistence and distribution of income in equilibrium depends on the heritability of traits and the random assignment of skill among children. While this literature

[1] Becker and Tomes (1986); Becker, Kominers, Murphy and Spenkuch (2018); Lee and Seshadri (2019); Loury (1981); Solon (2004)

explores endogenous decisions to educational choices and labor supply,[2] it does not focus on savings and investment decisions, or the correlation of wealth across generations.

On the contrary, any model of intergenerational transmission of wealth will need to incorporate the wealth accumulation decisions of children and, thus, the intergenerational association of children's deep preference parameters with parents' social status. Without such knowledge it would be difficult to design effective policies that promote social mobility along the wealth distribution. To the best of our knowledge, the literature is silent on this issue, and this paper aims to fill this gap for the first time.

Recent progress in understanding wealth inequality highlights the importance of risk tolerance and disposition towards investing in real asset classes (such as real estate and private businesses). First, following up on the seminal work of Quadrini (1999), and Cagetti and De Nardi (2006) and Cagetti and De Nardi (2009), the most recent models of wealth inequality emphasize the importance of heterogenous returns to wealth across the population (see Benhabib and Bisin (2018), for a theoretical review, and Hubmer, Krusell and Smith Jr (2021), for a quantitative calibration). Access to detailed and comprehensive wealth data in Scandinavian countries has empirically confirmed that wealthier households earn persistently higher expected returns on their net wealth and that, at the same time, they hold substantial idiosyncratic risk in their holdings (Bach, Calvet and Sodini (2020b); Fagereng, Guiso, Malacrino and Pistaferri (2020)). Additionally, it is the variation in returns to wealth across the wealth distribution that matters the most for the dynamics of wealth inequality rather than the heterogeneity in saving rates (Bach, Calvet and Sodini, 2017). Overall, the heterogeneity in investment risk-taking and asset allocation seems a crucial ingredient to explain the degree of wealth inequality and its evolution over time. Yet, we do not have any study of how the deep preference parameters of children, which are at the foundation of the investment decisions that shape the wealth distribution of their generation, depend on parents' social status.

Second, the latest empirical studies on the intergenerational elasticity of wealth underscore the importance of family background beyond the direct impact of inheritances and gifts. Black, Devereux, Landaud and Salvanes (2023) and Black, Devereux, Landaud and Salvanes (2022) document that gifts and inheritances are a small share of total lifetime resources. Their importance becomes more pronounced for the top 1% wealthiest individuals, particularly as a source of capital income. Black, Devereux, Lundborg and Majlesi (2020) and Fagereng et al. (2021) find that the intergenerational correlation of wealth is primarily driven by environmental, rather than genetic factors, even prior to inheritance receipt.

[2] Lo Bello and Morchio (2022); Boar and Lashkari (2021); Heckman, Stixrud and Urzua (2006); Lee and Seshadri (2019)

Furthermore, nurture plays a key role in shaping offspring's approaches to saving and investment decisions, with important implications for the dynamics of wealth inequality. Nekoei and Seim (2023) find that investment choices are crucial in explaining how inheritances impact wealth inequality. While bequeathed wealth initially mitigates inequality by primarily flowing from richer parents to poorer children, in the long term, wealthy heirs' capacity to generate higher returns leads to a net increase in the share of aggregate wealth held by the top of the distribution. In conclusion, gifts and inheritances appear to constitute a modest component of total lifetime resources, and their impact on the evolution of inequality seem to depend on how they are managed by offsprings.

In this paper, we employ a structural approach to estimate how the deep preference parameters that govern individual wealth accumulation vary with family background. We propose a canonical model of consumption, saving, and portfolio choice in continuous time that extends Benhabib, Bisin and Zhu (2011) to explicitly consider endogenous risk-taking and portfolio allocation decisions.

Each individual in our model consumes, saves, and makes risky investments according to her time preference rate and risk aversion. Individuals have also warm-glow bequest type of preferences and can leave bequest to their offsprings. Wealth accumulation is thus endogenous, firstly due to active saving decisions, the pace at which wealth is saved (or consumed) relative to the inflow of labor earnings, and secondly due to wealth allocation decisions. Individuals may invest in multiple risky assets: common stocks, real estate, pension, and private business, as well as a risk-free asset. The return on wealth can vary across individuals for four reasons. First, the return premia on risky asset classes vary across the population and are directly estimated from the data. Second, return on risky assets includes both systematic and idiosyncratic risk, which are estimated from the individual asset holdings observed in our dataset. Third, individuals allocate endogenously the risky part of their portfolios across different risky asset classes. Fourth, and finally, individuals also endogenously decide how much to invest in the risky component of their wealth versus the risk-free one.

We classify individuals in groups depending on their education levels, business sectors, and family wealth backgrounds. Labor income profiles are heterogeneous with with level and growth rates that vary across groups. The variation in income prospects across family wealth backgrounds captures investment in human capital by parents (Becker and Tomes, 1986). We distinguish between non-rich, rich, and very-rich parents depending on their level of wealth when their children were in their mid twenties. We estimate the deep preference parameters of the model for each group of individuals with the minimum distance method, which consists of matching a set of targeted moments with their data counterparts. This allows us to estimate the dependence of preferences on family background while flexibly controlling for education and business sectors as the covariates. The deep parameters that we estimate are subjective time discount rate, bequest motive, and risk aversion.

We follow an exactly-identified method to estimate the preference parameters. In the class of models that we consider, individuals consume a fraction of their *total* wealth, defined as the sum of current tangible net wealth, human capital, and the present value of inheritances and gifts. The optimal consumption-wealth ratio depends on age and, importantly in our context, on patience and bequest motive. Identification of these two preference parameters is achieved through the active saving observed in the data in early and late adulthood. Active saving in early adulthood mostly depends on the subjective time discount factor, while in late adulthood, it depends both on the subjective time discount factor and the bequest motive. Risk aversion is pinned down by the share of wealth invested in all risky asset classes. The optimal portfolio risky share is governed by the excess return vector scaled by the variance-covariance matrix of returns and risk aversion so that less risk-averse individuals invest a larger share of their wealth in risky assets.

The study of the determinants of intergenerational wealth transmission has been hampered by the lack of reliable, detailed, and comprehensive data on the finances of households and their family relationship across generations. In particular, it is difficult to measure the wealth of parents in the early adult life of their children uniformly across the whole population. We are able to overcome these limitations by building a unique dataset, which fully characterizes the evolution of wealth and consumption at the individual level and connects individuals belonging to the same dynasty across generations.

The project combines data on Swedish resident individuals from two main sources: the Wealth, Income and Demographic Registers and the Flergeneration Register, both maintained by Statistics Sweden (SCB). We limit the study to the 1999-2007 period when detailed wealth data are available. In order to assess income prospects at the household level, we use income and demographic variables going back to 1983 and up to 2016. The cleaning and preparation of the wealth and income data follow closely Bach et al. (2020b) and Bach, Girshina and Sodini (2022).

We assess family background using data on taxable wealth from 1971. We carefully verify that rankings based on taxable wealth are a good proxy for actual net wealth rankings and classify individuals into different family backgrounds at ages between 20 and 30 years old. We distinguish between non-rich background (for children of parents that did not pay the wealth tax), rich background (parents that are in the bottom 75th percentile of taxable wealth), and very-rich background (parents that are in the top 25th percentile of taxable wealth). In our 1999-2007 data, individuals from non-rich backgrounds account for 90.7 percent of the population, while those from rich and very-rich backgrounds represent 7.0 and 2.3 percent, respectively.

Our paper has three key results. First, deep preference parameters are strongly influenced by individuals' wealth backgrounds. The median time discount factor in the population is about 12 percent, which is in line with the robust estimates in the existing literature (Catherine, Ebrahimian, Fereydounian, Sraer and Thesmar, 2022b). However, individuals from very-rich backgrounds have a discount rate which is 8 percent lower (having controlled for education and business sector), resulting in a significant gap in saving rates. We further find that individuals of very-rich backgrounds have significantly stronger bequest motives, which contributes to less consumption and more savings in older ages. Finally, we find a substantial gap in risk aversion. Consistent with the life-cycle optimal portfolio literature (Cocco, Gomes and Maenhout, 2005), risk aversion is estimated at about 10 for the average individual. But, children from a very-rich background have a relative risk aversion 5 units lower (within education level and business sector).

Second, we show that the documented heterogeneity in patience and risk tolerance, and their dependence on wealth backgrounds, crucially affect intergenerational wealth persistence. To do so, we simulate wealth accumulation from early-adulthood (age 25) to mid-adulthood (age 50) in counterfactual scenarios that assume uniform preferences across individuals of different family backgrounds. We find that the average wealth gap at the age of 50 between individuals of non-rich and very-rich backgrounds would shrink by at least a factor of four. It would reduce from the benchmark value of 4.5 million SEK to the counterfactual value of 0.5-1.2 million SEK (depending on specification). We find that about half of this reduction can be explained by risk aversion, while the other half is explained by patience parameters.

Third, we find that the gap in initial wealth, human capital, and parents' direct wealth transfers are not dominant forces in explaining wealth inequality later in life for adults of diverse wealth backgrounds. To show this result, we infer the initial endowment of 25-year-old individuals using the wealth accumulation rule of the model with heterogeneous preference parameter estimates. We then let the model simulate wealth accumulation over the lifecycle in the counterfactual scenario of no initial wealth gap and no heterogeneity in individual streams of labor income and intergenerational transfers (while maintaining the heterogeneous preferences estimated in the benchmark case). The wealth differential at the age of 50 between individuals of non-rich and very-rich backgrounds would shrink, but less than in the homogeneous preference case (from 4.5 to 2.6-3.7 million SEK, depending on specification). This result further confirms the first-order role of preferences in explaining intergenerational wealth mobility.

We extend the model to include a number of omitted economic forces to verify the robustness of our key results. We consider non-homothetic preferences, heterogeneous non-pecuniary benefits across asset classes, and Epstein-Zin utility. We also introduce labor income risk with cyclical skewness and borrowing constraints. Overall, we confirm that social stagnation mainly depends on what individuals do with their money, in terms of saving and risk-taking, and not just on the money they receive from their parents.

The rest of the paper is as follows. Section 2 describes the data. Section 3 defines our measure of family background and reports facts on wealth mobility in Sweden. Section 4 lays out the benchmark model. Section 5 estimates the structural parameters of the model. Section 6 studies various counterfactuals. Section 7 reports a battery of robustness checks. Section 8 concludes.

2 Data

2.1 Data Sources and Sample Construction

The panel is based on data from the Swedish Wealth Register (Statistics Sweden (2007a) Statistics Sweden (2007c), Statistics Sweden (2007d), Statistics Sweden (2007f)) which is compiled and maintained by Statistics Sweden. For every Swedish resident, the data include the debt and disaggregated worldwide financial and real estate holdings at year-end from 1999 to 2007. Bank account balances,[3] stock and mutual fund investments, and real estate holdings are observed at the level of each account, security, or property. Liquid financial wealth consists of bank account balances, mutual funds, stocks, bonds, derivatives, and capital insurance. Real estate wealth consists of residential properties (i.e., primary and secondary residences), and commercial properties (i.e., rental, industrial, and agricultural properties).[4] The panel also provides individual total debt outstanding at year end and the interest paid during the year.

For information on private equity and pension wealth holdings, we follow the procedures adopted by Bach et al. (2020b). We identify private equity holdings, i.e. the ownership of unlisted limited liability companies, using the income tax forms containing the number of

[3] Bank account balances are reported if the account yields more than 100 Swedish kronor during the year (1999 to 2005 period), or if the year-end bank account balance exceeds 10,000 Swedish kronor (2006 and 2007). At the end of 2004, one krona was worth 0.151 US dollars (Sveriges Riksbank, 2016). We impute unreported cash balances as in Bach et al. (2020b) (see section *I.D.* of Bach, Calvet and Sodini (2020a)).

[4] For apartments we use the dataset on co-op ownership (bostadrätt) developed in Bach et al. (2022) (see the data section therein for a detailed description). The database is built on the tax forms for transfers of co-op apartments (Statistics Sweden, 2016a), which are collected by Statistics Sweden and cover the universe of all apartment sales in Sweden during the period 1999 to 2016.

shares held by Swedish residents actively participating in the firm (Statistics Sweden, 2008). The dataset encompasses almost all stakes in private companies held by individuals from the year 2000 onward.[5] Pension wealth is the sum of each individual rights to pension and life insurance payments that are backed by financial assets. We impute funded pension wealth from Swedish national financial accounts and the IoT register (*Inkomst- och Taxeringsregistret*; Statistics Sweden, 2007c) following a method developed by Saez and Zucman (2016) for the US and applied to Sweden by Alstadsæter, Johannesen and Zucman (2019). We refer to sections *I.A.* of Bach et al. (2020a) for a detailed description.

In order to assess income prospects, we use income and demographic variables from the IoT register and the RTB register (*Registret över Totalbefolkningen*; Statistics Sweden, 2017b) going back to 1982 and up to 2015. Family ties are obtained from the Swedish Flergeneration register (*Flergenerationsregistret*; Statistics Sweden, 2007e) and allow us to identify the biological and adoptive parents of all the individuals in our sample. As we explain in detail in section 3 and A.8, we assess wealth rankings of parents using information on the wealth tax and taxable wealth from the IoT register back to 1971.

We restrict our sample in several ways. First, we only include individuals between 25 and 64 years old in each of the 8 years that we include in our analysis. Secondly, we do not include retired individuals, students, and workers from the agricultural sector. Furthermore, individuals are excluded if they have missing information in any of the datasets listed above. Our final sample includes 4,034,480 unique individuals and 27,830,392 observations over the 2000 to 2007 period. All nominal variables are deflated by the Swedish consumer price index with the base year 2001.

2.2 Asset Classes and Portfolio Allocation

Total net wealth throughout the paper is the sum of liquid financial wealth, pension wealth, real estate equity and private equity minus non-mortgage debt. Within each asset class we identify riskless and risky components as follows. We divide liquid financial wealth into cash, which is the sum of bank accounts and Swedish money market funds, and consider all other financial securities as risky financial wealth. All real estate equity is considered risky and is defined as real estate wealth minus mortgage debt capped at a maximum corresponding to a loan-to-value (LTV) ratio of 85%. For pension wealth, we follow Bach et al. (2020b) and use the annual reports of the main Swedish pension and insurance companies from 2000 to 2008 to decompose pension wealth into a safe component (cash and bonds) and a risky

[5] Using the subsample of households for which detailed dividend information is available (Statistics Sweden, 2006), we measure that active participation accounts for 90.5% of all dividends paid out by private firms to Swedish residents.

component (equities and commercial real estate). We refer to the appendix section A.2 for details. Risky wealth is defined as the sum of the following risky asset classes: risky financial assets, risky pension wealth, private equity and real estate equity.

2.3 Assets Valuation

Pricing data on Nordic stocks and mutual funds are available from FinBas (2016), a financial database maintained by the Swedish House of Finance. FinBas provides the monthly returns, market capitalization, and book value of each publicly traded company for the 1983 to 2009 period.[6]

Prices of real estate properties, other than apartments, are obtained from the *Real Estate Property Prices and Title Deeds Register* (Statistics Sweden, 2020b) and the *Real Estate Property Valuation Register* (Statistics Sweden, 2020a). Every 3 to 7 years, tax authorities assess the tax value of every real estate property using detailed property characteristics and hedonic pricing. In addition, Statistics Sweden continuously collects data on every real estate transaction in the country, which permits the construction of sales-to-tax-value multipliers for different geographic locations and property types. For the stock of non-apartment real estate, we apply a relative valuation strategy that uses sales-to-tax-value multiples. We proceed as follows. First, we filter out transactions that have very high or low multiples or are flagged by Statistics Sweden as irregular (e.g., non-market transactions). Second, we cluster transactions along three dimensions: year, real estate asset class, and geography.[7] Along the geographic dimension, we solve a max-p regions problem by clustering municipalities into larger, contiguous regions requiring a minimum number of transactions per cluster.[8] Third, we compute the geometric mean of multipliers at cluster-level. Finally, we value real estate properties in a given cluster by multiplying its tax value with the derived cluster-level multiplier.

We proceed in several steps to value apartment wealth. First, we estimate the size in square meters of each apartment in Sweden by merging the dataset on co-op transfers developed in Bach et al. (2022) with three external sources: the *Apartment Register* (Statistics Sweden, 2017a), the *Income Statement for Asset Value of Cooperative Flat* (*Förmögenhetsvärde bostadsrätt*; Statistics Sweden, 2007b) and a commercial dataset maintained by the *Swedish Real Estate Agent Association* (Svensk Mäklarstatistik, 2020). Second,

[6] For securities not covered by FinBas, we use pricing data from Citygate (2009), Datastream (2009), Morningstar (2009), NGM (2009), and OMX (2009)

[7] We consider the following real estate asset classes: agricultural units, single-family houses, holiday houses, rental housing units and industrial units.

[8] We choose contiguous regions that are maximally homogeneous with regards to mean municipality multipliers.

we estimate the price per square meter of each apartment transaction and extrapolate these estimates to all years using repeated sales indexes constructed at the municipality level, or county level if there are too few observations. Third, for apartments not sold at market value between 1999 and 2017, we assign a price per square meter in each year by taking the average price per square meter available at the most granular level among: apartment id, building, parish, municipality, and county. Finally, apartment wealth is then calculated by multiplying the apartment size by the price per square meter and the ownership share of each individual in our sample.

The valuation of unlisted business equity must overcome the lack of regular price information. We follow Bach et al. (2020b) and use valuation multiples of listed firms in the same industrial sector as the unlisted firm of interest. In line with national accounting practices, we employ a valuation multiple based on the market-to-book ratio. We construct multiples relative to the total assets of listed firms to value the assets of unlisted firms, and then subtract financial debt to estimate the market value of equity. If the difference is negative, we set the market value of equity to zero. Since financial assets (cash and stock investments with no control purpose) are recorded at market value, we apply multiples only to non-financial assets and price financial assets at book value. We use a 25% discount to the resulting equity value to account for the illiquidity of the private equity shares and the transition costs of a change in control.

2.4 Debt Components

Our individual-level debt data allows us to identify student debt but lack disaggregation between mortgage and other debt types. However, we exploit the richness of our data, and in particular the fact that we can attribute liabilities to specific lending institutions, to impute mortgage debt. By identifying whether an institution specializes in mortgages, provides all credit types, or solely consumer credit, we can categorize the origin of debt for a large fraction of the individuals in our sample.[9] This approach builds on the historical retail banking landscape in Sweden, where some banks (including some of the major ones) operate separate mortgage institutions and other don't. We impute the mortgage component within individuals' total debt by training and testing a machine learning algorithm on the subsample of individuals with known sources of debt (see the Appendix A.5 for a detailed description).

[9] Additionally, information on the assets of individuals, such as real estate holdings, is employed to further refine debt type classification. For instance, the absence of real estate wealth allows us to exclude the presence of mortgage debt for some individuals even though they are borrowing from institutions that provide both mortgage and consumer credit.

2.5 Risk and Returns

Asset return volatility makes sample means noisy estimates of expected returns, especially when measured over short and heterogeneous time periods (Merton, 1980). To address this issue we follow Calvet, Campbell and Sodini (2007) and Bach et al. (2020b) by specifying asset returns as function of pricing factors. This framework allows us to estimates factor loadings from second moments, which can be accurately measured with high frequency data, and to rely on first-moment estimation solely for a limited number of factors (for which data is typically available over long horizons). The approach has also the advantage of reducing significantly the dimensionality of robustness tests and scenario analysis from potentially thousands of parameters to a single-digit number.

We utilize an international version of the Fama and French (1993) three factor model for estimating the expected return of risky financial assets, risky pension assets, and private equity. For real estate assets, we employ local CAPM models where we proxy market portfolios with country-wide real estate indexes. We now review the overall methodology and refer the reader to section A.1 of the appendix for detailed definitions, procedures and data sources.

For every asset j in risky asset class $c = 1, \dots, C$, we model the return in period t as:

$$r^e_{j,t} = \alpha_j + \beta^{'}_j f_{c,t} + u_{j,t}, \tag{1}$$

where $r^e_{j,t}$ denotes the excess return on asset j at time t, α_j measures risk-adjusted performance, $f_{c,t}$ is the column vector of the excess returns of the pricing factors for asset class c, β_j is the column vector of factor loadings of asset j, and $u_{j,t}$ is a residual uncorrelated with the factors. We explain in sections A.2 and A.4 of the appendix how we estimate the vector of factor loadings $\beta_{i,c,t}$ of asset class c for investor i, as the estimation differ across asset classes.

We estimate the expected excess return of investor i on risky asset class c as $E_t(r^e_{i,c,t+1}) = \beta_{i,c,t} E(f_{c,t})$, where $E(f_{c,t})$ is the expected excess return vector of the pricing factors of class c, estimated with sample means over the longest time series available.[10] The vector of expected excess returns of individual i at asset class level is then:

$$\mu_{i,t} \equiv \left(E_t(r^e_{i,1,t+1}), ..., E_t(r^e_{i,C,t+1})\right)'. \tag{2}$$

As we shall see below, we group individuals in socio-economic groups by wealth background, education and industry sector. In order to estimate the risk exposure of each group, we

[10] See appendix table A.1 and A.3 for the time periods and estimated values of each factor.

first calculate systematic, idiosyncratic risk, and the expected returns at asset class level for each individual i. Denote with $\text{Var}(f_t)$ the sample variance-covariance matrix of the excess returns of all the pricing factors.[11] Then construct the matrix $B_{i,t}$ with columns corresponding to the estimated asset class betas $\beta_{i,c,t}$, $c = 1, ..., C$ of individual i.[12] The systematic variance-covariance matrix $\Omega^{\text{sys}}_{i,t}$ of individual i at asset class level is then:

$$\Omega^{\text{sys}}_{i,t} \equiv B^{'}_{i,t} \; \text{Var}(f_t) \; B_{i,t}. \tag{3}$$

The measurement of idiosyncratic risk varies across asset classes and we refer the reader to the appendix sections A.2 and A.4 for a detailed description. We assume that idiosyncratic risk is uncorrelated across asset classes so that the idiosyncratic variance-covariance matrix of investor i at asset class level is a diagonal matrix with the idiosyncratic variance of each asset class as diagonal elements:

$$\Omega^{\text{idio}}_{i,t} \equiv \text{diag}(\text{Var}^{\text{idio}}_{i,c,t}; c = 1, ..., C) \tag{4}$$

where $\text{Var}^{\text{idio}}_{i,c,t}$ is the idiosyncratic variance of asset class c, as defined in the appendix. The total risk of investor i at asset class level is then given by:

$$\Omega_{i,t} \equiv \Omega^{\text{sys}}_{i,t} + \Omega^{\text{idio}}_{i,t}. \tag{5}$$

2.6 Consumption

We follow the approach of Sodini, Van Nieuwerburgh, Vestman and von Lilienfeld-Toal (2023a) to impute consumption from data on disposable income, interests paid and active savings in: financial wealth, pension wealth, private equity, real estate wealth and debt:

$$\text{Cons} = \text{Income} - \text{Savings} = \text{Income} - r - d\text{Fin} - d\text{Pen} - d\text{Pe} - d\text{Housing} + d\text{Debt}, \tag{6}$$

where Income includes non-financial disposable income, rental yield, and dividends. Active changes in real estate and private equity are obtained from transaction data. We refer to section *C.* of Sodini, Van Nieuwerburgh, Vestman and von Lilienfeld-Toal (2023b) for details. Consumption is winsorized at 1 and 99 percentiles.

[11] The vector f_t stacks all the factors $f_{c,t}$ pricing the asset classes $c = 1, ..., C$, i.e. $f'_t = (f'_{1,t}, ..., f'_{C,t})$. We estimate variances and covariances with the highest frequency data available.

[12] More precisely, column c of $B_{i,t}$ has the same dimension of f_t with the elements corresponding to the factors $f_{c,t}$ pricing asset class c filled by the vector of class c estimated betas $\beta_{i,c,t}$, and otherwise with zero elements.

2.7 Human Capital and the Present Value of Gifts and Inheritance

Finally, we build the stock of human capital and the present value of gifts and inheritance received from parents for individuals and individual groups. Labor income, as well as transfers received, in present value terms, contribute to the total wealth of an individual and affect optimal choices of consumption and risky investments.

We follow a similar approach to Catherine, Sodini and Zhang (2022c) to calculate human capital. Basically, we fit a polynomial of degree 3 curve with age over the disposable income growth of individuals, separately for 36 groups (education-by-sector), using data from 1982 to 2015. We then use the predicted growth from the fit, as well as the current income of each individual, to project a stream of future expected income levels. Note that while our estimate of age profile for the growth of income does not depend on the wealth background (due to lack of data for the longer period on the background), the level of income may freely be determined by wealth background (to reflect the inter-generational transmission of human capital). We then discount back the projected income at the rate $r = 4.1\%$ (Calvet, Campbell, Gomes and Sodini, 2021; Catherine et al., 2022c), to construct human capital, again, at the individual level. We take into account retirement benefits in the calculation of human capital as well. Finally, the estimated level of human capital is aggregated at the education-by-sector-by-background level, to be used in structural estimation.

We follow a similar approach to measure the present value of gifts and inheritance from parents. Using the observed data on the level of transfers during 2000-2007, we fit a polynomial of degree 3 with age on the flow of transfers, aggregated at the 3 background group levels. We then project the expected values with the fitted profile (and scale with the average aggregate wealth growth index) into future ages/periods and then discount back to obtain an age profile for the present value of gifts and inheritance, per wealth background group.

2.8 Socio-economic Groups

We categorize individuals in three wealth background groups based on the within-cohort ranking of their parents' taxable wealth during their twenties (20 to 29 years old). We distinguish between "non-rich", "rich", and "very-rich" individuals which approximately represent 90.7 percent, 7.0 percent, and 2.3 percent of our sample, respectively. Table 1 reports the number of observations and individuals in our final sample by wealth background and cohort. We further discuss how we short individuals based into wealth background categories in section 3.

We further divide the individuals in each wealth background group into additional 36 groups based on education and business/employment sector. We consider three education

Table 1: Observations and Individuals per wealth background group in each IoT wave

	Group of Wealth Background			Individuals	Observations
Wave	Non-rich	Rich	Very-rich	Per wave	Per wave
1971	91.79%	6.18%	2.02%	1,018,161	7,382,500
1981	92.30%	5.77%	1.93%	962,845	7,327,534
1990	93.25%	5.06%	1.69%	1,093,192	8,120,766
2001	84.94%	11.31%	3.75%	960,282	4,999,592
All	90.68%	7.00%	2.32%	4,034,480	27,830,392

Note: The table shows the number of individuals and observations in the final sample and the contribution of each iot wave, as well as the percentage of individuals per wealth background group.

levels: "No high-school"; "High-school completed"; and "Post high-school studies"; and twelve broadly defined industry sectors: mining and quarrying, electricity, gas and water supply; manufacturing; construction; wholesale and retail trade; hotels and restaurants; transport, storage and communication; financial intermediation; real estate activities; public administration and defense, compulsory social security; education and social work; health care and veterinary services; and other services and activities.[13]

Overall, we have 108 socio-economic groups based on wealth background, education and industry sector.

3 Wealth Mobility in Sweden

Measuring inter-generational wealth mobility is a complex task, requiring the comparison of an individual's wealth during adulthood with their parents' wealth at a comparable age. This necessitates longitudinal micro-data on wealth and family relationships spanning a several decades, which is often challenging to obtain. Additionally, in our case, we would like to ideally measure wealth background at the beginning of working life, when preferences are still being formed and potentially influenced by parents.

Since our data contains comprehensive wealth information only from 1999 to 2007, we build parents' wealth rankings by using the Swedish Income Tax Register (Statistics Sweden, 2007c), which contains data on the taxable wealth of all families liable to pay the wealth tax from 1971 to 2007. We divide the individuals in our sample into different cohorts based on their age in 2001, and classify their parents into wealth groups using the taxable wealth

[13] We follow Calvet et al. (2021) and drop the agricultural sector.

data available back to 1971. More specifically, we rank the parents of children who are 50-59 years old using the parents' taxable wealth in 1971. For children who are 40-49, we use parents' taxable wealth information in 1981. For children aged 30-39, we use parents' 1990 taxable wealth. For those who are 20-29, we use parents' taxable wealth in 2001, the same year we observe the children's age. By doing so, we ensure that wealth background is based on parents' wealth when children are in the early adulthood age of 20-30 years old—with parents being in their 50s.

We group children in three wealth background groups. The first consists of children whose parents paid no wealth taxes (named "non-rich" background). The second consists of children whose parents belong to the bottom 75% of those who paid wealth taxes ("rich" background). Finally, the third consists of children whose parents belong to the top 25% of those who paid wealth taxes ("very-rich" background). In the end, 90.68 percent of our full sample of about 4 million unique individuals covered during 2000-2007 fall into the non-rich background, while 7.00 and 2.32 percent fall into the rich and very-rich background groups, respectively (see table 1).

Table 2 reports net wealth and position in the wealth distribution of children of different backgrounds when they reached the age of 46-54 years old in 2001, about the age of their parents when background was measured. Panel A shows a substantial average wealth gap of 4.49 million SEK between individuals of very-rich and non-rich backgrounds and a gap of 0.98 million SEK between those of rich and non-rich backgrounds. These gaps are sizable, compared to the average wealth of a non-rich background individual, which is 0.69 million SEK. The average wealth gap reflects a shift in the whole distribution of wealth across backgrounds: The 75th percentile of wealth among the non-rich background group (0.76 million SEK) is about the same as the *25*th percentile of wealth among the very-rich group (0.70 million). Indeed, as Panel B shows, 71 percent of individuals from very-rich backgrounds belong to the top 25 wealth percentiles (three times the odds of those of non-rich background), while only 7 percent fall into the bottom 25 percentiles (one-fourth less likely than the non-rich background group). Panel C further shows that individuals from very-rich backgrounds are 6, 10, and 20 times more likely to place into the top 10, top 5, and top 1 percent of wealth distribution, respectively, than those from a non-rich background.

The open issue is whether individuals of wealthy backgrounds are wealthier simply because of parents' transmission of human capital, and gifts and inheritances, or because of deeper forces that shape wealth accumulation, such as attitudes toward saving and investment risk-taking. In the following sections, we present and estimate a life-cycle model for wealth accumulation to explain the documented wealth gap across individuals from different wealth backgrounds.

Table 2: Wealth versus Family Wealth Background

Wealth Background	Panel A: Statistics of Wealth			
	Mean	P25	Median	P75
Non-rich	0.686	0.141	0.355	0.756
Rich	1.670	0.430	0.935	1.826
Very-rich	5.174	0.700	1.631	3.515
Wealth Background	**Panel B: Fraction in Wealth Quartiles**			
	P0-P25	P25-P50	P50-P75	P75-P100
Non-rich	26.37%	26.15%	25.32%	22.17%
Rich	9.51%	12.87%	23.36%	54.25%
Very-rich	7.03%	7.22%	14.98%	70.77%
Wealth Background	**Panel C: Fraction in Upper Wealth Percentiles**			
	P90-P95	P95-P97.5	P97.5-P99	P99-100
Non-rich	4.29%	1.96%	1.07%	0.63%
Rich	12.98%	8.01%	5.08%	2.90%
Very-rich	14.64%	11.54%	11.22%	12.68%

Note: The table provides statistics of individual wealth (mean, 25th percentile, median, and 75th percentile) in 2001 million SEKs in Panel A, the likelihood of getting into (within cohort) wealth quartiles in Panel B, and into upper percentiles in Panel C, for 46-54 years old children in the year 2001, separately for each wealth background group: Non-rich, Rich, and Very-rich. In this sample, 92.18% of individuals are in the non-rich background category, while 5.87% are in the rich and 1.95% are in the very-rich category.

4 Model

We capture wealth accumulation through a standard model of consumption, saving, and portfolio choice in continuous time. Individuals are endowed with exogenous initial wealth, and in each period decide how much to save or consume out of their accumulated wealth, labor income, and possibly parents' transfers (gifts and inheritance). They also decide how to invest their savings across multiple risky asset classes versus the risk-free. In our baseline setup, we follow Benhabib et al. (2011) and abstract from endowment risk and borrowing constraints.[14] However, we allow labor income and transfers to vary with each individual's group, which depends on wealth background, education, and sector of employment (see section 2.8).

[14]See Benhabib and Bisin (2018) for a discussion on the importance of lifetime earnings on wealth inequality and in particular on the right tail of the wealth distribution.

4.1 Environment and Notation

Time is continuous. Individuals make financial decisions at each time t in the interval $t \in [0, T_d]$, where $t = 0$ corresponds to the beginning of adult life and T_d is the time of death. An individual i earns a *deterministic* income $y_i(t)$, representing labor earnings at time $t \in [0, T]$, where T is retirement age, and pension benefits at $t \in [T, T_d]$. This income is exogenous and possibly depends on an individual's background, and thus reflects investment in a child's human capital by parents, as well as education and business sector. Besides labor income, individuals receive direct transfers in the form of inheritance and gifts from parents (at various stages in life), denoted by $p_i(t)$, which are also exogenous and possibly depend on the background. Each individual is endowed with exogenous initial wealth, denoted as $w_i(0)$. This represents the total tangible wealth accumulated by the beginning of adult life, including labor income earned during early adulthood, early direct transfers from parents, and any remaining funds after deducting living expenses and education costs.

The individual optimally consumes and saves over the lifecycle. Consumption is denoted by $c_i(t)$. Each individual invests in the risk-free asset and multiple risky assets *classes*—namely, financial stocks, real estate, private business, and risky pension, as described in section 2.2. We denote the vector of dollar investment in risky asset classes by $x_i(t)$. The realized returns on risky asset classes are *iid* across time and are normally distributed. The expected returns and variance-covariance structure of risky assets vary across individuals (and possibly depend on family background). The expected excess return vector is denoted by μ_i and the variance-covariance matrix of return shocks by the matrix Ω_i. The risk-free rate is r_f, which is the same for all individuals.

Each individual consumes, saves, and makes risky investments according to her time discount rate and risk aversion, ρ_i and γ_i. An individual also has a motive to leave bequest according to warm-glow preferences, which is controlled by the parameter χ_i. All preference parameters $(\rho_i, \gamma_i, \chi_i)$ depend on the individual's group, which importantly includes family wealth background.

4.2 Individual's Optimization Problem

To simplify notation, in what follows we drop the individual index i. Each individual solves the following optimization program:

$$\max_{\{c(\cdot),x(\cdot)\}} \mathbf{E}\left[\int_{t=0}^{T_d} e^{-\rho t}\cdot\frac{c(t)^{1-\gamma}}{1-\gamma} + e^{-\rho T_d}\cdot\chi^{\gamma}\ \frac{w(T_d)^{1-\gamma}}{1-\gamma}\right] \tag{7}$$

$$s.t. \quad dw(t) = \ w(t)r_f dt + x(t)'\mu dt + x(t)'\sqrt{\Omega}d\omega_t + y(t)dt + p(t)dt - c(t)dt,$$

where $dw(t)$ shows the change in wealth at time t; $d\omega_t$ represents the normalized vector of shocks to return on risky assets with $\mathbf{Var}(\sqrt{\Omega}d\omega_t) = \Omega dt$. Observe that wealth accumulation is endogenous, firstly due to the endogenous risky investment share, and secondly, due to the endogenous active saving rate — the pace at which wealth is consumed/saved relative to the inflow of earnings and transfers.

4.3 Optimal Consumption and Portfolio Choice

The model has closed-form solutions for optimal consumption and risky investments. In addition to "tangible" wealth w, it is convenient to define human capital h, i.e. the present value of future labor earnings, and the present value of future inheritance and gifts from parents g:

$$h(t) := \int_t^{T_d} y(\tau)e^{-r_f(\tau-t)}d\tau \quad , \quad g(t) := \int_t^{T_d} p(\tau)e^{-r_f(\tau-t)}d\tau.$$

In the appendix section B we show that optimal consumption is given by:

$$c^*(t) = a(t;\rho,\chi)[w(t) + h(t) + g(t)], \tag{8}$$

where $a(\cdot,\chi;\rho)$ is a deterministic functions of age:

$$a(t;\rho,\chi) := \frac{\tilde{\rho}}{1 + (\tilde{\chi}\tilde{\rho} - 1)e^{-\tilde{\rho}(T-t)}},$$

with

$$\tilde{\rho} := (\rho - (1-\gamma)\tilde{r})/\gamma, \quad \tilde{r} := r_f + \frac{\mu'\Omega^{-1}\mu}{2\gamma}, \quad \tilde{\chi} := [1 - e^{-\tilde{\rho}(T_d - T)}]/\tilde{\rho} + e^{-\tilde{\rho}(T_d-T)}\chi.$$

Here, $\tilde{\chi}$ represents the coefficient of indirect utility at the retirement age, reflecting utility over consumption during retirement plus bequest motives at the expected time of death. In a special case with $\tilde{\chi} = 1/\tilde{\rho}$, the consumption-wealth ratio is independent of age and is fixed at $\tilde{\rho}$. This case resembles the choice of an infinitely-lived agent. If $\tilde{\chi} > 1/\tilde{\rho}$ the individual cuts on consumption (relative to wealth) and saves aggressively when approaching the retirement age $t \to T$, i.e., $a(t)$ is decreasing in age t, and vice versa, if $\tilde{\chi} < 1/\tilde{\rho}$ the individual raises consumption relative to wealth when getting closer to the retirement age T, i.e., $a(t)$ is increasing in age t.

The optimal investment in risky asset classes follows the standard formula (Merton, 1969):

$$x^*(t) = \frac{\Omega^{-1}\mu}{\gamma}\,[w(t) + h(t) + g(t)] \tag{9}$$

x^* scales linearly with total wealth $(w+h+g)$ and depends on the vector of excess expected returns and on the inverse variance-covariance matrix of returns. It decreases with the relative risk aversion parameter γ, as expected.

5 Estimation

The preference parameters of the model—time discount rate ρ, bequest motive χ, and risk aversion γ—are estimated with the Minimum Distance Method by matching a set of targeted moments with their corresponding data counterparts. We follow an exactly-identified estimation procedure with the same number of moments as the number of estimated parameters. We conduct a separate estimation for each socio-economic group, ensuring that no parametric restrictions are imposed on the relationship between the model parameters and the socio-economic characteristics of each group. The following sections outline the identification strategy and present the set of the estimated parameters.

5.1 Identification

We use the optimality condition (8) to estimate the time discount rate ρ and the bequest motive χ. We target the average consumption-wealth ratio in ***e***arly and ***l***ate adulthood:

$$\begin{aligned}
\text{(mainly depends on } \rho) \leftarrow a_e &:= \int_{t=0}^{T/2} a(t;\rho,\chi)dt = \sum_{t=0}^{T/2} \frac{c_t^*}{w_t + h_t + g_t} \\
\text{(depends both on } \rho,\chi) \leftarrow a_l &:= \int_{t=T/2}^{T} a(t;\rho,\chi)dt = \sum_{t=T/2}^{T} \frac{c_t^*}{w_t + h_t + g_t}
\end{aligned} \tag{10}$$

It is easy to show that the mapping between these two moments and the two patience parameters is one-to-one. The intuition is that consumption in early adulthood mostly depends on the subjective time discount rate of individuals from period to period, ρ, while in late adulthood depends both on the time discount rate as well as the motive to leave bequest χ. By targeting the observed average consumption-wealth ratio in the two stages of life, we are able to identify both ρ and χ.

Identifying risk aversion γ is straightforward. We obtain a close form solution from the optimal solution of the dollar investment in risky asset classes (9):

$$x_t^* \;=\; [w_t + h_t + g_t]\frac{\Omega^{-1}\mu}{\gamma} \;\Rightarrow\; \gamma = (\mathbf{1}'\Omega^{-1}\mu) \;/\; \left(\sum_t \frac{\mathbf{1}'x_t^*}{w_t + h_t + g_t}\right) \tag{11}$$

Note that x_t^* is a *vector* of risky positions; hence, $\mathbf{1}'x_t^*$ is the sum of investment in all risky assets in *dollar* terms and $\frac{\mathbf{1}'x_t^*}{w_t+h_t+g_t}$ is the *share* of risky investments in total wealth.

5.2 Data Moments

We aggregate individual-level information up to the group level to build the counterparts of the targeted moments in the data. We construct consumption $\bar{c}_{m,t,\tau}$, tangible wealth $\bar{w}_{m,t,\tau}$, human capital $\bar{h}_{m,t,\tau}$ and the present value of gifts and inheritance $\bar{g}_{m,t,\tau}$ for each group, by taking the sum of the corresponding individual level variables for a given age t and group m in year τ. We use overhead bars to denote *group*-level variables.

We use these aggregated measures to calculate the consumption-wealth ratio $\bar{a}_{m,t,\tau} \equiv \bar{c}_{m,t,\tau}/\left(\bar{w}_{m,t,\tau} + \bar{h}_{m,t,\tau} + \bar{g}_{m,t,\tau}\right)$ and average it over years $\tau = 2000, ..., 2007$ within group separately for young and old adults, where young adults are aged 25 to 44 years old, and old adults are aged 45 to 64 years old:

$$\bar{a}_{m,young} = \tfrac{1}{20}\sum_{t=25}^{44} \tfrac{1}{8}\sum_{\tau=2000}^{2007} \bar{a}_{m,t,\tau} \quad , \qquad \bar{a}_{m,old} = \tfrac{1}{20}\sum_{t=45}^{64} \tfrac{1}{8}\sum_{\tau=2000}^{2007} \bar{a}_{m,t,\tau}.$$

In the model, these two moments correspond to the integral over early and late adulthood of an individual's optimal consumption-wealth ratio $a(t; \rho, \chi)$, from age $t = 0$ to $T/2$ and $t = T/2$ to T respectively, as defined in section 5.1.

We similarly compute the aggregate portfolio risky share. Denote by $\bar{x}_{m,\tau}$ the vector of the dollar risky investments in the four asset classes aggregated at group level, i.e. summing up x in year τ across all individuals (regardless of age) in group m. To get the portfolio risky share of group m, we average the corresponding vector of risky shares $\bar{x}_{m,\tau}/\left(\bar{w}_{m,\tau} + \bar{w}_{m,\tau} + \bar{g}_{m,\tau}\right)$ over the years $\tau = 2000, ..., 2007$, and then sum up its four elements to obtain the *total* risky share, which is data counterpart to the model object $\mathbf{1}'x^*/(w + h + g)$.

We set the risk-free rate r_f at 1% for all groups, which is approximately equal to the average value from 1984 to 2020. In order to map the targeted moments to the data, we also need to construct the asset return statistics $\mu'\Omega^{-1}\mu$ and $\mathbf{1}'\Omega^{-1}\mu$ at the group level, where μ is the vector of asset classes' expected excess return, and Ω is the variance-covariance matrix of asset classes' excess returns. $\mu'\Omega^{-1}\mu$ determines the effective return rate $\tilde{r} :=$

$r_f + (\mu'\Omega^{-1}\mu)/(2\gamma)$ in equation (10), which defines the consumption-wealth ratio $a(\cdot;\rho,\chi)$, and $\mathbf{1}'\Omega^{-1}\mu$ relates the *total* risky investment share $\mathbf{1}'x^*/(w+h+g)$ to the risk aversion parameter γ in equation (11). Note that both μ and Ω vary across individuals and groups.

To construct $\bar{\mu}$, the vector of expected excess returns at the group level, we take the weighted average of individuals' expected return vectors, with weights equal to the risky positions of each individual in a given asset class and in a given year. For example, to calculate the expected excess return $\bar{\mu}^c$ of a group of individuals for asset class c, we use the relative risky position of each individual $x^c/\bar{x}^c$ in asset class c as weights. The tricky part is to build $\bar{\Omega}$, the variance-covariance matrix of returns at the group level. Pooling the portfolios of individuals before estimating the variance of returns would eliminate idiosyncratic risks of individual portfolios and lower the total variance of returns (thereby, over-estimating the risk aversion parameter). Instead, in each year, we take the weighted mean across individuals of each element of their variance-covariance matrix, with weights that depend on the risky values of the corresponding asset classes divided by the total wealth of the individual. Take the two asset classes c and c' as given. The individual weights for calculating $\bar{\Omega}$'s element in row c and column c', $\bar{\Omega}^{cc'}$, is $\frac{x^c x^{c'}}{w+h+g} / \frac{\bar{x}^c \bar{x}^{c'}}{\bar{w}+\bar{h}+\bar{g}}$, where x^c is the risky position of the individual in asset class c, $w+h+g$ is the total wealth of the individual, with overhead bars referring to the same variables for the entire group. The group weighted average expected returns and variance-covariance matrices are then averaged across the years in our sample period (2000-2007). By aggregating expected excess returns and variance-covariance matrices as described here, we ensure that the first-order condition for the optimal risky shares at the individual level is preserved at the group level (with the same risk aversion).

Table 3 displays the statistics of targeted data moments across groups of individuals. Individuals of richer backgrounds on average have a larger risky share in their portfolio and lower consumption-wealth ratios (in both young and old ages) than those of non-rich backgrounds. This disparity in observed moments translates to a lower risk aversion and higher patience estimates for individuals of richer backgrounds, compared to those of non-rich backgrounds, as is shown in the next section.

5.3 Parameter Estimates

Table 4 reports summary statistics of the estimated preference parameters across all population groups, and appendix figure C.2 reports the corresponding histograms. Note that, in our estimation procedure, we require the time discount rate ρ to be non-negative and obtain corner estimates of $\rho = 0$ for less than 5% of the population. We also require the bequest motive parameter χ to be non-negative. Surprisingly, we obtain a zero estimate of χ for the

Table 3: Data Moments

Panel A: Risky Investment Share										
Wealth Background	# (million)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	3.658	0.149	0.033	0.096	0.104	0.129	0.138	0.174	0.194	0.221
Rich	0.282	0.250	0.038	0.183	0.210	0.214	0.255	0.284	0.311	0.311
Very-rich	0.094	0.409	0.068	0.267	0.335	0.341	0.420	0.479	0.483	0.498
All	4.034	0.162	0.058	0.096	0.104	0.132	0.144	0.177	0.220	0.498
Panel B: Consumption to Total Wealth Ratio for Young People										
Wealth Background	# (million)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	3.658	0.033	0.002	0.026	0.031	0.032	0.033	0.035	0.035	0.037
Rich	0.282	0.028	0.002	0.021	0.026	0.027	0.028	0.029	0.031	0.033
Very-rich	0.094	0.021	0.002	0.017	0.019	0.019	0.021	0.022	0.024	0.032
All	4.034	0.032	0.003	0.017	0.029	0.031	0.032	0.035	0.035	0.037
Panel C: Consumption to Total Wealth Ratio for Old People										
Wealth Background	# (million)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	3.658	0.051	0.004	0.044	0.047	0.048	0.052	0.054	0.056	0.059
Rich	0.282	0.041	0.004	0.033	0.035	0.037	0.041	0.046	0.046	0.051
Very-rich	0.094	0.028	0.007	0.016	0.021	0.022	0.028	0.037	0.037	0.048
All	4.034	0.050	0.006	0.016	0.044	0.048	0.052	0.054	0.056	0.059

Note: The table reports summary statistics of risky investment share (Panel A) and consumption to wealth ratio by wealth background groups. In Panel B we consider individuals aged 25 to 44 years old, in Panel C, individuals aged 45 to 64 years old. Moments are reported for all the 108 socio-economic groups (constructed by classification into 3 wealth backgrounds, 3 education levels, and 12 business sectors). All statistics are weighted by group size.

majority of the population. However, despite these restrictions, appendix figure C.3 verifies that the model provides a satisfactory fit to the targeted moments in the data.

The median value of relative risk aversion γ is 10.01, which is in line with the levels chosen in calibrated models of optimal portfolio choice over the life-cycle (Cocco et al., 2005). The median time discount rate ρ is 0.117, implying a subjective time discount factor of 0.890. The estimates of γ and ρ are of the same order of magnitudes to Calvet et al. (2021), which estimate preferences in the same cross-section of Swedish households (but with Epstein-Zin utility). Our median (and mean) estimates of γ and ρ are also close to the robust estimates of Catherine, Ebrahimian, Sraer and Thesmar (2022a) for a representative US household (using the Survey of Consumer Finance). We find that the median value of the bequest motive parameter χ is 0 and that $\tilde{\chi} < \tilde{\rho}^{-1}$ for almost all groups, implying that individuals consume more aggressively when older. Finally, we note that the cross-sectional variation of the estimated time discount rates is more pronounced than the variation in risk aversion. The ratio of the interquartile range to the median of ρ is 82%, whereas it is 43% for γ.

Table 4: Summary Statistics of Estimated Parameters

Parameter	mean	std	min	p10	p25	p50	p75	p90	max
γ	10.31	3.71	2.51	5.69	7.41	10.01	11.69	15.74	21.11
ρ	0.109	0.068	0.000	0.019	0.060	0.117	0.156	0.210	0.250
χ	1.5	4.7	0.0	0.0	0.0	0.0	1.7	2.7	50.0

Note: The table reports statistics of the estimated model preference parameters for all 108 groups of individuals (constructed by classification into 3 wealth backgrounds, 3 education levels, and 12 business sectors). These parameters include risk aversion (γ), time discount rate (ρ), and bequest motives (χ). All statistics are weighted by group size.

In Table 5, we regress the estimated preference parameters on wealth background across socio-economic groups. The observations are weighted by group size, and we report regressions with and without controlling for the education and business sector. The overall finding is that preferences vary strongly with wealth background. Even when we control for the education and business sector, individuals with richer parents are much less risk averse and much more patient (whether we measure patience by subjective discount rates or bequest motive). The average risk aversion γ for individuals of non-rich background is estimated at 10.8, and it falls by 3.5 and 5.3 in absolute terms for individuals with rich and very-rich parents, respectively. The time discount rate ρ drops by 7.3 and 7.8 percentage points for individuals with rich and very-rich parents compared to the base level of 11.9 percent for the average non-rich background individual. We also find that the bequest motives χ are relatively large for children of very-rich families, whereas they are almost zero for those of non-rich families. Finally, we find that the variation in wealth background across our groups explains 16% of the variation in risk aversion and 17% of the variation in the rate of time preferences (adjusted R^2 of 15.5% and 16.6%, respectively). The explanatory power is much higher for the bequest motive, with parents' wealth explaining two-thirds of the variation (adjusted R^2 of 65.4%).

Interestingly, the gap in preferences between individuals of non-rich, rich, and very-rich backgrounds remains quite stable once we control for education and business sector fixed effects. Even though educational attainment and business sector are able to explain a large part of the variation in preferences, they do not affect the relation between the wealth of parents and the risk or bequest attitudes of their children much. The exception is the time

Table 5: Preference Parameters versus Wealth Background

Panel A: Risk Aversion (γ)				
	(1)	(2)	(3)	(4)
(Non-rich)	10.79	10.79	10.79	10.79
$\mathbf{1}\{\text{Rich}\}$	-4.57	-3.95	-4.33	-3.52
$\mathbf{1}\{\text{Very-rich}\}$	-6.94	-6.11	-6.37	-5.28
Education	No	Yes	No	Yes
Business Sector	No	No	Yes	Yes
Adjusted R2	0.155	0.348	0.586	0.934
Panel B: Impatience (ρ)				
	(1)	(2)	(3)	(4)
(Non-rich)	0.119	0.119	0.119	0.119
$\mathbf{1}\{\text{Rich}\}$	-0.095	-0.081	-0.090	-0.073
$\mathbf{1}\{\text{Very-rich}\}$	-0.113	-0.094	-0.101	-0.078
Education	No	Yes	No	Yes
Business Sector	No	No	Yes	Yes
Adjusted R2	0.166	0.368	0.526	0.869
Panel C: Bequest Motives (χ)				
	(1)	(2)	(3)	(4)
(Non-rich)	0.64	0.64	0.64	0.64
$\mathbf{1}\{\text{Rich}\}$	4.78	4.91	4.66	4.71
$\mathbf{1}\{\text{Very-rich}\}$	24.55	24.73	24.27	24.34
Education	No	Yes	No	Yes
Business Sector	No	No	Yes	Yes
Adjusted R2	0.654	0.651	0.726	0.721

Note: The table reports the weighted average of estimated parameters (γ, ρ, χ) for individuals of non-rich background groups, as well as the variation in parameters across wealth backgrounds. We use weighted regressions across 108 groups (constructed by classification into 3 wealth backgrounds, 3 education levels, and 12 business sectors). Weights are based on group size. We control for education and business sector fixed effects as labeled at the bottom of the table.

discount rate ρ which correlates less with background when controlling for education. In addition, education has a strong explanatory power for the estimated ρ (adjusted R^2 of 37%), whereas the variation in risk and bequest attitudes is better explained by business sector (with adjusted R^2 of 58.6% and 72.6%, respectively). Given that individuals with wealthier backgrounds are more likely to attain higher education, and considering that enrolling in higher education programs might require the patience to postpone earnings, it is not surprising that the effect of wealth background weakens once we control for education. In addition, when educational choice is driven by time preferences, it becomes necessary to control for it to accurately quantify the effect of wealth background on patience. However, the weaker correlation can also be due to a potential direct impact of education on preferences, and, to the extent that wealthier parents invest more in their children's education, a regression controlling for educational attainment might underestimate the impact of family background on time preferences.

We do not intend to take a stand on the direction of causality here and instead adopt a revealed preference approach that estimates, through the lens of the model, the set of preference parameters that rationalizes the behavior observed in the data *depending* on wealth background. Accordingly, in the next section, we study the impact of preferences on wealth accumulation with counterfactual scenarios in which preference parameters are equalized across wealth backgrounds *within* education levels and business sectors. In this way, we effectively shut down the correlation between parents' wealth and children's patience that operates through the educational and business sector channels.

6 Counterfactual Results

Variations in patience parameters ρ and χ across individuals of different wealth backgrounds translate into substantial heterogeneity in saving attitudes, both in early adulthood and close to retirement. Differences in risk aversion γ instead imply substantial heterogeneity in portfolio risk-taking. Both higher saving rates and more aggressive risk-taking contribute to a sizable gap in wealth accumulation across individuals of non-rich, rich, and very-rich backgrounds. In this section, we quantify the impact of the variation in preference parameters across family backgrounds on wealth accumulation.

We first derive a closed-form expression for aggregate wealth accumulation at the socio-economic group level. Subsequently, we focus on the cohort that was 50 years old in 2001 and apply the rule backwards to 1976 to infer their (unobserved) wealth at age 25. To validate our procedure, we compare our inferred wealth estimates with the wealth data observed for younger cohorts at age 25. Equipped with initial wealth estimates, we simulate wealth accumulation forward under counterfactual scenarios in which preferences are equalized across individuals of different wealth background. We also consider counterfactuals in which initial wealth, as well as human capital and the present value of direct gifts and inheritance, are considered to be the same across family backgrounds.

Overall, we find that preferences have a strong explanatory power for the wealth gap observed at age 50 across individuals of different wealth backgrounds. Initial wealth and labor income and inheritance heterogeneity are second-order determinants of the wealth gap for senior adults.

6.1 Wealth Accumulation

We derive a closed-form representation of the evolution of *total* wealth $\bar{w}(t)+\bar{h}(t)+\bar{g}(t)$ for a given cohort of individuals within a specific socio-economic group in the model. Following section 5.2, overhead bars denote group-level quantities, which are calculated as weighted means across the individuals of a given cohort in a given group. Here we sketch the overall idea and refer to the Online Appendix for detailed derivations.

We rewrite the wealth accumulation equation expressing income $\bar{y}(t)$ in terms of changes in human capital $d\bar{h}(t) = r_f\bar{h}(t)dt - \bar{y}(t)dt$, and, similarly, expressing the flow of gifts and inheritances $\bar{p}(t)$ in terms of changes in their present value $d\bar{g}(t) = r_f\bar{g}(t)dt - \bar{p}(t)dt$. We then substitute the expressions for optimal consumption and risky investments, $\bar{c}(t) = a(t)[\bar{w}(t) + \bar{h}(t) + \bar{g}(t)]dt$ and $\mathbf{1}'\bar{x}(t) = \frac{\mathbf{1}'\bar{\Omega}^{-1}\bar{\mu}}{\gamma}[\bar{w}(t)+\bar{h}(t)+\bar{g}(t)]$, to obtain the evolution of total wealth in continuous time format:

$$d(\bar{w}(t)+\bar{h}(t)+\bar{g}(t)) = \underbrace{\left(r_f + \frac{\mathbf{1}'\bar{\Omega}^{-1}\bar{\mu}}{\gamma}(\bar{r}(t)-r_f) - a(t)\right)}_{\text{growth rate of total wealth} := gr_{tw}(t)}[\bar{w}(t)+\bar{h}(t)+\bar{g}(t)]dt. \tag{12}$$

where t is the age/year of the given cohort of individuals in the given group and $\bar{r}(t) - r_f$ is the realized excess return on risky investments of those individuals. Since, by the law of large numbers, the idiosyncratic returns experienced by the members of the group cancel out, $\bar{r}(t) - r_f$ is equal to the systematic component of excess return realization and is calculated by averaging individual factor loadings multiplied by the excess return realizations of the corresponding factors.

Preferences parameters ρ, χ, γ show up in the consumption-wealth ratio $a(\cdot)$ and in the denominator of the aggregated risky shares $\frac{\mathbf{1}'\bar{\Omega}^{-1}\bar{\mu}}{\gamma}$. The growth rate of total wealth $gr_{tw}(\cdot)$ is decreasing with $a(\cdot)$—hence, increasing with the patience parameters ρ and χ, and decreasing with risk aversion γ since excess return realizations are positive in most of the times.

6.2 Initial Wealth Gap

We use the model prediction for wealth accumulation at group level to trace back the evolution of total wealth over time. Compounding the growth rate of total wealth gr_{tw} via equation (12) results in the following wealth dynamics in discrete time:

$$(\bar{w} + \bar{h} + \bar{g})_t = \left\{ \prod_{s=1}^{t} [1 + gr_{tw}(s)] \right\} (\bar{w} + \bar{h} + \bar{g})_0, \tag{13}$$

where $(\bar{w} + \bar{h} + \bar{g})_0$ denotes the total wealth own by a cohort of a given group of individuals at age 25.

In order to run counterfactual scenarios on wealth accumulation, we focus on the cohort of individuals that are 50 years old in 2001 and will refer to this cohort as the "old children" cohort. We back out their wealth in 1976, at 25 years old, using their observed wealth in our data in 2001, at 50 years old, and wealth growth rates $gr_{tw}(\cdot)$ in equation (13). We calibrate wealth growth rates with the preference parameters estimated in section 5.3 and the corresponding model-implied optimal consumption-wealth ratio $a(\cdot)$ and risky share $\frac{\mathbf{1}'\bar{\Omega}^{-1}\bar{\mu}}{\gamma}$. Note that the consumption-wealth ratio $a(\cdot)$ varies with age/year but depends only on preference parameters, which are estimated at the group level. Note also that the optimal risky share $\frac{\mathbf{1}'\bar{\Omega}^{-1}\bar{\mu}}{\gamma}$ is constant over the lifecycle and can be calibrated for all individuals in each socio-economic group. Consistently, we calibrate the realized excess return on risky investments $\bar{r}(t) - r_f$ using the average factor loadings of all individuals in each group calculated over the period in which we have access to detailed individual wealth data (2000-2007). These loadings are then multiplied by the historical excess return realizations of the factors from 1977 to 2001. Appendix figure C.1 reports the time series of the realized excess return on risky wealth, averaged across socio-economic groups, and the historical evolution of the riskfree rate.[15]

Table 6 reports the results for the estimation of the initial total wealth (i.e., at age 25) of the old children cohort (who are 50 years old in 2001). It also reports a validation exercise that uses the cohort of individuals who are 25 years old in 2001, referred to as "young children" cohort, for whom we can directly compute their initial total wealth and its composition from the data. In order to make the 25 years-old wealth of the two cohorts

[15] The risk-free rate and factor returns are not available in 1977-1983. In our simulations, we use the mean factor values in the entire period of available factor data (1984-2015) for the missing factor values during 1977-1983 to set the excess realized returns in those years, and we also use the average riskfree return in the first three years of available data 1984-1986 (given its downward trend) to set the missing riskfree returns in that period 1977-1983. Our results are robust to alternative ways of imputing missing data on returns in this early period 1977-1983.

comparable, we choose 1976 as base year and deflate the wealth components of the young children from 2001 to 1976. The real index of net personal wealth per-capita in Sweden is used to deflate tangible wealth $\bar{w}$ and the present value of gifts and inheritance $\bar{g}$, while the real Swedish national income per-capita is used for human capital $\bar{h}$. Both indexes are taken from *World Inequality Database* (World Inequality Database, 2023).

In the columns labeled "Old" ("Young"), the figure reports the total wealth for the old (young) children cohort. Additionally, the column label "Model" refers to quantities from the lifecycle model, and the label "Data" refers to quantities calculated directly from the data without using the model. Panel A reports wealth at the beginning of working life (25 years old), while Panel B shows wealth quantities at the age of 50.

Overall, the model-implied initial total wealth of the old cohort matches the deflated observed initial wealth of the young cohort across individuals of non-rich, rich, and very-rich families. The disparity in initial wealth across wealth background is driven by all components of tangible wealth, human capital, and the present value of gifts and inheritances. However, at the age of 50, human capital and the present value of inheritance and gifts contribute significantly less to wealth differences, with tangible wealth accounting for the lion's share. In the next section, we investigate the extent to which the gap in wealth accumulation across backgrounds is attributable to disparities in endowments versus differences in wealth accumulation behavior, as reflected by preferences in our context.

6.3 Background-dependent Preferences and Wealth Mobility

In this section, we run counterfactual simulations to investigate how wealth accumulation is influenced by the variation in preferences or initial endowments and earnings across wealth backgrounds. We explore counterfactual scenarios in which individuals accumulate wealth from the age of 25 to 50 under the assumption that either preferences or endowments are equalized across individuals of different wealth backgrounds. Throughout this section, we consider the old children cohort of individuals that were 50 years old in 2001 and compare their wealth at 50 with how much they would have accumulated if they had the same preferences (or endowments) *within each* education level and business sector group. In other words, we simulate all the counterfactual scenarios, controlling for education and sector.

The first column of table 7 reports the average tangible wealth accumulated by individuals of different wealth backgrounds. It reveals a gap between individuals with very-rich and non-rich parents of 4.48 million SEK, which is seven times the gap observed at age 25 in the 1976 cohort of young children (see the first column of table 6, Panel A). To understand the relative contributions of initial wealth versus wealth accumulation behavior to this widening wealth

Table 6: Tangible Wealth ($\overline{w}$), Human Capital ($\overline{h}$), and Present Value of Gifts and Inheritance ($\overline{g}$) over the Lifecycle, by Wealth Background in Data and Model

Panel A: Mean of $\overline{w}$, $\overline{h}$, and $\overline{g}$ at Age 25					
Wealth Background	Data/Young cohort				Model/Old cohort
	$\overline{w}$	$\overline{h}$	$\overline{g}$	$\overline{w}+\overline{h}+\overline{h}$	$\overline{w}+\overline{h}+\overline{g}$
Non-rich	0.03	3.33	0.17	3.54	3.74
Rich	0.14	3.77	0.38	4.30	4.05
Very-rich	0.64	4.03	0.74	5.41	4.56
Panel B: Mean of $\overline{w}$, $\overline{h}$, and $\overline{g}$ at Age 50					
Wealth Background	Data/Old cohort				Model/Old cohort
	$\overline{w}$	$\overline{h}$	$\overline{g}$	$\overline{w}+\overline{h}+\overline{g}$	$\overline{w}+\overline{h}+\overline{g}$
Non-rich	0.69	2.83	0.08	3.60	3.60
Rich	1.67	3.16	0.15	4.99	4.99
Very-rich	5.17	3.38	0.25	8.80	8.80

Note: This table presents the mean values of wealth (taken across 3 education and 12 sector groups) in 2001 million SEKs for two cohorts of individuals: the old children, who were 50 in 2001, and the young children, who were 25 in 2001. Panel A reports initial wealth at 25 years old using 1976 as base year. The first four columns report total initial wealth and its components of the young cohort as observed in 2001 but deflated to 1976. We deflate tangible wealth $\bar{w}$ and the present value of gifts and inheritance $\bar{g}$ using the real index of net personal wealth per-capita in Sweden. We deflate human capital $\bar{h}$ using the real Swedish national income per-capita. Both indexes are taken from the *World Inequality Database* (World Inequality Database, 2023). The last column of Panel A reports the initial total wealth in 1976 of the old children cohort estimated from the model equation (13). To increase precision, data values in Panel A are measured by taking an average of individuals aged 25-28 in year 2001. Panel B reports wealth of the old cohort at 50 in 2001. The first four columns show total wealth and its components as calculated directly from the data. The last column reports total wealth generated by the model starting from the initial wealth values in 1976 reported in column five of Panel A. Column four and five of Panel B are identical by construction. To increase precision, data values in Panel B are measured by taking an average of individuals aged 46-54 in year 2001. All averages are weighted according to the population of each group and they are categorized across non-rich, rich and very-rich backgrounds.

disparity, we now quantify the extent to which each factor drives the increase in wealth inequality among children from different family backgrounds over their working lives.

The second column of table 7 reports how much the old children cohorts of non-rich, rich, and very-rich backgrounds would have accumulated in tangible wealth were risk aversion γ set equal to the non-rich group. The gap in tangible wealth at 50 years old between the children of non-rich and very-rich families would have shrunk to 2.34 million SEK. In other words, differences in risk attitudes alone are responsible for 48 percent of the wealth gap between individuals of non-rich and very-rich backgrounds at age 50. The third column shows that the gap in tangible wealth would narrow even further, by 77 percent, to 1.02 million, when individuals were equally patient in terms of time preferences ρ and bequest motive χ. Altogether, under the same preference parameters γ, ρ, and χ, the wealth gap would decrease by 88 percent—down to 0.51 million SEK, or from the seven-fold difference at age 25 to about the same difference. This reduction highlights the substantial impact of the heterogeneity in wealth accumulation behavior, both in terms of saving rates and risk-taking, on the observed wealth disparities across family backgrounds. A comparable pattern emerges regarding the wealth gap between individuals with rich and non-rich parents. The existing gap would be almost entirely eliminated if preferences and wealth accumulation behavior were not dependent on wealth background.

Table 7: Counterfactual Results for Tangible Wealth ($\overline{w}$) at Age 50 by Wealth Background

Wealth Background	Data/Model (Benchmark)	Model, Counterfactuals			
		Same γ	Same χ, ρ	Same γ, χ, ρ	Same $w_0, \{h\}_t, \{g\}_t$
Non-rich	0.69	0.69	0.69	0.69	0.69
Rich	1.67	1.37	0.68	0.70	1.71
– gap (% of benchmark)	100	70	−1	1	104
Very-rich	5.17	3.03	1.71	1.20	4.40
– gap (% of benchmark)	100	52	23	12	83

Note: This table presents the results of counterfactual analyses for tangible wealth for the cohort of 50-year-old individuals in 2001. All quantities are expressed in 2001 million SEKs and are categorized by groups of individuals from non-rich, rich and very-rich backgrounds. Column 1 reports the benchmark values of tangible wealth $\overline{w}$ as reported in Panel B of table 6. Columns 2-5 present simulated mean tangible wealth under various counterfactual scenarios where preferences (γ, ρ and χ) or initial wealth $\overline{w}_0$ at 25 years old and the series of human capital and the present value of gifts and inheritance over the lifecycle, $\{\overline{h}_t\}$ and $\{\overline{g}\}_t$, are set equal to the levels of the non-rich background groups. Preference parameters and endowments are equalized across the wealth background dimension within each education level and business sector. Column (2) equalizes risk version γ, column (3) equalizes patience parameters ρ and χ, column (4) equalizes all preference parameters γ, ρ and χ, and column (5) equalizes endowment components $\overline{w}_0, \{\overline{h}\}_t, \{\overline{g}\}_t$. Mean wealth is calculated across 3 education levels and 12 sectors for each wealth background group, weighted according to the population of each group. The gap in mean wealth relative to the non-rich group, in percentage of the benchmark, is shown in small fonts for the rich and very-rich groups.

The last column of table 7 runs counterfactual scenarios maintaining the estimated preference heterogeneity of the benchmark case while assuming that initial tangible wealth, as well as the values of human capital and the present value of gifts and inheritances, are set equal to the ones of individuals with non-rich parents. Under this counterfactual scenario, the accumulated wealth at age 50 would be 4.40 million SEK for individuals from very-rich backgrounds and the gap between very-rich and rich would be 3.71. In other terms, the wealth gap between very-rich and non-rich backgrounds would be reduced by 17 percent from the benchmark. This reduction is substantially less than the scenario where preferences (both patience and risk-taking attitudes) are equalized across wealth background groups, as described above. The two channels—preference heterogeneity and endowment gaps—are clearly complementary in driving wealth inequality. What is perhaps surprising is the larger quantitative implication of differential wealth accumulation behavior due to preference heterogeneity across family backgrounds.

In summary, we find that the significant portion of the wealth gap at age 50 between individuals of non-rich and very-rich backgrounds can be explained by the preferences channel, i.e., the dependence of patience and risk-taking on family wealth background. Importantly, the impact of preference heterogeneity on the wealth gap at age 50 is much more than the impact of the initial wealth gap at age 25, consisting of differences in tangible wealth likely due to parents' direct wealth transfers early in life, as well as parents' transmission of human capital and expected inheritance and gifts over the lifecycle. In the following section, we consider a number of extensions and robustness checks to address the concern that this result may be specific to the stylized nature of our model.

7 Extensions and Robustness

In this section, we discuss the robustness of our key results by considering a number of extensions to our benchmark model. In particular, we discuss the role of (non-financial) attitudes towards alternative asset classes, decreasing relative risk aversion with non-homothetic preferences, Epstein-Zin utility, labor income risk, and borrowing constraints. The results are summarized in table 8, which has the same structure as table 7, but compares the counterfactual wealth accumulation in the benchmark model in Column (1) with the one generated by the alternative models in Columns (2) – (7).[16] Overall, we confirm that preferences play a crucial role in explaining the wealth gap between adults of different family backgrounds, accounting for at least 74 percent of the gap among all specifications. In the following sections, we briefly present the results of the extensions to our benchmark model and refer the reader to the Online Appendix for the details.

[16] Appendix table C.1 reports the corresponding heterogeneity in preferences controlling for education and business sector in alternative models.

Table 8: Robustness of Counterfactual Results for Tangible Wealth ($\bar{w}$) at Age 50

Wealth Background	Data/Model (Benchmark)	Panel A: Same γ						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-rich	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Rich	1.67	1.37	1.81	1.44	1.34	1.49	1.62	1.63
– gap (% of benchmark)	100	70	114	77	66	81	95	96
Very-rich	5.17	3.03	3.82	3.44	3.28	3.59	3.93	4.24
– gap (% of benchmark)	100	52	70	61	58	65	72	79
Wealth Background	**Data/Model (Benchmark)**	**Panel B: Same γ, χ, ρ**						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-rich	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Rich	1.67	0.70	1.11	0.92	0.70	0.81	0.75	0.81
– gap (% of benchmark)	100	1	43	24	2	13	7	12
Very-rich	5.17	1.20	1.72	1.86	0.81	1.56	1.43	1.55
– gap (% of benchmark)	100	12	23	26	3	19	17	19
Wealth Background	**Data/Model (Benchmark)**	**Panel C: Same $w_0, \{h\}_t, \{g\}_t$**						
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-rich	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
Rich	1.67	1.71	1.72	1.45	1.70	1.70	1.66	1.65
– gap (% of benchmark)	100	104	105	78	103	103	99	98
Very-rich	5.17	4.40	4.40	3.33	5.39	4.41	3.87	3.92
– gap (% of benchmark)	100	83	83	59	105	83	71	72

Note: This table presents the results of counterfactual analyses for tangible wealth for the cohort of 50-year-old individuals in 2001. We consider three counterfactual scenarios in Panels (A) to (C) as described in table 7. Each column corresponds to a different model: Column (1) refers to the benchmark model reported in table 7; Column (2) refers to the model with heterogeneous non-pecuniary benefits across asset classes; Column (3) refers to the model with non-homothetic preferences; Column (4) refers to the model with Epstein-Zin utility; Column (5) refers to the model with income risks; Column (6) refers to the estimation addressing borrowing constraints, which is based on individual behavior later in working life. Column (7) refers to the estimation based on individual behavior later in working life and also considers labor income risk. Mean wealth is calculated across 3 education levels and 12 sectors for each wealth background group, weighted according to the population of each group. The gap in mean wealth relative to the non-rich group, in percentage of the benchmark, is shown in small fonts for the rich and very-rich groups.

7.1 Heterogeneous Attitudes to Alternative Asset Classes

In the benchmark case, we have estimated risk aversion by using the share of risky investments in all asset classes out of the total wealth observed in the data. In other words, we estimate γ by imposing that the observed sum of risky shares $\mathbf{1}'\bar{x}/(\bar{w}+\bar{h}+\bar{g})$ is equal to the model counterpart $\mathbf{1}'x^*/(w+h+g) = \frac{\bar{\Omega}^{-1}\bar{\mu}}{\gamma}$. The detailed nature of our data allows us to observe the components of the risky asset allocation vector $\bar{x}$ and to estimate the joint risk-return trade-off $(\bar{\mu}, \bar{\Omega})$ across risky asset classes (sections 2.5 and 5.2). We can then use the optimal investment *vector* x^* to estimate a set of non-pecuniary benefits, denoted by the vector of δ, that are needed to justify the asset allocation observed in the data. Specifically, we identify δ, alongside γ, that satisfies $\bar{x}/(\bar{w}+\bar{h}+\bar{g}) = \frac{\bar{\Omega}^{-1}(\bar{\mu}+\delta)}{\gamma}$ element by element. By assuming that financial risky assets do not provide non-pecuniary benefit (i.e. $\delta^{FW}=0$) we solve for γ, and then obtain the remaining elements of δ (for real-estate, risky pension, and private business wealth).

Counterfactual results are provided in Column (2) of table 8, where we control on estimated δs (thereby fixing the variation of δ in all its components across the family background, education, and business sector groups). Column (1) and (2) of appendix table C.1 show that risk aversion is now less heterogeneous across wealth backgrounds, hence the counterfactual with homogeneous risk aversion γ across groups has smaller effect on the wealth accumulation gap between individuals of different backgrounds. In the end, however, the variation in all preference parameters has an impact of more than 75% on the wealth gap between individuals of non-rich and very-rich backgrounds.

7.2 Non-Homothetic Preferences

Individuals from wealthier backgrounds may save more and take greater risks due to their ability to more easily satisfy basic consumption needs rather than solely being more patient and less risk-averse. In a model with non-homothetic preferences, wealthier individuals display lower risk aversion, resulting in higher optimal levels of investment in risky assets. They also feature lower optimal consumption-to-wealth ratios, given the smaller portion of non-discretionary consumption in their budget. This implies that our benchmark model with CRRA preferences could overestimate the gap in risk aversion and patience parameters across wealth backgrounds.

In this section, we extend the benchmark model to consider individuals who need to maintain a minimum level of consumption (habit) and assume that they have CRRA utility over consumption *net* of a minimum level $c^m(t)$. In this case, formulas (8) for net consumption and (9) for risky shares in section 4.3 still hold, but total wealth should be expressed net of the habit liability $l(t)$, which is defined as the present value of the minimum required consumption $c^m(\cdot)$ in the rest of an individual's life: $l(t) = \int_t^{T_d} c^m(\tau)e^{-r_f(\tau-t)}d\tau$. Specifically, the optimal consumption and vector or risky investments become $c(t) - c^m(t) = a(t;\rho,\chi)[w(t)+h(t)+g(t)-l(t)]$ and $x(t) = \frac{\Omega^{-1}\mu}{\gamma}[w(t)+h(t)+g(t)-l(t)]$, with the same function $a(\cdot;\rho,\chi)$ as in the benchmark model. We calibrate the minimum required consumption $c^m(\cdot)$ with the Swedish concept of basic consumption (baskonsumption), as defined by Statistics Sweden, to measure the absolute poverty line for consumption. We use the 2001 official value of 65,000 SEK and scale over the years with the average growth of income per capita. Counterfactual analyses are done using the modified rules of savings and risk-taking with habit.

Results are provided in table 8, Column (3). The counterfactual with homogeneous risk aversion yields weaker wealth accumulation implications than in the benchmark model but yet similar in order of magnitudes. The impact implied by the gap in all preference parameters γ, ρ, χ is slightly weaker but still close to the main model (the explanatory power of 74 versus 88 percent for the wealth gap between very-rich and non-rich backgrounds). Finally, when individuals of different backgrounds are endowed with the same initial wealth and lifetime earnings, the reduction in the wealth gap at middle age is stronger than in the benchmark model (41 percent versus 17 percent for the gap between very-rich and non-rich). In the end, we still find a larger role of preferences compared with endowment heterogeneity as in the baseline model.

7.3 Epstein-Zin Utility

Since estimating the distribution of the Elasticity of Intertemporal Substitution (EIS) across individuals is notoriously challenging (Calvet et al., 2021), we assess the robustness of our results to the introduction of Epstein-Zin utility by considering the case in which EIS is set equal to 1.[17] We extend the standard Epstein-Zin utility specification for infinitely lived agents by considering individuals with a finite lifespan and a bequest motive parametrized by χ. More specifically, the value function solves the HJB equation: $\rho\log((1-\gamma)J) = \ max_{c,x}\ \rho(1-\gamma)\log(c) + \mu_w J_w/J + \frac{1}{2}\sigma_w^2 J_{ww}/J + \dot{J}/J$, with terminal condition $\log((1-\gamma)J)|_T = (1-\gamma)\rho\chi\log(w_T+h_T+g_T) + const$, where $\mu_w = wr_f + x'\mu - c + y$ and $\sigma_w^2 = x'\Omega x$ are the drift and volatility of wealth w.

The model has closed-form solutions. The optimal consumption-to-wealth ratio is given by the modifed rule $c(t)/[w(t)+h(t)+g(t)] = \rho/[1+(\chi\rho-1)e^{-\rho(T-t)}]$, defined as $\hat{a}(t;\rho,\chi)$.

[17] This is approximately the average value estimated by Calvet et al. (2021) in the same sample of Swedish households.

Note that, in the special case of $\chi\rho = 1$, we get the standard result that the consumption-to-wealth ratio $\hat{a}(t; \rho, \chi)$ is independent of age and equals the time discount rate ρ. Also, unlike the benchmark model, risk aversion γ does not enter $\hat{a}(t; \rho, \chi)$. The risky investment follows the modified rule $x(t)/[w(t) + h(t) + g(t)] = (\Omega^{-1}\mu)/[1 + (\gamma - 1)\rho/\hat{a}(t)]$. We estimate preference parameters by matching average risk-taking over the lifecycle and consumption-wealth ratio in early and late adulthood stages, as in the benchmark estimation. Column (4) of table 8 shows that the impact of preference heterogeneity on the wealth gap is stronger than in the benchmark model.

7.4 Labor Income Risks

The benchmark model assumes a deterministic labor income process and abstracts from any form of labor income risks. The effect of risky human capital on optimal consumption/saving and risk-taking decisions depends crucially on the form of income risk. Idiosyncratic risk has a limited impact on risk taking and mainly induces precautionary savings (Viceira, 2001). The effect is particularly strong for individuals from poorer backgrounds, whose lifetime wealth consists mostly of human capital. As a result, the estimates of the time discount rate ρ for such individuals are biased downward in our benchmark model, and the *gap* in ρ between non-rich and richer background groups is *under*estimated. In other words, introducing idiosyncratic labor income risk would only reinforce our main result that heterogeneity in time discounting plays a large role in explaining the wealth gap across individuals. In the following, we take a conservative approach and abstract from idiosyncratic income risk and instead focus on systematic income risk exposure.

Systematic labor income risk can potentially have a strong effect on risk taking (Catherine, 2021). One may then argue that low investment in risky assets could be explained by risky human capital rather than risk aversion, and particularly so for individuals of non-rich backgrounds, who have a larger share of their lifetime wealth in human capital. Ignoring risks to human capital would then result in overestimating the gap in risk aversion across individuals and, along with it, in wealth accumulation rates.

We re-estimate risk aversion by controlling for labor income risk in the portfolio choice for individuals of different groups. Campbell and Viceira (2002) characterize the optimal risky share in the presence of labor income risk as $\frac{\mathbf{1}'x(t)}{w(t)+h(t)+g(t)} = \frac{\mathbf{1}'\Omega^{-1}\mu}{\gamma} - \omega_h\beta_h$, where ω_h is the share of total wealth held in human capital and β_h is the covariance of the return on human capital and the market return r. Catherine et al. (2022c) approximate β_h up to the third order: $\beta_h = \frac{\text{Cov}(\delta\bar{h}, r)}{\sigma_r^2} + \omega_h \frac{\gamma}{2} \frac{\text{Cov}(-\Delta\text{Var}(\epsilon_h), r)}{\sigma_r^2} + \omega_h^2 \frac{\gamma(\gamma+1)}{6} \frac{\text{Cov}(\Delta\text{Skew}(\epsilon_h), r)}{\sigma_r^2}$ where $\delta\bar{h}$ is the growth in average human capital and ϵ_h is the realized shock to human capital growth.

The three covariance terms represent the average income growth covariance, countercyclical variance, and cyclical skewness with respect to the market index, respectively. We obtain these covariance moments directly from the data for each occupation and education group and estimate risk aversion γ via the Campbell and Viceira (2002)'s rule for optimal risky investment. Finally, we estimate the patience and bequest ρ, χ preferences using the optimal consumption-wealth ratio implied by the benchmark model and the benchmark data moments defined in section 5.1 (together with the re-estimated γs). As discussed above, ignoring labor income risk in saving decisions is a conservative strategy since it underestimates the wedge in ρ and χ across background groups.

Appendix table C.1, Column (5) shows that the estimated risk aversion with income risk is 6.73 for non-rich background, which is close to the estimate of Catherine (2021) (with countercyclical variance and cyclical skewness) for US households. The estimated γ is less than the baseline value of 10.8 in Column (1), which ignores income risk, as expected. In any specification, though, rich and very rich backgrounds feature lower risk aversions than non-rich backgrounds. Ultimately, counterfactual results in table 8, Column (5), show that heterogeneous preferences, controlling for labor income risk, explain a large part of the difference in wealth accumulated at middle age across wealth backgrounds: risk aversion explain 35 percent, and both risk aversion and patience parameters explain 81 percent of the gap between non-rich and very-rich background groups.

7.5 Borrowing Constraints

In the benchmark model, individuals can freely borrow against their human capital to finance consumption and investment. However, in reality, they can instead face borrowing constraints, which are more likely to be binding earlier in the lifecycle and for individuals of non-rich backgrounds. In this section, we consider the possibility that the preference parameters estimated with the benchmark model might be biased due to borrowing constraints. We re-estimate the model by relying solely on moments constructed from individuals older than 34 years old, who are less likely to face binding borrowing constraints. Wealth accumulation from 25 to 34 years old is simulated by capping risky investments to the available financial resources, defined as total net tangible wealth plus the current year's labor income and gifts/inheritance from parents, i.e., $w + y + p$, net of optimal consumption. We also consider a specification based on moments from individuals older than 34 years old to address concerns for borrowing constraints, as well as considering labor income risk in the optimal portfolio choice, as we did in section 7.4.

The counterfactual results are reported in Columns (6) and (7) of table 8. Compared with the baseline model in Column (1), differences in risk aversion γ across background groups play a diminished role in accounting for the observed wealth gap at age 50 (Panel A). In contrast, patience parameters ρ, χ have a more pronounced effect, resulting in a similar impact of all preference parameters together across alternative specifications (Panel B). Furthermore, in any case, the variations in preferences explain a larger portion of the wealth gap compared to initial disparities in wealth at the beginning of working life (cf. Panel B and C). Overall, the main message remains largely unchanged from the baseline findings.

Conceptually, the implications of borrowing constraints for our results are not trivial. On the one hand, individuals lower consumption early in life to save out of borrowing constraints, which can potentially result in an *under*estimation of impatience (ρ) for individuals of non-rich backgrounds in a misspecified model. On the other hand, risky investment is dampened for such (hand-to-mouth) individuals, which results in *over*estimating γ for these individuals. Hence, the estimated *gap* in ρ and γ across individuals of non-rich and richer backgrounds in the benchmark model will be biased in the opposite direction. This argument supports our finding that abstracting from borrowing constraints does not significantly alter the baseline conclusions regarding the overall role of preferences in wealth accumulation.

8 Conclusion

It is not just about the money that individuals receive from their parents, but also what they do with it...

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Appendices

A Data

A.1 Sources of Financial Asset Pricing Data

In this section we describe the data sources we use to build the factors we use to price financial assets and private equity. The risk-free rate is proxied by the monthly average yield on the one-month Swedish Treasury bill (Sveriges Riksbank, 2016). We proxy the local stock market portfolio, L_MKTt, with the SIX return index (SIXRX), which tracks the value of all the shares listed on the Stockholm Stock Exchange (Datastream, 2016). We obtain the global stock market portfolio, MKTt, the global value factor, HMLt, and the global size factor, SMBt, from AQR Capital Management (2016). For all equity benchmarks, we use data from 1984 to 2015 at monthly frequency. The exchange rate factor, EXCHt, consists of monthly returns on the carry trade in which the investor is long the US Treasury bill and short its Swedish equivalent, which we construct between 1984 and 2015 (Datastream (2016), French, Kenneth (2016), Sveriges Riksbank (2016)). Table A.1 reports the sample periods included in the analysis, the frequency of observation, the annualized mean excess return, volatility and Sharpe ratio of each pricing benchmark.

Table A.1: Expected Return and Volatility Ratios of Financial Pricing Benchmarks Proxies

		Expected Return and Volatility		
Factor (k) (1)	Period (2)	$\mathbb{E}\left[R^e_{t,k}\right]$ (3)	$\sigma\left(R^e_{t,k}\right)$ (4)	$\mathrm{SR}\left(R^e_{t,k}\right)$ (5)
L_mkt	1984 - 2015	7.17%	19.77%	0.36
MKTt	1984 - 2015	4.76%	12.83%	0.37
SMBt	1984 - 2015	0.04%	5.59%	0.01
HMLt	1984 - 2015	3.01%	6.77%	0.45
EXCHt	1984 - 2015	-0.84%	9.27%	-0.09

Note: This table reports the sample period and measures of the annualized expected return and volatility of the financial pricing benchmarks used in the empirical analysis. The asset pricing metrics reported are the annualized mean excess return (3) $\mathbb{E}\left[R^e_{t,k}\right]$, (4) volatility $\sigma\left(R^e_{t,k}\right)$, and (5) the Sharpe ratio SR of each real estate index. The pricing benchmarks includes the local Swedish equity market factor, (L_MKT), the global stock market factor (MKTt), the global value factor (HMLt), the global size factor (SMBt), the exchange rate factor (EXCHt). All pricing benchmarks have a monthly frequency of observation and the reported signal and noise estimates are subsequently annualized.

A.2 Return and Risk of Financial Assets and Private Equity

In this section we outline how we estimate factor loadings at single security and property level, and idiosyncratic risk at asset class level.

Financial Wealth. We price financial assets with an international version of the Fama and French (1993) three factor model with the following factors: the local equity market factor, L_MKT, the global stock market factor, MKTt, the global value factor, HMLt, the global size factor, SMBt, and the exchange rate factor, EXCHt. We assume that bank accounts and money market funds yield zero excess returns.

We estimate the vector of factor loadings β_j for individual stocks and funds as follows.[1] Denote with $Var(f_{FW,t})$ the sample variance covariance matrix of the excess returns of the asset pricing factors and with $\text{Cov}(r^e_{j,t}, f_{FW,t})$ the vector of sample covariances between the excess returns of asset j and the factors.[2] The vector of financial asset j's factor loadings is:

$$\beta_j = \text{Var}(f_{FW,t})^{-1}\ \text{Cov}(r^e_{j,t}, f_{FW,t}), \tag{14}$$

and the vector of factor loadings of investor i's risky financial assets is:

$$\beta_{i,FW,t} = \sum_{j=1}^{J_{FW}} \omega_{FW,i,j,t}\beta_j, \tag{15}$$

where $\omega_{FW,i,j,t}$ is the weight that investor i places at the beginning of year t on fund or stock j within the stock and fund portfolio.

To calculate idiosyncratic risk for investor i we first compute the variance covariance matrix $\text{Var}_{FW}(u_{j,t})$ of the residuals $u_{j,t}$ of equation (1) in section 2 for all stocks and funds. The idiosyncratic variance of investor i is:

$$\text{Var}^{\text{idio}}_{i,FW,t} = \omega'_{FW,i,t}\ \text{Var}_{FW}(u_{j,t})\ \omega_{FW,i,t}. \tag{16}$$

where $\omega_{FW,i,t} = (\omega_{FW,i,1,t}, \ldots, \omega_{FW,i,J_{FW},t})'$ is the vector of risky portfolio weights defined above. Idiosyncratic variance is expressed in annual terms and net of the 30% capital gain and income tax.

[1] We limit the estimation to financial assets with at least 24 monthly observations in our data and assume that they are representative of the remaining risky financial assets in individual financial portfolios.

[2] We estimate $\text{Cov}(r^e_{j,t}, f_{FW,t})$ using all months asset j and the factors have in common. $Var(f_{FW,t})$ is estimated during the period in which individual financial assets are available in FinBas (1983-2009).

Private Equity. Similar to shares in publicly traded companies, equity stakes in private companies are considered a risky component of individual wealth. Estimating expected returns, systematic and idiosyncratic risk for private equity investments presents a significant challenge. Unlike publicly traded firms with readily available high frequency historical data, private firm valuations rely on much less frequent financial statements, leading to a typically limited time series of returns. To circumvent this limitation, we adopt a well-established approach in the academic and practitioner literature (Bach et al., 2020b and Damodaran, 2012) and leverage the characteristics of publicly traded firms to infer the risk profile of their private counterparts. For the purpose of estimating the moments needed in our structural estimation, we define the risk profile of a firm as the vector of the firm's factor loadings and its idiosyncratic volatility.

The estimation process unfolds in four stages. First, we estimate the risk profiles of Swedish listed firms' equity as in the previous section and then unlever them to obtain factor loadings and idiosyncratic risk of the firms' total assets. Second, we regress the risk profiles of total assets on the following public firm characteristics: industry sector, log of book asset, profitability, asset tangibility, and international exposure.[3] Third, we impute the average risk profiles of private firms' total assets by running the corresponding predictive regressions on the same characteristics of private firms. We assume that the distribution of the residuals are the same between private and public markets and simulate 100 risk profiles for each private firm. We view each of the profiles as representative of a pseudo-firm with the same observable characteristics of the private firm. Importantly, we use this approach only for the non-financial assets within each firm. For financial assets we assume that risk exposures are drawn independently from the risk exposures of investment vehicles that are listed during our sample period on the Swedish stock market and are controlled by few individuals (such as Investor AB, controlled by the Wallenberg family, and Ratos AB, controlled by the Söderberg family).

In the fourth and final step, we impute the risk profile of the equity of each private firm as follows. For each pseudo-firm we use the international Fama French model to cumulate forward the value of (non-financial and financial) assets to calculate the monthly growth rate of asset values. More specifically, for each pseudo-firm in each month of each year, we simulate 100 realizations $\tilde{f}_{FW,t}$ of the international Fama French factors drawn from their joint empirical distribution of that year. We then apply the risk profile simulated in step three to simulate monthly asset values. We then lever up the total asset values to obtain the corresponding simulated monthly equity returns, which we regress on the observed pricing factors $f_{FW,t}$ using equation (1) to obtain the risk profile of each pseudo-firm. Finally, we

[3]International exposure is defined as a dummy of at least one subsidiary domiciled in the US

average the risk profiles of pseudo-firms to obtain each private firm j's equity factor loadings β_j and idiosyncratic variance $\text{Var}^{\text{idio}}_{PE,j}$.

We follow closely the procedure developed by Bach et al. (2020b) and refer to section *V.B.* of their appendix Bach et al. (2020a) for further details. Here we note that the random imputation methodology guarantees that the correlation among factor loadings and between factor loadings and idiosyncratic risk among private firms is similar to the correlation observed within listed firms conditional on common observables. This is important because, for example, in the data we find that listed firms with high idiosyncratic risk tend to have low market betas. Furthermore, the methodology ensures that the heterogeneity in risk exposures across private firms will be at least as high as the one we observe among public firms.

Denote by $\omega_{PE,i,j,t}$ the weights that investor i places at the beginning of year t in firm j within her portfolio of private equity. Investor's i vector of factor loadings for private equity is:

$$\beta_{i,PE,t} = \sum_{j=1}^{J_{PE}} \omega_{PE,i,j,t}\ \beta_j, \tag{17}$$

and the idiosyncratic risk for investor i is:

$$\text{Var}^{\text{idio}}_{i,PE,t} = \sum_{j=1}^{J_{PE}} \omega_{PE,i,j,t}\ \text{Var}^{\text{idio}}_{PE,j}. \tag{18}$$

assuming that private equity firms idiosyncratic risk is uncorrelated. Idiosyncratic variance is expressed in annual terms and net of the 30% capital gain and income tax.

Pension Wealth. In the period we consider, Swedish households had little discretion over the investment of their funded pension wealth. For this reason, we assume that all individuals hold the same fully diversified pension portfolio, and we estimate its composition using the annual reports of Swedish life insurance companies (Bach et al., 2020b). Table A.2 provides the average share of each asset class in funded pension investments during our sample period. We set the factor loadings and portfolio weights of the risky pension components accordingly using L_MKT as proxy for Swedish equity, MKTt as proxy for foreign equity, and the FASTPI index as proxy for real estate. We also hedge half of the foreign equity exposure against currency risk and assume that safe pension holdings yield zero excess returns.

Table A.2: Share of Funded Pension Investments (1999-2007)

Safe assets (cash, bills, bonds, etc.)	45.5%
Swedish equity	18.5%
Foreign equity	32.6%
Not currency-hedged	16.3%
Real estate	3.4%

Note: Average share of various asset classes in the portfolio of Swedish life insurance companies from December 1999 to December 2007. The numbers are drawn from the annual reports of the Swedish FSA, the AP7 public pension fund, and four life insurance companies: Alecta, AMF, Skandia and SEB-Gamla Liv.

Pension wealth accumulates untaxed but is taxed upon withdrawal. To convert pre-tax pension wealth into after-tax units, we follow Calvet et al. (2021) and multiply pre-tax wealth by $(1-\tau)$, where $\tau = 31.9\%$ is the average tax rate on non-financial income paid by retired individuals.

A.3 Sources of Real Estate Asset Pricing Data

In this section we describe the data sources we use to to estimate the factors, the factor loadings and idiosyncratic risk for real estate assets. The national real estate index is proxied by the FASTPI index (FAStighetsPrisIndex, Statistics Sweden (2016b)) which is based on all transactions of single-dwelling homes and is available at yearly frequency for the 1984 - 2014 period. We follow the procedure adopted by Bach et al. (2022) to construct a national index of apartment prices at annual frequency, which we label LAGPI index (or LÄGenhetPrisIndex), based on all apartment transactions in Sweden (Statistics Sweden, 2017a) for the years between 1991 and 2014. We use both indexes to estimates the betas of real estate assets as described in section A.4.

To calculate real estate idiosyncratic risk we use individual property transaction data and characteristics. For apartments we use the dataset on co-op transfers developed in Bach et al. (2022), which in turn uses three external sources: the *Apartment Register* (Statistics Sweden, 2017a), the *Income Statement for Asset Value of Cooperative Flat* (Förmögenhetsvärde bostadsrätt) (Statistics Sweden, 2007b) and a commercial dataset maintained by the *Swedish Real Estate Agent Association* (Svensk Mäklarstatistik). For transactions of real estate properties other than apartments, we use the *Real Estate Property Prices and Title Deeds Register* (Statistics Sweden, 2020b) and the *Real Estate Property Valuation Register* (Statistics Sweden, 2020a).

A.4 Return and Risk of Real Estate Equity

In this section we outline how we define the after tax excess return of real estate and how we estimate factor loadings and idiosyncratic risk of real estate holdings.

Real Estate Returns. Estimating betas of real estate assets is challenging because crucial components of returns, such as rental yields and depreciation rates, are typically unobservable at the single property level. The nominal return on a real estate asset j after taxes is given by the following defining identity:

$$r_{j,t}^{at} \equiv pg_{j,t}(1-\tau_{RE}) + d_{j,t} - \delta_{j,t} - \kappa, \tag{19}$$

where the price growth $pg_{j,t}$, the property tax rate κ and the tax on real estate capital gains τ_{RE} are observable, but the rental yield after taxes $d_{j,t}$ and the maintenance and depreciation rate $\delta_{j,t}$ are typically not observable at individual property level.[4] To address this issue, we express real estate returns as a function of the growth rate of real estate prices and the risk-free rate. We propose two complementary arguments to rationalize this approach.

The first argument rests on the macro-evidence that the rental yield after depreciation appears to be close to the real risk free rate after real estate taxes:

$$d_t - \delta_t - \kappa \approx r_{f,t}^{\text{real}}(1-\tau_{RE}) \tag{20}$$

where $r_{f,t}^{\text{real}} = r_{f,t} - \pi_t$ is the real risk free rate and π_t the inflation rate. Panel A of Figure A.1 plots the LHS and RHS of equation (20) from 1994 to 2016. The rental yield after depreciation tracks quite well the real rate net of real estate taxes after the turn of the millennium. In the 90's we instead observe a larger-than-usual wedge in the empirical relationship (20) most likely due to the financial crisis that hit Sweden during 90-94'. In Panel B of Figure A.1 we document that the real rate surged to a 70-year high, as the crisis halted the high inflation rates of the 1980s and the Swedish Central Bank sharply increased the federal funds rate in 1992 to protect the fixed ECU-SEK exchange rate (Sveriges Riksbank, 2024).

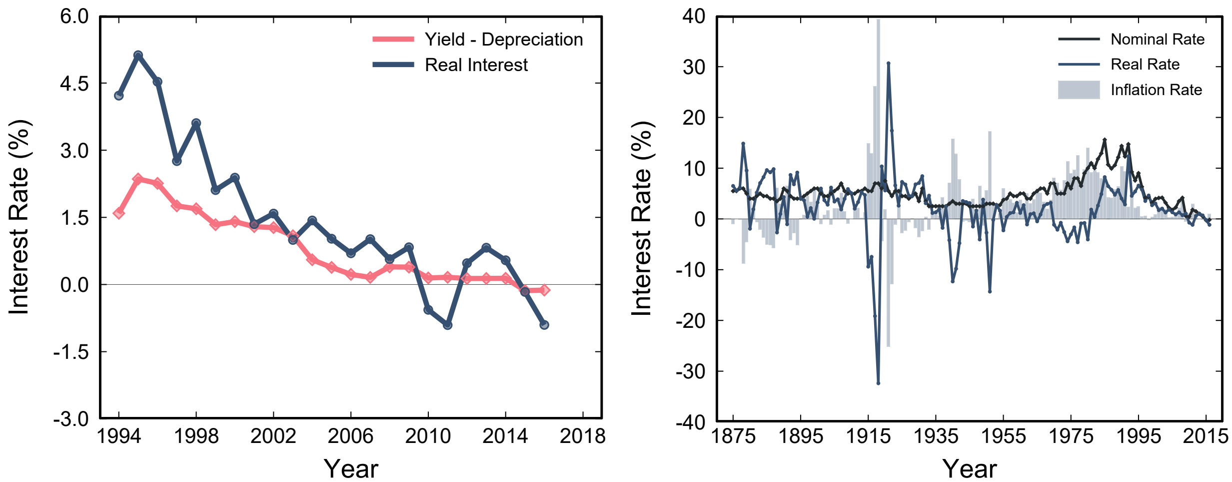
By plugging (20) in (19), we obtain that the excess return on real estate after taxes can be measured from the growth rate of real estate prices and the (nominal and real) risk-free rate:

$$r_t^e \equiv r_t^{at} - r_{f,t}(1-\tau) = \left(pg_t + r_{f,t}^{\text{real}}\right)(1-\tau_{RE}) - r_{f,t}(1-\tau) \tag{21}$$

where τ is the tax rate on capital income.

[4] We define $d_{j,t}$ as the yield from housing services when the property is owner-occupied.

Figure A.1: Rental Yields Less Depreciation and Real Interest Rates



Panel A: Rental Yields and Real Rates   Panel B: Long-Term Rates & Inflation

Note. Panel A illustrates the time series of after-tax rental yields less depreciation and property tax; i.e. $d_t(1-\tau_d) - \delta_t - \kappa$ (in red) and real interest rates after real estate capital gain taxes; i.e. $r^{\text{real}}_{f,t}(1-\tau_{\text{RE}})$ (in blue). The effective tax rate on rental yield τ_d is 24% as the general tax rate on real estate rental income is 30% but only 80% of the total rental income is taxable for single-dwelling houses and vacation homes. Data on aggregate rental yields d_t and depreciation rates δ_t are retrieved from the Swedish national accounts (Statistics Sweden, 2024). The tax rate on real estate capital gain τ_{RE} is 22% in accordance with the Swedish tax code post-2007. Panel B illustrates annualized real interest rates (blue line), nominal interest rates (black line), and inflation (gray bars) for the period 1875-2016. The recorded interest rate is the annualized yield on the Swedish 1-month T-bill throughout each year. Data on inflation and interest rates before 1984 are taken from Waldenström (2014) and data on and after 1984 are taken from Sveriges Riksbank (2016). Inflation is defined as the yearly growth in the consumer price index (CPI) and the real interest rate is defined as the difference between the nominal rate and the inflation within that year.

The second argument rationalizes why expression (21) should be used to calculate betas at individual property level. We follow the user cost of housing approach (Poterba, 1992 and Himmelberg, Mayer and Sinai, 2005) and express the equilibrium condition in the real estate market as:

$$E\left[pg_{j,t}(1-\tau_{RE}) - \pi_t\right] + d_{j,t} - \delta_{j,t} - \kappa = E\left[r_{f,t}(1-\tau) - \pi_t\right] + \Gamma, \tag{22}$$

which says that, in real terms and net of taxes, one dollar invested in real estate must yield the same as the risk free rate plus a risk premium Γ. Alternatively, equation (22) represents the indifference condition between renting and owning. Combining (19), (22) and rearranging, we obtain:

$$r^e_{j,t} = \left(pg_{j,t} + r^{\text{real}}_{f,t}\right)(1-\tau_{RE}) - r_{f,t}(1-\tau) + \Gamma - \left[E(pg_{j,t} - \pi_t)\right](1-\tau_{RE}) + \Lambda(\pi_t, r_{f,t}), \tag{23}$$

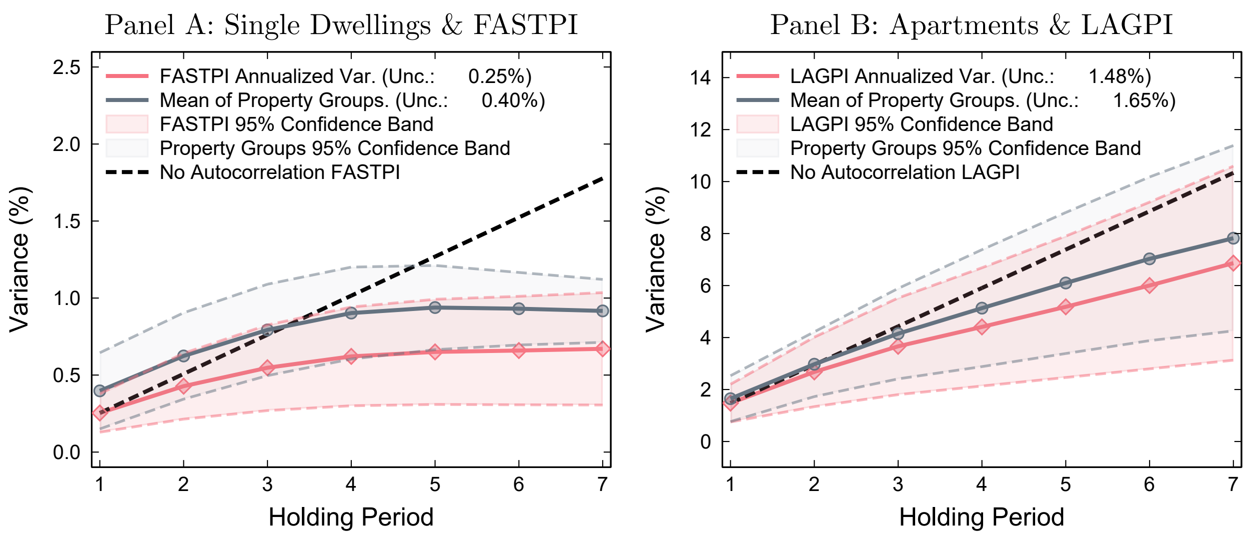
where $\Lambda(\pi_t, r_{f,t}) \equiv \left[\pi_t - E(\pi_t)\right](1-\tau_{RE}) + r_{f,t}(\tau_{RE} - \tau)$.

The term $r_{f,t}(\tau_{RE} - \tau)$ is empirically negligible, as financial and real estate capital gains in Sweden have had similar tax treatments (30% and 22% respectively). Consequently, under rational expectations, the term $\Lambda(\pi_t, r_{f,t})$ is close to zero, or, at least, we expect it to be orthogonal to real estate market excess returns

To the extent that the expected real price growth $E(pg_{j,t} - \pi_t)$ and the risk premium Γ are time-invariant, the betas of after-tax real estate excess returns can be estimated empirically using the excess returns given by (21). Throughout the paper, we measure post-tax real estate excess returns for indexes and single properties using equation (21).

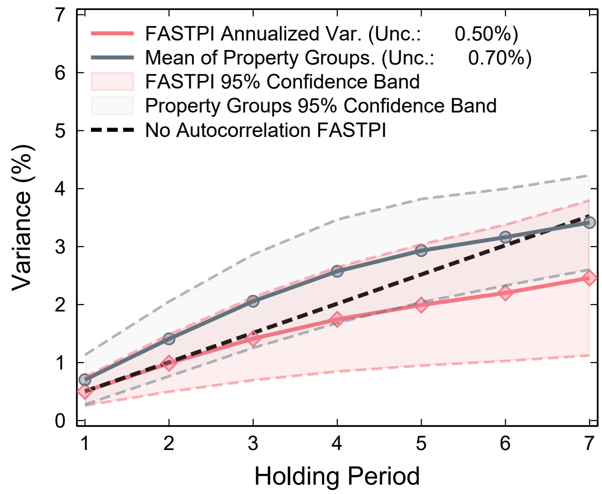
Real Estate Betas and Idiosyncratic Risk. In Figure A.2 we report the annualized sample variance of cumulative returns on the real estate market indexes over different holding periods. With stationary and i.i.d. real estate returns r_t^e, the variance of cumulative returns (reported in full lines) should grow proportionally to the investment horizon (dashed lines). The figure illustrates that this is clearly violated for the FASTPI index, whereas it cannot be statistically rejected for the LAGPI index.

Figure A.2: Variance of Returns by Holding Period for Single Dwellings and Apartments



Note. The figure reports the annualized sample variance on the cumulative returns earned on single dwelling property groups and the FASTPI (left) as well as for apartment property groups and the LAGPI (right) over different holdings periods h. The yearly returns r_t^e are defined in equation (21). The cumulative return over holding period h at time t is $r_{t,h}^e = \prod_{\tau=t-h}^{t}(1 + r_\tau^e) - 1$. Red lines illustrate the resulting annualized variance for the FASTPI (left) and the LAGPI (right). Similarly, the blue lines indicate the weighted average cumulative variance for all single dwelling property groups (left) and for all apartment property groups (right). The 95% confidence bands of these cumulative variances are illustrated in shaded regions. The black dashed line in each panel plots the product of the unconditional sample variance ("Unc.") of annual returns and the holding period h. All moments are estimated over the whole sample period available to us, i.e. 1984 - 2014 for FASTPI and 1991 - 2014 for LAGPI.

Figure A.3: Variance of Returns by Holding Period for 3-Year Corrected FASTPI



Notes. The figure reports the annualized sample variance on the cumulative 3-year corrected returns earned on single dwelling property groups and the FASTPI over different holding periods h. Specifically, the 3-year corrected returns at time τ are defined as $r^e_\tau = \sum_{s=0}^{2} r^e_{\tau-s}/\sqrt{3}$ where the yearly return observations r^e_t come from equation (21). The cumulative return over holding period h at time t is $r^e_{t,h} = \prod_{\tau=t-h}^{t}(1+r^e_\tau) - 1$. The red line illustrate the resulting annualized variance for the FASTPI. Similarly, the blue line indicate the weighted average cumulative variance for all single dwelling property groups. The 95% confidence bands of the cumulative variances are illustrated in shaded regions. The black dashed line plots the product of the unconditional sample variance ("Unc.") of annual returns and the holding period h. All moments are estimated over the whole sample period available to us, i.e. 1984 - 2014 for FASTPI and 1991 - 2014 for LAGPI.

This implies that, in contrast to stocks, the after-tax excess annual returns of the FASTPI index (as defined in equation (21)) are positive autocorrelated, so that the risk of holding single-family dwellings over longer horizons is proportionally smaller than over shorter horizons. Since households tend to hold real estate assets over several years, measuring second moments with annual returns would underestimate the risk households face in their real estate positions. Figure A.3 reports panel A of Figure A.2 with the cumulative variance estimated on a three-year moving average of the FASTPI return $\sum_{s=0}^{2} r^e_{t-s}/\sqrt{3}$. Over a three-year holding period, we cannot reject the hypothesis that the FASPTI index returns are stationary and i.i.d. Since households are likely to hold real estate assets over multiple years, Figures A.2 and Figure A.3 suggest a potential approach for estimating second moments. This consists of using annual returns for apartments and the transformation $\sum_{s=0}^{2} r^e_{t-s}/\sqrt{3}$ of the after-tax excess returns defined by (21) for all the other forms of real estate. Table A.3 reports the corresponding annualized mean excess return, volatility and

Sharpe ratio of each real estate index (as well as the sample periods included in the analysis and the frequency of observation). FASTPI and LAGPI have a similar Sharpe ratio of 42 and 43 percent respectively. With returns measured at yearly horizon, the volatility of FASTPI would have been 5.04% and the Sharpe ratio 59 percent.

Table A.3: Expected Return and Volatility of Real Estate Market Proxies

		Signal and Noise		
Factor (k) (1)	Period (2)	$\mathbb{E}\left[R^e_{t,k}\right]$ (3)	$\sigma\left(R^e_{t,k}\right)$ (4)	$\mathrm{SR}\left(R^e_{t,k}\right)$ (5)
FASTPI	1984 - 2014	3.00%	7.10%	0.42
LAGPI	1991 - 2014	5.25%	18.82%	0.28

Note: This table reports the sample period and measures expected return and volatility of the real estate market proxies, i.e. the Swedish national real estate index (FASTPI) and the Swedish national apartment index (LAGPI). The empirical asset pricing metrics reported are the annualized mean excess return (3) $\mathbb{E}\left[R^e_{t,k}\right]$, (4) volatility $\sigma\left(R^e_{t,k}\right)$, and (5) the Sharpe ratio SR of each real estate index. The FASTPI and LAGPI are observed at an annual data frequency; hence the reported measures of expected return and volatility are annualized by construction.

To price real estate properties, we specify (1) into a CAPM model with nationwide indexes as market proxies. We use the LAGPI index as market proxy for apartments and the FASTPI index for all remaining real estate assets. Due to the low frequency of property transactions, it is not possible to estimate asset pricing characteristics at the individual property level. We adopt the approach of building and using repeated-sale indexes by real estate class and geographical area at the most disaggregated level possible given the data available. We group single-family dwellings by the 290 municipalities existing in Sweden during the period. Vacation, rental, agricultural, and industrial properties are each aggregated by the 25 Swedish counties. Finally, for apartments we solve a max-p-region algorithm to combine adjacent municipalities into 145 regional clusters with at least 25 sales of unique properties per year. In total we have six types of real estate classes c_{RE} and 535 groups rg of properties. The beta β_j of a property j in group $rg(j)$ is given by:

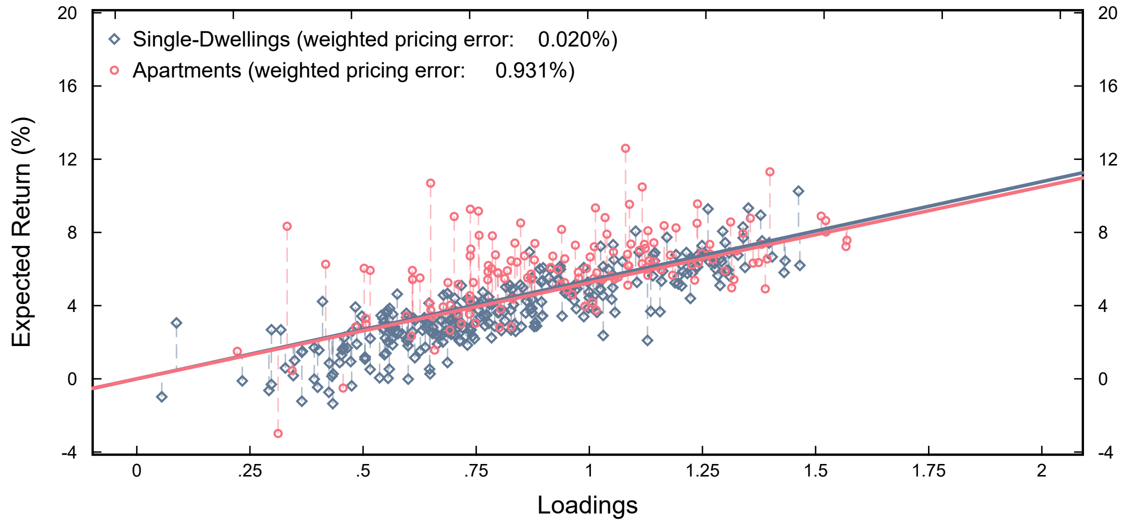
$$\beta_j = \frac{\mathrm{Cov}(r^e_{rg(j),t}, r^e_{RE,t})}{\mathrm{Var}(r^e_{RE,t})}. \tag{24}$$

where $r^e_{rg(j),t}$ is the excess return of the index of group $rg(j)$ and $r^e_{RE,t}$ is the excess return of the LAGPI if j is an apartment and the FASTPI otherwise.[5] Figure A.4 shows the security

[5]More precisely, in reference to the notation introduced in section 2, we assume that the loading of any

market lines for apartments (red) and other real estate properties (blue). The average alpha is estimated to be economically small and insignificant at 93bp and 2bp for apartments and single-dwellings respectively.[6]

Figure A.4: Security Market Lines of Corrected FASTPI and Uncorrected LAGPI



Note. This figure illustrates the empirical Security Market Line (solid lines) in $(\mathbb{E}[R^e_{\mathrm{RE},j}], \beta_j)$-space for Single-Dwellings with a 3-year correction (blue diamonds) and Apartments with no correction (red circles). All returns are annualized, post-tax and in excess terms; hence the vertical dashed lines indicate the annualized & post-tax pricing error ("alpha"). We report the value-weighted average pricing errors across regions for both asset classes in the legend entries. The value-weights are calculated using the time series average of the *real* total market value (2001 terms) of all the apartments within each region. There are 145 regions in total for apartments (determined by a max-p-region algorithm) and 290 regions for single-dwellings, which is defined by Swedish municipalities. The time periods used are 1984-2014 for Single-Dwellings and 1991-2014 for Apartments.

Denote by $\omega_{RE,i,j,t}$ the weight of property j in investor i's real estate gross wealth at the beginning of year t. Investor's i vector of factor loadings for her real estate assets is:

$$\beta_{i,RE,t} = \sum_{j=1}^{J_{RE}} \omega_{RE,i,j,t}\ \beta_j, \tag{25}$$

We decompose the idiosyncratic return $u_{j,t}$ of property j from the asset pricing equation (1) into a component $\varepsilon_{rg(j),t}$ common to all properties in group $rg(j)$ and a property-specific shock $v_{j,t}$ that is uncorrelated to the idiosyncratic returns of other properties in the group:

$$u_{j,t} = \varepsilon_{rg(j),t} + v_{j,t}. \tag{26}$$

apartment on the FASTPI index is always zero and the loading of any other real estate asset on the LAGPI index is always zero.

[6] The t-stat for apartments is 0.97 and for single-dwellings is 0.26.

We estimate the variance of the common shock, $\text{Var}(\varepsilon_{rg(j),t})$, with the sample variance of the residuals $r^e_{rg(j),t} - \beta_j r^e_{RE,t}$. To obtain the variance of the property-specific shock, $\text{Var}(v_{j,t})$, we use the dataset of individual property transactions and characteristics described at the beginning of this section. The dataset contains the dates and prices of each property transaction. We restrict the sample to properties that have been transacted more than once and with holding period between 3 and 10 years. We proceed in several steps. First, we compute the holding period return R_{j,t_b,t_s} for each property j by adjusting the transaction prices by the corresponding nation-wide market index value (FASTPI or LAGPI) at the time of the transaction:

$$R_{j,t_s,t_b} = \frac{P_{j,t_s}/\text{Index}_{t_s}}{P_{j,t_b}/\text{Index}_{t_b}}. \tag{27}$$

where $P_{j,t}$ is the price of at which property j has been transacted at time t.[7] Second, we compute the log return normalized by the square root of holding period in years, $r_{j,t_b,t_s} \equiv \log(R_{j,t_b,t_s})/\sqrt{t_s - t_b}$, and project it on a vector of property characteristics d_j measured at time of purchase t_b:

$$r_{j,t_b,t_s} = a_j + b_j^{'} d_j + \xi_j. \tag{28}$$

The observable characteristics are (i) the natural logarithm of the total property area $\log(P_{j,t_b})$, (ii) the log of the purchase price, and (iii) dummies for: real estate asset classes c_{RE}, real estate location groups rg, holding periods in years and purchase years t_b. We estimate the sample variance $\text{Var}(\xi_j)$ of the residuals in (28) within each group rg, year of sale t_s and holding period $t_s - t_b$. For all properties j in group $rg(j)$, we estimate the variance $\text{Var}(v_{j,t})$ of property j's specific shock $v_{j,t}$ with the average of $\text{Var}(\xi_j)$ at the group level $rg(j)$.

Denote by $\omega_{RE,i,j,t}$ the weight that investor i places at the beginning of year t in property j within her real estate wealth.

We assume that idiosyncratic risk is uncorrelated across properties so that the idiosyncratic risk of real estate assets for investor i is:

$$\text{Var}^{\text{idio}}_{i,RE,t} = \sum_j \omega_{RE,i,j,t} \, [\text{Var}(\varepsilon_{rg(j),t}) + \text{Var}(v_{j,t})]. \tag{29}$$

So far, we have focused on the systematic and idiosyncratic risk exposures of investors'

[7] The purchase t_b and sale t_s dates are expresses in calendar days. As a result the holding period in years is defined as round$[(t_s - t_b)/365]$.

real estate *assets*. To calculate the exposures of real estate *equity*, denote with $W_{RE,i,t}$ the value of investor i's total real estate assets and with $M_{i,t}$ investor i's mortgage balance. The after-tax excess return on real estate equity is

$$r_{i,REE,t} = \frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} r^{at}_{i,RE,t} - \frac{M_{i,t}}{W_{RE,i,t} - M_{i,t}} i_{i,t}(1 - \tau_M). \tag{30}$$

where $r_{i,RE,t} = \sum_{j=1}^{J_{RE}} \omega_{RE,i,j,t} r^{at}_{j,t}$ is the after-tax return on investor i's real estate assets, $i_{i,t}$ is the mortgage interest rate and τ_M is the mortgage interest tax deduction of interest payments. We realistically assume that the mortgage rate is known at the beginning of each year and so it is deterministic. Hence the factor loading of the after-tax excess return of real estate equity of investor i is:

$$\beta_{i,REE,t} = \frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} \beta_{i,RE,t}. \tag{31}$$

and the idiosyncratic variance is:

$$\text{Var}^{\text{idio}}_{i,REE,t} = \left(\frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} \right)^2 \text{Var}^{\text{idio}}_{i,RE,t}. \tag{32}$$

A.5 Algorithm for mortgage debt imputation

We improve on the standard capitalization method for debt imputation by training, validating, and testing a machine learning algorithm on a subsample of the population for which we a priori can categorize the origin of liabilities into mortgages and other debt (which we call consumer debt, for brevity). First, we employ a three-step procedure in which we first use a random forest classifier model to predict whether an individual has mortgage or consumer debt or both. Second, we employ a cubist rule-based regression model to predict mortgage interest expense for individuals who are predicted to have mortgages from the first step. In training the algorithms we make use of a large set of observable characteristics related to demographics, wealth, income, consumption, real estate holdings, and financial information of relatives. In addition, we also use cluster-level average interest rates as predictive variable, where clusters span the entire Swedish population along the dimensions of age, income, municipality, and year. The interest expense corresponding to consumer debt is then calculated as the difference between observed total interest expense and predicted mortgage interest. In the third and final step, we predict mortgage debt, using a similar methodology of step two augmented by lagged observable characteristics. Observed total debt is used both as a predictor for the estimation of mortgage debt, as well as upper bound to predicted mortgage debt.

A.6 Human Capital

We follow Catherine et al. (2022c) to compute a measure of human capital for each individual in our sample, where we define human capital as the present value of expected labor earnings over the life cycle. To compute it, we assume that workers correctly anticipate the expected growth of their log disposable income conditional on their industry of work, education level, and age. Using the income and demographic data from 1983 to 2015, we regress the yearly changes in the log of disposable income on a polynomial of age, where disposable income is the sum of all non-financial sources of after-tax income, including social transfers, and we deflate it using the CPI index of 2001. We define 36 different groups (12 industries and 3 education levels) and estimate an OLS regression for each of them, which captures the heterogeneity in life-cycle profiles of earnings across groups.[8] Specifically, we estimate:

$$y_{it} - y_{it-1} = f(a_{it-1}, g_{it-1}) + \epsilon_{it}, \tag{33}$$

where $f(a, g)$ is a third-order polynomial estimated for each group capturing the expected growth rate of earnings.

Having estimated the growth rates for each group, we impute the future labor earnings of each individual and discount it in order to obtain a measure of human capital. We define current earnings as the average disposable income of individuals of the same age, working in the same industry, with the same level of education, and with the same wealth background group in each year. For each year and age, there are 108 different groups (12 industries, 3 education levels, and 3 wealth background groups). Equation (34) provides the procedure implemented to obtain the present value of expected future earnings.

$$H_{it} = \sum_{k=0}^{Ti} s_{i,t+k} \frac{E[Y_{i,t+k}]}{(1+r)^k}, \tag{34}$$

where T_i denotes the number of years before worker i retires, which we assume to be at age 65, and $s_{i,t+k}$ is her survival probability up to year k. Survival probabilities are imputed from life tables computed by the National Statistics Central Bureau. As Calvet et al. (2021) and Catherine et al. (2022c) we discount future earnings at r=4.1%.

We follow Calvet et al. (2021) to compute the present value of future pensions and

[8] We restrict the sample to all individuals between 25 and 64 years old that are not students, are not retired and do not work in the agricultural sector.

compute a replacement ratio for each industry$x$education group, which imputes state and occupational after-tax pension benefits for retired individuals. The ratio is estimated for each of the 36 groups as the fraction of the average disposable income of retired 65-year-old individuals to the disposable income of non-retired ones at 64 years old. We multiply this ratio by the expected disposable income of 64-year-old individuals and consider it as the fixed post-retirement disposable income. We discount this stream of estimated riskfree post-retirement income and count it as part of the human capital.

A.7 Present Value of Expected Gifts and Inheritances

To obtain the present value of expected gifts and inheritances received from parents we implement a procedure similar to the one implemented for human capital. We first fit a polynomial of age of degree 3 on the level of gifts and inheritances observed in the data, separately for each wealth background group of each individual (leading to 3 different age profiles of gifts and inheritances). To fit the polynomial, we use the average gifts and inheritances received from parents by age and wealth background group, which are winsorized at the 0.1 and 99.9 percentiles. We also collapse the average gifts and transfers across different years of reported data (2000 to 2007), after scaling with the personal wealth growth index in Sweden.

The estimated age profile of gifts and inheritance is based on flows received by individuals at the current time. To measure the present value of future gifts and inheritances for an individual in our data at a given age, we first use the estimated age profile and scale up numbers by the average personal wealth growth index, to set the expected gifts and inheritance received in upcoming years for that individual. We cut estimated flow values by zero (focusing only on gifts received and inheritance as a source of exogenous income, not bequests, which is endogenous) and further assume that from 64 years old onwards gifts received and inheritances are zero. Note that due to our lack of data on the wealth background of older individuals, we may not obtain numbers from the data, but given the pattern observed close to age 64, it is a reasonable assumption to ignore gifts received from age 64 onward. Finally, we discount the imputed future expected stream of gifts and inheritance at r=4.1% (similar to the case of measuring human capital).

A.8 Measuring Wealth Mobility

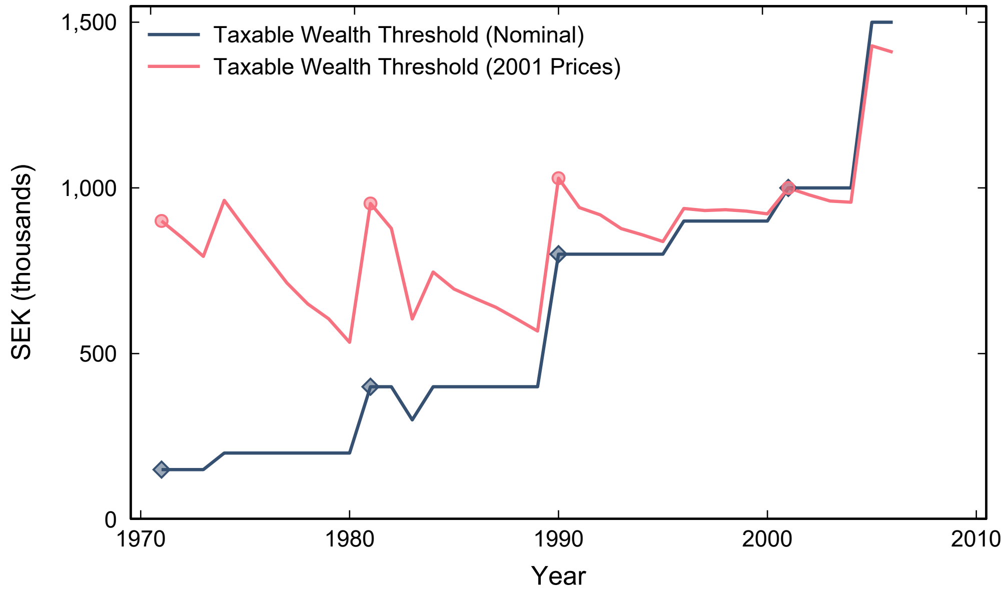
The net wealth of parents, our proxy for wealth background, should be measured at a young age when preferences are still being formed and potentially influenced by parents. Unfortunately, comprehensive and detailed data on wealth is only available in Sweden between 1999 and 2007, preventing us from measuring accurately wealth background at young ages for most of the individuals in our sample. It is however possible to obtain information on the wealth taxes paid by residents in Sweden all the way from 1971 using the Swedish Income Tax Register (Statistics Sweden, 2007c). In this section, we explain how we use this data to build a reliable proxy of wealth background and verify the accuracy of our approach using the information available in 2001, when we have data both on taxable wealth and on total net wealth.

The wealth tax in Sweden was implemented using a progressive taxation structure and levied only above a certain threshold of taxable wealth. The tax was paid at individual level but calculated at the household level, excluding the individuals living with their parents aged at least 18 years old, who were considered independent tax-paying units. Taxable wealth is defined as the total value of assets subject to the wealth tax minus the part of liabilities used to finance taxable assets. Even though all asset classes, besides pension wealth, were subject to the tax, the code allowed for the following deductions and exception. Real estate was taxed at the tax-assessed value, which was set to approximately 75% of the market value. Stocks were generally taxed at 80% of their market value from 1997 to 2006; at 75% from 1978 to 1996 and at 100% before 1978, but specific rules applied to different types of shares and ownership structures.[9] Private business wealth was taxed at 30% of the book value of equity until 1990. Du Rietz and Henrekson (2015) provide a comprehensive summary of the Swedish wealth tax rules and their changes over the years.

Figure A.5 plots the wealth tax threshold over time in nominal and in 2001 prices. As clear from the figure, the threshold has been reset to a value close to 1,000,000 SEK in real terms every 10 years from 1971. We use this institutional feature to define our wealth background variable. More specifically, we measure parents' wealth during the years 1971, 1981, 1990 and 2001, as indicated by the red dots of Figure A.5. We choose 1990 instead of 1991 as it was the last year private business wealth was taxed. In 2001, business wealth was not taxed, but the detailed information on private business holdings available in our data from 1999 to 2007 allows us to virtually reconstruct a taxable wealth variable comparable to the one observed before 1991. Figure A.6 reports the percentage of households paying wealth taxes from 1971 to 2007 among households with at least one individual between 45 and 55 years old, the age bracket that characterizes the "parents" of the individuals who are in our sample between 1999 and 2007. The percentage oscillates between 3 and 15 percent, but it is far more stable, between 6 and 8 percent, in the years when we measure wealth

[9]Before 1992, shares of listed companies on the O-list were tax at 30% and after 1992, shares of listed companies on the O-list were tax-exempt. An additional exemption for major shareholders owning at least 25% of the company was introduced in 1998.

Figure A.5: Thresholds of Taxable Wealth for Paying Wealth Tax



Note: The figure indicates the minimum taxable wealth threshold at which the wealth tax becomes applicable. Between 2001 and 2006, we report the threshold applied to single households. Values are adjusted to 2001 prices using the official CPI index provided by Statistics Sweden. Line markers illustrate data points in years 1971, 1981, 1990, and 2001, respectively.

Figure A.6: Percentage Paying Wealth Pax

Note: The figure reports the percentage of households paying wealth tax out of the sample of households with at least one individual between 45 and 55 years old in each year. Line markers illustrate data points in years 1971, 1981, 1990, and 2001, respectively.

background.

To construct the wealth background ranking, we divide the individuals in our sample into different cohorts based on their age in 2001, and then classify their parents into wealth groups using the taxable wealth data available in the Swedish Income Tax Register during the years mentioned above and highlighted in Figure A.5. More specifically, we rank the parents of children who are 50-59 years old using the parents' taxable wealth in 1971. For children who are 40-49, we use parents' taxable wealth information in 1981. For children aged 30-39, we use parents' 1990 taxable wealth. For those who are 20-29, we use parents' taxable wealth in 2001, the same year we observe the children's age. In this way, we make sure that we collect information on parents' wealth at a time when the individuals in our sample were between 20 and 29 years old - with parents being in their 50s.

In order to consistently proxy for wealth ranking in 2001 versus 1971, 1981 and 1990, we use the detailed and comprehensive information of the Swedish Wealth Register available in 2001 to synthetically replicate taxable wealth based on the pre-1991 rules, and thus include business wealth in taxable wealth.

We group children in three wealth background groups. The first consists of children whose parents paid no wealth taxes (Non-rich background). This is the group whose family's taxable wealth has been below the threshold in the year of observation. The second consists of children whose parents belong to the bottom 75% of those who paid wealth taxes (Rich background). Finally, the third consists of children whose parents belong to the top 25% of those who paid wealth taxes (Very-rich background). The classification is done separately within each of the four children cohorts, so that each child's rankings are relative to individuals in the same cohort.

We next validate our approach by comparing the (synthetic) taxable wealth with actual net wealth in 2001. The analysis is done for the sample of households with at least one individual between 45 and 55 years old. Net wealth is defined in the same way as in the rest of the paper, i.e. the sum of financial wealth, pension wealth, real estate equity and private equity, minus non-mortgage debt. Table A.4 reports the distribution of net wealth for each group of taxable wealth. Table A.5 reports the fraction of different wealth percentiles populated by each wealth tax group. The "Non-rich" group includes households who did not pay any wealth tax in 2001, the "Rich" group includes households up to the seventy-fifth percentile of positive taxable wealth in 2001, and the "Very-rich" group includes households in the top 25% of positive taxable wealth in 2001. Wealth percentiles are defined based on different brackets of the household net wealth distribution in 2001. Overall, we find that rankings based on taxable wealth proxy well the ranking created with actual net wealth. The distribution of household wealth based on taxable wealth substantially shifts for households of non-rich, rich, and very-rich categories with only partial overlaps. Moreover, the households in the non-rich category mostly populate wealth percentiles below the 90th, while the rich fall in the 90th to 97.5th percentiles, and the very-rich take up the top percentiles (above 97.5th) of the net wealth distribution.

Table A.4: Distribution of household net wealth for different wealth tax groups in 2001

Wealth tax group	Statistics of wealth									
	Mean	P1	P5	P10	P25	P50	P75	P90	P95	P99
Non-rich	0.76	-0.42	-0.04	0.02	0.13	0.45	1.04	1.71	2.28	4.69
Rich	3.09	1.26	1.61	1.80	2.15	2.67	3.43	4.50	5.68	9.95
Very-rich	13.46	2.79	3.43	3.78	4.55	6.05	9.52	17.64	28.76	93.59
All	1.29	-0.38	-0.02	0.03	0.15	0.57	1.37	2.66	3.93	9.29

Note: The table shows the statistics of net wealth in 2001 for households with at least one individual between 45 and 55 years old. Statistics are reported separately for households of each of the taxable wealth tax groups in each row. The "Non-rich" group includes the households that did not pay any wealth tax in 2001, the "Rich" group includes those that were between the first and seventy-fifth percentile of the positive taxable wealth distribution in 2001 and the "Very-rich" group includes the families that were in the top 25% of the taxable wealth distribution in 2001. P1 indicates percentile 1, and so on. Values are in 2001 million SEKs.

Table A.5: Distributions on wealth tax groups for different household wealth groups in 2001

Wealth group	Wealth tax group		
	Non-rich	Rich	Very-rich
P0-P75	99.81%	0.19%	0.00%
P75-P90	73.97%	25.92%	0.11%
P90-P95	36.55%	56.99%	6.45%
P95-P97.5	30.22%	34.95%	34.83%
P97.5-P99	25.39%	20.98%	53.64%
Top 1%	19.59%	9.98%	70.44%

Note: This table is based on the sample of households with at least one individual between 45 and 55 years old in 2001. P0–P75 refers to households ranked between the first and the seventy-fifth percentiles of the household net wealth distribution, and so on. The "Non-rich" group includes the households that did not pay any wealth tax in 2001, the "Rich" group includes those that were between the first and seventy-fifth percentile of the positive taxable wealth distribution in 2001 and the "Very-rich" group includes the families that were in the top 25% of the taxable wealth distribution in 2001. Each row sums up to 100%, given that the distribution over taxable wealth groups is reported conditional on household net wealth group.

B Analytical Derivation of Lifecycle Decisions

The HJB equation associated with the stochastic optimal control problem is given by:

$$\rho J = \max_{c,x} \; \frac{c^{1-\gamma}}{1-\gamma} + \dot{J} + J_w \left[w r_f + x'\mu - c + y(t) + p(t) \right] + \frac{J_{ww}}{2} x'\Omega x \tag{35}$$

where $J(w,t)$ is the continuation value and $\dot{J}$ and J_w are first derivatives of J with respect to time and wealth, and J_{ww} is the second derivative with respect to wealth. The first-order conditions for x and c are achieved as

$$x^* = \frac{-J_w \Omega^{-1}\mu}{J_{ww}}, \tag{36}$$

$$c^{*-\gamma} = J_w. \tag{37}$$

We conjecture the following solution for $J(w,t)$:

$$J(w,t) = f(t)^{\gamma} \; \frac{[w + h(t) + g(t)]^{1-\gamma}}{1-\gamma}, \tag{38}$$

where $f(t)$ is an arbitrary deterministic function of time, $h(t)$ is human capital defined as the expected stream of future labor earnings:

$$h(t) := \int_t^{T_d} e^{-r_f(\tau - t)} y(\tau) d\tau, \tag{39}$$

and, likewise, $g(t)$ represents the sum discounted expected future transfers $p(\cdot)$:

$$g(t) := \int_t^{T_d} e^{-r_f(\tau - t)} p(\tau) d\tau. \tag{40}$$

By substituting this guess into optimality equations (36) and (37) we obtain:

$$x^* = \frac{\Omega^{-1}\mu}{\gamma} [w(t) + h(t) + g(t)], \tag{41}$$

$$c^* = f(t)^{-1} [w(t) + h(t) + g(t)]. \tag{42}$$

Substitute back our guess and the optimal values c^* and x^* into the HJB equation (35) to obtain:

$$\rho = \gamma f(t)^{-1} + \gamma \frac{\dot{f}(t)}{f(t)}$$
$$+ (1-\gamma)\frac{\dot{h}(t) + \dot{g}(t)}{w + h(t) + g(t)} + (1-\gamma)\frac{y(t) + p(t) + r_f w}{w + h(t) + g(t)} \tag{43}$$
$$+ \frac{(1-\gamma)\mu'\Omega^{-1}\mu}{2\gamma}.$$

For the conjecture of J to be verified, the terms containing w should vanish from this equation for $f(\cdot)$. Thus, the following equation needs to be satisfied:

$$y(t) - r_f h(t) + \dot{h}(t) = 0\ , \quad p(t) - r_f g(t) + \dot{g}(t) = 0, \tag{44}$$

which is the case using the definitions of $h(t)$ and $g(t)$ in equations (39) and (40). Hence, the conjecture for J is verified.

Finally, after deducting w, and $h(t)$ and $g(t)$ terms, the ordinary differential equation (43) simplifies to

$$\rho = \frac{\gamma}{f(t)} + \frac{\gamma \dot{f}(t)}{f(t)} + (1-\gamma)r_f + \frac{(1-\gamma)\mu'\Omega^{-1}\mu}{2\gamma}, \tag{45}$$

which can be solved for $f(\cdot)$. Note that the terminal condition is $f(T_d) = \chi$ (the parameter of the bequest motives). Straightforward calculation delivers the following equation for $f(t)$:

$$f(t) = \left(\tilde{\chi} - \frac{1}{\tilde{\rho}}\right) e^{-\tilde{\rho}(T-t)} + \frac{1}{\tilde{\rho}}, \tag{46}$$

where

$$\tilde{\rho} := (\rho - (1-\gamma)\tilde{r})/\gamma, \quad \tilde{r} := r_f + \frac{\mu'\Omega^{-1}\mu}{2\gamma}, \quad \tilde{\chi} := [1 - e^{-\tilde{\rho}(T_d - T)}]/\tilde{\rho} + e^{-\tilde{\rho}(T_d - T)}\chi.$$

Substitute back for $f(t)$ in the optimal consumption-wealth ratio in equation (42) to derive

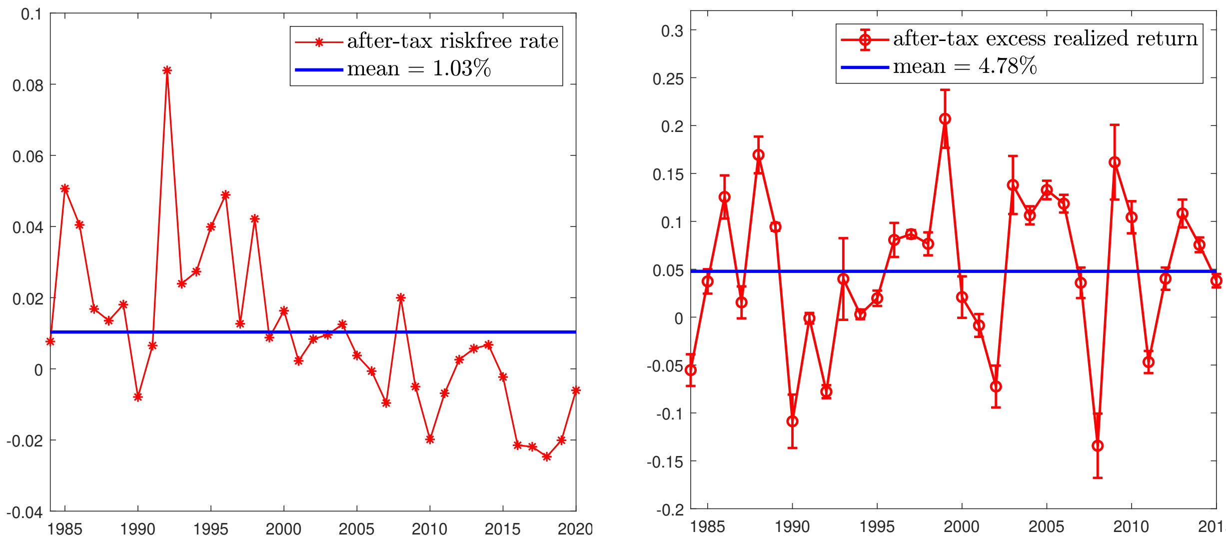
$$c^*(t) = \frac{\tilde{\rho}}{1 + (\tilde{\chi}\tilde{\rho} - 1)e^{-\tilde{\rho}(T-t)}}[w(t) + h(t) + g(t)]. \tag{47}$$

The risky investment is also verified to follow

$$x^* = \frac{\Omega^{-1}\mu}{\gamma}[w(t) + h(t) + g(t)]. \tag{48}$$

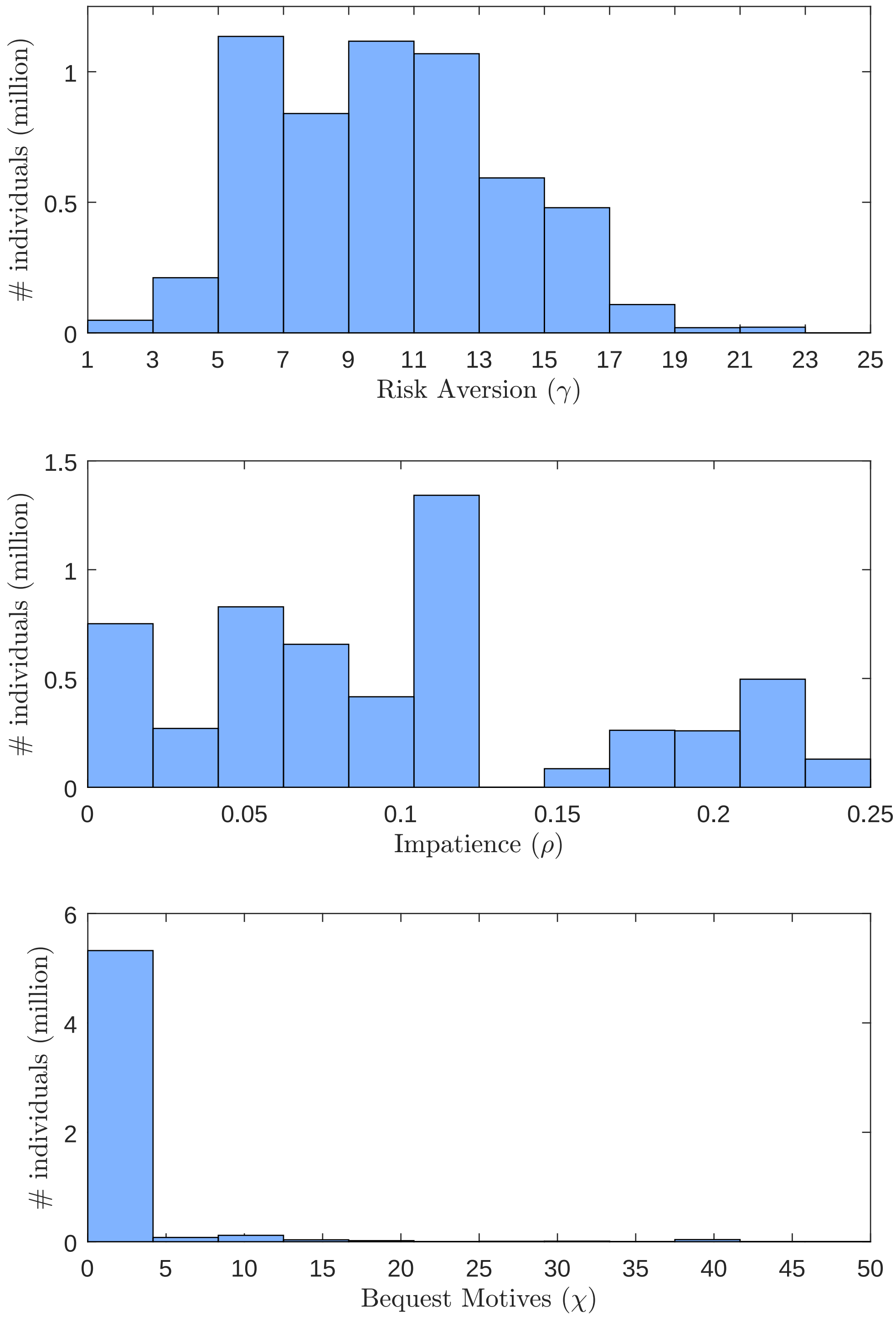
C Supplementary Tables and Figures

Figure C.1: After-Tax Riskfree Rate and Average Excess Realized Return on Risky Assets for Groups of Individuals



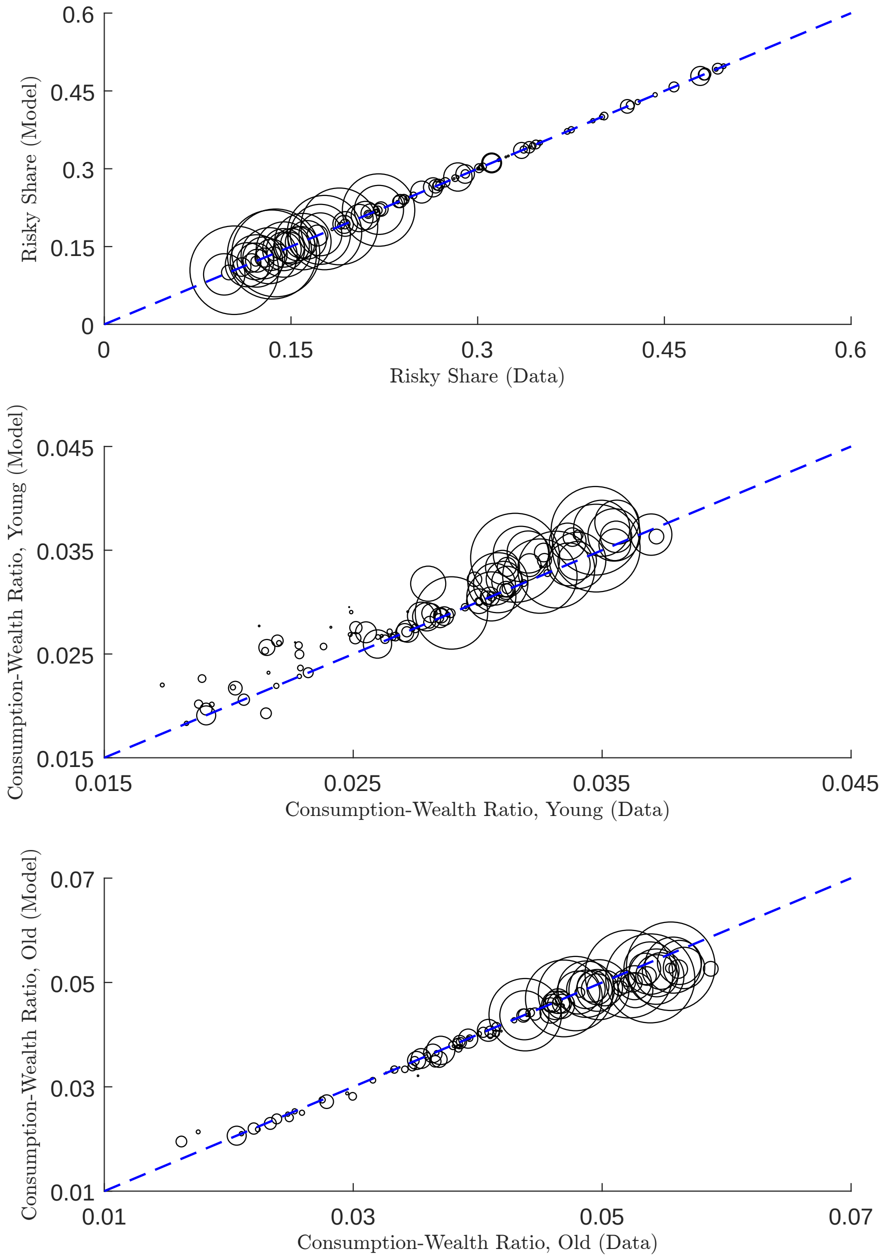
Note: This plot shows the riskfree rate (left Panel) and the estimate of average excess realized return on risky assets for groups of individuals (right Panel) using the history of available data. To measure the average excess realized return, for each group of individuals we measure the average exposure to risk factors (betas) in the risky portfolio of individuals using 2000-2007 data and then multiply betas by the realized factor returns over time (1984-2015) to get the time series of the average excess realized return for a group of individuals. The time series is achieved for 108 groups of individuals (by education, sector, and wealth background), while the plot shows the weighted average plus and minus one standard deviation (with error bars) in the cross-section of 108 groups of individuals at each point in time. The horizontal line shows the mean over average returns over time. Both plots demonstrate the after-tax implied returns.

Figure C.2: Histogram of Estimated Parameters per Group in the Population



Note: This figure presents a histogram of the estimated parameters of the model for all 108 groups of individuals, with frequencies showing the population size of each group. The parameters include risk aversion (γ), impatience (ρ), and bequest motives (χ).

Figure C.3: Model Fit



Note: The scatter plots depict model moments via benchmark estimates (y-axis) againsts targeted moments in the data (x-axis) for the consumption-wealth ratio of young individuals (aged 25-44), the consumption-wealth ratio of old individuals (aged 45-64), and the risky share in portfolio. Circle sizes are proportionate to the population of groups. A 45-degree line is added as the benchmark to show the model fit performance.

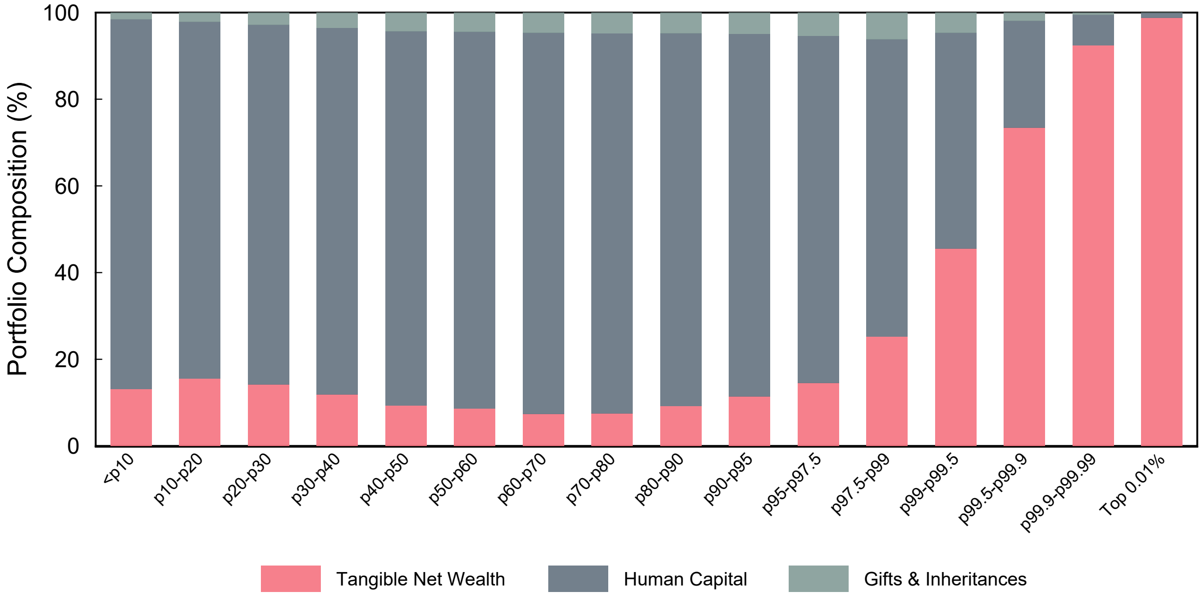
Table C.1: Preference Parameters versus Wealth Background — Model Extensions

Panel A: Risk Aversion (γ)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Non-rich)	10.788	8.737	5.363	10.509	6.732	10.918	7.395
1{Rich}	-3.525	-0.148	-1.178	-3.402	-1.166	-3.021	-1.119
1{Very-rich}	-5.282	-3.289	-2.261	-5.784	-2.726	-5.348	-3.131
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.934	0.906	0.829	0.940	0.705	0.943	0.687
Panel B: Impatience (ρ)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Non-rich)	0.119	0.101	0.059	0.022	0.078	0.147	0.103
1{Rich}	-0.073	-0.059	-0.039	-0.005	-0.048	-0.081	-0.054
1{Very-rich}	-0.078	-0.068	-0.038	-0.009	-0.058	-0.109	-0.083
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.869	0.843	0.839	0.821	0.775	0.878	0.768
Panel C: Bequest Motives (χ)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(Non-rich)	0.641	0.641	0.770	0.639	0.641	1.893	1.891
1{Rich}	4.705	4.688	7.399	4.632	4.675	6.306	6.294
1{Very-rich}	24.340	24.500	30.572	20.771	24.182	25.222	25.195
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Business Sector	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.721	0.724	0.752	0.600	0.719	0.793	0.793

Note: The table reports the weighted average of estimated parameters (γ, ρ, χ) for individuals of non-rich background groups, as well as the variation in parameters across wealth backgrounds, from alternative models specified in Section 7. We use weighted regressions across 108 groups (constructed by classification into 3 wealth backgrounds, 3 education levels, and 12 business sectors). Weights are based on group size. We control for education and business sector fixed effects in all specifications. Column (1) refers to the benchmark model and thus reports Column (4) of table 5; Column (2) refers to the model with heterogeneous non-pecuniary benefits across asset classes; Column (3) refers to the model with non-homothetic preferences; Column (4) refers to the model with Epstein-Zin utility; Column (5) refers to the model with income risks; Column (6) refers to the estimation addressing borrowing constraints, which is based on individual behavior later in working life. Column (7) refers to the estimation based on individual behavior later in working life and also considers labor income risk.

D Upcoming Tables and Figures

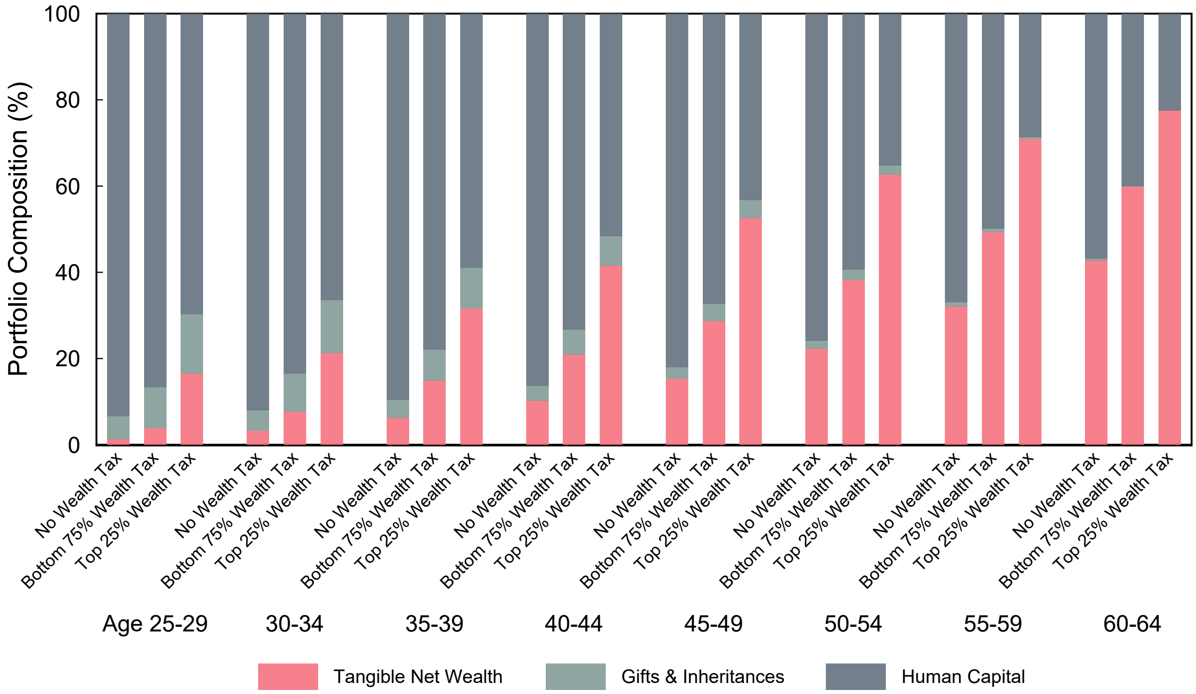
Figure D.1: Allocation of Total Net Wealth



Number of Individuals															
$< p_{10}$	$p_{10} - p_{20}$	$p_{20} - p_{30}$	$p_{30} - p_{40}$	$p_{40} - p_{50}$	$p_{50} - p_{60}$	$p_{60} - p_{70}$	$p_{70} - p_{80}$	$p_{80} - p_{90}$	$p_{90} - p_{95}$	$p_{95} - p_{97.5}$	$p_{97.5} - p_{99}$	$p_{99} - p_{99.5}$	$p_{99.5} - p_{99.9}$	$p_{99.9} - p_{99.99}$	Top 0.01%
403,448	403,448	403,448	403,448	403,448	403,448	403,448	403,448	403,448	201,724	100,862	60,518	20,172	16,138	3,631	403

Note: This figure illustrates the average asset allocation of total net wealth held by Swedish individuals in tangible net wealth (red), present value human capital (dark blue), and in present value of gifts and inheritances (dark green). The present value of human capital includes both that of labor income but also the present value of pension income of the individual in retirement. The graph should be read as follows: an individual in the top 0.01% holds about 98.81% tangible net wealth, 1.11% human capital, and 0.08% in gifts and inheritances. There are a total 4,034,480 individuals in the sample.

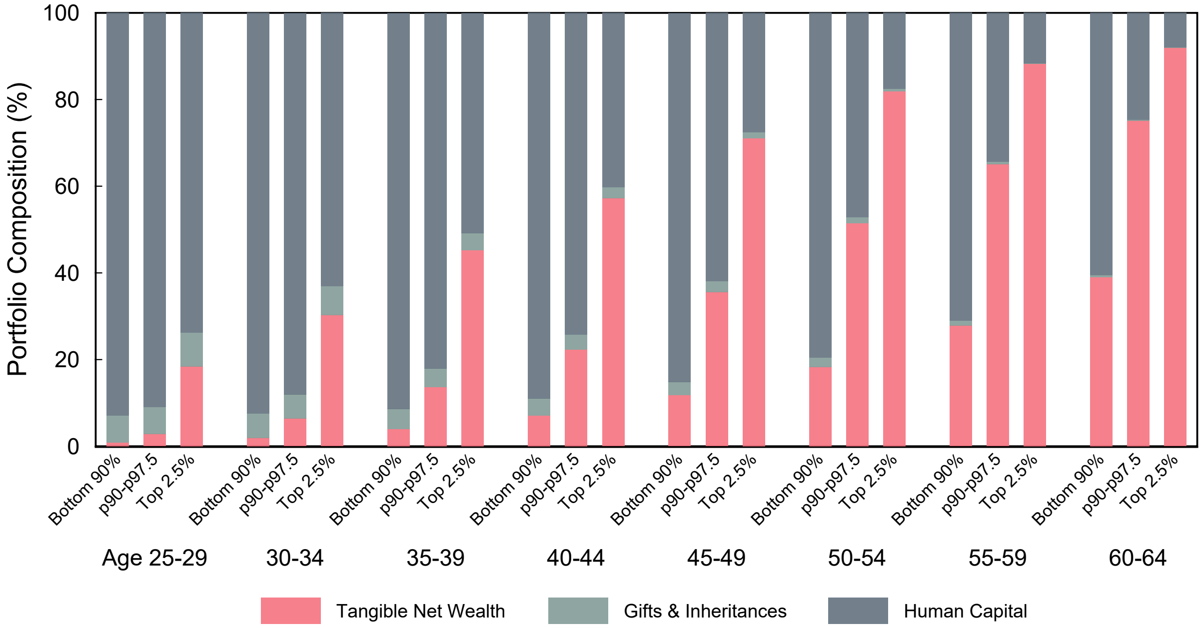
Figure D.2: Allocation of Total Net Wealth by Wealth Background and Age Bracket



	Population Within Age Bracket by Wealth Background							
Wealth Background	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
No Wealth Tax	333,082	428,335	476,316	448,256	424,079	435,872	433,989	249,404
Bottom 75% Wealth Tax	41,285	41,708	27,142	27,273	26,776	27,743	29,355	18,034
Top 25% Wealth Tax	13,398	13,946	8,985	8,799	8,850	9,239	9,473	5,762

Note: This figure illustrates the average asset allocation of total net wealth held by Swedish individuals by wealth background and age bracket for the period 2000-2007. Total net wealth components include tangible net wealth (red), present value human capital (dark blue), and in present value of gifts and inheritances (dark green). The present value of human capital includes both that of labor income but also the present value of pension income of the individual in retirement. The graph should be read as follows: an individual aged 25-29 whose parents paid the top 25% of wealth tax has one average 16.53% tangible net wealth, 69.64% human capital, and 13.83% in gifts and inheritances. There are a total 4,034,480 individuals in the sample.

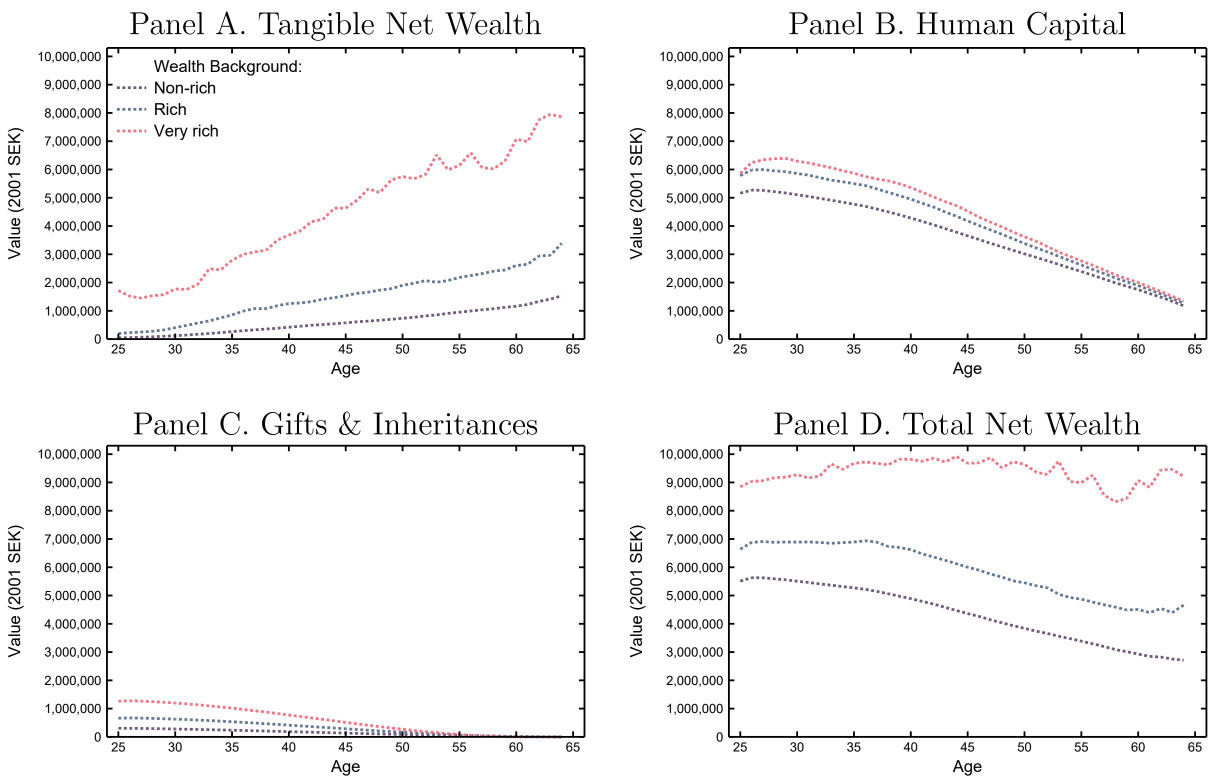
Figure D.3: Allocation of Total Net Wealth by Total Net Wealth and Age Bracket



Total Net Wealth	Population Within Age Bracket by Total Net Wealth							
	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
Bottom 90%	302,180	395,626	449,629	440,731	432,877	453,809	457,314	265,006
$q_{90} - q_{97.5}$	68,479	73,912	49,761	30,968	16,956	10,424	7,638	3,697
Top 2.5%	17,106	14,451	13,054	12,629	9,872	8,621	7,864	4,496

Note: This figure illustrates the average asset allocation of total net wealth held by Swedish individuals by net wealth and age bracket for the period 2000-2007. Net wealth is split into 3 brackets: (1) those at the bottom 90% of the wealth distribution within each year, (2) those at the 90th - 97.5th percentile of wealth in each year, and (3) the top 2.5% of the wealth distribution within each year. People may transition between wealth brackets over the years. Total net wealth components include tangible net wealth (red), present value human capital (dark blue), and in present value of gifts and inheritances (dark green). The present value of human capital includes both that of labor income but also the present value of pension income of the individual in retirement. The graph should be read as follows: an individual aged 25-29 at the top 2.5% of the wealth distribution has 18.46% tangible net wealth, 73.80% human capital, and 7.74% in gifts and inheritances.

Figure D.4: Cross-Sectional Average Wealth by Age and Wealth Background (2000-2007)



Note. This figure illustrates the cross-sectional averages of total net wealth conditional on age and wealth background. Averages of wealth by age are first calculated by age, wealth background, and year and then subsequently averaged over the years (2000-2007). Total net wealth (panel D) is the sum of tangible net wealth (panel A), total human capital (present value of labor and pension income) net of student debt (panel B), and the present value of gifts & inheritances (Panel C). All currency amounts are denominated in 2001 SEK units. Each categories of wealth background is displayed in dashed lines; these categories includes individuals with non-rich parents (purple), rich parents (dark blue), and very rich parents (red).