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

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Abstract

We structurally estimate the individual attitudes that regulate wealth accumulation in a model that explains the wealth gap between individuals of different wealth backgrounds. To this purpose, we use rich micro-level data on the balance sheets, consumption, and risky investments of Swedish residents, in addition to wealth-based family background measured during the offspring's early adulthood. We find that patience and risk-taking highly correlate with parents' wealth status. Inherited preferences explain up to 70% of the wealth gap between adult individuals of non-rich backgrounds (making up 91 percent of the population) and very-rich backgrounds (2.2 percent of the population). Early-adulthood heterogeneity in wealth, gifts, inheritances, and transmission of human capital across generations are not dominant determinants of wealth mobility.

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JEL Classifications: D14, D31, E21, H24

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1 Introduction

Social mobility is a foundational concept of modern democracies, considered essential for their continued prosperity and the preservation of social justice (Rawls, 2005). Investigating its determinants is crucial for at least two key reasons: first, to analyze the underlying causes of evolving social disparities, and second, to inform the design of 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.

Even though both income and wealth are important aspects of social status, the academic focus on the former 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, with wealth transfers, and indirectly, through their saving and investment behavior.

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 depends on the heritability of traits and the random assignment of skill among children. While this literature explores endogenous decisions to educational choices and labor supply,[2] it does not focus on savings and investment decisions, or the resulting persistence of wealth across generations.

On the contrary, any model of intergenerational transmission of wealth will need to

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

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

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 precisely at filling this gap for the first time.

Recent progress in understanding wealth inequality highlights the need to examine how offspring's risk tolerance and disposition towards investing in real asset classes (such as real estate and private businesses) are shaped by family background. 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 matter 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 in wealth allocation seems crucial 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, at the foundation of the investment decisions that shape the wealth distribution of their generation, depend on parents' social status.

Second, the latest studies on the determinants of 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. They become important only for the top 1% wealthiest individuals and particularly as a source of capital income, thus depending on the way they are invested. 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 before inheritance is received. Additionally, nurture plays a key role in how offsprings approach saving and investment decisions. This is particularly true for investment choices, as Nekoei and Seim (2023) find that investment choices, rather than saving behavior, are crucial in explaining how inheritances impact wealth inequality. Bequeathed wealth initially reduces inequality as it is mostly flowing from richer parents to poorer children. However,

in the long run, wealthy heirs are able to earn higher returns which results in a net increase of the share of aggregate wealth held at the top of the distribution. In summary, not only gifts and inheritances are a modest part of total lifetime resources but it is also crucial to study how they are used to understand the evolution of inequality.

In this paper, we employ a structural approach to estimate how the deep preference parameters, that govern the wealth accumulation of individuals, are shaped by 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 subjective time discount rate and risk aversion. As their parents, children can leave bequest to their offspring and have warm-glow bequest type of preferences, which, again, possibly depends on the attitudes towards bequeathing wealth to the next generations in the family dynasty. 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, and private business. The return on investment can vary across individuals for three reasons. First, the return premia on risky asset classes vary across the population and are directly estimated from the data. Second, individuals allocate endogenously the risky part of their portfolios across different risky asset classes. Third, and finally, individuals also endogenously decide how much to invest in the risky component of their wealth versus the risk-free one.

We consider labor income profiles with level and growth rates that depend on the individual type, which is defined by education, business sector, and family background, in order to reflect 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 25 years old. Preferences vary across individuals also based on their types. We estimate the deep parameters of the model with the minimum distance method, which consists of matching a set of targeted moments with their data counterparts. We consider an exact-identified model and perform separate estimations for each type of individuals, resulting in a non-parametric variation of the underlying parameters with respect to their type in the population. This allows us to estimate the dependence of preference parameters on family background. The deep parameters that we estimate are: subjective time discount rate, bequest motive and risk aversion.

In the class of models that we consider, the individual tends to consume a fraction of

her total wealth defined as current tangible net wealth plus human capital and the present value of inheritances and gifts. The optimal consumption-wealth ratio typically 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 risky assets. At each point in time, the optimal risky share in portfolio is governed by the excess return vector scaled by the variance-covariance matrix of returns and by the individual's risk aversion. Less risk-averse individuals put a larger share into risky assets, and, among risky assets, invest proportionally more into asset classes with larger return premia, less variance, and less covariance with other assets (to enjoy diversification).

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 family background early in adult life 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 Register 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 data cleaning and preparation follow closely Bach et al. (2020b) and Bach, Girshina and Sodini (2022). We assess family background by using wealth tax data from 1971. We carefully verify that taxable wealth is a good proxy for net wealth ranking and classify individuals into different family backgrounds when they were between 25 and 35 years old. We distinguish between non-rich background (parents did not pay the wealth tax), rich background (parents are in the bottom 75th percentile of taxable wealth), and very-rich background (parents are in the top 25th percentile of taxable wealth). In the end, individuals coming from non-rich backgrounds make about 91 percent of the population in our data in 1999-2007, those of rich and very-rich backgrounds make 6.8 percent and 2.2 percent of the population, respectively.

Our paper has three key results. First, deep preference parameters are strongly influenced by individuals' wealth backgrounds. Our estimate for the time discount factor in the population is about 10 percent, which is in line with the existing literature (Catherine, Ebrahimian,

Sraer and Thesmar, 2022a). However, individuals of very-rich backgrounds have a 5 percent lower discount rate (having controlled for one's education and business sector), resulting in a significant gap in saving rates. We further find that individuals of richer 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 nearly 10 for the average population. But, coming from a very-rich background is associated with a reduction in relative risk aversion of 6 units (given education and business sector).

Second, we show that the documented heterogeneity in patience and risk taking, and their dependence on wealth backgrounds, crucially affects inter-generational wealth persistence. To do so, we simulate wealth accumulation from early adulthood (age 25) to mid-age (age 50), in counterfactual scenarios with uniform risk aversion, time discount rate, and bequest motive across individuals of different family backgrounds. With equal preferences, the average wealth gap at the age of 50 between individuals of non-rich and very-rich backgrounds shrinks by more than two-thirds. It reduces from the data/benchmark estimation value of 4.5 million SEK to the counterfactual value of 1.2-1.9 million SEK (depending on specification). We find that nearly forty percent of this reduction can be explained by risk aversion, while sixty percent is explained by patience parameters.[3] Hence, we document that both inherited risk-taking and saving attitudes have a non-trivial impact on wealth mobility across generations.

Third, we find that the gap in initial wealth, human capital, and transfers coming from parents, is not a dominant force in explaining wealth inequality between adults of diverse wealth backgrounds. To show this result, we back out the initial endowment of a 25-year-old individual (in the year 1976), using the wealth accumulation rule of the model with *benchmark* parameter estimates. We then let the model simulate wealth accumulation over the lifecycle assuming there was no initial wealth gap across individuals (holding fixed preferences). The wealth differential at the age of 50 (in the year 2001) between individuals of non-rich and very-rich backgrounds shrinks, but it yet stays non-trivial. It reduces from 4.5 to 2.3 million SEK. This result further confirms the role of inherited preferences (besides direct parents' financial support and human capital investment), in explaining the determinants of 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 in the form of habit, heterogeneous non-pecuniary benefit across asset classes, and Epstein-Zin utility. We also

[3]There is interaction between risk aversion and patience as well.

introduce labor income risk with cyclical skewness and borrowing constraints. Overall, we confirm that social stagnation crucially depends on what individuals of rich backgrounds do with their money, 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. In section 4 we lay out the benchmark model, which we structurally estimate in section 5. 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[4], 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).[5] 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 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

[4]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)).

[5]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.

year 2000 onward.[6] 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 4,034,479 unique individuals and 27,830,384 observations over the 2000 to 2007 period. All nominal variables are deflated by the Swedish consumer price index with 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 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

[6] 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.

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.[7]

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.[8] 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.[9] 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, 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

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

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

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

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.[10] 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).

[10] 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 $c = 1, \ldots, C$, 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.[11] 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

[11] 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.[12] 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.[13] 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.

[12] 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.

[13] 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 (2022b) 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., 2022b), 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 91 percent, 6.8 percent, and 2.2 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.

Table 1: Observations and Individuals by Wealth Background Ranking

	Wealth Background			Observations	Individuals
Cohort	Non-rich	Rich	Very-rich		
1971	91.81%	6.19%	2.00%	7,382,500	1,018,161
1981	92.29%	5.79%	1.92%	7,327,534	962,845
1990	93.23%	5.09%	1.69%	8,120,766	1,093,192
2001	84.49%	11.69%	3.82%	4,999,592	960,282
All	91.04%	6.75%	2.21%	27,830,392	4,034,480

Note: The table shows the number of observations and individuals in the final sample by wealth background and cohort.

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 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.[14]

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

[14]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 (Non-rich background). The second consists of children whose parents belong to the bottom 75% of those who paid wealth taxes (Rich background). And, 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, about 90 percent of our final sample of 4 million individuals covered during 2000-2007 fall into the non-rich background, while about 7 and 2 percent fall into the rich, and very-rich backgrounds, respectively (see table 1).

Table 2 reports net wealth and position in the wealth distribution of children of different backgrounds when they reach the age of 46-54 years old in 2001, i.e. the age of their parents when background was measured. Panel A shows a substantial average wealth gap of 4.51 million SEK, between individuals of very-rich and non-rich backgrounds, and a gap of 0.94 million SEK between those of rich and non-rich backgrounds. The 75th percentile of wealth among the non-rich background group (0.781 million SEK) is less than the 25th percentile of wealth among the very-rich group (0.782 million). Indeed, as Panel B shows, 73 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 5 percent fall into the bottom 25 percentiles (one-fifth 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, gifts and inheritances, or because of deeper forces that shape decision-making, such as attitudes toward saving and investment risk taking. In the coming 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	0.756	0.200	0.390	0.781
Rich	1.698	0.462	0.931	1.767
Very-rich	5.270	0.782	1.698	3.532
Wealth Background	**Panel B: Fraction in Wealth Quartiles**			
	P0-P25	P25-P50	P50-P75	P75-P100
Non-rich	26.40%	26.10%	25.24%	22.26%
Rich	9.00%	13.24%	24.40%	53.36%
Very-rich	5.20%	7.23%	15.08%	72.49%
Wealth Background	**Panel C: Fraction in Upper Wealth Percentiles**			
	P90-P95	P95-P97.5	P97.5-P99	P99-100
Non-rich	4.32%	2.00%	1.11%	0.65%
Rich	12.53%	7.39%	4.66%	2.80%
Very-rich	15.30%	12.08%	11.05%	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 full-sample (within cohort) wealth quartiles in Panel B, and into upper percentiles in Panel C, for 46-54 years old individuals in the year 2001, separately for each wealth background group: non-rich, rich, and very-rich (categorized based on parents' wealth tax reports in the year 1981). In this sample, 92.36% of individuals are in the non-rich background category, while 5.73% are in the rich and 1.91% 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.[15] 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).

[15] 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. An individual i earns a *deterministic* labor income $y_i(t)$ at time $t \in [0, T]$, where T is retirement age and $t = 0$ corresponds to the beginning of adult life. Labor 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, direct transfers in the form of inheritance and gifts from parents (at various stages in life), denoted by $p_i(t)$, are also exogenous and possibly depend on background. Each individual is endowed with exogenous initial wealth, denoted as $w_i(0)$. This represents the total tangible wealth accumulated by the age of 25, including labor income earned during early adulthood, early direct transfers from parents, and any remaining funds after deducting living expenses and education costs. Consumption, denoted by $c_i(t)$, is endogenous over the lifecycle. 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 (ρ, γ, χ) 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:

$$\begin{aligned} \max_{\{c(\cdot),x(\cdot)\}} \mathbf{E}\left[\int_{t=0}^{T} e^{-\rho t}\cdot\frac{c(t)^{1-\gamma}}{1-\gamma} + e^{-\rho T}\cdot\chi^{\gamma}\,\frac{w(T)^{1-\gamma}}{1-\gamma}\right] \\ s.t. \quad dw(t) = \; w(t)r_f dt + x(t)'\mu dt + x(t)'\sqrt{\Omega}d\omega_t + y(t)dt + z(t)dt - c(t)dt, \end{aligned} \tag{7}$$

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 portfolio choice. 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:

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

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:

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

with

$$\tilde{\rho} := (\rho - (1-\gamma)\tilde{r})/\gamma, \quad \tilde{r} := r_f + \frac{\mu'\Omega^{-1}\mu}{2\gamma}.$$

In a special case where bequest motives is $\chi = 1/\tilde{\rho}$, 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 $\chi > 1/\tilde{\rho}$ 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 $\chi < 1/\tilde{\rho}$ 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 relationship (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 inversely depends on

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 choose an exactly-identified model with the same number of moments as the number of estimated parameters, and 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 characterize 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:

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

$$\text{(depends both on } \rho,\chi) \leftarrow a_l := \int_{t=T/2}^{T} a(t;\rho,\chi)dt = \sum_{t=T/2}^{T} \frac{c_t^*}{w_t + h_t + g_t}$$

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):

$$x_t^* \;=\; [w_t + h_t + g_t]\frac{\Omega^{-1}\mu}{\gamma} \;\Rightarrow\; \gamma = (\mathbf{1}'\Omega^{-1}\mu) \;/\; \left(\sum_t \frac{\mathbf{1}'x_t^*}{w_t + h_t + g_t}\right) \tag{10}$$

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 $C_{m,t,\tau}$, tangible wealth $W_{m,t,\tau}$, human capital $H_{m,t,\tau}$ and the present value of gifts and inheritance $G_{m,t,\tau}$ 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 capitalized letters to denote *group*-level variables.

We use these aggregated measures to calculate the consumption-wealth ratio $A_{m,t,\tau} \equiv C_{m,t,\tau}/\left(W_{m,t,\tau} + H_{m,t,\tau} + G_{m,t,\tau}\right)$ and average it within group 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:

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

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 $X_{m,\tau}$ 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 *total* portfolio risky share of group m, we average the corresponding vector of risky shares $X_{m,\tau}/\left(W_{m,\tau} + H_{m,\tau} + G_{m,\tau}\right)$ over the years $\tau = 2000, ..., 2007$ and then sum up its four elements to obtain the data counterpart to the model object $\mathbf{1}'x^*/(w+h+g)$.

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. Note that both μ and Ω vary across individuals. $\mu'\Omega^{-1}\mu$ determines the effective return rate $\tilde{r} := r_f + (\mu'\Omega^{-1}\mu)/(2\gamma)$ in equation (8), 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 (10). We set the risk-free rate r_f at 1%, which is approximately equal to the average value from 1984 to 2020. Below we explain how we measure μ and Ω.

To construct the vector of asset classes' expected excess returns μ, 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 μ^c of a group of individuals for asset class c, we use the relative risky position of each individual x^c/X^c in asset class c as weights.

The tricky part is to build the variance-covariance matrix of risky returns at the aggregate 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. More precisely, take the two asset classes c and c' as given. The individual weights for calculating Ω's element in row c and column c', $\Omega^{cc'}$, aggregated at the group level, is $\frac{x^c x^{c'}}{w+h+g} / \frac{X^c X^{c'}}{W+H+G}$, 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 capitalized letters 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 above, we ensure that the first-order condition for the optimal risky shares at 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. The median value of relative risk aversion γ is 10.27, 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 0.079, implying a subjective time discount factor of 0.927. Note that, in our estimation procedure, we require ρ to be non-negative, and obtain corner estimates of $\rho = 0$ for about 5% of the groups. Despite this restriction, appendix figure C.3 verifies that the model provides a satisfactory fit to the targeted moments in the data. The estimates of γ and ρ are comparable 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 et al. (2022a) for

Table 3: Data Moments

Panel A: Risky Investment Share										
Wealth Background	# (million)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	4.255	0.125	0.028	0.083	0.086	0.107	0.120	0.139	0.173	0.201
Rich	0.399	0.182	0.040	0.120	0.148	0.163	0.173	0.181	0.237	0.440
Very-rich	0.135	0.368	0.059	0.263	0.295	0.310	0.358	0.420	0.428	0.500
All	4.789	0.137	0.052	0.083	0.086	0.110	0.123	0.149	0.178	0.500
Panel B: Consumption to Total Wealth Ratio for Young People										
Wealth Background	# (million)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	4.255	0.034	0.002	0.026	0.031	0.033	0.034	0.036	0.036	0.039
Rich	0.399	0.031	0.002	0.024	0.028	0.030	0.031	0.032	0.034	0.036
Very-rich	0.135	0.025	0.003	0.021	0.022	0.022	0.025	0.026	0.028	0.036
All	4.789	0.033	0.003	0.021	0.030	0.032	0.033	0.036	0.036	0.039
Panel C: Consumption to Total Wealth Ratio for Old People										
Wealth Background	# (million)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	4.255	0.051	0.004	0.042	0.046	0.047	0.052	0.054	0.055	0.059
Rich	0.399	0.041	0.005	0.032	0.035	0.037	0.041	0.046	0.047	0.051
Very-rich	0.135	0.028	0.008	0.017	0.019	0.022	0.027	0.036	0.037	0.050
All	4.789	0.049	0.006	0.017	0.042	0.046	0.051	0.054	0.055	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.

a representative US household (using the Survey of Consumer Finance). We find that the median value of the bequest motive parameter χ is 14.1 and that $\chi < \tilde{\rho}^{-1}$ for almost all groups, implying that individuals tend to consume more aggressively when older. Finally, we note that the cross-sectional variation of the estimated time discount rates is much more pronounced than the variation in risk aversion and bequest motive. The ratio of the interquartile range to the median of ρ is more than 107%, whereas it is below 37% and 28% for γ and χ, respectively.

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 regres-

Table 4: Summary Statistics of Estimated Parameters

Parameter	mean	std	min	p10	p25	p50	p75	p90	max
γ	9.82	2.61	2.42	6.39	7.76	10.27	11.54	13.33	14.13
ρ	0.092	0.049	0.000	0.033	0.054	0.079	0.139	0.166	0.198
χ	15.1	3.4	11.8	12.3	12.5	14.1	16.4	18.2	30.0

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.

sions 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 about 10, and it falls by about 3 and 6 in absolute terms for individuals with rich and very-rich parents, respectively. The time discount rate ρ drops by at least 2 and 5 percentage points for individuals with rich and very-rich parents compared to the base level of 9.7 percent for the average non-rich background individual. We also find that the bequest motives χ are almost double for children of very-rich families. Finally, we find that the variation in wealth background across our groups explains 23% of the variation in risk aversion and 11% for the rate of time preferences. The explanatory power is much higher for the bequest motive with parents' wealth explaining more than half of the variation (R^2 of 54%).

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. The exception is the time 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 62%), whereas the variation in risk and bequest attitudes is better explained by business sector (with adjusted R^2 of 62% and 90% respectively). Given that individuals with wealthier background 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

Table 5: Preference Parameters versus Wealth Background

Panel A: Risk Aversion (γ)				
	(1)	(2)	(3)	(4)
(Non-rich)	10.31	10.31	10.31	10.31
1{Rich}	-3.58	-3.38	-3.35	-3.05
1{Very-rich}	-6.87	-6.56	-6.40	-5.96
Education	No	Yes	No	Yes
Business Sector	No	No	Yes	Yes
Adjusted R2	0.227	0.374	0.672	0.940
Panel B: Impatience (ρ)				
	(1)	(2)	(3)	(4)
(Non-rich)	0.097	0.097	0.097	0.097
1{Rich}	-0.039	-0.023	-0.035	-0.019
1{Very-rich}	-0.080	-0.057	-0.074	-0.050
Education	No	Yes	No	Yes
Business Sector	No	No	Yes	Yes
Adjusted R2	0.111	0.625	0.218	0.810
Panel C: Bequest Motives (χ)				
	(1)	(2)	(3)	(4)
(Non-rich)	14.27	14.27	14.27	14.27
1{Rich}	5.75	5.84	5.56	5.52
1{Very-rich}	12.82	12.94	12.42	12.37
Education	No	Yes	No	Yes
Business Sector	No	No	Yes	Yes
Adjusted R2	0.541	0.535	0.898	0.898

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.

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 which 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 channel itself.

6 Counterfactual Results

The gap in patience parameters ρ and χ across individuals of different wealth background translates into substantial heterogeneity in saving attitudes, both in early adulthood and close to retirement. The gap in risk aversion γ implies instead substantial heterogeneity in portfolio risk-taking. Both higher saving rates and more agressive 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 wealth accumulation over the life-cycle in closed forms for groups of individuals. We apply the wealth accumulation rule backward on the observed group-level wealth for the cohort of 50-year-old individuals in 2001 to back out (unobserved) wealth at age 25 of this cohort (in 1976). We validate our procedure using indirect proxies from the data for individuals' wealth at the age of 25. Fixing initial wealth, we simulate wealth accumulation forward in counterfactual scenarios with alternative preferences to find the wealth gap that rises due to inherited (heterogeneous) preferences. We compare outcomes with a counterfactual case in which initial wealth, as well as human capital and the present value of direct gifts and inheritance are the same across individuals of different backgrounds. We show that inherited preferences have significant explanatory power for the observed wealth gap at age 50 across individuals of different wealth backgrounds.

Throughout this section, we use a separate wealth accumulation model, implied by heterogeneous preferences, for each group of individuals (by education, business sector, and wealth background in 2001). When displaying the results, we report collapsed data at the

wealth-background level via taking weighted means.

Wealth Accumulation. The model provides a closed-form representation for the evolution of *total* wealth over the lifecycle. We analyze dynamics of mean wealth for a *group* of individuals since, thanks to the law of large numbers, (unobservable) idiosyncratic returns on assets at the individual level vanish when aggregating. As in the previous section, we show quantities at the group level with capital letters.

Wealth accumulation depends on savings/consumption, risky investments and return on risky assets, and the flow of labor income and gifts. By rewriting the flow of income with changes in human capital over time: $dH = r_f H dt - Y dt$ (and a similar relationship for the *flow* of gifts and inheritance versus its *present value* G), and substituting for the optimal consumption $C = a(t)(W + H + G)$ at age/year t for a given cohort of individuals and risky investments $\mathbf{1}'X = \frac{\mathbf{1}'\Omega^{-1}\mu}{\gamma}(W + H + G)$ we derive

$$d(W + H + G) = \underbrace{\left(r_f + \frac{\mathbf{1}'\Omega^{-1}\mu}{\gamma} er(t) - a(t)\right)}_{\text{growth rate of wealth:}=gr_w(t)}(W + H + G). \tag{11}$$

Derivations are provided in the Online Appendix. Here $W+H+G$ is *total* wealth aggregated up to a group level, and $d(W + H + G)$ represents the change in wealth for a cohort of individuals (in the given group) over time. $er(t)$ is defined as the realized excess return on risky investments for the group of individuals in time t. The idiosyncratic component of return on risky assets for individuals vanishes in the cross-sectional average at each time period when aggregating the evolution of wealth up to the group level. $er(\cdot)$ then equals the average exposure to *systemic* risk factors for individuals of a given group multiplied by the realized factor values in a given period. Preferences parameters ρ, χ, γ, which are common at the group level, show up in $a(\cdot)$ and in the denominator of risky shares $\frac{\mathbf{1}'\Omega^{-1}\mu}{\gamma}$. The growth rate of total wealth $gr_w(\cdot)$ is decreasing with consumption-wealth ratio $a(\cdot)$—hence, increasing with ρ and χ, and is decreasing with risk aversion γ (note that the average realized excess return on risky assets over time equals μ, which is positive).

Initial Wealth Gap. Given the observed level of wealth at the group level at each point in time for a cohort of individuals, the model prediction for wealth accumulation can be used to trace back the level of wealth in an earlier period. Specifically, compounding the return

on total wealth via equation (11) results in

$$(W+H+G)_t = \left\{\prod_{s=1}^{t}(1+gr_w(s))\right\}(W+H+G)_0,$$

where $(W+H+G)_0$ denotes the initial total wealth possessed by a cohort of a given group of individuals (at age 25), and $(W+H+G)_t$ is the total wealth in the arbitrary age/time t.

We aim to run counterfactuals for wealth accumulation to assess the role of preferences, having controlled for the initial wealth gaps. To do so, we back out the initial wealth of the cohort of 25-year-old individuals in 1976 of a given group, using their observed wealth in the data at age 50 (i.e., in 2001). We use the model-implied consumption-wealth ratio at each age $a(\cdot)$ and risky investment share $\frac{\mathbf{1}'\Omega^{-1}\mu}{\gamma}$, as well as the realized excess return on risky assets $er(\cdot)$ measured directly from the history of the data from the beginning of 1977 to the end of 2001. When setting $er(\cdot)$, we use the average factor exposure for the group of individuals from the available data on individuals' risky portfolios during 2000-2007 while using the realized factor values at each point in time in the history of the data from 1977-2001. We also use a *time-varying* risk-free rate using the history of the data in simulating wealth accumulation. See the time series of excess realized return for groups of individuals and the riskfree rate in the appendix figure C.1.[16]

Table 6 shows the results on inferred values of *initial* wealth for the aforementioned cohort of individuals (at age 25, year 1976) using the model and compares them with the targeted wealth (at age 50, year 2001) in the data. While the model provides implications for the evolution of *total* wealth $(W+H+G)$ over time, we also separately demonstrate tangible wealth (W), human capital (G), and the present value of gifts and inheritance (G) in the data as well, to show the relevance of each component in total wealth across individuals of different wealth backgrounds.

To validate our inferred initial wealth, we compare the model fit for initial wealth for this cohort of individuals (i.e., at age 25, in 1976) with indirect proxies for the wealth of 25-year-old individuals from the data. Our proxy is the wealth of the cohort of 25-year individuals *in 2001*, as we observe in the data, "*de*-scaled" with indexes of economic outcome growth from 1976 to 2001. This validation is based on the assumption that wealth in early adulthood is the same across different cohorts of Swedish individuals, except that it grows at the same rate

[16]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.

as the aggregate economic outcomes over time. Overall, the model can reasonably replicate the observed accumulation of total wealth for the studied cohort of individuals from different wealth backgrounds, from age 25 to age 50 (from the year 1976 to 2001). In particular, the model can replicate the widening of the wealth gap from age 25 to age 50 across individuals of non-rich, rich, and very-rich families.

Table 6: Tangible Wealth (W), Human Capital (H), and Present Value of Gifts and Inheritance (G) over the Lifecycle, by Wealth Background in Data and Model

Panel A: Mean of W, H, and G at Age 25					
Wealth Background	Data				Model
	W	H	G	$W+H+G$	$W+H+G$
Non-rich	0.06	3.28	0.18	3.52	3.94
Rich	0.15	3.75	0.37	4.27	4.73
Very-rich	0.68	4.00	0.70	5.38	5.74
Panel B: Mean of W, H, and G at Age 50					
Wealth Background	Data				Model
	W	H	G	$W+H+G$	$W+H+G$
Non-rich	0.76	2.83	0.08	3.67	3.67
Rich	1.70	3.24	0.17	5.11	5.11
Very-rich	5.27	3.42	0.26	8.96	8.96

Note: This table presents the mean values of wealth (across 3 education and 12 sector groups for each wealth background group) in 2001 million SEKs for a cohort of individual groups from non-rich, rich, and very-rich backgrounds, who turn 50 in the year 2001. Model values of $W+H+G$ at age 25 are set such that the model fits data values of $W+H+G$ at age 50. To increase precision, data values in Panel B are measured by taking an average of individuals aged 46-54 in the year 2001. Data values of W, H, and G in Panel A (25 years individuals in the year 1976) are proxied by the mean values of W, H, and G for 25 to 28 years-old individuals in the year 2001, scaled by the change in the index of net personal wealth per capita (for W and G) and national income per capita (for H) in Sweden between 1976 and 2001 provided by World Inequality Database. All averages are weighted according to the population of each group.

Inherited Preferences and Wealth Mobility. Table 7 shows the counterfactual results for the wealth of 50-year-old individuals from different wealth backgrounds in year 2001, in case preferences were not depending on the background. In this exercise, we equalize preference parameters to the values of the non-rich group, within each education and business sector group. The gap in mean wealth in the data/benchmark model between very-rich and non-rich background individuals is 4.51 million SEK. This gap would shrink to 2.78 million

SEK, in case of the same risk aversion γ, and to 1.68 million, in case of the same patience ρ, and χ. Altogether, under the same preference parameters γ, ρ, and χ, the wealth gap would reduce by 70 percent — down to 1.29 million SEK. A similar pattern emerges regarding the wealth gap between individuals of rich and non-rich backgrounds: The existing gap would reduce from the benchmark level of .94 million SEK to .37 million SEK if there were no preference dependence on wealth background.

Notably, the impact of inherited preferences on the wealth gap in mid-adulthood ages is stronger (or about the same) than the impact of equalized initial endowments across individuals. See table 7, the last column. Under the same initial wealth (representing direct transfers from parents in early adulthood stages), human capital (present value of future income, influenced by the intergenerational transmission of human capital in the benchmark case), and direct inheritance and gifts from parents (during the lifetime, in present value terms, which is more for wealthier background groups), the accumulated wealth up to age 50 would reduce to 3.03 and 1.12 million SEK for the very-rich and rich background individuals, respectively, which are yet non-trivial and comparable (indeed more in the case of the very-rich background) to the value under the counterfactual of (unchanged) unequal initial wealth, but equalized risk aversion and patience. Finally, we highlight the complementarity between the two forces: a relatively small initial wealth gap across individuals of different backgrounds translates to a substantial wealth gap in mid-adulthood ages, due to aggressive wealth accumulation — further savings and investing in risky assets — by individuals of richer backgrounds.

In summary, we find that *more than two-thirds* of the wealth gap at age 50 between individuals of non-rich and very-rich backgrounds can be explained by the dependence of preferences (patience and risk-taking attitudes) on background — i.e., the "inherited" preferences. Importantly, the impact of preference heterogeneity on the wealth gap at age 50 is more than (or at least equals) the impact of the initial wealth gap at age 25, which represents direct transfers from parents early in life, transmission of human capital from parents, and expected inheritance and gifts, across non-rich and rich and very-rich background individuals.

Table 7: Counterfactual Results for Tangible Wealth (W) at Age 50 by Wealth Background

Wealth Background	Data	Model				
		Benchmark	Same γ	Same χ, ρ	Same γ, χ, ρ	Same $(W+H+G)_0$
Non-rich	0.76	0.76	0.76	0.76	0.76	0.76
Rich	1.70	1.70	1.63	1.10	1.13	1.12
Very-rich	5.27	5.27	3.54	2.44	2.05	3.03

Note: This table presents the results of counterfactual analyses for the wealth of the cohort of 50-year-old individuals in 2001 in million SEKs. Column 1 reports values in data, by taking an average over individuals aged 46-54 in the year 2001 to increase precision. Column 2 reports values in the model, which sets the initial wealth of this cohort (at age 25 in the year 1976), $(W+H+G)_0$, to fit data values at age 50 in the year 2001. Columns 3-6 report mean wealth in case preference parameters: risk aversion (γ), time discount rate (ρ), or bequest motives (χ), or the initial wealth: $(W+H+G)_0$ for all individual groups, are set to the corresponding values for the non-rich background groups. Parameters and initial wealth are collapsed across the wealth background dimension, at each level of education and group of business sector. Average wealth is calculated across 3 education levels and 12 sectors for each wealth background group, weighted according to the population of each group.

7 Extensions and Robustness

In this section, we introduce extensions to the original model and discuss the robustness of our key results. In particular, we discuss the role of heterogeneous attitudes toward alternative asset classes, non-homothetic preferences with habit, Epstein-Zin utility, risks to human capital (taking into account covariance, counter-cyclical variance, and cyclical skewness of the labor income with respect to the market return), and borrowing constraint in consumption smoothing and risky investment for younger adults. table 8 shows the summary of counterfactual results with alternative models in Columns (2-6) and compares them to the counterfactual results with the main model in Column (1). The values in the data/benchmark prediction of models are shown in Column (Data/Model, Benchmark). Overall, we achieve a robust result, that inherited preferences play a crucial role in explaining the wealth gap between individuals of different family backgrounds. In what follows, we briefly discuss the model extensions and alternative specifications; we postpone details to the Online Appendix.

Heterogeneous Asset Return Wedge. In the benchmark model, we only consider the financial gains of investment in alternative assets. However, individuals may enjoy non-pecuniary benefits per dollar of holdings in alternative risky assets, e.g., convenience yield regarding real estate, or entrepreneurship joy as a private business owner. Essentially, one may yet estimate risk aversion, using only the data on holdings in risky financial assets.

Table 8: Robustness of Counterfactual Results for Tangible Wealth (W) at Age 50

Wealth Background	Data/Model (Benchmark)	Panel A: Same γ					
		(1)	(2)	(3)	(4)	(5)	(6)
Non-rich	0.76	0.76	0.76	0.76	0.76	0.75	0.76
Rich	1.70	1.63	1.78	1.58	1.19	1.53	1.69
Very-rich	5.27	3.54	4.50	3.53	2.82	4.04	4.48
Wealth Background	Data/Model (Benchmark)	Panel B: Same γ, χ, ρ					
		(1)	(2)	(3)	(4)	(5)	(6)
Non-rich	0.76	0.76	0.76	0.76	0.76	0.75	0.76
Rich	1.70	1.13	1.24	1.21	1.00	1.05	1.18
Very-rich	5.27	2.05	2.70	2.37	1.92	2.51	2.54
Wealth Background	Data/Model (Benchmark)	Panel C: Same $(W+H+G)_0$					
		(1)	(2)	(3)	(4)	(5)	(6)
Non-rich	0.76	0.76	0.76	0.76	0.76	0.75	0.76
Rich	1.70	1.12	1.23	1.01	1.23	1.60	1.29
Very-rich	5.27	3.03	2.91	2.44	3.19	3.41	2.63

Note: This table presents the mean wealth of the groups of individuals for the cohort of 50-year-olds in 2001 in million SEKs, for three counterfactual scenarios in Panels (A) to (C) as described in table 7, and compares that with values in data/benchmark prediction of models. Alternative models are used in doing counterfactuals: Column (1) provides the counterfactual results for the main model as the reference point; Column (2) provides the results for the model with a non-pecuniary return regarding alternative asset classes; Column (3) provides the results for the model with habit formation; Column (4) provides the results for the model with Epstein-Zin utility; Column (5) provides the results for the model with risks to human capital; Column (6) provides results for the case with considering borrowing constraints in early adulthood stages.

We follow this approach in a robustness test. Specifically, in an extension of the model, we assume that, per dollar of investment in asset class a, the individual may get a non-pecuniary return rate of δ^a (positive or negative), which represents a wedge per dollar of investment, on top of the expected financial return μ^a. Importantly, we allow for μ^a to depend on wealth background, as well as education and sector, in a non-parametric way. This dependency, for example, captures the fact that the offspring of business-owner parents have more incentives to hold a private business, controlling for the same risk and return to the private business wealth. In contrast, as the reference asset, all individuals set a zero wedge for investing in risky financial assets (publicly traded stocks).

One can simply augment the optimal risky shares in the portfolio from the baseline model

to get $x_t^* = \frac{\Omega^{-1}\tilde{\mu}}{\gamma}(w_t+h_t+g_t)$, with $\tilde{\mu} := \mu+\delta$. We use the share invested in the financial risky assets (common stocks), which has a zero wedge by definition, to estimate the risk aversion γ for each group of individuals. As in the benchmark model, we match the consumption-wealth ratio moments in early and late adulthood stages, to estimate (im)patience (ρ, χ). Finally, we use shares invested in alternative asset classes, relative to the optimal level implied solely by the financial motives, to estimate the set of asset return wedges $\{\delta^a\}$. We run counterfactual analyses as with the main model, except that here we control for and fix the set of δ^as. Counterfactual results are provided in table 8, Column (2), and are compared to those of the main model in Column (1). We find that the estimated risk aversion is now less heterogeneous across wealth backgrounds, hence a counterfactual with the same γ 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 50% on the wealth gap between individuals of non-rich and very-rich backgrounds.

Non-Homothetic Preferences: The Case with Habit. Individuals of wealthier backgrounds may save more and take more risks since they may easily meet a base level of consumption out of their current wealth. Non-homothetic preferences by implying a decreasing relative risk aversion result in an increasing risky *shares* and lower consumption *ratios* with wealth, which would overestimate the gap in our risk-aversion and patience parameters. In an extension of the model, we incorporate habit, by assuming that individuals have CRRA utility over consumption *net* of an exogenous base consumption level $\bar{c}(t)$. One can show that the optimal consumption and risky investments are proportionate to the total wealth $w_t + h_t + g_t$ net of the habit liability, defined as $p_t = \int_t^T \bar{c}(\tau)e^{-r_f(\tau-t)}d\tau + \bar{w}(T)e^{-r_f(T-t)}$. Specifically, $c_t = a(t;\rho,\chi)(w_t + h_t + g_t - p_t)$, and $x_t = \frac{\Omega^{-1}\mu}{\gamma}(w_t + h_t + g_t - p_t)$, with the same $a(\cdot;\rho,\chi)$ as in the benchmark model. We set the base consumption $\bar{c}$ in the model directly from the variable capturing the concept of basic consumption[17] in the data, which is around 65,000 SEK in 2001 (35% of the median disposable income), and scale it year by year with average income per capita growth. Next, we build the habit liability p_t via discounting the stream of future base consumption levels. Finally, we estimate parameters γ, ρ, and χ, via adjusted moments of consumption (for old and young adults) and risky investment ratios, $c_t/(w_t + h_t + g_t - p_t)$ and $x_t/(w_t + h_t + g_t - p_t)$, measured at the group level in the data. Counterfactual analyses are done using the modified rules of savings and risk-taking with habit.

Results are provided in table 8, Column (3). As expected, the impact implied by gap in preferences is weaker but still comparable to the main model. Finally, it is worth mentioning

[17]The Swedish word 'baskonsumption', which is used to measure absolute poverty by Statistics Sweden.

that the initial wealth gap at any level (through parental financial support), combined with decreasing relative risk aversion, could also be considered part of the "inherited preferences" channel in a broader interpretation.

Epstein-Zin Utility. We assess the robustness of our results with the Epstein-Zin utility when the Elasticity of Intertemporal Substitution (EIS) is set equal to 1 — the average estimate by Calvet et al. (2021) for the same set of Swedish households, which allows us to have close-form solutions for optimal choices. We augment the standard Epstein-Zin utility specification to allow for arbitrary bequest motives (represented by χ) for individuals with a finite life span. Specifically, the consumption-wealth ratio follows $c_t/(w_t + h_t + g_t) = \frac{\rho}{1+(\chi\rho-1)e^{-\rho(T-t)}}$. In the special case with $\chi\rho = 1$, we get the standard result for infinitely lived individuals — that consumption-wealth ratio equals the time discount rate ρ independently of age. Regardless, unlike the baseline model, risk aversion γ does not enter the optimal consumption-wealth ratio. We use the set of moments as in the benchmark estimation to identify parameters of patience and risk aversion. Counterfactual results are achieved with wealth accumulation under the modified consumption-wealth ratios. See table 8, Column (4). The implication of heterogeneity in preferences for the wealth gap is stronger than in the baseline model.

Labor Income Risks. In the benchmark model, we ignore labor income risks in specifying the optimal portfolio choices of individuals. One may argue that the riskiness of human capital in the real world can explain smaller shares of investment in risky assets, in particular for individuals of non-rich backgrounds, who have a larger share of their lifetime wealth in the form of human capital. Ignoring risks to human capital then would result in the overestimation of the gap in risk aversion in the cross-section of individuals and in the impact of the inter-generational link in preferences for wealth accumulation.[18]

Following Campbell and Viceira (2002) the optimal risky share in total wealth with labor income risk can be written by $\mathbf{1}'x_t/(w_t + h_t + g_t) = \frac{\mathbf{1}'\Omega^{-1}\mu}{\gamma} - \omega_h\beta_h$, where $\omega_h := h_t/(w_t + h_t + g_t)$ is the share of human capital in total wealth and β_h is the covariance of return on human capital with the market return and determines the riskiness of human capital. One can approximate β_h up to the third order of fluctuations, using $\beta_h = \text{Cov}(\delta\bar{h}, r)/\sigma_r^2 + \omega_h\frac{\gamma}{2}\text{Cov}(-\Delta\text{Var}(\epsilon_h), r)/\sigma_r^2 + \omega_h^2\frac{\gamma(\gamma+1)}{6}\text{Cov}(\Delta\text{Skew}(\epsilon_h), r)/\sigma_r^2$ (as character-

[18]Labor income risks together with borrowing constraints also might induce significant precautionary savings in the real world, especially by individuals of non-rich background. This aspect is not featured in the benchmark model. As a result, the estimates of the time discount factor ρ for such individuals are biased downward. Consequently, the *gap* in ρ between non-rich and rich background groups is *under*estimated. We discuss the various implications of borrowing constraints separately in the next robustness check.

ized by Catherine et al., 2022b), where $\delta\bar{h}$ is the growth in average human capital and ϵ_h is the realized shock to the human capital growth; the three covariance terms represent the average income growth covariance, counter-cyclical variance, and cyclical skewness with respect to the market index, respectively. We use these covariance moments estimated directly from the data for each occupation and education group, as well as the data on risky investment shares (as in our benchmark specification), to estimate risk aversion γ via the modified rule for the optimal risky investment. We also estimate patience and bequest preferences from the consumption-wealth ratio moments as in the benchmark model and then re-run the counterfactual analyses. Results are provided in table 8, Column (5). Overall, the impact of inherited preferences versus the gap in initial wealth does not materially change from the results of the benchmark model.

Borrowing Constraints. In the benchmark model, individuals may freely borrow (against their human capital) to finance consumption and investments in risky assets. But indeed borrowing constraints, especially for individuals of non-rich backgrounds (with less financial wealth) and in the earlier adulthood stages, may prevent setting consumption and risky investment at the optimal level. To address concerns of mismeasuring preferences, in a robustness check, we estimate the main model by relying solely on moments constructed from individuals aged 35 and more in the data (together with the corresponding predictions from the model). Also, in simulating wealth accumulation, during ages 25-34 we cap risky investments by 1.5 times the available financial resources (wealth plus current year's labor income and gifts/inheritance from parents $w + y + z$) net of the desired consumption.[19] Counterfactual results of this modified specification are shown in table 8, Column (6). Compared with the benchmark, we find that differences in risk aversion γ across background groups have a diminished role in explaining the observed wealth gap at age 50 (Panel A). At the same time, patience parameters ρ, χ have a larger impact. Hence, the implication of preferences altogether for the wealth gap does not materially change from the baseline (Panel B).

Conceptually, the implication of borrowing constraints for our results is not trivial. On the one hand, borrowing constraints may lower the desired consumption early in life, which results 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 bench-

[19] In Sweden, individuals can take on a mortgage to finance the purchase of real estate, up to 85% of the asset value. Indeed individuals aged 25-34 in the data on average take a mortgage by nearly 80 percent of their *net* wealth value.

mark model will be biased in the opposite direction. This argument supports our finding that in the end abstracting from borrowing constraints would not change the implications of preferences altogether much. Lastly, we highlight that in our robustness test, the gap in initial endowments has a bigger role than in the benchmark model in explaining the wealth gap at age 50 (Panel C). Regardless, the impact of inherited preferences remains stronger than the gap in initial wealth for wealth accumulation up to age of 50.

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)	Period	$\mathbb{E}\left[R^e_{t,k}\right]$	$\sigma\left(R^e_{t,k}\right)$	$\text{SR}\left(R^e_{t,k}\right)$
(1)	(2)	(3)	(4)	(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:

$$\beta_j = \text{Var}(f_{FW,t})^{-1} \text{ Cov}(r^e_{j,t}, f_{FW,t}), \tag{12}$$

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

$$\beta_{i,FW,t} = \sum_{j=1}^{J_{FW}} \omega_{FW,i,j,t} \beta_j, \tag{13}$$

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:

$$\text{Var}^{\text{idio}}_{i,FW,t} = \omega'_{FW,i,t} \text{ Var}_{FW}(u_{j,t}) \ \omega_{FW,i,t}. \tag{14}$$

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:

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

and the idiosyncratic risk for investor i is:

$$\text{Var}^{\text{idio}}_{i,PE,t} = \sum_{j=1}^{J_{PE}} \omega_{PE,i,j,t} \ \text{Var}^{\text{idio}}_{PE,j}. \tag{16}$$

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. Indeed the nominal return on a real estate asset j after taxes is given by the following defining identity:

$$r^{at}_{j,t} \equiv pg_{j,t}(1-\tau_{RE}) + d_{j,t} - \delta_{j,t} - \kappa, \tag{17}$$

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:

$$d_t - \delta_t - \kappa \approx r^{\text{real}}_{f,t}(1-\tau_{RE}) \tag{18}$$

where $r^{\text{real}}_{f,t} = r_{f,t} - \pi_t$ 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 (18) 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 (18) 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).

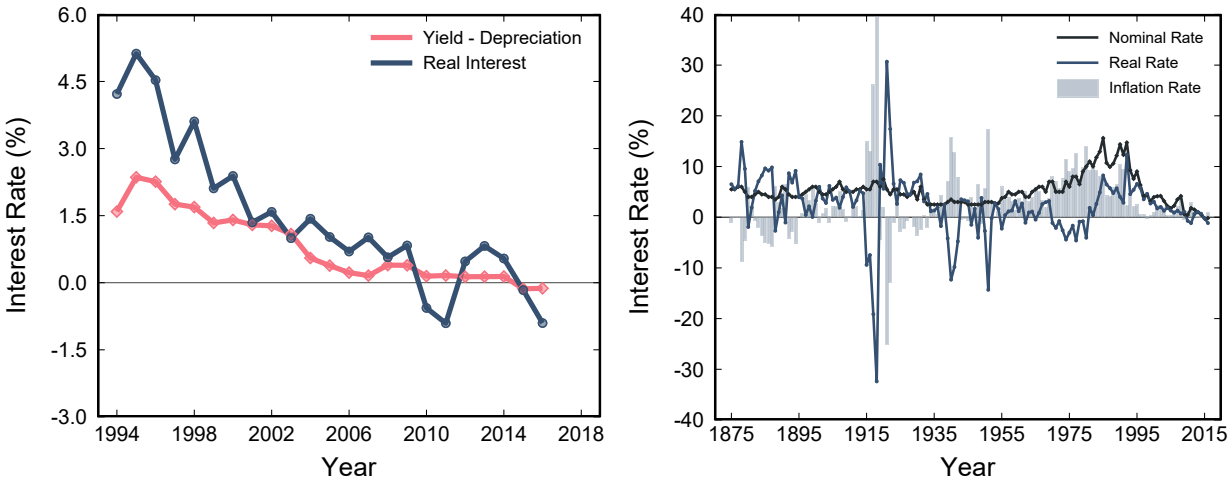
By plugging (18) in (17), we obtain that the excess return on real estate after taxes can be measured from the growth rate of real estate prices and the (nominal and real) risk-free rate:

$$r^e_t \equiv r^{at}_t - r_{f,t}(1-\tau) = \left(pg_t + r^{\text{real}}_{f,t}\right)(1-\tau_{RE}) - r_{f,t}(1-\tau) \tag{19}$$

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. $r_{f,t}^{\text{real}}(1-\tau_{\text{RE}})$ (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 (19) 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:

$$E\left[pg_{j,t}(1-\tau_{RE})-\pi_t\right]+d_{j,t}-\delta_{j,t}-\kappa=E\left[r_{f,t}(1-\tau)-\pi_t\right]+\Gamma, \tag{20}$$

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 (20) represents the indifference condition between renting and owning. Combining (17), (20) and rearranging, we obtain:

$$r_{j,t}^{e}=\left(pg_{j,t}+r_{f,t}^{\text{real}}\right)(1-\tau_{RE})-r_{f,t}(1-\tau)+\Gamma-\left[E(pg_{j,t}-\pi_t)\right](1-\tau_{RE})+\Lambda(\pi_t,r_{f,t}), \tag{21}$$

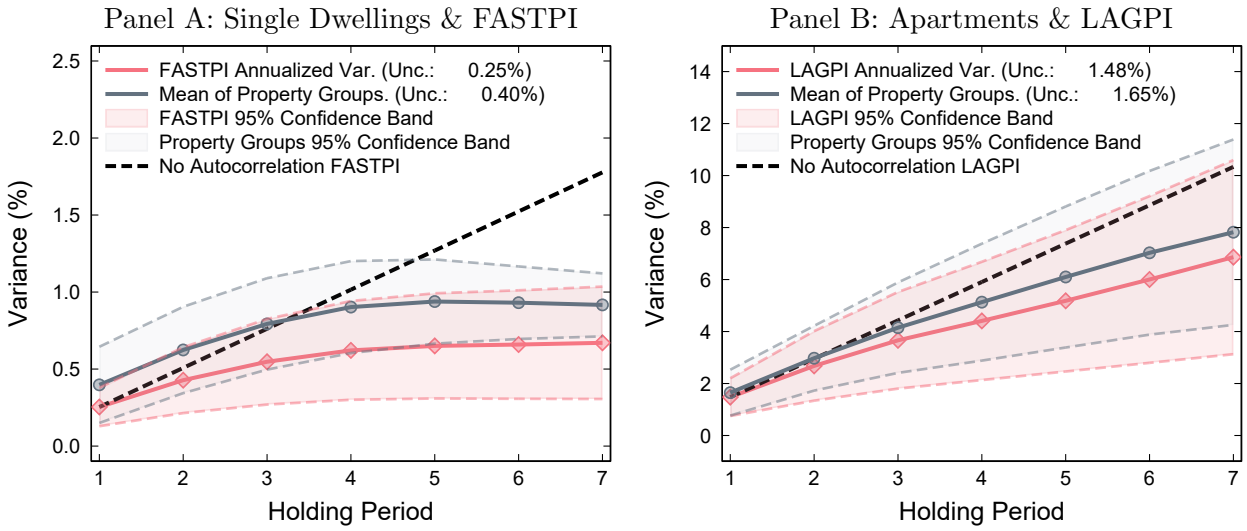
where $\Lambda(\pi_t,r_{f,t})\equiv\left[\pi_t-E(\pi_t)\right](1-\tau_{RE})+r_{f,t}(\tau_{RE}-\tau)$.

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 (19). Throughout the paper, we measure post-tax real estate excess returns for indexes and single properties using equation (19).

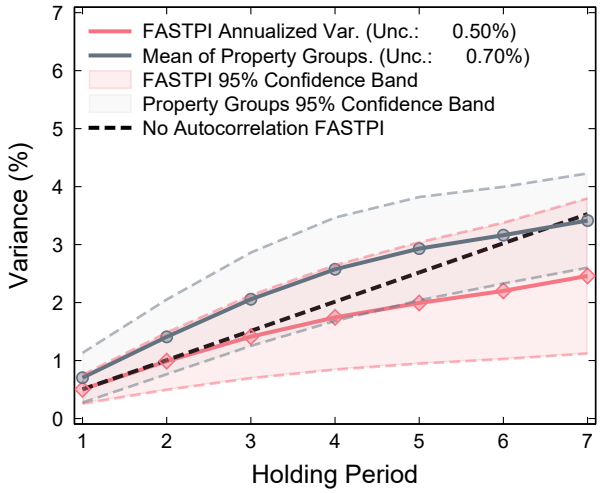
Real Estate Betas and Idiosyncratic Risk. In Figure A.2 we report the annualized sample variance of cumulative returns on the real estate market indexes over different holding periods. With stationary and i.i.d. real estate returns r_t^e, the variance of cumulative returns (reported in full lines) should 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 (19). 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 (19). 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 (19)) 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 (19) 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

		Expected Return and Volatility		
Factor (k)	Period	$\mathbb{E}\left[R^e_{t,k}\right]$	$\sigma\left(R^e_{t,k}\right)$	$\mathrm{SR}\left(R^e_{t,k}\right)$
(1)	(2)	(3)	(4)	(5)
FASTPI	1984 - 2014	3.00%	7.10%	0.42
LAGPI	1991 - 2014	5.25%	12.15%	0.43

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 535 groups gr of properties. The beta β_j of a property j in the group $gr(j)$ is given by:

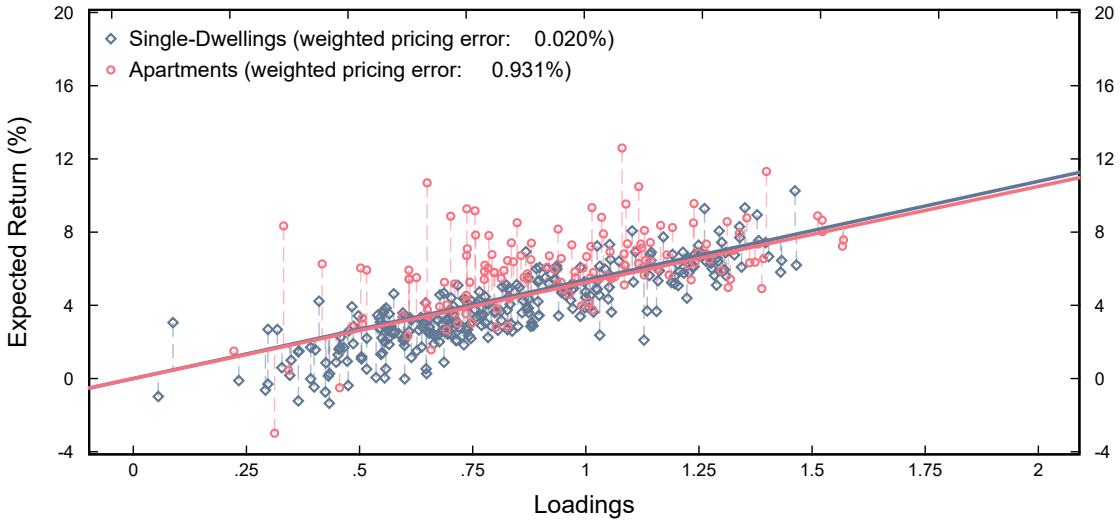
$$\beta_j = \frac{\mathrm{Cov}(r^e_{gr(j),t}, r^e_{RE,t})}{\mathrm{Var}(r^e_{RE,t})}. \tag{22}$$

where $r^e_{gr(j),t}$ is the excess return of the index of group $gr(j)$ 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 apartment on the FASTPI index is always zero and the loading of any other real estate asset on the LAGPI index is always zero.

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:

$$\beta_{i,RE,t} = \sum_{j=1}^{J_{RE}} \omega_{RE,i,j,t} \ \beta_j, \tag{23}$$

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

$$u_{j,t} = \varepsilon_{gr(j),t} + v_{j,t}. \tag{24}$$

We estimate the variance of the common shock, $\mathrm{Var}(\varepsilon_{gr(j),t})$, with the sample variance

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

of the residuals $r^e_{gr(j),t} - \beta_j r^e_{RE,t}$. 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:

$$R_{j,t_s,t_b} = \frac{P_{j,t_s}/\text{Index}_{t_s}}{P_{j,t_b}/\text{Index}_{t_b}}. \tag{25}$$

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:

$$r_{j,t_b,t_s} = a_j + b_j^{'} d_j + \xi_j. \tag{26}$$

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 gr, holding periods in years and purchase years t_b. We estimate the sample variance $\text{Var}(\xi_j)$ of the residuals in (26) within each group gr, year of sale t_s and holding period $t_s - t_b$. For all properties j in group $gr(j)$, 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 $gr(j)$.

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:

$$\text{Var}^{\text{idio}}_{i,RE,t} = \sum_j \omega_{RE,i,j,t} \left[\text{Var}(\varepsilon_{gr(j),t}) + \text{Var}(v_{j,t})\right]. \tag{27}$$

So far, we have focused on the systematic and idiosyncratic risk exposures of investors' real estate *assets*. To calculate the exposures of real estate *equity*, denote with $W_{RE,i,t}$ the

[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$[(t_s - t_b)/365]$.

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

$$r_{i,REE,t} = \frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} r^{at}_{i,RE,t} - \frac{M_{i,t}}{W_{RE,i,t} - M_{i,t}} i_{i,t}(1 - \tau_M). \tag{28}$$

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:

$$\beta_{i,REE,t} = \frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} \beta_{i,RE,t}. \tag{29}$$

and the idiosyncratic variance is:

$$\mathrm{Var}^{\mathrm{idio}}_{i,REE,t} = \left(\frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} \right)^2 \mathrm{Var}^{\mathrm{idio}}_{i,RE,t}. \tag{30}$$

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. (2022b) 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:

$$y_{it} - y_{it-1} = f(a_{it-1}, g_{it-1}) + \epsilon_{it}, \tag{31}$$

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 (32) provides the procedure implemented to obtain the present value of expected future earnings.

$$H_{it} = \sum_{k=0}^{Ti} s_{i,t+k} \frac{E[Y_{i,t+k}]}{(1+r)^k}, \tag{32}$$

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. (2022b) we discount future earnings at r=4.1%.

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

[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.

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.

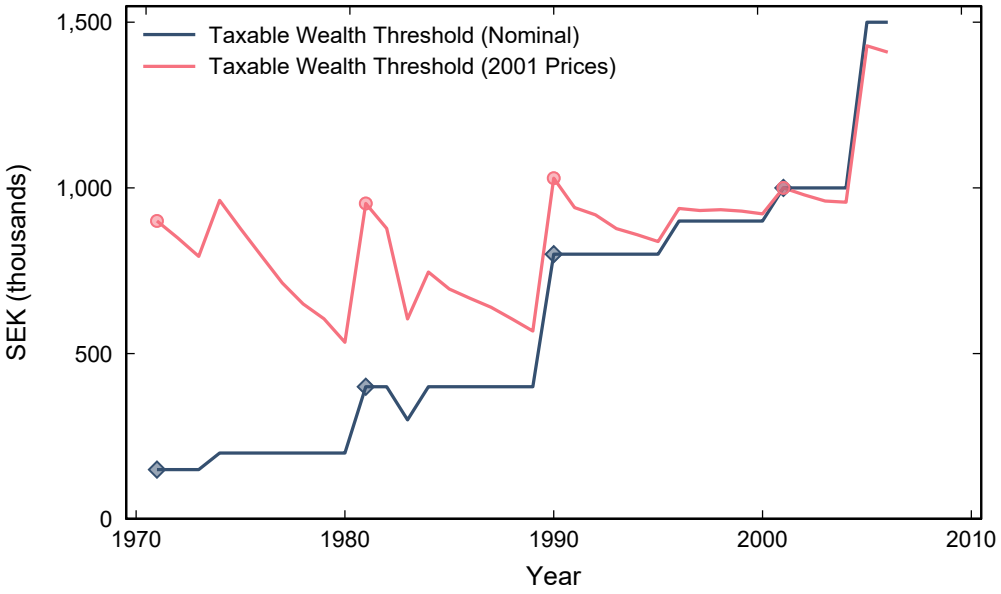
The wealth tax in Sweden was implemented using a progressive taxation structure and levied only above a certain threshold of taxable wealth. The tax was paid at individual level but calculated at the household level, excluding the individuals living with their parents aged at least 18 years old, who 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 background.

To construct the wealth background ranking, we divide the individuals in our sample

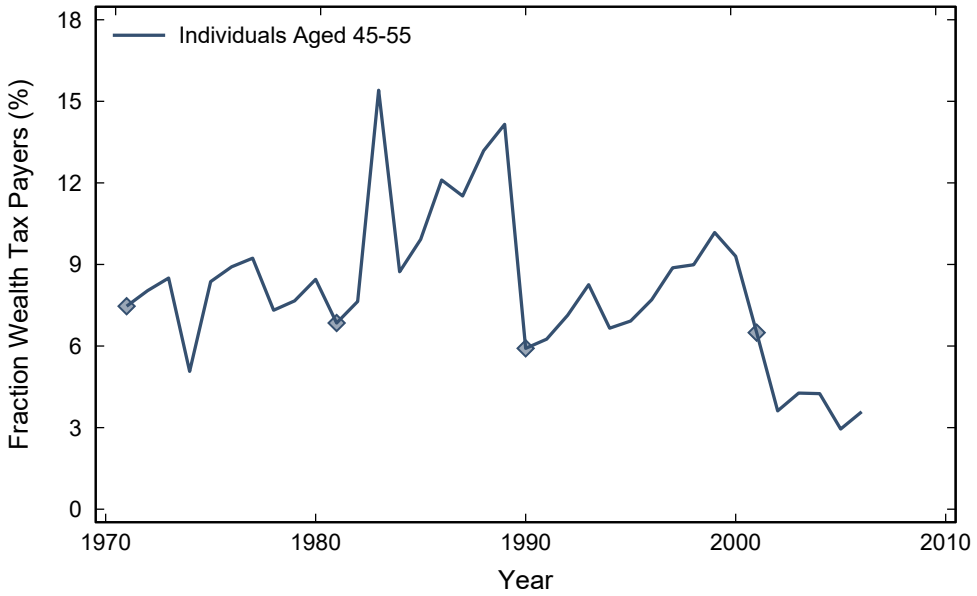
[9]Before 1992, shares of listed companies on the O-list were tax at 30% and after 1992, shares of listed companies on the O-list were tax-exempt. An additional exemption for major shareholders owning at least 25% of the company was introduced in 1998.

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.

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 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). And, 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 tthe 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	0.84	0.02	0.05	0.09	0.20	0.53	1.11	1.78	2.34	4.67
Rich	3.08	1.28	1.63	1.82	2.19	2.73	3.50	4.52	5.50	8.80
Very-rich	13.79	2.82	3.54	3.92	4.73	6.36	9.98	18.25	29.58	95.44
All	1.40	0.02	0.06	0.10	0.23	0.65	1.45	2.74	4.03	9.50

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	99.74%	0.26%	0.00%
P75-P90	72.81%	27.05%	0.14%
P90-P95	36.24%	57.64%	6.12%
P95-P97.5	28.46%	37.11%	34.43%
P97.5-P99	23.63%	19.32%	57.05%
Top 1%	17.69%	6.47%	75.84%

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:

$$\rho J = \max_{c,x} \ \frac{c^{1-\gamma}}{1-\gamma} + J_t + J_w \left[w r_f + x'\mu - c + y(t) + p(t) \right] + \frac{J_{ww}}{2} x'\Omega x \tag{33}$$

where $J(w,t)$ is the continuation value and J_t 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 optimal first-order conditions for x and c are achieved as

$$x^* = \frac{-J_w \Omega^{-1} \mu}{J_{ww}}, \tag{34}$$

$$c^{*-\gamma} = J_w. \tag{35}$$

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

$$J(w,t) = f(t)^\gamma \ \frac{[w + h(t) + g(t)]^{1-\gamma}}{1-\gamma}, \tag{36}$$

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

$$h(t) := \int_t^T e^{-r_f(\tau - t)} y(\tau) d\tau, \tag{37}$$

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

$$g(t) := \int_t^T e^{-r_f(\tau - t)} p(\tau) d\tau. \tag{38}$$

By substituting our guess into optimality equations (34) and (35) we obtain:

$$x^* = \frac{\Omega^{-1}\mu}{\gamma} [w(t) + h(t) + g(t)], \tag{39}$$

$$c^* = f(t)^{-1} [w(t) + h(t) + g(t)]. \tag{40}$$

Substitute back our guess and the optimal values c^* and x^* into the HJB equation (33) to

obtain:

$$\begin{aligned}\rho = \gamma f(t)^{-1} + \gamma\frac{\dot{f}(t)}{f(t)} \\ + (1-\gamma)\frac{\dot{h}(t)+\dot{g}(t)}{w+h(t)+g(t)} + (1-\gamma)\frac{y(t)+p(t)+r_f w}{w+h(t)+g(t)} \\ + \frac{(1-\gamma)\mu'\Omega^{-1}\mu}{2\gamma}.\end{aligned} \tag{41}$$

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:

$$y(t) - r_f h(t) + \dot{h}(t) = 0\ , \quad p(t) - r_f g(t) + \dot{g}(t) = 0, \tag{42}$$

which is the case using the definitions of $h(t)$ and $g(t)$ in equations (37) and (38). Hence, the conjecture for J is verified.

Finally, the ordinary differential equation (41), after deducting w, and $h(t)$ and $g(t)$ terms, simplifies to

$$\rho = \frac{\gamma}{f(t)} + \frac{\gamma\dot{f}(t)}{f(t)} + (1-\gamma)r_f + \frac{(1-\gamma)\mu'\Omega^{-1}\mu}{2\gamma}, \tag{43}$$

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

$$f(t) = \left(\chi - \frac{1}{\tilde{\rho}}\right) e^{-\tilde{\rho}(T-t)} + \frac{1}{\tilde{\rho}}, \tag{44}$$

where

$$\tilde{\rho} := (\rho - (1-\gamma)\tilde{r})/\gamma, \quad \tilde{r} := r_f + \frac{\mu'\Omega^{-1}\mu}{2\gamma}.$$

Substitute back for $f(t)$ in the optimal consumption-wealth ratio in equation (40) to derive

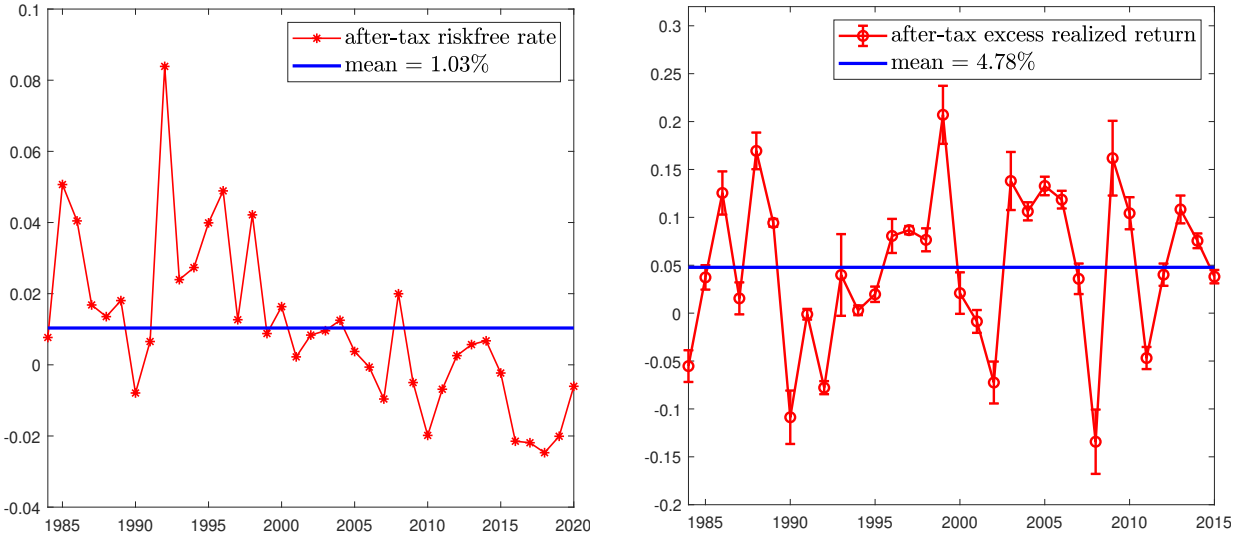
$$c^*(t) = \frac{\tilde{\rho}}{1 + (\chi\tilde{\rho} - 1)e^{-\tilde{\rho}(T-t)}}[w(t) + h(t) + g(t)]. \tag{45}$$

The risky investment is also verified to follow

$$x^* = \frac{\Omega^{-1}\mu}{\gamma}[w(t) + h(t) + g(t)]. \tag{46}$$

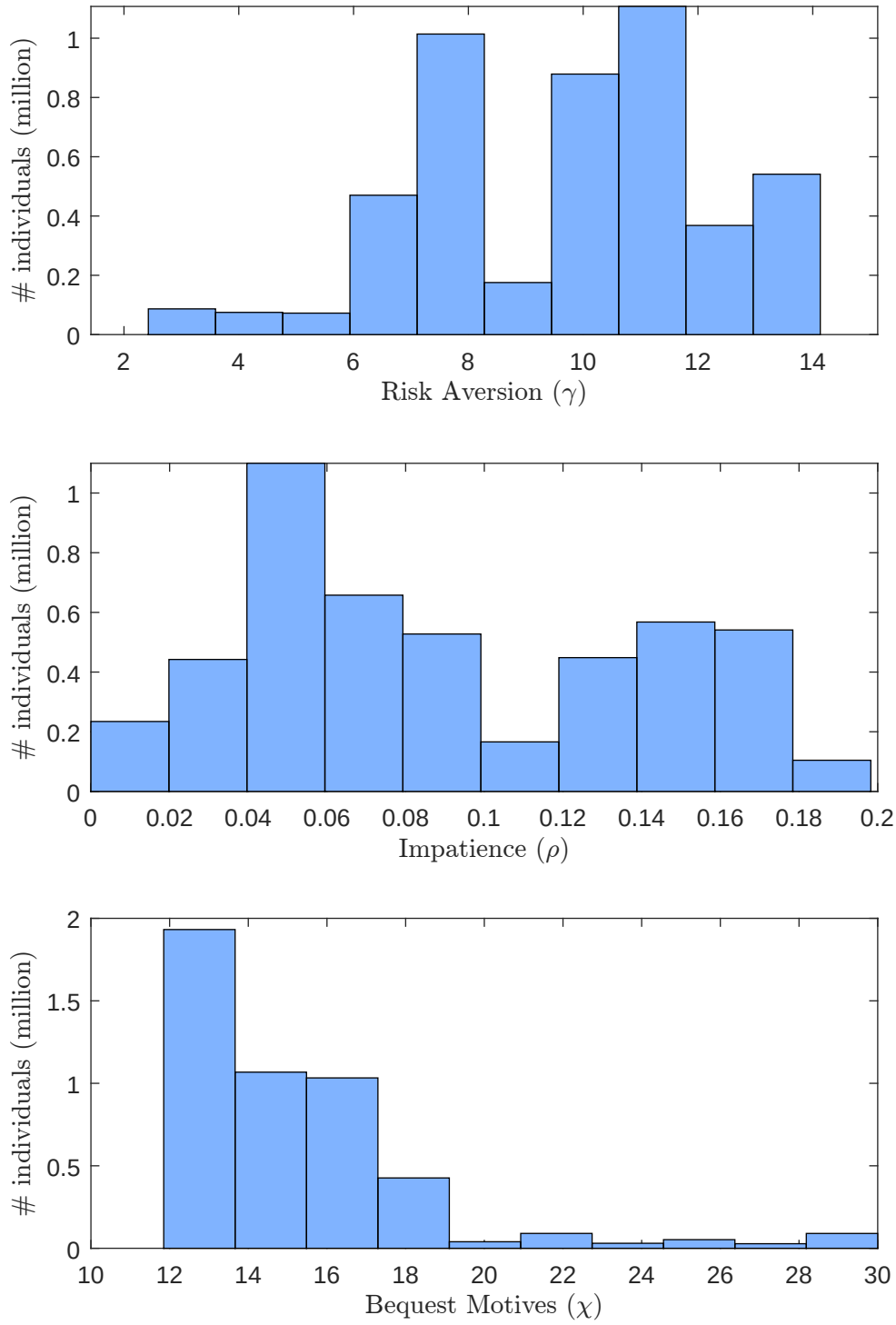
C Supplementary Tables and Figures

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



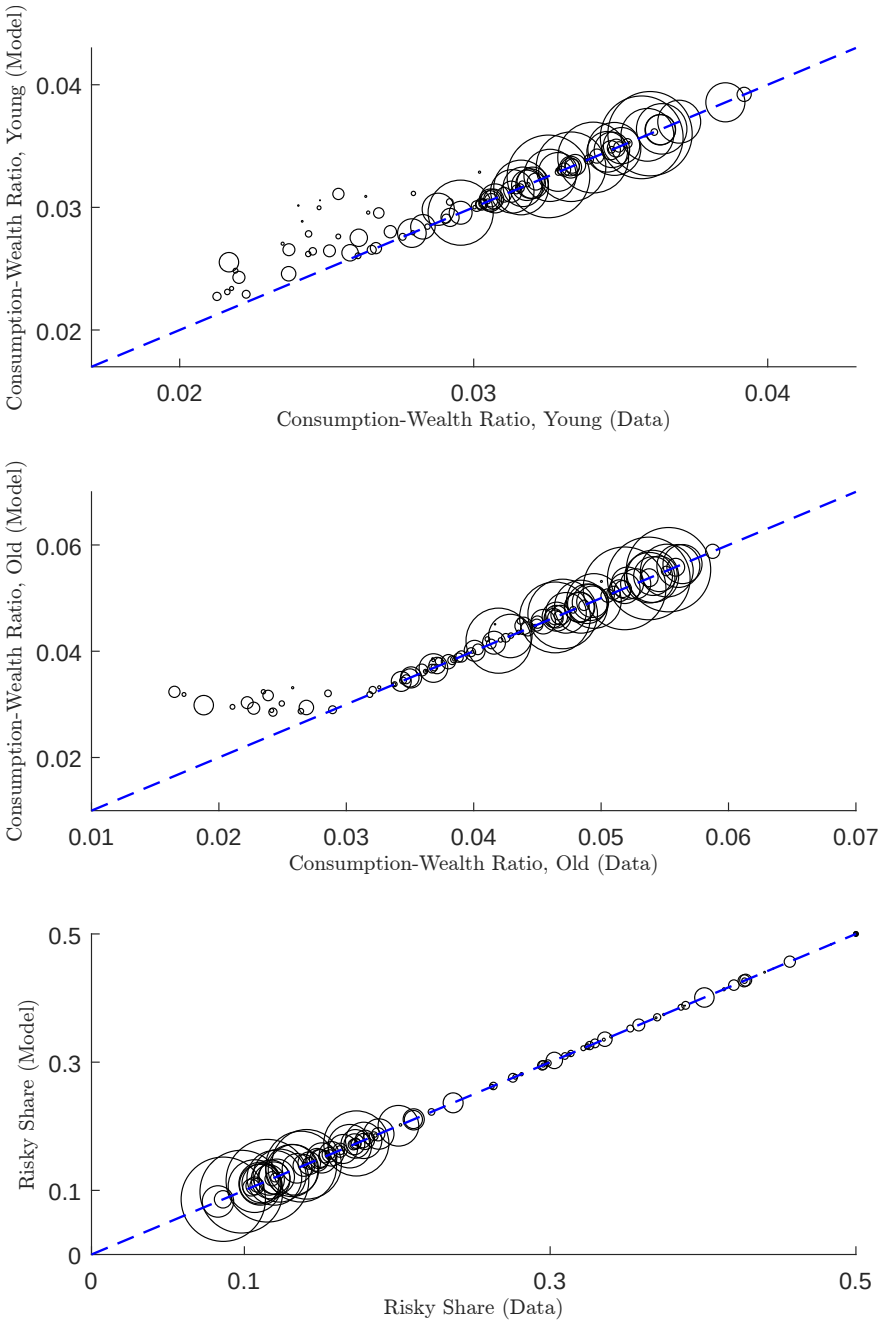
Note: This plot shows the riskfree rate (left Panel) and the estimate of average excess realized return on risky assets for groups of individuals (right Panel) using the history of available data. To measure the average excess realized return, for each group of individuals we measure the average exposure 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).

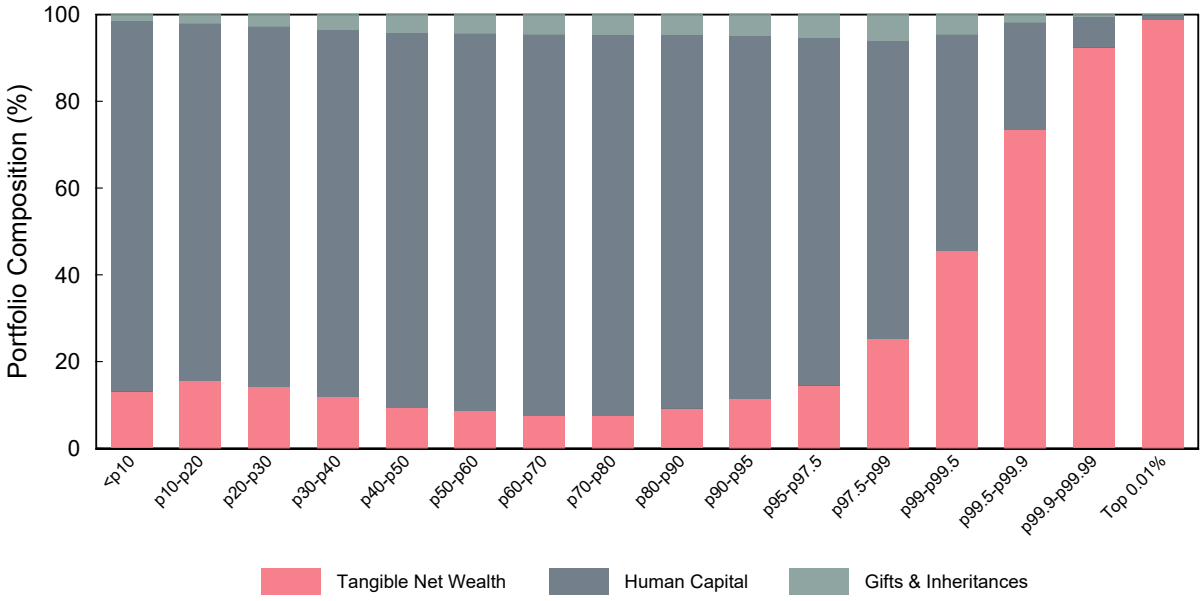
Figure C.3: Model Fit



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.

D Upcoming Tables and Figures

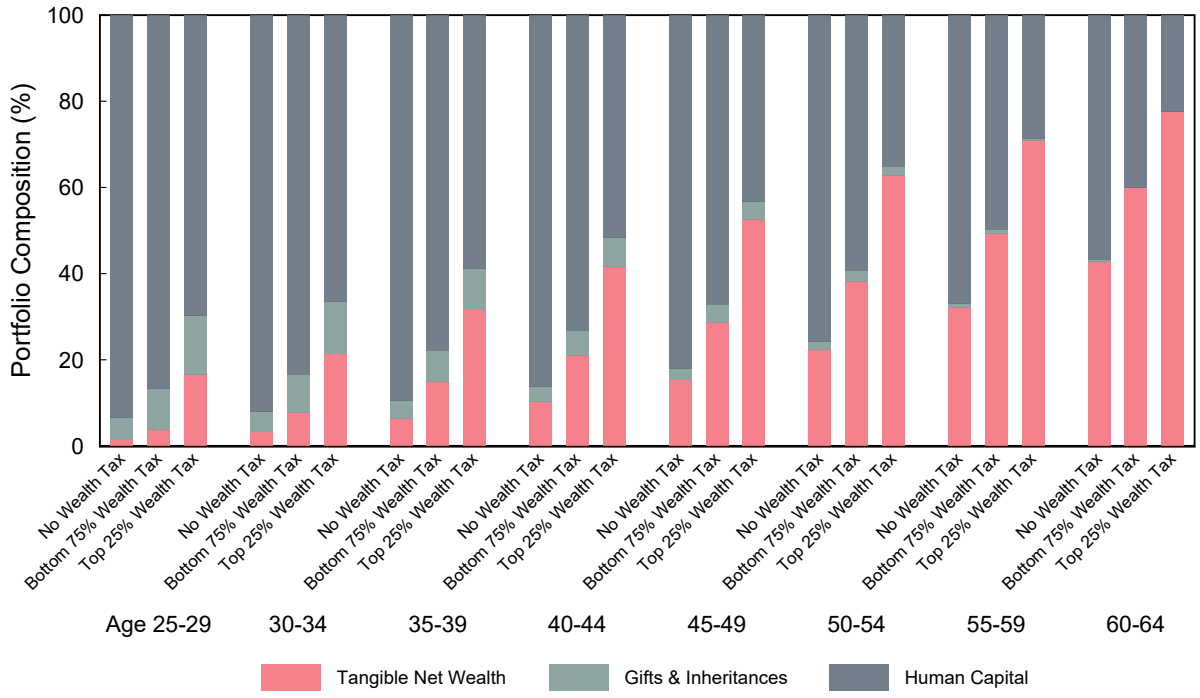
Figure D.1: Allocation of Total Net Wealth



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.

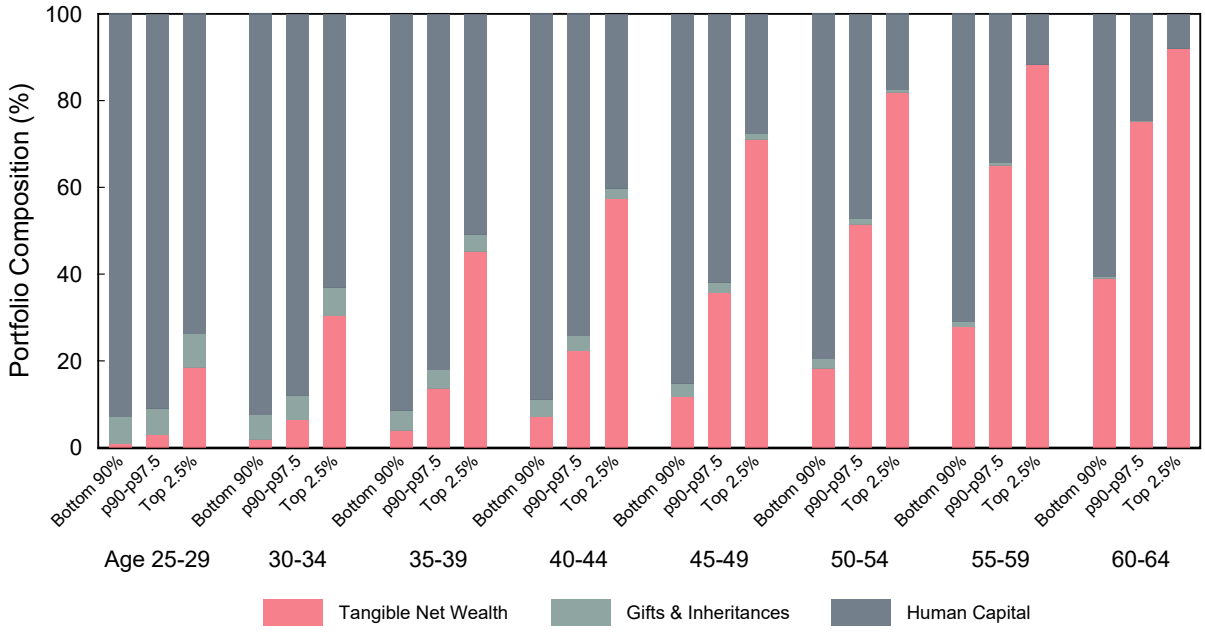
Figure D.2: Allocation of Total Net Wealth by Wealth Background and Age Bracket



	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



	Population Within Age Bracket by Total Net Wealth							
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).