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

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Abstract

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

Keywords: Household Finance, Wealth Mobility, Consumption, Savings, Risky Investment, Asset Allocation, Return Heterogeneity, Preferences

JEL Classifications: D14, D31, E21, G51, J62

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1 Introduction

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

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

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

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

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

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

On the contrary, any model of intergenerational transmission of wealth will need to incorporate the wealth accumulation decisions of children and, thus, the intergenerational association of children's deep preference parameters with parents' social status. Without such knowledge, it would be difficult to design effective policies that promote social mobility along the wealth distribution. To the best of our knowledge, the literature is silent on this issue, and this paper aims to fill this gap for the first time. A central challenge is to employ a model that realistically captures individual wealth accumulation decisions while maintaining sufficient clarity to trace how assumptions map into outcomes and to make the identification strategy transparent. To address this, we adopt a stepwise approach: we begin with a stylized model that lies at the intersection of the household finance and wealth inequality literatures, incorporating key insights from recent work on heterogeneous returns and portfolio choice. We then assess the robustness of our findings across a range of model extensions and alternative specifications.

Recent progress in understanding wealth inequality highlights the importance of risk tolerance and disposition towards investing in real asset classes (such as real estate and private businesses). First, following up on the seminal work of Quadrini (1999), and Cagetti and De Nardi (2006) and Cagetti and De Nardi (2009), the most recent models of wealth inequality emphasize the importance of heterogeneous returns to wealth across the population (see Benhabib and Bisin (2018) for a theoretical review, and Hubmer, Krusell and Smith Jr (2021) for a quantitative calibration). Access to detailed and comprehensive wealth data in Scandinavian countries has empirically confirmed that wealthier households earn persistently higher expected returns on their net wealth and that, at the same time, they hold substantial idiosyncratic risk in their holdings (Bach, Calvet and Sodini, 2020b; Fagereng, Guiso, Malacrino and Pistaferri, 2020). Additionally, it is the variation in returns to wealth across the wealth distribution that matters the most for the dynamics of wealth inequality, rather than the heterogeneity in active wealth accumulation behavior (Bach, Calvet and Sodini, 2017). Overall, the heterogeneity in investment risk-taking and asset allocation seems a crucial ingredient in explaining the degree of wealth inequality and its evolution over time.[3] Yet, we do not have any study of how wealth accumulation behavior transmits across generations.

Second, the latest empirical studies on the intergenerational elasticity of wealth under-

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

[3] Azzalini, Kondziella and Rácz (2025) show that an economy with two types of agents with different preferences and attitudes towards idiosyncratic risk can generate a wealth distribution close to the one observed in the data.

score the importance of family background beyond the direct impact of inheritances and gifts. Black, Devereux, Landaud and Salvanes (2023) and Black, Devereux, Landaud and Salvanes (2022) document that gifts and inheritances are a small share of total lifetime resources. Their importance becomes more pronounced for the top 1% wealthiest individuals, particularly as a source of capital income. Black, Devereux, Lundborg and Majlesi (2020) and Fagereng et al. (2021) find that the intergenerational correlation of wealth is primarily driven by environmental, rather than genetic factors, even prior to inheritance receipt. Furthermore, nurture plays a key role in shaping offspring's approaches to saving and investment decisions, with important implications for the dynamics of wealth inequality. Nekoei and Seim (2023) find that investment choices are crucial in explaining how inheritances impact wealth inequality. While bequeathed wealth initially mitigates inequality by primarily flowing from richer parents to poorer children, in the long term, wealthy heirs' capacity to generate higher returns leads to a net increase in the share of aggregate wealth held by the top of the distribution. In conclusion, gifts and inheritances appear to constitute a modest component of total lifetime resources, and their impact on the evolution of inequality seems to depend on how they are managed by the offspring.

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

We employ a structural approach to estimate how the deep preference parameters that govern individual wealth accumulation vary with family background. We consider a canonical model of consumption, saving, and portfolio choice in continuous time that extends Benhabib, Bisin and Zhu (2011) to explicitly consider endogenous risk-taking and portfolio allocation decisions. Each individual in our model consumes, saves, and makes risky investments according to her time preference rate and risk aversion. Individuals also have warm-glow bequest preferences and can leave bequests to their offspring. Wealth accumulation is thus endogenous, first due to active saving decisions, the pace at which wealth is saved (or consumed) relative to the inflow of labor earnings, and second due to wealth allocation decisions. Indeed, in addition to the risk-free asset, individuals may invest in multiple risky asset classes. In each class, they may face distinct exposures to both systematic and idiosyncratic risk. As a result, the expected return on wealth varies across individuals for three reasons. First, individuals can have different systematic risk exposures within each

asset class. Second, they endogenously allocate the risky portion of their portfolios across these classes, taking into account the idiosyncratic risks they face. Third, they choose how much of their wealth to allocate to risky versus risk-free assets.

We classify individuals in groups depending on their education levels, business sectors, and family wealth backgrounds. Labor income profiles are heterogeneous with level and growth rates that vary across groups. The variation in income prospects across family wealth backgrounds captures investment in human capital by parents (Becker and Tomes, 1986). We distinguish between non-rich, rich, and very-rich parents depending on their level of wealth when their children were in their mid-twenties. We estimate the deep preference parameters of the model for each group of individuals, which allows us to estimate the dependence of preferences on family background while flexibly controlling for education and business sectors as the covariates.

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

We combine data on Swedish resident individuals from two main sources: the Wealth, Income and Demographic Registers and the Flergeneration Register, both maintained by Statistics Sweden (SCB). We limit the study to the 1999-2007 period when detailed wealth data are available. We follow closely the cleaning and preparation of the wealth data in Bach et al. (2020b) and Bach, Girshina and Sodini (2022). Wealth is divided into four asset classes: riskless and risky financial assets, real estate equity, private business, and defined contribution pension. Net wealth subtracts liabilities other than mortgages from tangible wealth. The wealth register records ownership at the individual asset level, so that the return on asset classes can vary across individuals depending on the specific asset they hold in the asset classes. In order to assess income prospects at the household level, we use income and

demographic variables going back to 1983 and up to 2016. We follow Catherine, Sodini and Zhang (2024) in estimating income profiles over the life cycle and human capital.

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

Our paper has three key results. First, deep preference parameters are strongly influenced by individuals' wealth backgrounds. The average time discount factor in the population is about 11 percent, which is in line with the robust estimates in the existing literature (Catherine, Ebrahimian, Fereydounian, Sraer and Thesmar, 2022). However, individuals from very-rich backgrounds have a discount rate which is 8 percentage points lower (having controlled for education and business sector), resulting in a significant gap in saving rates. We further find that individuals of very-rich backgrounds have significantly stronger bequest motives, which contribute to less consumption and more savings in older ages. Finally, we find a substantial gap in risk aversion. Consistent with the life-cycle optimal portfolio literature (Cocco, Gomes and Maenhout, 2005), risk aversion is estimated at about 10 for the average individual. But, children from a very-rich background have a relative risk aversion of 5 units lower (within education level and business sector).

Second, we show that the documented heterogeneity in patience and risk tolerance, and their dependence on wealth backgrounds, crucially affect intergenerational wealth persistence. To do so, we simulate wealth accumulation from early-adulthood (age 25) to mid-adulthood (age 50) in counterfactual scenarios that consider uniform preferences across individuals of different family backgrounds. We find that the average wealth gap at the age of 50 between individuals of non-rich and very-rich backgrounds would shrink by at least a factor of four. It would reduce from the benchmark value of 4.5 million SEK to the counterfactual value of 0.5-1.2 million SEK (depending on specification). We find that up to half of this reduction can be explained by risk tolerance alone.[4]

Third, we find that the gap in initial wealth, human capital, and parents' direct wealth transfers is not a dominant force in explaining wealth inequality later in life for adults of

[4]The reduction in the gap from equalizing risk aversion is less if patience is already equalized, which reflects complementarities between risk tolerance and patience.

diverse wealth backgrounds. To show this result, we infer the initial endowment of 25-year-old individuals using the wealth accumulation rule of the model with heterogeneous preference parameter estimates. We then let the model simulate wealth accumulation over the lifecycle in the counterfactual scenario of no initial wealth gap and no heterogeneity in individual streams of labor income and intergenerational transfers (while maintaining the heterogeneous preferences estimated in the benchmark case). The wealth differential at the age of 50 between individuals of non-rich and very-rich backgrounds would shrink, but less than in the homogeneous preference case (from 4.5 to 2.6-3.7 million SEK, depending on specification). This result further confirms the first-order role of preferences in explaining intergenerational wealth mobility.

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

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 defines our measure of family background and reports facts on wealth mobility in Sweden. Section 4 lays out the benchmark model. Section 5 estimates the structural parameters of the model. Section 6 studies the counterfactuals. Section 7 reports the extensions of the benchmark model. 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,c,d,f), 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,[5] 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,

[5]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).

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).[6] 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 year 2000 onward.[7] 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, 2017c) going back to 1982 and up to 2015. All nominal variables in the datasets above are deflated by the Swedish consumer price index with base year 2001.

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.7, 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 eight years that we include by our analysis, with 64 being the retirement age in Sweden. Second, we do not include retirees, students, and workers from the agricultural sector. Furthermore, individuals are excluded if they have missing information in any of the datasets listed above. Our final sample includes 4,034,480 unique individuals and 27,830,392 observations over the 2000 to 2007 period.

[6] 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.

[7] 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.

2.2 Asset Classes and Portfolio Allocation

Net tangible 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. For liquid financial wealth, we measure the portfolio risky share by classifying bank accounts and Swedish money market funds as safe assets, and treating stocks and mutual funds as risky. All real estate equity is considered risky and is defined as real estate wealth minus mortgage debt.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 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.[8]

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.[9] Along the geographic dimension, we solve a max-p regions problem by clustering municipalities into

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

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

larger, contiguous regions requiring a minimum number of transactions per cluster.[10] Third, we compute the geometric mean of multipliers at the cluster-level. Finally, we value real estate properties in a given cluster by multiplying their tax value by 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 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 types of liabilities. However, we exploit the richness of our data,

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

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.[11] 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 others 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).

2.5 Risk and Returns

Estimating expected returns from historical data is challenging, as return series are volatile and often span relatively short and heterogeneous periods (Merton, 1980). To address this, we follow Calvet, Campbell and Sodini (2007) and Bach et al. (2020b) in modeling expected returns as a function of pricing factors. This framework allows us to estimate factor loadings from second moments, which can be reliably measured with high-frequency data. Expected returns then depend only on a small set of pricing factors, whose means can be estimated over long and consistent time horizons. A key advantage of this framework is that it reduces the complexity of robustness checks and counterfactual analyses, shrinking the parameter space from potentially thousands of variables to just a handful of factor means.

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 and procedures as well as 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

[11] 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.

with the factors. Since the methodology differs across asset classes, we report in sections A.2 and A.4 of the appendix how we progress from equation 1 to the estimation of the vector of factor loadings $\beta_{i,c,t}$ of asset class c for investor i. Equipped with these factor loadings, we can then estimate the expected return, systematic and idiosyncratic risk at asset class level for each individual i.

We evaluate the expected excess return of investor i on risky asset class c as:

$$E_t(r^e_{i,c,t+1}) = \beta_{i,c,t} E(f_{c,t}), \tag{2}$$

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.[12] The vector of expected excess returns of individual i at asset class level is then:

$$\mu_{i,t} \equiv \left(E_t(r^e_{i,1,t+1}), ..., E_t(r^e_{i,C,t+1})\right)'. \tag{3}$$

We measure the systematic risk as follows. Denote with $\text{Var}(f_t)$ the sample variance-covariance matrix of the excess returns of all the pricing factors.[13] 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.[14] The systematic variance-covariance matrix $\Omega^{\text{sys}}_{i,t}$ of individual i at asset class level is then:

$$\Omega^{\text{sys}}_{i,t} \equiv B'_{i,t} \ \text{Var}(f_t) \ B_{i,t}. \tag{4}$$

Since the measurement of idiosyncratic risk varies across asset classes; we report the methodology in the appendix sections A.2 and A.4. We assume that idiosyncratic risk is uncorrelated across asset classes so that the idiosyncratic variance-covariance matrix of investor i is a diagonal matrix:

$$\Omega^{\text{idio}}_{i,t} \equiv \text{diag}(\text{Var}^{\text{idio}}_{i,c,t}; c = 1, ..., C) \tag{5}$$

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 the asset class level is then given by:

$$\Omega_{i,t} \equiv \Omega^{\text{sys}}_{i,t} + \Omega^{\text{idio}}_{i,t}. \tag{6}$$

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

[13] 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.

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

2.6 Consumption, Gifts and Inheritances

We adopt the methodology of Sodini, Van Nieuwerburgh, Vestman and von Lilienfeld-Toal (2023) to impute consumption C_t as the difference between disposable income Y_t and how much individuals actively save S_t^{active} during each year:

$$C_t = Y_t - S_t^{\text{active}}.$$

The granularity of the Swedish data allows us to measure active savings at the level of each individual asset. Disposable income excludes contributions to occupational and state pension, while private pension savings are observed directly. Real estate transactions—including purchases and sales of houses and apartments—are also directly recorded. Property purchases are treated as positive active savings, while property sales reduce active savings. Sales and net purchases of private businesses are also observed directly over the year. For each financial asset, we observe the value of end-of-year holdings and impute active savings by subtracting the beginning-of-year holdings, revalued using end-of-year asset prices. This allows us to net out capital gains and isolate net purchases. Finally, we directly observe changes in total debt over the year.

Gifts and inheritances are inferred residually by comparing individuals' end-of-year net wealth to the level that would be expected based solely on active savings and capital returns. Specifically, we define passive transfers P_t as:

$$P_t = W_t - S_t^{\text{active}} - (1 + r_t)W_{t-1}, \tag{7}$$

where r_t is the return on net wealth. This residual captures unobserved wealth inflows such as inter vivos gifts and inheritances, which are not reflected in income or asset-level transactions.[15]

2.7 Human Capital and the Present Value of Gifts and Inheritance

Finally, we construct individual-level measures of human capital and the present value of received gifts and inheritances. Both labor income and inter-generational transfers, expressed in present value terms, contribute to an individual's total wealth and influence their optimal consumption and portfolio choices.

[15]By definition, this methodology abstracts from gifts and inheritances in the form of financial wealth. As they contribute to an individual's total wealth, omitting these financial gifts in the denominator of the consumption-wealth ratio and risky share moments will result in an under-estimate of patience parameters and an over-estimate of risk aversion for children of wealthier families.

To compute human capital—the present value of expected future labor income—we follow an approach similar to Catherine et al. (2024). 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 estimate income growth profiles over the working life by regressing annual changes in the log of real disposable income on a third-degree polynomial in age. We restrict the estimation sample to individuals aged 25 to 64 who are not students, retired, or working in the agricultural sector. Real disposable income is defined as the sum of all non-financial after-tax income sources, including social transfers, deflated using the 2001 CPI. We estimate separate Ordinary Least Squares (OLS) regressions for 36 distinct groups defined by the intersection of 12 industries and 3 education levels:

$$y_{it} - y_{it-1} = f(a_{it-1}, g_{it-1}) + \epsilon_{it}, \tag{8}$$

where $f(a, g)$ is a third-order polynomial in age a, estimated separately for each group g. The predicted income growth rates are then applied to group-specific current income to generate a projected path of expected future earnings until the age of 64 years old. Current income is defined 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. Accordingly, for each age and year, current income is calculated across 108 distinct groups (12 industries $\times$ 3 education levels $\times$ 3 wealth background categories). In this framework, the inter-generational transmission of human capital arises through three channels: differences in educational attainment, sorting into specific industries, and variation in current income levels—all of which are systematically related to parental wealth.

We follow Calvet, Campbell, Gomes and Sodini (2021) to compute the present value of future defined benefit state and occupational pension payouts. We calculate group-specific replacement ratios for each of the 36 industry$\times$education groups as the fraction of the average pension payouts of retired 65-year-old individuals to the disposable income of non-retired ones at 64 years old during the 1999 to 2007 period. We multiply this ratio by the expected disposable income of 64-year-old individuals and assume that individuals expect pension income to remain constant in real terms throughout retirement.

Human capital is the present value of expected future labor and retirement pension income:

$$H_{it} = \sum_{k=0}^{T_d,i} s_{i,t+k} \frac{E[Y_{i,t+k}]}{(1+r)^k}, \tag{9}$$

where $s_{i,t+k}$ is her survival probability up to year k and is read out of the life tables

provided by Statistics Sweden (2017b). $T_{d,i}$ denotes the number of years before worker i's end of life, which we assume to be the highest age available in the life tables. We choose the discount rate r=4.1% used in Calvet et al. (2021) and Catherine et al. (2024).

We adopt a similar approach to estimate the present value of gifts and inheritances. We first calculate the average amount of received gifts and inheritances for each wealth background and age during the period 2000-2007. We then fit a third-order polynomial in age on average transfers, conditioning on wealth background. We treat the fitted age profile as the expected transfers of received gifts and inheritances at any age, after scaling it by the average aggregate wealth growth index. We discount the expected transfers and adjust for survival probability using the same discount rate of r=4.1% to obtain the age profile of the present value of gifts and inheritances by wealth background.

2.8 Socio-economic Groups

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

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

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

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

We further divide the individuals in each wealth background group into 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.[16] In the end, 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 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 data available back to 1971. More specifically, we rank the parents of children who are 50-59 years old using the parents' taxable wealth in 1971. For children who are 40-49, we use parents' taxable wealth information in 1981. For children aged 30-39, we use parents' 1990 taxable wealth. For those who are 20-29, we use parents' taxable wealth in 2001, the same year we observe the children's age. By doing so, we ensure that wealth background is based on parents' wealth when children are in the early adulthood age of 20-30 years old—with parents being in their 50s.

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

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

respectively (see table 1).

Table 2 reports net wealth and position in the wealth distribution of children of different backgrounds when they reached the age of 46-54 years old in 2001, about the age of their parents when background was measured. Panel A shows a substantial average wealth gap of 4.49 million SEK between individuals of very-rich and non-rich backgrounds and a gap of 0.98 million SEK between those of rich and non-rich backgrounds. These gaps are sizable, compared to the average wealth of a non-rich background individual, which is 0.69 million SEK. The average wealth gap reflects a shift in the whole distribution of wealth across backgrounds: The 75th percentile of wealth among the non-rich background group (0.76 million SEK) is about the same as the 25th percentile of wealth among the very-rich group (0.70 million). Indeed, as Panel B shows, 71 percent of individuals from very-rich backgrounds belong to the top 25 wealth percentiles (three times the odds of those from

Table 2: Wealth versus Family Wealth Background

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

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

non-rich backgrounds), while only 7 percent fall into the bottom 25 percentiles (one-fourth less likely than the non-rich background group). Panel C further shows that individuals from very-rich backgrounds are 6, 10, and 20 times more likely to be placed into the top 10, top 5, and top 1 percent of wealth distribution, respectively, than those from a non-rich background.

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

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.[17]

4.1 Environment and Notation

Time t is continuous. The lifespan of each individual is denoted by $[0, T_d]$, where $t = 0$ corresponds to the beginning of adult life and T_d is the time of death. Individual i earns deterministic income $y_i(t)$ throughout the lifecycle, where $y_i(t)$ are labor earnings until retirement age T, and pension benefits afterwards. Income is exogenous and its dynamics vary across education and business sectors. We also allow income level to depend on family background to capture investment in children's human capital by parents. Besides income, individuals receive direct transfers, denoted by $p_i(t)$, in the form of inheritance and gifts from parents, which are also exogenous and depend on the background. Each individual is endowed with exogenous initial tangible wealth $w_i(0)$, which represents savings (net of debt) and direct transfers from parents accumulated by the beginning of adult life.

[17] 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.

Individuals optimally consume over the lifecycle and invest their savings 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 consumption by $c_i(t)$ and 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 thus depend also 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 r_f is the same for all individuals.

Each individual consumes, saves, and makes risky investments according to her time discount rate and risk aversion, ρ_i and γ_i. An individual also has a motive to leave bequest according to warm-glow preferences, which is controlled by the parameter χ_i. All preference parameters $(\rho_i, \gamma_i, \chi_i)$ depend on the individual's group, which importantly includes family wealth background (see section 2.8).

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:

$$\begin{aligned} \max_{\{c(\cdot),x(\cdot)\}} \mathbf{E}\left[\int_{t=0}^{T_d} e^{-\rho t}\cdot\frac{c(t)^{1-\gamma}}{1-\gamma} + e^{-\rho T_d}\cdot\chi^{\gamma}\,\frac{w(T_d)^{1-\gamma}}{1-\gamma}\right] \\ s.t. \quad dw(t) = \; w(t)r_f dt + x(t)'\mu dt + x(t)'\sqrt{\Omega}d\omega_t + y(t)dt + p(t)dt - c(t)dt, \end{aligned} \tag{10}$$

where $w(t)$ denotes wealth at time t, $dw(t)$ is the change in wealth at time t, and $d\omega_t$ represents the normalized vector of shocks to return on risky assets. Wealth accumulation is then endogenous, firstly due to the endogenous risky investment share, and secondly, due to the endogenous active saving rate—the pace at which wealth is consumed/saved relative to the inflow of earnings and transfers.

4.3 Optimal Consumption and Portfolio Choice

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

parents g:

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

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

$$c^*(t) = a(t; \rho, \chi)[w(t) + h(t) + g(t)], \tag{11}$$

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

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

with

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

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

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

$$x^*(t) = \frac{\Omega^{-1}\mu}{\gamma} \, [w(t) + h(t) + g(t)] \tag{12}$$

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

5 Estimation

The preference parameters of the model—time discount rate ρ, bequest motive χ, and risk aversion γ—are estimated with the Minimum Distance Method, which finds parameters to

match a set of targeted moments with their data counterparts. The model is just identified in our specification: The number of targeted moments equals the number of estimated parameters. We conduct a separate estimation for each socio-economic group (see section 2.8), ensuring that no parametric restrictions are imposed on the relationship between the model parameters and the socio-economic characteristics of each group. The following sections outline the identification strategy and present the estimated parameters.

5.1 Identification

We use the optimal consumption-wealth ratio (11) to estimate the time discount rate ρ and the bequest motive χ. We target the average consumption-wealth ratio in ***e***arly and ***l***ate adulthood:

$$\begin{aligned} \text{(mainly depends on } \rho) \leftarrow a_e &:= \int_{t=0}^{T/2} a(t;\rho,\chi)dt = \sum_{t=0}^{T/2} \frac{c_t^*}{w_t + h_t + g_t} \\ \text{(depends both on } \rho,\chi) \leftarrow a_l &:= \int_{t=T/2}^{T} a(t;\rho,\chi)dt = \sum_{t=T/2}^{T} \frac{c_t^*}{w_t + h_t + g_t} \end{aligned} \tag{13}$$

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 it depends both on the time discount rate as well as the motive to leave bequests 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 rely on the optimal investment in risky asset classes (12) and estimate γ by targeting the share of risky investments in the data:

$$x_t^* \;=\; [w_t + h_t + g_t]\frac{\Omega^{-1}\mu}{\gamma} \;\Rightarrow\; \gamma = (\mathbf{1}'\Omega^{-1}\mu) \;/\; \left(\sum_t \frac{\mathbf{1}'x_t^*}{w_t + h_t + g_t}\right) \tag{14}$$

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

5.2 Data Moments

We aggregate individual-level information up to the group level to build the counterparts of the targeted moments in the data. We construct consumption $\bar{c}_{m,t,\tau}$, tangible wealth $\bar{w}_{m,t,\tau}$,

human capital $\bar{h}_{m,t,\tau}$ and the present value of gifts and inheritance $\bar{g}_{m,t,\tau}$ for each group, by taking the sum of the corresponding individual level variables for a given age t and group m in year τ. Overhead bars denote *group*-level variables.

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

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

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

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

We set the risk-free rate r_f at 1% for all groups, which is approximately equal to the sample mean value from 1984 to 2020 in Sweden. In order to map the targeted moments to the data, we also need to construct the asset return statistics $\mu'\Omega^{-1}\mu$ and $\mathbf{1}'\Omega^{-1}\mu$ at the group level, where μ is the vector of asset classes' expected excess return, and Ω is the variance-covariance matrix of asset classes' excess returns. $\mu'\Omega^{-1}\mu$ determines the effective return rate $\tilde{r} := r_f + (\mu'\Omega^{-1}\mu)/(2\gamma)$ in equation (13), 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 (14). Note that both μ and Ω vary across individuals and groups.

To construct $\bar{\mu}$, the vector of expected excess returns at the group level, we take the weighted average of individuals' expected return vectors, with weights equal to the risky positions of each individual in a given asset class and in a given year. For example, to calculate the expected excess return $\bar{\mu}^c$ of a group of individuals for asset class c, we use the relative risky position of each individual in the group $x^c/\bar{x}^c$ in asset class c as weights. The tricky part is to build $\bar{\Omega}$, the variance-covariance matrix of returns at the group level. Pooling the portfolios of individuals before estimating the variance of returns would eliminate

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

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

5.3 Parameter Estimates

Table 4 reports summary statistics of the estimated preference parameters across all population groups, and appendix figure C.2 reports the corresponding histograms. Note that, in our estimation procedure, we require the time discount rate ρ and bequest motive parameter χ to be non-negative. We obtain corner estimates of $\rho = 0$ for less than 5% of the population. Interestingly, χ is estimated to be zero for the majority of the population—the non-rich, but not rich and very-rich background individuals. Overall appendix figure C.3 verifies that the model provides a satisfactory fit to the targeted moments in the data.

The median value of relative risk aversion γ is 10.01, which is in line with the levels chosen in calibrated models of optimal portfolio choice over the life-cycle (Cocco et al., 2005). The median time discount rate ρ is 0.117, implying a subjective time discount factor of 0.890. The estimates of γ and ρ are of the same order of magnitude as Calvet et al. (2021), who 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. (2022) for a representative US household (using the Survey of Consumer

Table 3: Data Moments

Panel A: Risky Investment Share										
Wealth Background	#(1,000)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	3,658	0.149	0.033	0.096	0.104	0.129	0.138	0.174	0.194	0.221
Rich	282	0.250	0.038	0.183	0.210	0.214	0.255	0.284	0.311	0.311
Very-rich	94	0.409	0.068	0.267	0.335	0.341	0.420	0.479	0.483	0.498
All	4,034	0.162	0.058	0.096	0.104	0.132	0.144	0.177	0.220	0.498
Panel B: Consumption to Total Wealth Ratio for Young People										
Wealth Background	#(1,000)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	3,658	0.033	0.002	0.026	0.031	0.032	0.033	0.035	0.035	0.037
Rich	282	0.028	0.002	0.021	0.026	0.027	0.028	0.029	0.031	0.033
Very-rich	94	0.021	0.002	0.017	0.019	0.019	0.021	0.022	0.024	0.032
All	4,034	0.032	0.003	0.017	0.029	0.031	0.032	0.035	0.035	0.037
Panel C: Consumption to Total Wealth Ratio for Old People										
Wealth Background	#(1,000)	mean	std	min	p10	p25	p50	p75	p90	max
Non-rich	3,658	0.051	0.004	0.044	0.047	0.048	0.052	0.054	0.056	0.059
Rich	282	0.041	0.004	0.033	0.035	0.037	0.041	0.046	0.046	0.051
Very-rich	94	0.028	0.007	0.016	0.021	0.022	0.028	0.037	0.037	0.048
All	4,034	0.050	0.006	0.016	0.044	0.048	0.052	0.054	0.056	0.059

Note: The table reports summary statistics of risky investment share in Panel A and consumption to wealth ratio by wealth background groups in Panels B and C. In Panel B, we consider individuals aged 25 to 44 years old, and 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.

Finance). We find that the median value of the bequest motive parameter χ is 0 and that $\tilde{\chi} < \tilde{\rho}^{-1}$ for almost all groups, implying that individuals consume more aggressively when older. Finally, we note that the cross-sectional variation of the estimated time discount rates is more pronounced than the variation in risk aversion. The ratio of the interquartile range to the median of ρ is 82%, whereas it is 43% for γ.

In Table 5, we regress the estimated preference parameters on wealth background across socio-economic groups. The observations are weighted by group size, and we report regressions with and without controlling for the education and business sector. The overall finding

Table 4: Summary Statistics of Estimated Parameters

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

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

is that preferences vary strongly with wealth background. Even when we control for the education and business sector (column 4), 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 a non-rich background is estimated at 10.8, and it falls by 3.5 and 5.3 in absolute terms for individuals with rich and very-rich parents, respectively. The time discount rate ρ drops by 7.3 and 7.8 percentage points for individuals with rich and very-rich parents, respectively, relative to the base level of 11.9 percent for the average non-rich background individual. We also find that the bequest motives χ are relatively large for children of very-rich families, whereas they are almost zero for those of non-rich families. Finally, we find that the variation in wealth background across our groups explains by itself 16% of the variation in risk aversion and 17% of the variation in the rate of time preferences (see adjusted R^2 of 15.5% and 16.6% in column 1, respectively). The explanatory power is much higher for the bequest motive, with parents' wealth explaining two-thirds of the variation (adjusted R^2 of 65.4%).

The gap in preferences between individuals of non-rich, rich, and very-rich backgrounds remains remarkably stable once we control for education and business sector fixed effects. We find that these fixed effects account for a very large share of the variation in risk aversion and time discounting (the adjusted R^2 climbs from 15.5% and 16.6% to 93.4% and 86.9%, respectively). But, despite this explanatory power, their influence on the estimated effect of background on the two preference parameters remains limited. Education fixed effects slightly attenuate the estimated impact, which is expected, given that individuals from wealthier backgrounds tend to achieve higher levels of education. Educational attainment is correlated with human capital, which encourages risk-taking to the extent that human capital resembles a bond-like asset. Moreover, enrolling in higher education programs might require the patience to defer earnings later in life. Interestingly, as one would expect, education and

Table 5: Preference Parameters versus Wealth Background

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

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

business sector have limited explanatory power for the bequest motive. This parameter is mostly dependent on family background.

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 preferences that operates through the educational and business sector channels.

6 Counterfactual Results

Variations in patience parameters ρ and χ across individuals of different wealth backgrounds translate into substantial heterogeneity in saving attitudes, both in early adulthood and close to retirement. Differences in risk aversion γ, instead, imply substantial heterogeneity in portfolio risk-taking. Both higher saving rates and more aggressive risk-taking may 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 on wealth accumulation of the variation in preference parameters across family backgrounds.

We begin by deriving a closed-form expression for aggregate wealth accumulation at the socio-economic group level. Subsequently, we focus on the cohort that was 50 years old in 2001 and apply the rule backwards to 1976 to infer their (unobserved) wealth at age 25. To validate our approach, we compare the inferred wealth estimates with the actual wealth of the cohort aged 25 in 2001, deflated to 1976 values.

Equipped with initial wealth estimates, we simulate wealth accumulation forward under counterfactual scenarios in which preferences are assumed to be identical across individuals from different wealth backgrounds. We further examine scenarios in which initial wealth, as well as human capital and the present value of direct gifts and inheritance, are equalized across family backgrounds.

Overall, we find that preferences have a strong explanatory power for the wealth gap observed at age 50 across individuals of different wealth backgrounds. Heterogeneity in initial wealth, labor income, and inheritance is a second-order determinant of the wealth gap for senior adults.

6.1 Wealth Accumulation

We derive a closed-form representation of the evolution of *total* wealth $\bar{w}(t) + \bar{h}(t) + \bar{g}(t)$ for a given cohort of individuals within a specific socio-economic group in the model. Following

section 5.2, overhead bars denote group-level aggregated quantities, which are calculated as weighted means across the individuals of a given cohort in a given group.

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

$$d(\bar{w}(t) + \bar{h}(t) + \bar{g}(t)) = \underbrace{\left(r_f + \frac{\mathbf{1}'\bar{\Omega}^{-1}\bar{\mu}}{\gamma}(\bar{r}(t) - r_f) - a(t)\right)}_{\text{growth rate of total wealth } := gr_{tw}(t)}[\bar{w}(t) + \bar{h}(t) + \bar{g}(t)]dt. \tag{15}$$

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

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

6.2 Initial Wealth Gap

We use the model prediction for wealth accumulation at the group level to trace the evolution of total wealth back in time. Compounding the growth rate of total wealth gr_{tw} via equation (15) results in the following wealth dynamics in discrete time:

$$(\bar{w} + \bar{h} + \bar{g})_t = \left\{\prod_{s=1}^{t}[1 + gr_{tw}(s)]\right\}(\bar{w} + \bar{h} + \bar{g})_0, \tag{16}$$

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

In order to run counterfactual scenarios on wealth accumulation, we focus on the cohort of individuals who are 50 years old in 2001 and will refer to this cohort as the "old children"

cohort. We back out their wealth in 1976 (at age 25), using the wealth observed in our data in 2001 (at age 50), and the growth rates $gr_{tw}(\cdot)$ in equation (16). The wealth growth rates are calculated with the preference parameters estimated in section 5.3 and the corresponding model-implied optimal consumption-wealth ratio $a(\cdot)$ and risky share $\frac{\mathbf{1}'\bar{\Omega}^{-1}\bar{\mu}}{\gamma}$. We calibrate the realized excess return on risky investments $\bar{r}(t) - r_f$ using the average factor loadings of all individuals in each group, calculated over the period in which we have access to detailed individual wealth data (2000-2007). These loadings are then applied to the historical excess return realizations of the factors from 1977 to 2001. Appendix figure C.1 reports the time series of the realized excess return on risky wealth, averaged across socio-economic groups, and the historical evolution of the riskfree rate.

Panel A of Table 6 reports the estimated initial total wealth of the old children cohort (i.e., at age 25, in 1976) from the model. It also reports a validation exercise that uses the cohort of individuals who are 25 years old in 2001, referred to as the "young children" cohort, for whom we can directly compute their initial total wealth and its composition from the data. We make the wealth at age 25 of the two cohorts comparable by deflating the wealth components of the young children from 2001 to 1976. The real index of net personal wealth per capita in Sweden is used to deflate tangible wealth $\bar{w}$ and the present value of gifts and inheritance $\bar{g}$, while the real Swedish national income per capita is used for human capital $\bar{h}$. Both indices are taken from World Inequality Database (2023). Panel B shows the wealth quantities midlife for the old children cohort (i.e., at age 50, in 2001). By construction, the total wealth in the model tab matches the data.

Overall, the model-implied initial total wealth of the old cohort aligns closely with the deflated observed initial wealth of the young cohort. Children from wealthier families have higher initial wealth in all components, including human capital. Wealthier parents invest more in the human capital of their children, in line with the literature on the intergenerational correlation of income. By age 50, the wealth gap across wealth background groups becomes much wider, and differences in tangible wealth account for the majority of the gap, while disparities in human capital and the present value of inheritance and inter-vivos transfers play a comparatively smaller role. In the next section, we investigate the extent to which the growing gap in the tangible wealth across individuals of different wealth backgrounds is attributable to disparities in endowments versus differences in wealth accumulation behavior, as reflected by preferences in our context.

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

Panel A: Mean of $\overline{w}$, $\overline{h}$, and $\overline{g}$ at Age 25					
Wealth Background	Data/Young cohort				Model/Old cohort
	$\overline{w}$	$\overline{h}$	$\overline{g}$	$\overline{w}+\overline{h}+\overline{h}$	$\overline{w}+\overline{h}+\overline{g}$
Non-rich	0.03	3.33	0.17	3.54	3.74
Rich	0.14	3.77	0.38	4.30	4.05
– gap (% of Non-rich)	326	13	120	21	8
Very-rich	0.64	4.03	0.74	5.41	4.56
– gap (% of Non-rich)	1794	21	321	53	22

Panel B: Mean of $\overline{w}$, $\overline{h}$, and $\overline{g}$ at Age 50					
Wealth Background	Data/Old cohort				Model/Old cohort
	$\overline{w}$	$\overline{h}$	$\overline{g}$	$\overline{w}+\overline{h}+\overline{g}$	$\overline{w}+\overline{h}+\overline{g}$
Non-rich	0.69	2.83	0.08	3.60	3.60
Rich	1.67	3.16	0.15	4.99	4.99
– gap (% of Non-rich)	143	12	93	39	39
Very-rich	5.17	3.38	0.25	8.80	8.80
– gap (% of Non-rich)	654	19	221	145	145

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

6.3 Preferences and Wealth Mobility

In this section, we run counterfactual simulations to investigate how the wealth gap across wealth backgrounds is influenced by the variation in preferences and endowments. We explore counterfactual scenarios in which individuals accumulate wealth from the age of 25 to 50 under the assumption that either preferences or initial wealth and lifetime income are equalized across background groups. Throughout this section, we consider individuals from the old children cohort, who were 50 years old in 2001, and compare their wealth at 50 with how much they would have accumulated in the counterfactual scenarios. We run all counterfactuals with equalizing preferences or initial wealth across wealth backgrounds *within each* education level and business sector group, thus controlling for education and sector in assessing the role of background for the wealth gap across adults.

The first column of table 7 corresponds to the first column of table 6, Panel B, and reports the average tangible wealth accumulated by old children of different wealth backgrounds. The gap between individuals with very-rich and non-rich parents amounts to 4.48 million SEK, which is seven times the gap observed at age 25 in the 1976 cohort of young children. We now quantify the extent to which heterogeneity in patience and risk tolerance that regulate wealth accumulation behavior contributes to this wealth disparity over working lives.

The second column of table 7 reports how much the old children cohorts of non-rich, rich, and very-rich backgrounds would have accumulated in tangible wealth were risk aversion γ set equal to the non-rich group. The gap in tangible wealth at 50 years old between the children of non-rich and very-rich families would have shrunk to 2.34 million SEK. In other words, differences in risk attitudes alone are responsible for 48 percent of the wealth gap between individuals of non-rich and very-rich backgrounds at age 50. The third column shows that the gap in tangible wealth would narrow even further, by 77 percent, to 1.02 million, when individuals were equally patient in terms of time preferences ρ and bequest motive χ. Here, we highlight the complementarity between risk tolerance and patience in wealth accumulation: the reduction in the gap from equalizing patience (risk tolerance) would be less if risk tolerance (patience) were already equalized.[18] Therefore, the *reduction* in the wealth gap when equalizing *all* preference parameters is less than additive, but yet substantial as we report next.

Altogether, under the same preference parameters γ, ρ, and χ, the wealth gap would at age 50 decrease by 88 percent—down to 0.51 million SEK, or from the seven-fold difference

[18] If individuals of a richer background were investing in similarly risky assets to those of non-rich, an extra dollar of savings would have contributed less to wealth accumulation rate and resulted in a narrower wealth gap across background groups. Likewise, if they saved at the same rate, an extra dollar of risky investment would contribute to a lesser wealth gap over time.

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

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

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

relative to the gap at age 25 to about the same gap at age 25. This reduction highlights the substantial impact of the heterogeneity in wealth accumulation behavior, both in terms of saving rates and risk-taking, on the observed wealth disparities across family backgrounds. A comparable pattern emerges regarding the wealth gap between individuals with rich and non-rich parents. The existing gap would be almost entirely eliminated if preferences and wealth accumulation behavior were not dependent on wealth background.

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

wealth inequality. What is perhaps surprising is the larger quantitative impact of differential wealth accumulation behavior across family backgrounds.

In the following section, we consider a number of extensions and robustness checks to address the concern that the counterfactual results presented above may be specific to the stylized nature of our model.

7 Extensions and Robustness

In this section, we discuss the robustness of our key results by considering a number of extensions to our benchmark model. In particular, we discuss the role of (non-financial) attitudes towards alternative asset classes, decreasing relative risk aversion with non-homothetic preferences, Epstein-Zin utility, labor income risk, and borrowing constraints. The results are summarized in table 8, which has the same structure as table 7, but compares the counterfactual wealth accumulation in the benchmark model —Column (1)— with the one generated by the alternative models —Columns (2) – (7).[19] Overall, we confirm that preferences play a crucial role in explaining the wealth gap between adults of different family backgrounds, accounting for at least 74 percent of the gap among all specifications. In the following sections, we briefly present the results of the extensions to our benchmark model and refer the reader to the Online Appendix for the details.

7.1 Attitudes towards Alternative Asset Classes

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

[19] In appendix table C.1, we report the distribution of estimated preference parameters corresponding to each robustness check.

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

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

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

Counterfactual results are provided in Column (2) of table 8, where we control on estimated δs (thereby fixing the variation of δ in all its components across the family background, education, and business sector groups). Columns (1) and (2) of appendix table C.1 show that risk aversion is now less heterogeneous across wealth backgrounds, as part of the variation observed in the benchmark case stems from differences in the allocation of alternative assets. As a result, the counterfactual with homogeneous risk aversion γ across groups has a smaller impact on the wealth gap at age 50 between individuals from different backgrounds. In the end, however, the variation in all preference parameters has an impact of more than 75% on the wealth gap between individuals of non-rich and very-rich backgrounds.

7.2 Decreasing Relative Risk Aversion

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

In this section, we consider the class of DRRA models with non-homothetic preferences, considering that individuals need to consume a minimum of non-discretionary consumption or habit level, $c^m(t)$. Individuals have CRRA utility over consumption, $c(t)$, *net* of the habit level, $c^m(t)$. The optimal (net) consumption and risky investments are then proportionate to total wealth $w(t) + h(t) + g(t)$ *net* of the habit liability, denoted by l_t. In particular,

$$c(t) - c^m(t) = a(t; \rho, \chi)[w(t) + h(t) + g(t) - l(t)]$$
$$x(t) = \frac{\Omega^{-1}\mu}{\gamma}[w(t) + h(t) + g(t) - l(t)]$$

with the same function $a(\cdot; \rho, \chi)$ as in the baseline model (11). The habit liability, l_t, is the present value of the habit $c^m(\cdot)$ consumed during the rest of an individual's life:

$$l(t) = \int_t^{T_d} c^m(\tau) e^{-r_f(\tau - t)} d\tau.$$

We calibrate $c^m(\cdot)$ as the minimum required/non-discretionary consumption for individuals, defined and reported by Statistics Sweden ('Baskonsumption,' the Swedish concept of

basic consumption). We use the 2001 official value of 65,000 SEK and scale it for subsequent years in an individual's lifetime with the average growth of income per capita. Note that this basic consumption level is non-trivial, as the average consumption in 2001 is 161,000, 191,000, and 227,000 SEK for individuals of non-rich, rich, and very rich backgrounds.

Results are provided in table 8, Column (3). The counterfactual with homogeneous risk aversion yields weaker wealth accumulation implications than in the benchmark model, but similar in order of magnitude. The impact implied by the gap in all preference parameters γ, ρ, χ remains sizable and first-order, even though it is weaker than in the benchmark (CRRA) model. It accounts for 74 percent of the wealth gap between very-rich and non-rich backgrounds (compared to 88 percent in the benchmark model). Finally, when individuals of different backgrounds have the same initial endowment, the reduction in the wealth gap at middle age is stronger than in the benchmark model (41 percent versus 17 percent for the gap between very-rich and non-rich). In the end, we still find a larger role of preferences compared with endowment heterogeneity, as in the baseline model.

7.3 Epstein-Zin Utility

Under standard CRRA preferences, the elasticity of intertemporal substitution (EIS) is constrained to be the inverse of the coefficient of relative risk aversion. This implies that cross-sectional estimates of one parameter mechanically determine the other. This restriction is not empirically realistic, as individuals' attitudes toward risk and intertemporal substitution are conceptually distinct and may vary independently (e.g. Bansal and Yaron (2004)). Epstein-Zin preferences (Epstein and Zin, 1989) allow for decoupling risk aversion from intertemporal substitution but are notoriously difficult to estimate in the cross-section of individuals (Calvet et al., 2021).

To test the robustness of our results to Epstein-Zin preferences, we then consider the case where EIS is set to 1.[20] We also extend the standard Epstein-Zin utility specification for infinitely lived agents by considering individuals with a finite lifespan and a bequest motive parametrized by χ. More specifically, the value function solves the HJB equation: $\rho \log((1-\gamma)J) = \max_{c,x} \rho(1-\gamma)\log(c) + \mu_w J_w/J + \frac{1}{2}\sigma_w^2 J_{ww}/J + \dot{J}/J$, with the terminal condition $\log((1-\gamma)J)|_T = (1-\gamma)\rho\chi \log(w_T + h_T + g_T) + const$, where $\mu_w = wr_f + x'\mu - c + y$ and $\sigma_w^2 = x'\Omega x$ are the drift and volatility of wealth w.

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

[20] This value is in between the median of 0.7 and the mean of 2 estimated by Calvet et al. (2021) using the same sample of Swedish households.

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

7.4 Labor Income Risks

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

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

We re-estimate risk aversion by controlling for labor income risk in the portfolio choice for individuals of different groups. Campbell and Viceira (2002) characterize the optimal risky share in the presence of labor income risk as

$$\frac{\mathbf{1}'x(t)}{w(t)+h(t)+g(t)} = \frac{\mathbf{1}'\Omega^{-1}\mu}{\gamma} - \omega_h\beta_h,$$

where ω_h is the share of total wealth held in human capital and β_h is the covariance of the

return on human capital and the market return r. Catherine et al. (2024) approximate β_h up to the third order:

$$\beta_h = \frac{\text{Cov}(\delta\bar{h}, r)}{\sigma_r^2} + \omega_h \frac{\gamma}{2} \frac{\text{Cov}(-\Delta\text{Var}(\epsilon_h), r)}{\sigma_r^2} + \omega_h^2 \frac{\gamma(\gamma+1)}{6} \frac{\text{Cov}(\Delta\text{Skew}(\epsilon_h), r)}{\sigma_r^2}$$

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

Appendix table C.1, Column (5) shows that the estimated risk aversion with income risk is 6.73 for the non-rich background, which is close to the estimate of Catherine (2021) (with countercyclical variance and cyclical skewness) for US households. As expected, the estimated γ is less than the baseline value of 10.79 in Column (1), which ignores income risk. In all specifications, though, rich and very rich backgrounds feature lower risk aversions than non-rich backgrounds. Ultimately, counterfactual results in table 8, Column (5), show that heterogeneous preferences, controlling for labor income risk, explain a large part of the difference in wealth accumulated at middle age across wealth backgrounds: risk aversion explain 35 percent, and both risk aversion and patience parameters explain 81 percent of the gap between non-rich and very-rich background groups.

7.5 Borrowing Constraints

In the baseline model, individuals can freely borrow against their human capital to finance consumption and investment. However, in reality, they can instead face borrowing constraints. In this section, we consider the possibility that the preference parameters estimated with the baseline model might be biased due to borrowing constraints. Conceptually, the implications of borrowing constraints for our results are not trivial. On the one hand, individuals cannot borrow to smooth consumption over time and consume less when constraints are binding (typically for poorer individuals and early in life), which can potentially result in an *under*estimation of impatience (ρ) for individuals of non-rich backgrounds in the baseline

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 baseline model will be biased in the opposite direction.

In a robustness check, we re-estimate the model by relying solely on moments constructed from individuals older than 34 years old, who are less likely to face binding borrowing constraints. Wealth accumulation from 25 to 34 years old is simulated by capping risky investments to the available financial resources, defined as total net tangible wealth plus the current year's labor income and gifts/inheritance from parents, i.e., $w + y + p$, net of optimal consumption. In a further robustness check, we continue to rely on moments from individuals older than 34 years old to limit the impact of borrowing constraints, and we also consider labor income risk in the optimal portfolio choice, as we did in section 7.4.

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

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:

$$\beta_j = \text{Var}(f_{FW,t})^{-1} \text{ Cov}(r^e_{j,t}, f_{FW,t}), \tag{17}$$

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

$$\beta_{i,FW,t} = \sum_{j=1}^{J_{FW}} \omega_{FW,i,j,t} \beta_j, \tag{18}$$

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:

$$\text{Var}^{\text{idio}}_{i,FW,t} = \omega'_{FW,i,t} \text{ Var}_{FW}(u_{j,t}) \ \omega_{FW,i,t}. \tag{19}$$

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:

$$\beta_{i,PE,t} = \sum_{j=1}^{J_{PE}} \omega_{PE,i,j,t} \ \beta_j, \tag{20}$$

and the idiosyncratic risk for investor i is:

$$\text{Var}^{\text{idio}}_{i,PE,t} = \sum_{j=1}^{J_{PE}} \omega_{PE,i,j,t} \ \text{Var}^{\text{idio}}_{PE,j}. \tag{21}$$

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

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

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

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

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

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

A.3 Sources of Real Estate Asset Pricing Data

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

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

A.4 Return and Risk of Real Estate Equity

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

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

$$r^{at}_{j,t} \equiv pg_{j,t}(1-\tau_{RE}) + d_{j,t} - \delta_{j,t} - \kappa, \tag{22}$$

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:

$$d_t - \delta_t - \kappa \approx r^{\text{real}}_{f,t}(1-\tau_{RE}) \tag{23}$$

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 (23) 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 (23) 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).

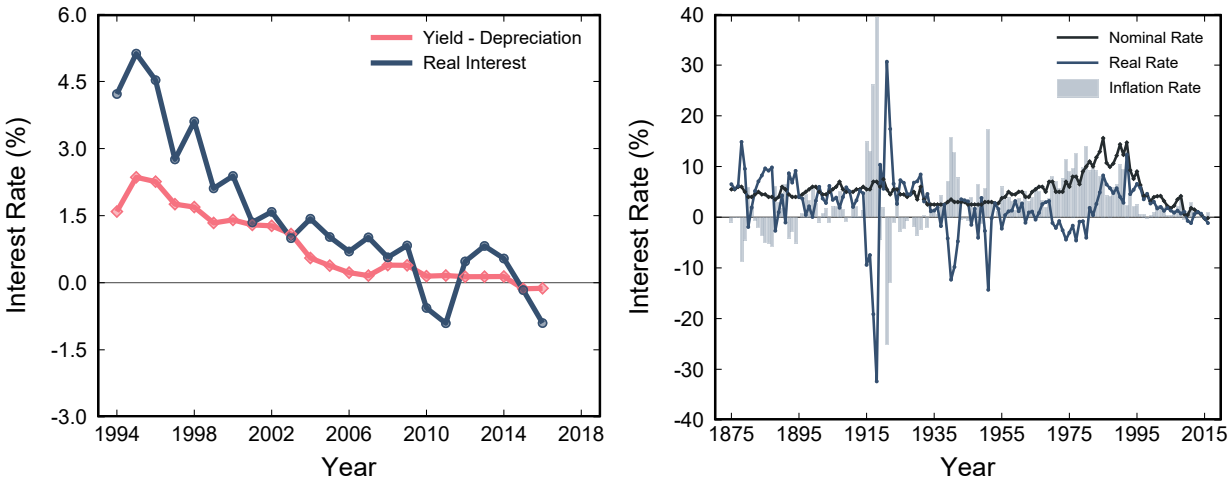
By plugging (23) in (22), we obtain that the excess return on real estate after taxes can be measured from the growth rate of real estate prices and the (nominal and real) risk-free rate:

$$r^e_t \equiv r^{at}_t - r_{f,t}(1-\tau) = \left(pg_t + r^{\text{real}}_{f,t}\right)(1-\tau_{RE}) - r_{f,t}(1-\tau) \tag{24}$$

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 (24) 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:

$$E\left[pg_{j,t}(1-\tau_{RE})-\pi_t\right]+d_{j,t}-\delta_{j,t}-\kappa=E\left[r_{f,t}(1-\tau)-\pi_t\right]+\Gamma, \tag{25}$$

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 (25) represents the indifference condition between renting and owning. Combining (22), (25) and rearranging, we obtain:

$$r_{j,t}^{e}=\left(pg_{j,t}+r_{f,t}^{\text{real}}\right)(1-\tau_{RE})-r_{f,t}(1-\tau)+\Gamma-\left[E(pg_{j,t}-\pi_t)\right](1-\tau_{RE})+\Lambda(\pi_t,r_{f,t}), \tag{26}$$

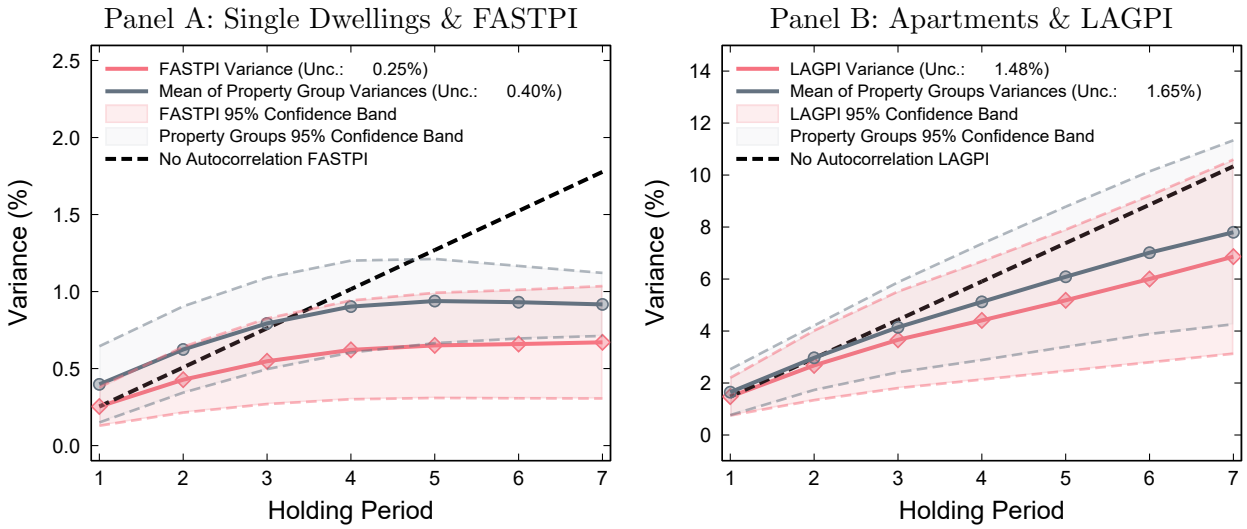
where $\Lambda(\pi_t,r_{f,t})\equiv\left[\pi_t-E(\pi_t)\right](1-\tau_{RE})+r_{f,t}(\tau_{RE}-\tau)$.

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 (24). Throughout the paper, we measure post-tax real estate excess returns for indexes and single properties using equation (24).

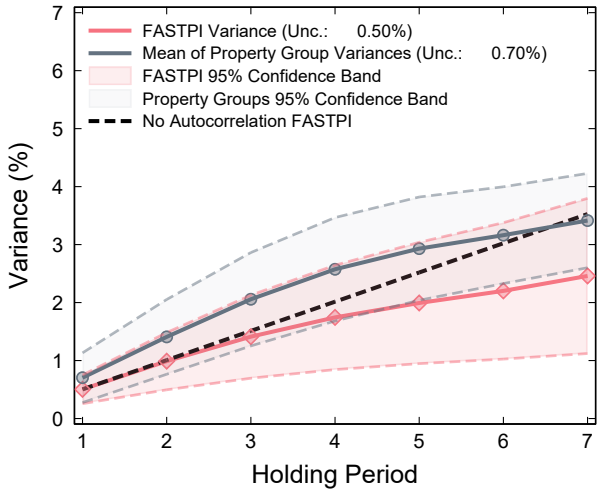
Real Estate Betas and Idiosyncratic Risk. In Figure A.2 we report the annualized sample variance of cumulative returns on the real estate market indexes over different holding periods. With stationary and i.i.d. real estate returns r_t^e, the variance of cumulative returns (reported in full lines) should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



Note. The figure reports the 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 (24). The cumulative return over a 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 variance for the FASTPI (left) and the LAGPI (right). Similarly, the blue lines indicate the weighted average variance on cumulative returns for all single dwelling property groups (left) and for all apartment property groups (right). The 95% confidence bands of these variances are illustrated in shaded regions. The black dashed line in each panel plots the unconditional variance ("Unc.") of the annual FASTPI (LAGPI) returns, scaled by the holding period h, which corresponds to the case where returns are not autocorrelated. 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 Cumulative Returns by Holding Period for 3-Year Corrected FASTPI



Notes. The figure reports the 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 (24). The cumulative return over holding period h at time t is defined as $r^e_{t,h} = \prod_{\tau=t-h}^{t}(1+r^e_\tau) - 1$. The red line illustrate the variance for the FASTPI. Similarly, the blue line indicate the weighted average variance for all single dwelling property groups. The 95% confidence bands of the variances are illustrated in shaded regions. The black dashed line plots the unconditional sample variance ("Unc.") of annual FASTPI returns, scaled by the holding period h, which corresponds to the case where returns are not autocorrelated. All moments are estimated over the whole sample period available to us, i.e. 1984 - 2014 for the FASTPI.

This implies that, in contrast to stocks, the after-tax excess annual returns of the FASTPI index (as defined in equation (24)) 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 (24) 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 Variance		
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%	18.82%	0.28

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

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

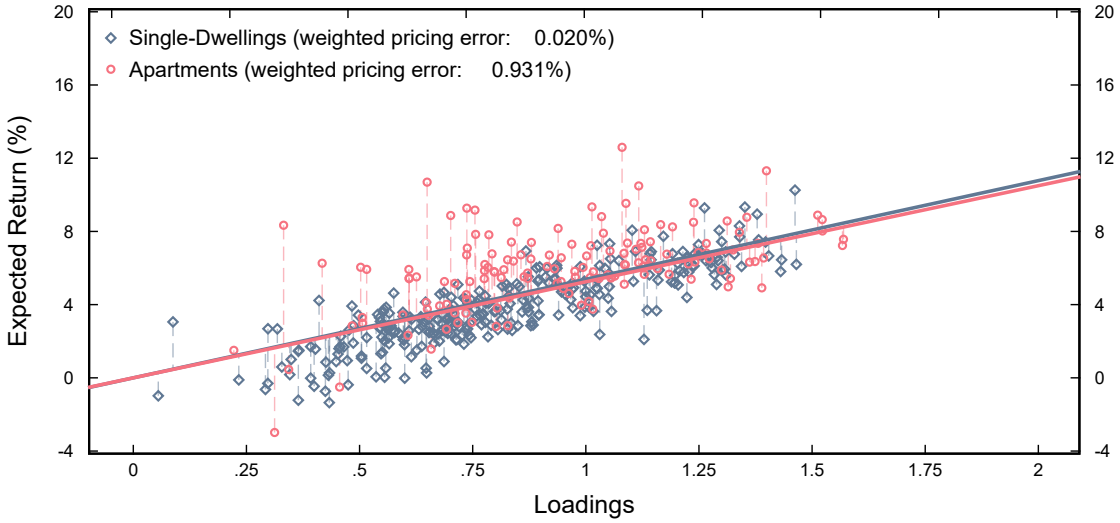
$$\beta_j = \frac{\mathrm{Cov}(r^e_{rg(j),t}, r^e_{RE,t})}{\mathrm{Var}(r^e_{RE,t})}. \tag{27}$$

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

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

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

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



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

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

$$\beta_{i,RE,t} = \sum_{j=1}^{J_{RE}} \omega_{RE,i,j,t} \ \beta_j, \tag{28}$$

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

$$u_{j,t} = \varepsilon_{rg(j),t} + v_{j,t}. \tag{29}$$

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

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

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

$$R_{j,t_s,t_b} = \frac{P_{j,t_s}/\text{Index}_{t_s}}{P_{j,t_b}/\text{Index}_{t_b}}. \tag{30}$$

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:

$$r_{j,t_b,t_s} = a_j + b_j^{'} d_j + \xi_j. \tag{31}$$

The observable characteristics are (i) the natural logarithm of the total property area $\log(P_{j,t_b})$, (ii) the log of the purchase price, and (iii) dummies for: real estate asset classes c_{RE}, real estate location groups rg, holding periods in years and purchase years t_b. We estimate the sample variance $\text{Var}(\xi_j)$ of the residuals in (31) within each group rg, year of sale t_s and holding period $t_s - t_b$. For all properties j in group $rg(j)$, we estimate the variance $\text{Var}(v_{j,t})$ of property j's specific shock $v_{j,t}$ with the average of $\text{Var}(\xi_j)$ at the group level $rg(j)$.

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

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

$$\text{Var}^{\text{idio}}_{i,RE,t} = \sum_j \omega_{RE,i,j,t} \left[\text{Var}(\varepsilon_{rg(j),t}) + \text{Var}(v_{j,t})\right]. \tag{32}$$

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

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

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

$$r_{i,REE,t} = \frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} r^{at}_{i,RE,t} - \frac{M_{i,t}}{W_{RE,i,t} - M_{i,t}} i_{i,t}(1 - \tau_M). \tag{33}$$

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:

$$\beta_{i,REE,t} = \frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} \beta_{i,RE,t}. \tag{34}$$

and the idiosyncratic variance is:

$$\mathrm{Var}^{\mathrm{idio}}_{i,REE,t} = \left(\frac{W_{RE,i,t}}{W_{RE,i,t} - M_{i,t}} \right)^2 \mathrm{Var}^{\mathrm{idio}}_{i,RE,t}. \tag{35}$$

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 Consumption, Gifts, and Inheritances Imputation

Objective and Main Equation. In this appendix, we describe the procedure for imputing individual-level consumption $C_{i,t}$ from observed income and estimated active savings, following Sodini et al. (2023). The approach relies on the wealth accumulation equation (budget constraint):

$$W_{i,t} = (1 + pg_{i,t} + \delta_{i,t})\, W_{i,t-1} + Y_{i,t} - C_{i,t} \tag{36}$$

where $Y_{i,t}$ denotes disposable income, $pg_{i,t}$ and $\delta_{i,t}$ represent capital gains and yields, respectively. Tangible net wealth $W_{i,t}$ includes six components: financial wealth (FW), pension wealth (Pen), real estate wealth (RE), apartment wealth (Apt), private business wealth (PE), and debt (D). Rearranging the identity defines active savings $S_{i,t}^{\text{active}}$ in tangible net wealth as the difference between disposable income and consumption;

$$\underbrace{W_{i,t} - (1 + pg_{i,t} + \delta_{i,t})\, W_{i,t-1}}_{\text{Active savings: } S_{i,t}^{\text{active}}} = Y_{i,t} - C_{i,t} \tag{37}$$

where active savings reflect deliberate individual decisions beyond passive fluctuations in wealth. The granularity of the holdings data from the Wealth & Tax Registry (Statistics Sweden, 2007f) allows us to construct estimates of active savings within each wealth component. Active savings $S_{i,t}^{\text{active}}$ in net wealth is the sum across all six components.

Treatment of Disposable Income. Capital gains and yields must be classified either as passive changes in wealth (left-hand side of (37)) or as components of disposable income (right-hand side). Including them on both sides would double-count income and distort estimates of consumption. Our methodology attributes all capital gains and capital income associated with financial wealth, as well as interest accrual on debt, to passive changes in wealth (left-hand side). For real estate, apartments, and private businesses, we instead include the yield on capital $\delta_{i,t}$ as part of disposable income (right-hand side), while capital gains $pg_{i,t}$ remain on the left-hand side.

Observed disposable income $Y_{i,t}^*$ $Y_{i,t}^*$ is obtained from the Income & Tax Registry (Statistics Sweden, 2007c) and *includes* realized capital gains $pg_{i,t}^*$ and capital income $\delta_{i,t}^*$ on financial, real estate, apartment, and private business wealth. We therefore subtract all these elements and add back only the capital income from real estate, apartments, and private

business to obtain an adjusted measure of disposable income:[8]

$$Y_{i,t} = Y^*_{i,t} - \left(pg^*_{i,t} + \delta^*_{i,t}\right) W_{i,t-1} + \delta^{\text{RE}}_{i,t} W^{\text{RE}}_{i,t-1} + \delta^{\text{Apt}}_{i,t} W^{\text{Apt}}_{i,t-1} + \delta^{\text{PE}}_{i,t} W^{\text{PE}}_{i,t-1} \tag{38}$$

The second term removes realized gains and capital income embedded in $Y^*_{i,t}$, and the remaining terms add back capital income from real estate, apartments, and private business. In contrast, we do *not* add back capital income on financial wealth, by construction. As pension contributions are already excluded from observed disposable income, no further adjustment is required. Likewise, no additional tax adjustments are necessary, since $Y^*_{i,t}$ already nets out realized tax payments and further adjustments would over-adjust.

Construction of Active Savings. For financial wealth and debt, active savings are computed as end-of-year holdings less beginning-of-year holdings revalued using end-of-year asset prices. This removes passive changes in wealth (capital gains and yields), so the residual captures households' *deliberate* savings behavior. This procedure requires wealth estimates $W_{i,t}$ over two consecutive periods, along with estimates of $pg_{i,t}$ and $\delta_{i,t}$. For real estate, apartment, and private business wealth, we estimate active savings directly from observed transactions. Any discrepancies between wealth observed at the end of the year and the wealth resulting from passive appreciation and active savings capture passive transfers $P_{i,t}$ arising from gifts or inheritances:

$$P_{i,t} := W_{i,t} - (1 + pg_{i,t} + \delta_{i,t}) W_{i,t-1} - S^{\text{active}}_{i,t} \tag{39}$$

These represent wealth accumulation that is independent of active financial decisions or revaluations and provide measures of intergenerational wealth flows. Observed private contributions to pension savings accounts are treated as active savings in pension wealth.

Financial Wealth. Financial wealth consists of six subclasses: (1) bank accounts, (2) money market funds, (3) equities, (4) funds, (5) capital insurance, and (6) other financial assets. An individual's financial wealth $W^{\text{FW}}_{i,t}$ is the sum of holdings across subclasses, and the portfolio return $r^{\text{FW}}_{i,t}$ (inclusive of *both* capital gains *and* income) is the value-weighted average of the observed returns on each subclass. Active savings in financial wealth $S^{\text{active}}_{\text{FW},i,t}$ follow from:

$$S^{\text{active}}_{\text{FW},i,t} = W^{\text{FW}}_{i,t} - \left(1 + r^{\text{FW}}_{i,t}\right) W^{\text{FW}}_{i,t-1} \tag{40}$$

[8] We also correct for the rental income already included in disposable income. Specifically, observed disposable income $Y^*_{i,t}$ already includes the amount of rental income in excess of 4,000 SEK.

Pension Wealth. Active savings in pension wealth $S^{\text{active}}_{\text{Pen},i,t}$ equal the observed private pension contributions to private pension savings accounts made by individuals, retrieved from the Income & Tax Registry (Statistics Sweden, 2007c). Contributions to state or occupational defined-contribution schemes are made by the employer and are therefore neither part of disposable income nor made directly at individual's discretion.

Real Estate Wealth. We use data on real estate transactions and transfers from the Income & Tax Registry (Statistics Sweden, 2007c) to estimate active savings. For each transaction, we observe the consideration paid for object j, and whether an individual is a seller or a buyer. Active savings in real estate $S^{\text{active}}_{\text{RE},i,t}$ are defined as the *net* consideration (purchases minus sales) across all real estate objects transacted by an individual over the year. The rental yield $\delta^{\text{RE}}_{j,t}$ on each object is approximated by the annualized real risk-free rate $r^{\text{real}}_{f,t}$. The capital gain $pg_{j,t}$ is the growth rate in the object's valuation between $t-1$ and t.

Aggregate capital gains $pg^{\text{RE}}_{i,t}$ and rental yields $\delta^{\text{RE}}_{i,t}$ are value-weighted averages throughout the individual's real estate portfolio. Passive transfers in real estate wealth $P^{\text{RE}}_{i,t}$ are given by the residual between realized wealth and the the sum of active savings and passive returns:

$$P^{\text{RE}}_{i,t} = W^{\text{RE}}_{i,t} - S^{\text{active}}_{\text{RE},i,t} - \left(1 + pg^{\text{RE}}_{i,t} + \delta^{\text{RE}}_{i,t}\right) W^{\text{RE}}_{i,t-1} \tag{41}$$

That is, passive transfers in real estate represent wealth changes that are not explained by active transactions or passive appreciation through capital gains and rental yields. These transfers are attributed to real estate objects obtained through gifts or inheritances.

Apartment Wealth. Using 1999–2017 apartment transaction data from the Income & Tax Registry (Statistics Sweden, 2007c), we estimate active savings in apartments $S^{\text{active}}_{\text{Apt},i,t}$ as the total net cash flow from *arm's-length* transactions over the year (allowing multiple purchases and sales by the same individual). Rental yields $\delta^{\text{Apt}}_{j,t}$ are approximated by $r^{\text{real}}_{f,t}$, as for real estate.

Portfolio-level capital gains $pg^{\text{Apt}}_{i,t}$ and rental yields $\delta^{\text{Apt}}_{i,t}$ are value-weighted averages across apartment holdings, and $W^{\text{Apt}}_{i,t}$ is the sum of object values. Passive transfers in apartment wealth are:

$$P^{\text{Apt}}_{i,t} = W^{\text{Apt}}_{i,t} - S^{\text{active}}_{\text{Apt},i,t} - \left(1 + pg^{\text{Apt}}_{i,t} + \delta^{\text{Apt}}_{i,t}\right) W^{\text{Apt}}_{i,t-1} \tag{42}$$

Private Business Wealth. We identify active savings in private business wealth $S^{\text{active}}_{\text{PE},i,t}$ as the *net* purchases in all private businesses held by an individual over a year.

Aggregate capital gains $pg_{i,t}^{\text{PE}}$ and capital-income yields $\delta_{i,t}^{\text{PE}}$ are computed as value-weighted averages across the portfolio. Passive transfers in private business wealth $P_{i,t}^{\text{PE}}$ capture wealth changes not accounted for by active financing decisions, capital appreciation, or payout yields:

$$P_{i,t}^{\text{PE}} = W_{i,t}^{\text{PE}} - S_{\text{PE},i,t}^{\text{active}} - \left(1 + pg_{i,t}^{\text{PE}} + \delta_{i,t}^{\text{PE}}\right) W_{i,t-1}^{\text{PE}} \tag{43}$$

Debt. We separate *student debt accounts* $D_{i,t}^{(\text{S})}$ from total debt, i.e. $D_{i,t} = D_{i,t}^{(\text{S})} + D_{i,t}^{(\text{NS})}$, and define *non-student debt* $D_{i,t}^{(\text{NS})}$ accordingly. We use non-student debt to measure borrowing activity related to tangible wealth, and consider student debt as borrowing for human capital. *Active borrowing* $S_{\text{D},i,t}^{\text{active}}$ arises when non-student debt increases beyond passive interest accumulation:

$$S_{\text{D},i,t}^{\text{active}} = D_{i,t}^{(\text{NS})} - D_{i,t-1}^{(\text{NS})} \cdot \left(1 + r_{i,t}^{D}\right)$$

where the *interest rate on debt* $r_{i,t}^{D}$ is estimated as the average observed interest expense paid on debt throughout the year.[9]

Consumption and Passive Transfers. Once active savings for each tangible component have been estimated, a rearrangement of the savings identity (37) defines consumption as:

$$Y_{i,t} - S_{i,t}^{\text{active}} = C_{i,t}$$

where $Y_{i,t}$ is adjusted disposable income from (38), and total active savings is the sum across wealth components:

$$S_{i,t}^{\text{active}} = S_{\text{FW},i,t}^{\text{active}} + S_{\text{Pen},i,t}^{\text{active}} + S_{\text{RE},i,t}^{\text{active}} + S_{\text{Apt},i,t}^{\text{active}} + S_{\text{PE},i,t}^{\text{active}} - S_{\text{D},i,t}^{\text{active}}$$

where the negative sign on debt reflects that active saving in debt corresponds to debt repayments. Finally, total passive transfers are the sum of passive transfers in real estate, apartments, and private business wealth:

$$P_{i,t} = P_{i,t}^{\text{RE}} + P_{i,t}^{\text{Apt}} + P_{i,t}^{\text{PE}} \tag{44}$$

[9] If the interest expense of the individual is not directly observable, we assume the interest rate equals the annualized risk-free rate plus a fixed risk premium of 2%

A.7 Measuring Wealth Mobility

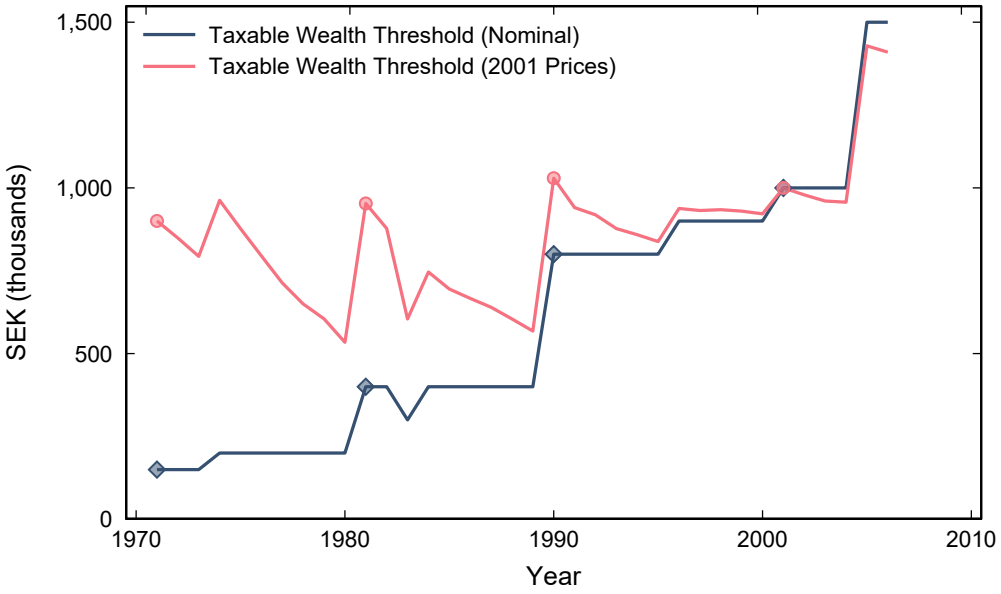
The net wealth of parents, our proxy for wealth background, should be measured at a young age when preferences are still being formed and potentially influenced by parents. Unfortunately, comprehensive and detailed data on wealth is only available in Sweden between 1999 and 2007, preventing us from measuring 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.[10] 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

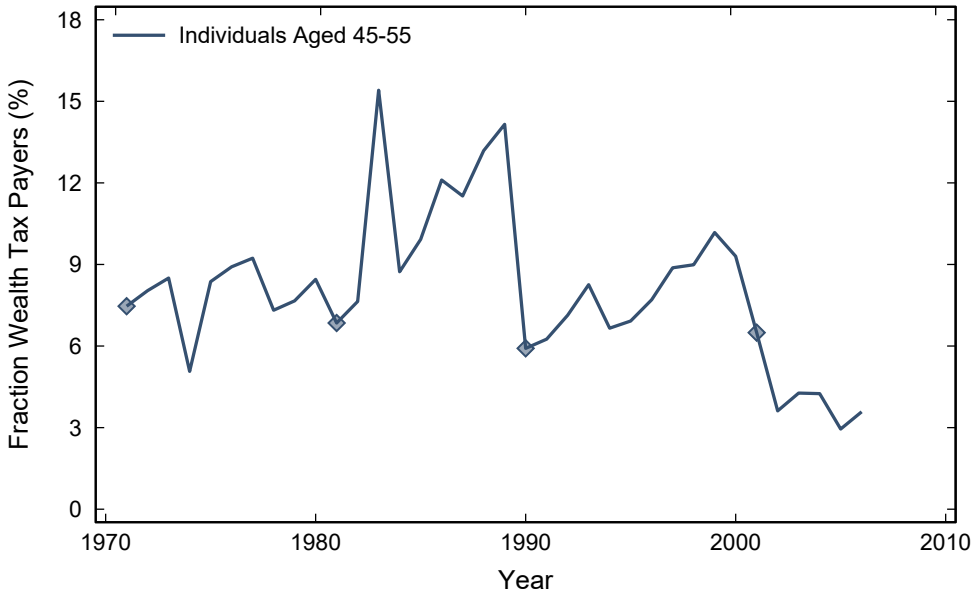
[10] Before 1992, shares of listed companies on the O-list were tax at 30% and after 1992, shares of listed companies on the O-list were tax-exempt. An additional exemption for major shareholders owning at least 25% of the company was introduced in 1998.

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.

wealth tax 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 in our main sample between 1999-2007). 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 into different cohorts based on their age in 2001, and then classify their parents into wealth groups using the taxable wealth data available in the Swedish Income Tax Register during the years mentioned above and highlighted in Figure A.5. More specifically, we rank the parents of children who are 50-59 years old using the parents' taxable wealth in 1971. For children who are 40-49, we use parents' taxable wealth information in 1981. For children aged 30-39, we use parents' 1990 taxable wealth. For those who are 20-29, we use parents' taxable wealth in 2001, the same year we observe the children's age. In this way, we make sure that we collect information on parents' wealth at a time when the individuals in our sample were between 20 and 29 years old—with parents being in their 50s.

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

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

We next validate our approach by comparing the (synthetic) taxable wealth with actual net wealth in 2001. The analysis is done for the sample of households with at least one individual between 45 and 55 years old. Net wealth is defined in the same way as in the rest of the paper, i.e. the sum of financial wealth, pension wealth, real estate equity and private equity, minus non-mortgage debt. Table A.4 reports the distribution of net wealth for each group of taxable wealth. Table A.5 reports the fraction of different wealth percentiles populated by each wealth tax group. The "Non-rich" group includes households who did not pay any wealth tax in 2001, the "Rich" group includes households up to the seventy-fifth percentile of positive taxable wealth in 2001, and the "Very-rich" group includes households

in the top 25% of positive taxable wealth in 2001. Wealth percentiles are defined based on different brackets of the household net wealth distribution in 2001. Overall, we find that rankings based on taxable wealth proxy well the ranking created with actual net wealth. The distribution of household wealth based on taxable wealth substantially shifts for households of non-rich, rich, and very-rich categories with only partial overlaps. Moreover, the households in the non-rich category mostly populate wealth percentiles below the 90th, while the rich fall in the 90th to 97.5th percentiles, and the very-rich take up the top percentiles (above 97.5th) of the net wealth distribution.

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

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

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

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

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

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

B Analytical Derivation of Lifecycle Decisions

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

$$\rho J = \max_{c,x} \ \frac{c^{1-\gamma}}{1-\gamma} + \dot{J} + J_w \left[w r_f + x'\mu - c + y(t) + p(t) \right] + \frac{J_{ww}}{2} x'\Omega x \tag{45}$$

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

$$x^* = \frac{-J_w \Omega^{-1} \mu}{J_{ww}}, \tag{46}$$

$$c^{*-\gamma} = J_w. \tag{47}$$

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

$$J(w,t) = f(t)^\gamma \ \frac{[w + h(t) + g(t)]^{1-\gamma}}{1-\gamma}, \tag{48}$$

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

$$h(t) := \int_t^{T_d} e^{-r_f(\tau - t)} y(\tau) d\tau, \tag{49}$$

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

$$g(t) := \int_t^{T_d} e^{-r_f(\tau - t)} p(\tau) d\tau. \tag{50}$$

By substituting this guess into optimality equations (46) and (47) we obtain:

$$x^* = \frac{\Omega^{-1}\mu}{\gamma} [w(t) + h(t) + g(t)], \tag{51}$$

$$c^* = f(t)^{-1} [w(t) + h(t) + g(t)]. \tag{52}$$

Substitute back our guess and the optimal values c^* and x^* into the HJB equation (45) to

obtain:

$$\begin{aligned}\rho = &\gamma f(t)^{-1} + \gamma \frac{\dot{f}(t)}{f(t)} \\ &+ (1-\gamma)\frac{\dot{h}(t)+\dot{g}(t)}{w+h(t)+g(t)} + (1-\gamma)\frac{y(t)+p(t)+r_f w}{w+h(t)+g(t)} \\ &+ \frac{(1-\gamma)\mu'\Omega^{-1}\mu}{2\gamma}.\end{aligned} \tag{53}$$

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:

$$y(t) - r_f h(t) + \dot{h}(t) = 0 \ , \quad p(t) - r_f g(t) + \dot{g}(t) = 0, \tag{54}$$

which is the case using the definitions of $h(t)$ and $g(t)$ in equations (49) and (50). Hence, the conjecture for J is verified.

Finally, after deducting w, and $h(t)$ and $g(t)$ terms, the ordinary differential equation (53) simplifies to

$$\rho = \frac{\gamma}{f(t)} + \frac{\gamma \dot{f}(t)}{f(t)} + (1-\gamma)r_f + \frac{(1-\gamma)\mu'\Omega^{-1}\mu}{2\gamma}, \tag{55}$$

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

$$f(t) = \left(\tilde{\chi} - \frac{1}{\tilde{\rho}}\right) e^{-\tilde{\rho}(T-t)} + \frac{1}{\tilde{\rho}}, \tag{56}$$

where

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

Substitute back for $f(t)$ in the optimal consumption-wealth ratio in equation (52) to derive

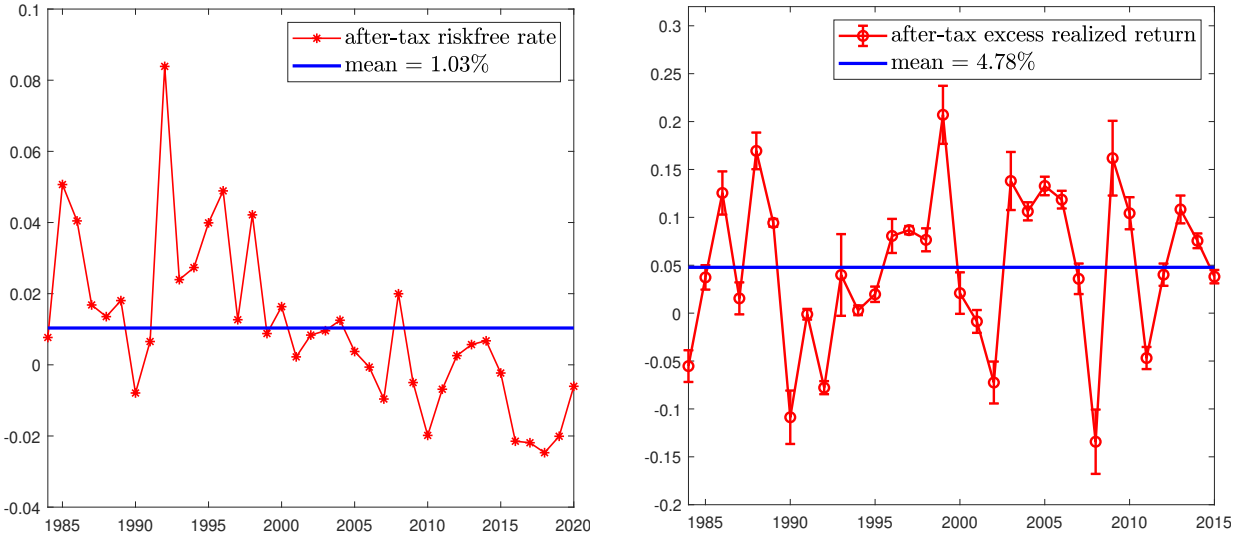
$$c^*(t) = \frac{\tilde{\rho}}{1 + (\tilde{\chi}\tilde{\rho} - 1)e^{-\tilde{\rho}(T-t)}}[w(t) + h(t) + g(t)]. \tag{57}$$

The risky investment is also verified to follow

$$x^* = \frac{\Omega^{-1}\mu}{\gamma}[w(t) + h(t) + g(t)]. \tag{58}$$

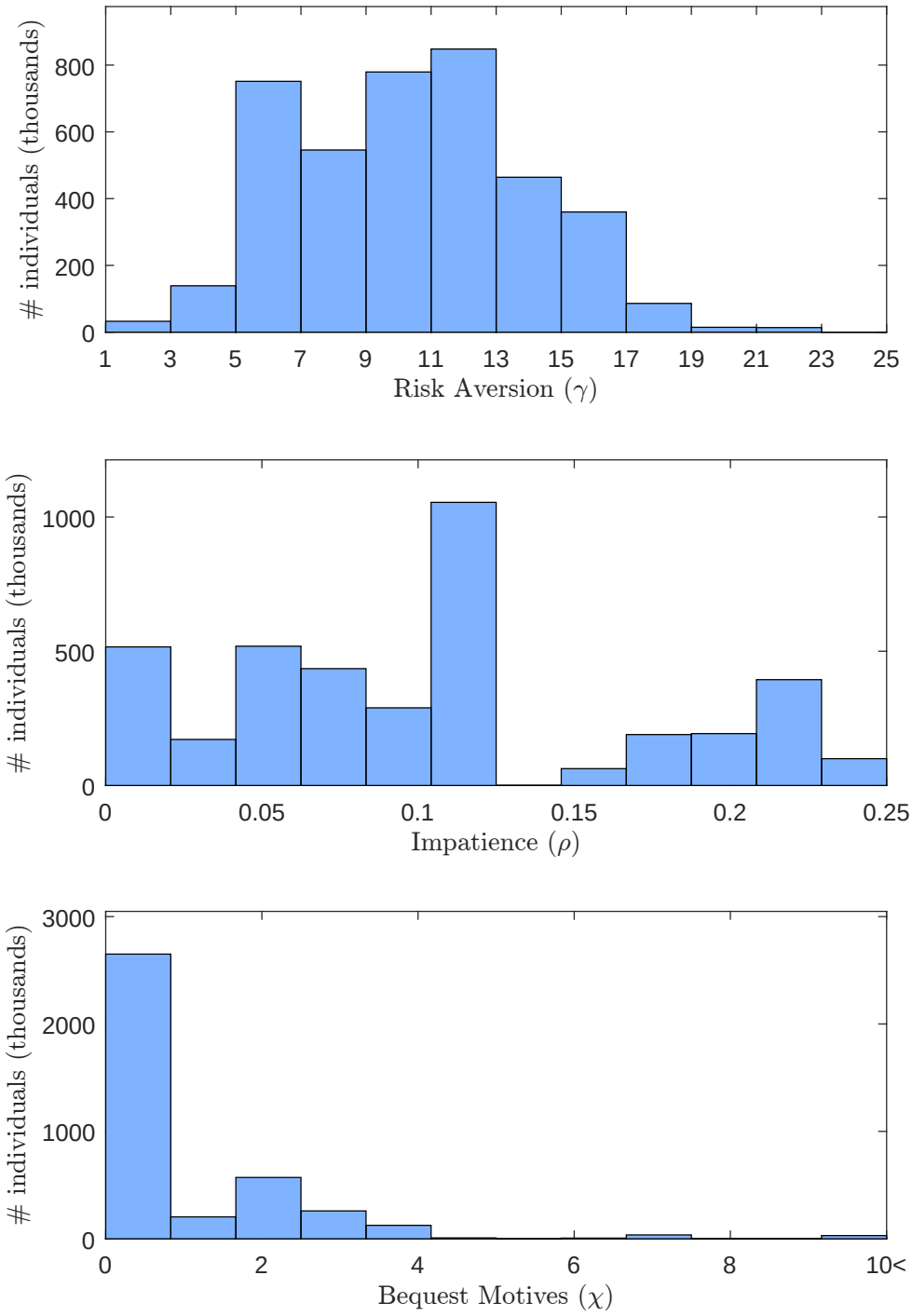
C Supplementary Tables and Figures

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



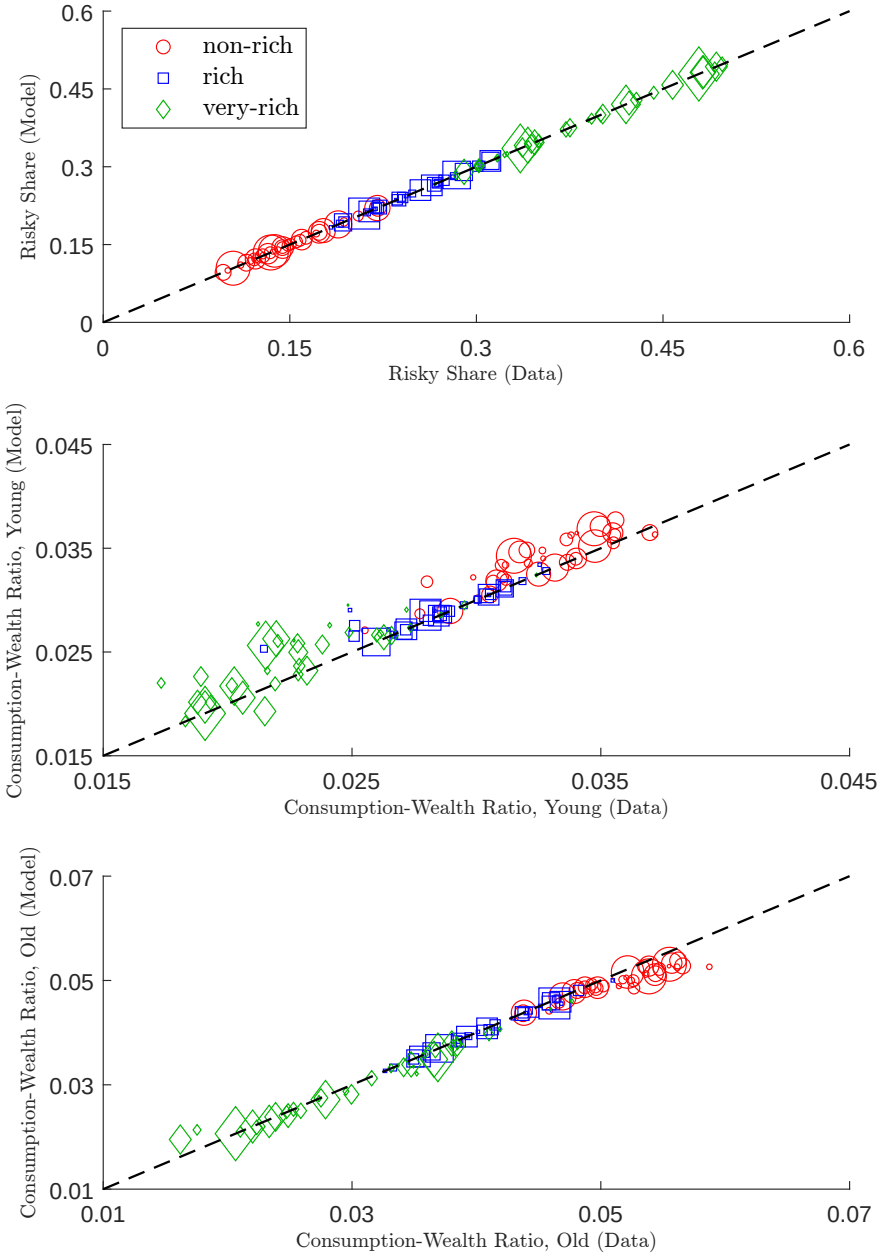
Note: This plot shows the riskfree rate (left Panel) and the estimate of average excess realized return on risky assets for groups of individuals (right Panel) using the history of available data. To measure the average excess realized return, for each group of individuals we measure the average exposure 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 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 targeted moments via benchmark model estimate (y-axis) against moments in the data (x-axis) for the risky share in portfolio, the consumption-wealth ratio of young individuals (aged 25-44), and the consumption-wealth ratio of old individuals (aged 45-64). Circles show moments for individuals of the non-rich background, squares show the rich background, and diamonds show the very-rich background. Marker sizes are proportionate to the group population, as a share of the total wealth background population. A 45-degree line is added as the reference to show the model fit performance.

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

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

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