Savvy Parent, Savvy Child?
Intergenerational Correlations in Returns to Financial Wealth*

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Abstract

The returns individuals earn on financial wealth correlate positively across generations. We establish this result by analyzing the full population of household investors in Finland. The correlation extends to both historical and expected returns and the intergenerational spread in returns implies sizeable differences in wealth accumulation over time. Asset holdings reveal that returns correlate mostly because family members choose the same securities. An instrument using non-overlapping peer groups and a natural experiment based on mergers allow us to address causality. We find causal influence not only from parents to children but also in the opposite direction. Our findings have implications for understanding wealth inequality and portfolio heterogeneity.

Keywords: Social mobility, intergenerational correlation, wealth inequality, portfolio choice

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1. Introduction

This paper documents the intergenerational correlation in returns to financial wealth and provides a detailed account of its sources. Figure 1 presents our key finding. It ranks investors in the distribution of returns and plots the investors' percentile ranks against those of their fathers and mothers in Finland during 2004-2008. The investors whose parents are at the 90th and 10th percentiles are on average at the 57th and 42nd percentiles of the return distribution, respectively. This positive intergenerational correlation implies sizeable differences in returns: the 90th to 10th percentile spread in parent's expected return translates into a difference of 1.9 percent in the investor's expected annual return. Compounded over time, such a spread would produce substantial differences in wealth accumulation and have implications for understanding wealth inequality.[1]

Our detailed investigation of the intergenerational correlation in returns takes advantage of data that record all stock and mutual fund holdings of the entire adult population in Finland at the end of each year in 2004–2008. These records, coupled with the time-series of asset returns, allow us to accurately calculate historical portfolio returns for each investor. We also estimate expected returns that are unaffected by transitory shocks during our sample period.

Characteristics of assets held by investors make it possible to address sources of return correlation. Our data set records asset class of all securities and it includes detailed mutual fund information that is informative about the role financial literacy plays in generating the return

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[1] See Benhabib and Bisin (2016), Roine and Waldenström (2015), and Piketty and Zuckman (2015) for reviews of wealth inequality. Recent empirical work include Piketty, Postel-Vinay, and Rosenthal (2006), Roine and Waldenström (2009), and Saez and Zuckman (2016). Piketty (2014) proposes a framework for interpreting the data; see Acemoglu and Robinson (2015), Blume and Durlauf (2015), Krusell and Smith (2015) and Jones (2015) for discussion. Benhabib, Bisin and Luo (2015), Campbell (2016), Gabaix et al. (2015), and Lusardi, Michaud, and Mitchell (2015) presents models that feature heterogeneity in returns to wealth.

correlation. The investor data map each individual to her parents and include rich information on investors' socioeconomic and demographic characteristics.

We start by generalizing Figure 1 in a regression framework. Regressing investors' returns on those of their parents yields intergenerational correlations of 0.17 for fathers and 0.21 for mothers (*t*-values 91.3 and 101.7). These results imply a 1.7 to 2.1 percentage points increase in the investor's historical return for a 10 percentage point increase in her parent's return. Parent's return alone accounts for 59 to 60 percent of heterogeneity in investor's return, which makes it by far the most powerful explanatory variable. The large number of cohorts in our data reveals that our estimates do not suffer from life-cycle biases. The return correlation also is virtually unaffected when we estimate the correlation from ranks of returns in lieu of raw returns and expected returns that we calculate from the factor loadings of investors' portfolios display similar patterns.

We next explore the sources of the return correlations by examining how much of the intergenerational correlation remains when we control for investor attributes and asset characteristics. Controlling for investor's wealth, income, field and level of education, industry of work, and various demographics does little to change the intergenerational correlation in returns. Characteristics of the assets that make up an investor's portfolio—a direct measurement of preferences investors may have for different types of assets—capture a larger fraction of the intergenerational correlation. Controlling for asset classes and mutual fund characteristics, together with observable investor characteristics, leads to a conditional intergenerational return correlation that is 23 to 25 percent lower than the baseline estimate. The choice of investing in risky asset classes explains the bulk of this reduction. This result suggests a large share of the return transmission across generations arises from systematic differences in investment styles that the high-return and low-return investors follow. The remaining intergenerational association in returns is, however, still sizeable with estimates of 0.13 and 0.16 (t-values 78.9 and 86.0) for fathers and mothers, respectively.

How do investors end up following the investment styles of their parents? Intergenerational correlations in risk preferences may lead investors to choose investment styles that are similar to those of their parents. Correlated investor attributes, such as education and occupation, can generate commonalities in background risks that justify similar exposures to different styles. Transmission of financial literacy may explain why members of the same family shy away from investments they deem inappropriate. Alternatively, investors may choose precisely the same assets as their parents, which gives the appearance that family members are following similar investment styles. Choosing the same assets may result from sharing investment ideas and giving financial advice. This latter mechanism suggests the identity of a particular asset carries an important weight in the investor's decision over and above the risk-return tradeoff of an investor's portfolio.

We present an anatomy of intergenerational return correlation by using the detailed asset holdings in our data. We identify the assets held by the investor and her parent and calculate the share of the investor's portfolio that overlaps with that of her parent. Using the overlap of an investor's portfolio with that of her parent, we stratify the sample and run the baseline regressions in each subsample. We find that the intergenerational return correlation monotonically increases in the overlap of an investor's and her parent's portfolio. Completely non-overlapping portfolios yield small correlation estimates of 0.005 and 0.004 for fathers and mothers, respectively (t-values 2.8 and 2.6). These results show that the magnitude of the return correlation hinges crucially on investments in exactly the same assets within a family.

The central role of overlapping investments leads us to analyze the choice of a particular security. We relate an investor's decision to invest in a security to that of her parent while flexibly controlling for preferences an investor may have for specific types of assets. Of particular interest is our analysis that estimates the correlations from the buy and sell decisions of a particular security. This estimation controls for any shared time-invariant preferences an investor and her parent have for a security and speaks to correlated risk attitudes, background risks, or financial literacy as the source of intergenerational transmission.

Unconditional estimates show the propensity to invest in a security increases by 58 to 60 percent when the investor's father or mother holds the asset. The estimation that identifies the effect from buy and sell decisions of a security implies a 26 to 33 percent increase in the likelihood of investing in the asset. These estimates are highly significant with *t*-values exceeding 45. The time-varying nature of this correlation is consistent with the idea that family members share investment ideas at the granular level of a security. Yet, family members may share unobservable attributes that make them malleable to time-varying influences. For example, they may respond to sales efforts of an asset management company in the same way, which would generate the year-to-year correlation in security choice across generations. We investigate this possibility by employing two identification strategies that are immune to such concerns.

First, we use a strategy that takes advantage of the rich information on social networks in our data. We match every parent with her likely peers and calculate the share of the parent's peers that invests in a particular security. We define peers as other investors of similar age, living in the same zip code, and speaking the same native language (Finland's two native languages, Finnish and Swedish, define many social networks). When investor's peers do not overlap with those of her parent, the investment decisions of the parent's peers are an attractive instrument for the parent's decision (see Bramoullé, Diebbari, and Fortin 2009, De Giorgi, Frederiksen, and Pistaferri 2016, De Giorgi, Pellizzari, and Redaelli 2010, Lee, Liu, and Lin 2010, Nicoletti, Salvanes, and Tominey 2016 for similar identification strategies).

Second, we analyze plausibly exogenous changes in ownership generated by mergers. In a stock-financed merger of two publicly listed companies or a merger of two mutual funds, the target shareholders become owners in the acquirer without making the active decision to invest in the acquirer. We identify all shareholders of the target security and analyze how the children of the target shareholders alter their investment behavior in response to their parents passively becoming shareholders in the acquirer.

Both identification approaches yield strong first-stage relations. A parent has a much higher likelihood to hold a security when many of her peers also hold the asset. The plausibly exogenous changes following mergers result in a strongly positive likelihood to invest in the acquirer for a parent who was a shareholder in the target. The IV estimates we obtain from the two identification approaches show that an increase in the parent's likelihood to hold the asset leads to a much higher ownership probability for the child. These estimates are statistically highly significant and somewhat larger in magnitude than the corresponding OLS results. These findings allow us to attach a causal interpretation to the intergenerational correlation in the choice of a particular asset and rule out intergenerational transmission of risk preferences, background risks, or financial literacy as the main driver of the correlation. Because the intergenerational correlation in security choice largely drives the corresponding correlation in returns, we can also extend the causal interpretation to the return correlation.

The merger-based natural experiment also allows us to investigate the possibility that not only parents affect their children but also the opposite influence is at play. This possibility does not typically feature in studies of intergenerational transmission because the outcome of interest determines the direction of causality. The most common outcomes in this literature—education and income—have a natural causal direction from older to younger generations. The investments we study in our paper do not have this feature. For example, financially literate children may advise their less literate parents in managing their assets, which would generate a causal relation from children to their parents.

We find a strong positive correlation that runs from the choice of an adult child to that of her parents. Its magnitude and statistical significance is comparable to the transmission we find from older to younger generations. This finding advances our understanding of linkages between family members by showing children may also influence their parents in economically meaningful ways.

This paper contributes to three strands of literature. First, we are among the first to document intergenerational correlations in returns to wealth. We complement the work by Fagereng et al. (2016) that provides estimates of intergenerational return correlations in Norway. Their measurement of returns relies on interest payments, dividends, and realized capital gains reported in an individual's tax return. The lack of data on unrealized capital gains—a sizeable contributor to returns on financial assets—may lead to measurement error that biases the intergenerational correlation downwards. The total returns on financial investments we use in our paper encompass dividends and capital gains, which enables a more comprehensive assessment of return correlations. Our paper also provides a detailed account of the sources of the intergenerational return correlation and addresses causality from parents to children and in the opposite direction. Bach, Calvet, and Sodini (2016) analyze how returns vary with wealth, but they do not consider intergenerational correlations.

Second, we contribute to the literature that documents intergenerational correlations in other settings. A large number of papers documents intergenerational correlations in income and education (see Björklund and Salvanes 2011, Black and Devereux 2011, Jäntti and Jenkins 2015, and Solon 1999 for reviews). In the financial domain, Charles and Hurst (2002), Boserup, Kopczuk, and Kreiner (2014), Black et al. (2015), and Fagereng, Mogstad, and Rønning (2015) study the correlation of wealth levels across generations whereas Kreiner, Leth-Petersen, and Willerslev-

Olsen (2016) analyze the intergenerational correlation in personal defaults. Dohmen et al. (2011) document intergenerational transmission in risk attitudes and trust. The focus on returns investors earn on wealth differentiates our paper from this line of work. Our analysis of the anatomy of the intergenerational return correlation may also inform us about the sources of intergenerational transmission in other settings.

Finally, we add to the literature on heterogeneity in investment decisions (Barnea, Cronqvist, Siegel 2015, Bertaut and Starr-McCluer 2002, Calvet, Campbell, and Sodini 2007, Calvet and Sodini 2013, Cesarini et al. 2010, Curcuru et al. 2010, Haliassos and Bertaut 1995, Heaton and Lucas 2000, Knüpfer, Rantapuska, and Sarvimäki 2016, and Vissing-Jorgensen 2003). Our paper shows intergenerational correlations explain a substantial share of variation in returns investors earn on their financial investments and pinpoints family influence as the most important observable determinant of return heterogeneity. The family correlation in the choice of a security further relates to studies that find peer effects in investment decisions. Our results are consistent with investors acquiring investment ideas and financial advice not only from their peers at work and from their neighborhood (Hvide and Östberg, 2015, Ivković and Weisbenner 2007), but also from their family members.[2]

The rest of the paper is organized as follows. Section 2 describes data and methods for estimating returns. Section 3 documents an investor's returns, attributes, and asset characteristics as a function of her parents' returns. Section 4 reports regressions that estimate and decompose the intergenerational return correlation. Section 5 investigates channels that generate the correlation in returns across generations. Section 6 concludes.

[2] Anderson et al. (2015) find an intergenerational correlation in the choice of an automobile's make and model.

2. Data and methods

2.1. Data

The bulk of our data originate from three registers maintained by various authorities. These data include a personal identification number that allows a merger of data across sources. We complement register-based data with information from public sources.

Statistics Finland (SF). The first source provides us with the individuals and their linking to their parents. The family links are comprehensively available for individuals born in 1955 or after. We further require that an individual is at least 18 years old in 2004 and her parents are alive in 2008. Our sample individuals are thus born between 1955 and 1986. These restrictions address the possibility that investments made on behalf of underage children and transfers related to inheritance drive the results. An investor appears in the data only in the years in which she and at least one of her parents hold some stocks or mutual funds. These criteria give us a final sample of 202,295 father-child and 185,916 mother-child pairs. We observe the individual's annual income, field and level of education, industry of work, year of birth, gender, marital status, and native language (Finland has two official languages, Finnish and Swedish). A household indicator identifies individuals who live in the same dwelling unit. For individuals who completed the 9-year comprehensive school in 1985 or after, the data set also records the final year grade point average across all subjects in the national curriculum.

Finnish Tax Administration (FTA). The second source records information on asset holdings in 2004-2008. Asset management firms directly report the ownership of mutual funds to the FTA. These records indicate the mutual funds in which an individual has invested and the year-end market value of each holding. FTA also receives information on stock holdings directly from Euroclear Finland. These data detail the end-of-year values of holdings in each publicly listed company on the

Helsinki Stock Exchange (part of the NASDAQ group). Registering transactions with Euroclear Finland is mandatory for household investors so these data represent a comprehensive and reliable account of shareholdings.

Finnish Armed Forces (FAF). The third source provides a cognitive-ability test score that we use as an additional control variable. Males in Finland take a battery of tests when entering the mandatory military service around the age of 19. Scores from the 120-question cognitive ability test are available for males who are enlisted in 1982 and onwards. See Grinblatt et al. (2011) for an extensive description of the test procedure.

Mutual Fund Report. Information on mutual funds originates from the Mutual Fund Report, a monthly industry publication compiled by *Investment Research Finland*. The data set include a monthly account of characteristics and returns on all mutual funds available to Finnish investors. The returns include the effects of management fees and distributions, but exclude front-end and back-end loads. The data also record the asset class in which a fund invests, the firm that manages the fund, whether the fund follows an active or passive investment philosophy, and an indicator for funds of funds. The information on asset management firm allows us to classify the funds into those distributed through the branch networks of the largest commercial banks and those independent of banks. We label these funds as retail and non-retail funds, respectively, as in Grinblatt et al. (2016).

Helsinki Stock Exchange. We calculate the returns on publicly listed stocks from data provided by the Helsinki Stock Exchange. The data set reports the daily closing prices for all stocks traded on the exchange, the dividends paid to each stock, and any events that influence the nominal share price. We use these data to construct a monthly time-series of total returns for all publicly listed stocks.

2.2. *Estimation of returns*

We measure portfolio returns by combining annual asset holdings with the time-series of total returns (including capital gains, dividends, and distributions) of each security. In each year, we calculate returns on the securities held by an investor in the preceding 24-month period and weight each asset by its share in the investor's portfolio. The average historical portfolio return is the average of the portfolio return calculated over the previous 24 months.

We also use the time-series of portfolio return to estimate factor loadings. Combining factor loadings with estimates of factor premia make it possible to calculate expected returns for each investor. Our asset pricing model is the four-factor model where the factors are the market factor, the value and size factors from Fama and French (1993), and the momentum factor from Carhart (1997). The loadings on these factors tell us how an investor tilts her portfolio towards high-beta securities, small companies, value firms, and assets that have gone up in value in the recent past.

The market factor is the total return on the MSCI Europe Index in excess of the yield of the one-year Euribor rate whereas the other factors are the SMB, HML, and MOM returns from Kenneth French's data library. We convert all factor returns to euros. Using monthly data over the years 1994 to 2008, we arrive at annual factor premia of 0.041, 0.019, 0.039, and 0.104 for the market, size, value, and momentum factors, respectively.

3. Returns, investor attributes, and asset characteristics across generations

We start by reporting how investors' returns vary as a function of their parents' returns. We also report how investor attributes and characteristics of the assets that make up an investor's portfolio correlate with the parents' return. Table 1 Panel A reports the historical return an investor earns on her financial portfolio as a function of that of her father and mother. Panel B calculates the expected return. These panels report both raw returns and percentile ranks of returns that rank investors according to their parents' historical or expected return. We divide the sample into five quintiles according to parents' returns and report the average return or its rank in each quintile.

3.1. Historical and expected returns

Table 1 Panel A shows that parents' historical return in the first row displays wide variation. The spread in annual returns between the top and bottom quintiles equals 34.5% and 33.1% for fathers and mothers, respectively. These large differences reflect the high average returns in financial markets during the 24 months that precede the years 2004-2008. The second and third rows report the averages of the investor's historical return and its percentile rank. The spreads in historical returns between the top and bottom quintiles equals 6.1% and 6.9% points for the investor's father and mother, respectively. This spread puts the average investors in the two extreme quintiles of the father's return distribution at the 43rd and 58th percentiles in their own return distribution. The corresponding ranks are the 42nd and 58th percentiles for the investor's mother. The other percentiles, reported in Figure 1, reveal a close-to-linear rank-rank relationship.

Panel B report the investor's loadings against the four factors in our four-factor asset pricing model. It also uses the factor loadings coupled with estimates of factor premia to arrive at an estimate of expected returns. The factor loadings reveal that the return spread generated by the intergenerational correlation partly reflects differential factor exposures. At the top of the parent's return distribution, investors have great exposure to the market and momentum factors. Their portfolios load relatively less on small firms and value firms compared to investors in the bottom quintile of parent's return.

On balance, the differences in factor loadings translate into a positive spread in expected returns. Investors in the bottom quintile of the father's return distribution have an expected excess return of 2.9% whereas the investors in the top quintile enjoy an expected excess return of 5.0%. This 2.2% spread is similar to the 2.0% spread that obtains for the investor's mother. The percentile ranks of expected returns tell a similar story as the historical returns in Panel A. Investors in the top and bottom quintiles of the father's distribution on average rank at the 43rd and 58th percentiles in their own return distribution. Corresponding percentiles are 42nd and 59th for the investor's mother. These results on expected returns show that the intergenerational correlation in historical returns does not solely reflect transitory shocks to returns during our sample period but that it largely arises from systematic differences in styles investors adopt in their portfolios.

3.2. Investor attributes and asset characteristics

Table 1 Panel C documents how investor attributes, such as wealth, income, and education correlate with the parents' historical returns. It follows the structure of Panels A and B in calculating averages of investor attributes for each of the five quintiles of the parents' return distributions. The panel shows that an investor's wealth positively associates with the return of the investor's parent. However, the relation is not monotonic but displays the largest differences between the bottom quintile compared to other quintiles. This pattern also applies to other investor attributes. Investors in the bottom quintile tend to have lower levels of education, cognitive ability scores, and comprehensive school GPAs and they are less likely to have graduated with a business or economics degree and to work in the finance industry. These patterns suggest that the intergenerational return correlation may partly reflect differences in the attributes of investors that constitute each quintile of the parents' return distributions.

Panel D displays the characteristics of the assets that make up an investor's portfolio at different points of parent's return distribution. Each number under the headings 'Asset classes' and 'Mutual fund types' corresponds to the average share an investor has invested in a given asset class or type of mutual fund.[3] The asset class composition reveals that investors whose parents experience low returns are much less likely to invest in riskier assets. However, this positive relation between returns and allocation to risky assets tapers off at the top of the distribution. Investors in the bottom decile are also more likely to invest in funds that are distributed through the branch networks of the large commercial banks and they also display a preference for actively managed funds and funds of funds. These patterns across different asset classes and mutual fund types are suggestive of risk aversion and financial literacy systematically varying across the parents' return distribution.

4. Regressions of returns across generations

The previous section shows strong intergenerational correlations in both historical and expected returns. It also documents heterogeneity in investor attributes and preferences for investment styles across the parents' return distribution. We now turn to regressions that give us an estimate of the intergenerational return correlation and allow us to decompose the correlation into contributions that come from investor attributes and investment styles.

Our regressions explain an investor's return in a given year with that of her father or mother. We estimate specification of the form

$$y_{it} = \alpha + \beta^P y_{it}^P + X_{it}\gamma + \varepsilon_i, \tag{1}$$

[3] In the calculation of shares invested in each fund type, we allocate investments in publicly listed stocks to the omitted category. For example, the 59.1% share invested in funds with retail distribution in the bottom quintile of the father's return distribution combined with the 39.8% allocation to publicly listed stock means that the share invested in non-retail funds equals 100% − 39.8% − 59.1% = 1.1% of the total financial portfolio. Of the average fund portfolio, non-retail funds account for 1.1%/(100% − 39.8%) = 1.8%.

where y_{it} is the return for an individual i in year t and y_{it}^P is the corresponding return calculated for her father or mother. The parameter of interest, β^P, measures the association of returns across generations. In some specifications, we add a vector of covariates X_i that includes observable attributes of the individual, such as wealth, income, and education. We also explore specifications that add measures of investment styles an investor follows.

4.1. Baseline results

Table 2 reports regressions that explain an investor's return with that of her parent. Panel A contains historical returns calculated over the previous 24 months whereas Panel B reports expected returns derived from the four-factor model. Both panels separately report regressions for an investor's father and mother.

Column 1 in Panel A reports the unconditional estimate from the regressions that only include the return of the investor's father as the independent variable. The coefficient estimate of 0.17 implies a 1.7 percentage points higher return for every 10 percentage points increase in the father's return. The estimate is highly statistically significant with a *t*-value of 91.3. This test statistic assumes clustering at the investor level, which takes into account the multiple years we observe an investor and the year-to-year overlap in the 24-month historical return window.

Column 2 adds investor attributes to the specification. These variables include decile dummies for the end-of-year value of financial wealth and for annual labor income. They also contain indicators for four levels and ten fields of education. We further include dummy variables for 11 industries of work, and dummies for gender, native language, and marital status. Finally, the regression controls for cohort effects by including indicators for the 32 birth years in our sample.

The investor attributes address the possibility that the intergenerational return correlation arises from correlation in investor attributes across generations. Previous literature shows that various economic outcomes, such as income, education, and wealth correlate across generations (see Björklund and Salvanes 2011, Black and Devereux 2011, Jäntti and Jenkins 2015, and Solon 1999 for reviews). Another strand of literature has found that wealth, income, education, and other investor attributes associate with investment decisions (Calvet, Campbell, and Sodini 2007, Haliassos and Bertaut 1995, Vissing-Jorgensen 2003, and others).

Column 2 reports an estimate of 0.16 (t-value 89.5). Comparing this estimate to column 1 tells us that 1 – 0.16 / 0.17 = 3.6% of the intergenerational correlation is attributable to observable investor attributes. This attribution suggests that observable investor attributes do not account for a substantial share of the intergenerational return correlation.

Column 3 turns the focus to preferences investors have for different investment styles. We evaluate the role of investment styles by calculating an investor's portfolio allocation across asset classes, types of mutual funds, and asset managers. Six variables capture asset class composition. Two variables measure the share of portfolio invested into actively managed mutual funds and funds of funds.[4] Six variables account for the possibility that different types of investors sort into different asset management companies. We calculate the fraction of portfolio invested with each of the five largest asset management companies and include a residual category that measures the fraction invested with the remaining asset managers.

The inclusion of asset characteristics is a more direct way than the inclusion of investor attributes to account for differences in investment styles. The assets chosen by an investor directly reveal her preferences for asset characteristics whereas the correlation between investor attributes and investment styles is much less perfect. For example, a typical regression model that explains

[4] Variables for asset management companies capture the retail distribution dimension we report in Table 2.

stock market participation with a comprehensive set of investor attributes has an explanatory power of less than 25% (see Grinblatt, Keloharju, and Linnainmaa 2011 for an example).

The regression in Column 3 yields a coefficient of 0.13 (*t*-value 78.9). Compared to the unconditional estimate in Column 1, the reduction in the coefficient suggests that 1 – 0.13 / 0.17 = 22.7% of the intergenerational return correlation can be attributed to observable differences in portfolio composition. Unreported work shows that most of this attribution comes from asset class composition rather than mutual fund types or asset managers: it captures 22.2% of the intergenerational return correlation.

The explanatory power of the models in Panel A reveals that the parental return alone is an important predictor of an investor's return. The explanatory power of the model that only includes the father's return equals 59.1 percent. Adding investor attributes results in an increase to 60.1 percent. Asset characteristics contribute an increase to 65.2 percent.

The remaining columns in Panel A report the intergenerational return correlations in regressions that replace the father's return with that of the mother. The number of observations in these regressions differ from the father's specifications because an investor's father and mother do not always hold financial assets at the same time. The unconditional estimate equals 0.21 (*t*-value 101.7) whereas the estimate that takes into account all observables is 0.16 (*t*-value 86.0). These estimates are somewhat higher than the correlations we obtain for the investor's father. The investor attributes and asset characteristics capture 1 – 0.16/0.21 = 24.9% of the mother's return correlation. These results suggest that our conclusions are not driven by the choice of the parent we use to measure the returns.

Panel B repeats the analysis for expected returns. We use estimated factor loadings for each investor and multiply them with estimates of factor premia to arrive at an estimate of expected returns for each investor. The structure of the panel is identical to Panel A and we regress an investor's expected return with that of her father or mother.

The intergenerational correlations estimated from expected returns are similar in magnitude to those estimated from historical returns. Fathers' estimates vary between 0.16 and 0.19 whereas those for mothers range between 0.17 and 0.22. The *t*-values that vary from 80.4 to 96.0 indicate that the estimates are highly significant. Investor attributes and asset characteristics capture 17.2% to 20.8% of the father's and mother's intergenerational correlation, respectively.

The explanatory power of the models considerably reduces when compared to Panel A. Expected returns generate an explanatory power of 8.0% and 8.6% for the investor's father and mother, respectively. These numbers increase to 22.3% and 22.7% in regressions that account for investor attributes and investment styles. The lower explanatory power reflect the fact that expected returns stem from estimates of factor loadings that contain noise. Nevertheless, the estimates of intergenerational correlations and their attribution to observables are in line with the results that obtain for historical returns in Panel A.

4.2. Robustness checks

Table 3 reports robustness checks that study life-cycle effects, measure returns in different ways, control for additional variables, and focus on new investors only.

Life-cycle effects. Estimates of intergenerational correlations may be sensitive to the age at which we measure the return (see Solon 1999 for discussion). We study this possibility by stratifying the core sample according to the investor's birth year in Panel A of Table 3. Columns 1 to 6 divide the sample into ten-year birth-year intervals. Investors born before 1960 appear in the highest age bracket whereas investors born after 1979 constitute the top category. In each of these birth year brackets, we rerun the regression from column 1 of Table 2. The coefficient estimates range from

0.15 to 0.21 (*t*-values from 25.2 to 56.5). The return correlation is highest for the youngest category of investors who are not more than 24 years old at the start of the sample period. The other brackets do not display a strong age-related pattern, suggesting that the youngest investors may be the most susceptible to parental influence.

Using ranks of returns in lieu of raw returns. Columns 1 and 2 in Panel B replace the historical return with its percentile rank in regressions that relate an investor return to that of her father. We rank returns against all investors in column 1 and against those in the same birth cohort in column 2 and transform the ranks so that they range between 0 and 100. These regressions yield an estimate of 0.18 in both specifications (*t*-values 108.4 and 109.1), which is in line with our baseline regressions in Table 2.

Controlling for cognitive skills. Columns 3 and 4 in Panel B investigate subsamples for which we have data on cognitive ability from the military enlistment or final year GPA from the 9-year comprehensive school. The 0.16 and 0.18 estimates (*t*-values 53.9 and 77.3) differ only slightly from the estimates in the core sample. These differences reflect the fact that we only observe cognitive ability for males and that GPA is only available for younger cohorts. Unreported analysis shows that the subsamples for which cognitive ability or GPA is available yield almost exactly the same estimates of 0.16 and 0.18 (*t*-values 54.0 and 77.3) when cognitive skills are omitted from the set of control variables.

Accounting for parents' direct purchases. Column 5 in Panel B addresses the possibility that return correlations arise from investment decisions that parents make for their underage children prior to our sample period. Parents may open and manage an investment account for their underage children. If these assets remain in portfolios throughout the investor's adult life, their legacy may generate a correlation in returns across generations.[5] We investigate this story by focusing on a subsample of investors who start our sample period with no asset holdings, but enter the market in later sample years. These investors are immune to the effects that arise from their parents' direct purchases. We find an estimate of 0.11 (*t*-value 27.4), which confirms that the legacy of parents' purchases is an unlikely driver of our results.

5. Understanding the channels that generate the return correlation

This section investigates channels that generate the intergenerational correlation in returns. Our aim is to differentiate between two stories. First, family members may share attributes that make them choose similar investment styles. For example, risk aversion that correlates across generations, perhaps due to genetic factors or upbringing, may drive family members to choose portfolios with similar investment styles. Second, family members may also share information about the securities that make up their financial portfolio, perhaps in an effort to make the search problem more manageable. Correlated purchases of particular securities may produce the appearance that returns and investment styles correlate across generations. In this section, we exploit information on holdings of specific securities to differentiate between the two stories.

5.1. Stratifying the sample according to portfolio overlap

Our first step in understanding the roles played by shared attributes and shared security choices involves an analysis of detailed asset holdings. These holdings make it possible to compare the exact portfolio composition of an investor to that of her parents. We calculate how much the two portfolios

[5] This mechanism begs the question of why children would keep the assets their parents have bought them. A sufficiently high capital gains tax overhang, for example, might justify an unwillingness to rebalance the portfolio. See Calvet, Campbell, and Sodini (2009) for empirical evidence on rebalancing by individual investors.

overlap, stratify the sample according to the extent of overlap, and estimate the intergenerational return correlations in the subsamples. Our measure of portfolio overlap indicates the securities in an investor's portfolio that are also held by her parent and calculates the value-weighted share of the common assets in the investor's overall portfolio. The measure has a range from 0 percent (no overlap) to 100 percent (full overlap).

Table 4 reports these regressions, separately for fathers in Panel A and for mothers in Panel B. Both panels further report estimates from the unconditional specification and the specification controlling for investor attributes and investment styles. The four columns vary the degree of overlap between the portfolios of the investor and her parent. The first column analyzes a subsample where no asset holdings match in the two portfolios. The three remaining columns estimate the return correlation in overlap categories of >0% to ≤25%, >25% to ≤75%, and >75% to ≤100%. The last row of the panels shows that the four subsamples make up 61%, 8%, 11%, and 20% of the total sample.

The investors with no overlap in column 1, by far the largest category, yield a small intergenerational return correlation of 0.005 (*t*-value 2.8). This correlation equals 0.004 (*t*-value 2.6) in column 5 that adds the controls for investor attributes and asset characteristics. The other subsamples show that the return correlation increases monotonically in overlap. The highest estimate in column 4 equals 0.71. Weighting the estimates in the four subsamples with their share of the total sample yields an average coefficient of 0.20, which is close to the baseline estimate in Table 2.

The mother's specifications in Panel B show the same monotonically increasing pattern as a function of portfolio overlap. As in Table 2, the estimates are somewhat larger for mothers than for fathers. Taken together, these results suggest that shared securities play a pivotal role in generating the intergenerational return correlation.

Why do family members share the same securities? Table 5 takes a first look at this question by relating portfolio overlap to four factors that likely vary the extent to how susceptible an investor is to parental influence. First, we analyze how overlap varies by the parent's absence in the investor's childhood. Kalil et al. (2015) find that father's presence in childhood increases the correlation of his education with that of his offspring. Björklund and Chadwick (2003) and Gould and Simhon (2015) find smaller intergenerational correlations in families where the parent has been present for a shorter time. Second, we investigate the strength of portfolio overlap as a function of family size. Price (2008) documents children born to smaller families benefit from spending more quality time with their parents. Third, we explore parent-child linkages stratified by gender. Bowles and Gintis (2002) find that intergenerational correlations between fathers and sons tend to be larger than those for fathers and daughters. Fourth, we indicate biological parents because they share their genetic makeup with their offspring whereas adoptive parents lack this connection. Black et al. (2015) and Fagereng, Mogstad, and Ronning (2015) find lower intergenerational correlations for adopted than biological children.

We estimate the heterogeneity in portfolio overlap by regressing it on an indicator for a parent that was present in the household when the child was 15 years old, and indicators for family size, biological parents, and females. Table 4 reports results for the core sample and for the younger cohorts for which information on parent's presence in childhood is available. Columns 1 to 4 report estimates for an investor's father whereas columns 5 to 8 report correlations for the mother. For both sets of regressions, we report unconditional estimates and coefficients that control for the set of investor attributes we use in Table 2.

Column 1 shows that family size is negatively associated with portfolio overlap. Compared to only children, investors with at least four siblings have 4.6 percentage points smaller portfolio overlap (*t*-value −8.4) with their father. This reduction is sizeable when compared to the average overlap of 58.5 percentage points. The insignificant coefficient on biological parents suggests that adoptive parents, which do not share genetic makeup with their children, do not systematically differ from biological parents. This result is consistent with the variation in overlap being largely driven by non-genetic factors. Column 2 shows that these effects remain when we control for other investor attributes.

For family size and biological parents, we obtain similar results for mothers in columns 5 and 6. The coefficient for the female indicator equals 1.5 percentage points for fathers in column 1 whereas it is much higher, 4.1 percentage points, for mothers in column 5. Both of these estimates are statistically highly significant, suggesting daughters' portfolios overlap more with those of their parents. Moreover, daughters tend to have portfolios that resemble more of their mother's portfolios than those of their father's.

Column 3 shows that father's absence in childhood strongly reduces portfolio overlap. For investors with absent fathers, portfolio overlap is 5.3 percentage points smaller than for others (*t*-value 12.0). In this sample, family size becomes statistically insignificant. We have verified in an unreported analysis that the younger cohorts that make up this sample fully drive the disappearance of the family size relation.

Overall, this section shows that the magnitude of return correlation depends strongly on how much financial portfolios overlap within families. Portfolio overlap is larger in families where relationships likely are stronger, which suggests that within-family influence drives the return correlation.

5.2. Intergenerational correlations in the choice of a security

The central role of overlapping investments in generating the return correlation motivate us to directly analyze how an investor's choice of a particular security associates with that of her parent.

We organize the asset holdings into a panel in which the unit of observation is an investor-security-year triplet. The dependent variable is an indicator that takes the value of one if an investor holds an asset in a year and zero otherwise. The independent variable is the same variable defined for either of the investor's parents.

The great number of investors observed over multiple years coupled with the wide menu of securities would result in a panel with more than 500 million observations. We adopt a randomization approach that economizes on sample size, but does not generate bias in the estimation. We determine the set of assets an investor held at any point in time during our sample period and match each security held by an investor with a randomly chosen asset that the investor did not hold at any point during the sample period. For the holding and the matched non-holding, we then retrieve the full time-series of investor-security-year triplets. Assets that do not exist in a given year do not enter the sample.

Table 6 reports results of five regressions that vary the set of control variables. Column 1 includes fixed effects for each security-year pairing. This model addresses the potential correlation in security choice that arises from the higher likelihood of two randomly selected investors to invest in assets that have higher market shares. Column 2 reports a regression that adds fixed effects for pairing an investor with each asset class. This estimation controls for the tendency to invest in a particular asset class that potentially arises from shared risk preferences or other shared determinants of risky investment. Intergenerational correlations in occupations, for example, may translate into correlations in labor income profiles, which may influence an investor's willingness to invest in risky assets (Cocco, Gomes, and Maenhout 2005, Heaton and Lucas 2000, Viceira 2001). Column 3 adds a further set of fixed effects for each asset management firm whereas column 4 includes each mutual fund type (actively managed, retail distribution, and fund of fund) paired with each investor.[6] These specifications capture shared preferences for investing in the same asset management firm, perhaps arising from the geographic reach of a firm's distribution channel, and preferences for different types of funds, possibly driven by financial literacy.

Column 5 replaces all pairings of investors with observable asset characteristics with fixed effects for each investor-security pairing. This estimation takes advantage of the time-series of asset holdings that allows us to estimate the correlation from instances in which an investor either buys a new security or sells her entire holding in an asset. The focus on changes in holdings makes it possible to rule out the role of any time-invariant preferences an investor and her parent have for a particular asset. Columns 6 to 10 repeat columns 1 to 5 for the investor's mother.

The first regression in column 1 shows an intergenerational correlation in security choice that equals 0.24 (*t*-value 139.5). This estimate implies that the likelihood to invest in a security is 24 percentage points higher for assets held by the investor's father. In the randomized sample we use in this estimation, the unconditional probability of investing in an asset equals 40 percentage points. Therefore, the father's holding of a security increases an investor's likelihood to invest in the security by 0.24 / 0.40 = 58.2 percent when compared to the average holding propensity. The fixed effects for pairing an investor with asset classes, asset management firms, and mutual fund types in column 4 generate an estimate of 0.18 (*t*-values 106.5). This estimate suggests that investor preferences for investment styles account for 1 – 0.18/0.24 = 21.9 percent of the correlation in security choice.

Column 5 estimates the security choice correlation from changes in asset holdings over time. The estimate suggests that an investor's probability to buy an asset goes up by 10.7 percentage

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[6] We assign investments in publicly listed stocks to the omitted category. See footnote 3 for details.

points in the year when the investor's father purchases the asset (*t*-value 45.2). Columns 6 to 10 report the corresponding estimates for the investor's mother. These correlations are somewhat higher than for fathers, but patterns in coefficient changes across specifications are similar to those in columns 1 to 5. These results show that investors are much more likely to invest in a security held by their parents, even when we account for preferences to invest in observable types of securities. The specifications that take advantage of time-series variation in holdings further suggest that time-invariant preferences for unobserved asset characteristics do not drive the security-choice correlation.

5.3. Using non-overlapping peer groups to identify causal effects

The time-varying nature of the intergenerational correlation can potentially be reconciled with a story in which investors and their parents respond to time-varying influences in the same way. For example, financial advisors may be more successful in selling a product to financially illiterate families. Such a mechanism might explain why members of a particular family tend to buy a security at the same time.

We use two settings that are immune to time-varying confounding factors. The first approach takes advantage of information that allows an approximation of social networks, and studies how decisions made by the peers of an investor's parent affect the investor. The overarching idea of this identification strategy is that peers may influence an investor's parent but these peers do not directly affect the investor. However, investors likely share a common set of peers with their parents. We circumvent this problem by focusing on peer groups that do not overlap between the investor and her parent. These non-overlapping peer groups break the direct link from parent's peers to the investor and allow us to use investments of the parent's peers as an instrument for the investor's decision (see Bramoullé, Diebbari, and Fortin 2009, De Giorgi, Frederiksen, and Pistaferri 2016, De Giorgi, Pellizzari, and Redaelli 2010, Lee, Liu, and Lin 2010, Nicoletti, Salvanes, and Tominey 2016).

We define peers of an investor's parent by matching the parent with investors who live in the same zip code and belong to the same age cohort. In additional specifications, we also stratify peer groups by whether the parent's native language is either of the two official languages, Finnish or Swedish. These dimensions of peer groups stem from people being likely to interact with geographically proximate people of the same age and cultural origin (native language determines many social networks in Finland as in many other countries). Our data has in total 2,995 zip codes and cohorts are ten-year intervals of parent's age so that the top and bottom categories include parents born before 1930 and after 1950.

The instrument for an investor's likelihood to hold a security is the share of the peers of the investor's parent who invest in the security. In this calculation, we exclude the parent to avoid the mechanical relation that arises from correlating the parent's decision with a variable that contains that same decision. We ensure non-overlapping peer groups by including fixed effects for each pairing of a security with a zip code. These fixed effects absorb any variation that comes from investors who interact with the same set of local peers as their parents.

Table 7 reports the results of regressions that follow the structure of Table 6. The dependent variable takes the value of one when an investor holds a particular asset. We match each investor-holding-year triplet with a control observation that contains a randomly chosen asset that the investor does not hold in the year. The dependent variable for this control observation takes the value of zero. (See Section 5.2 for details of the matching procedure.)

The 2SLS estimates use the peers of an investor's parent to construct the instrument. The table also reports the corresponding OLS estimates for comparison. The two leftmost columns report the results for the investor's father whereas the mother's estimates appear in the remaining two columns.

Columns 1 and 3 define peers according to zip codes and cohorts. A more refined version of peer groups that uses native language in addition to zip codes and cohorts features in columns 2 and 4. All columns report diagnostics for the first stage.

Column 1 shows that our identification approach has a strong first stage. The instrument's F-statistic of 768.6 surpasses reasonable critical thresholds for weak instruments and the partial R^2 equals 0.014. The IV estimate that appears in the row '2SLS' equals 0.25 (t-value 10.4). The sample here is smaller than the core sample because some investors do not have all the dimensions of the instrument available so we also report the corresponding OLS estimate in this sample. It equals 0.17 (t-value 52.5), which is somewhat smaller than the baseline OLS estimate of 0.21 in Table 6 and also smaller than the IV estimate in Table 7. A possible interpretation for the difference between the OLS and IV estimates is that a larger share of the parent's peers investing in a security makes the security more salient to the parent who then passes on information about the security to her offspring.

The more refined instrument that takes advantage of native language as an additional dimension of peer groups generates an equally impressive first stage (F = 671.6) and an IV estimate of 0.23 (t-value 9.2). The corresponding regressions for the investor's mother in columns 3 and 4 yield coefficient estimates that are somewhat larger in magnitude compared to the father's regression in columns 1 and 2. These results are consistent with the interpretation that the intergenerational correlation in security choice does not arise from time-varying confounding factors within families, but that parents influence their offspring.

5.4. Natural experiment based on mergers

The second identification approach considers instances in which an investor's parent becomes a shareholder without making the active decision to purchase a particular security. These events are either mergers of an existing security into another entity or spinoffs of a new entity from an existing security. In these cases, shareholders of the "target" become shareholders in the "acquirer" by default with no active investment decision. Prior to each event, we identify the target shareholders that will become shareholders in the acquirer by default and analyze how their offspring alter their investments in the acquirer following the event.[7]

Table 8 reports the results of this exercise. Our sample consists of all investors whose either parent was a shareholder of the target entity in the year prior to the event. We then match each of these treated investor-event pairs with a control observation that is a randomly chosen event in which the investor's parent was not a target shareholder. We exclude investors who themselves were shareholders in the target entity to avoid the mechanical increase in the likelihood to hold the acquirer.

Panel A reports an investor's propensity to hold the acquirer in the five years surrounding the merger, separately for the treatment and control observations. The panel further splits the sample according to whether it was the father or the mother of an investor who became a shareholder in the acquirer in the event.

In the two years prior to the event, $t-1$ and $t-2$, investors in the treatment and control groups have a 0.5% to 0.6% likelihood to own the acquirer. In the year of the event, the ownership propensities dramatically diverge with the treatment group having a 2.4 percentage points higher probability than the control group. This difference remains in the following two years. Similar patterns and magnitudes are present for the investor's mother in the three rightmost columns.

[7] During our sample period, 40 securities merge with another entity and two new securities are spun off from an existing entity. Four securities are publicly listed stocks whereas the remaining 38 are mutual funds. We include securities that have holding data two years before and after the event. This restriction, which makes it possible to observe changes in holdings before and after the event, leaves us with four publicly listed stocks and 14 mutual funds.

Panel B uses the changes in ownership generated by the events as an instrument for the parent's ownership of a security. It reports regressions that explain an investor's decision to hold the acquirer with that of her parent. The 2SLS regressions use an indicator for the treatment group in years $t = 0$ to $t = 2$ as the instrument for the parent's ownership. The indicator takes the value of zero for the treatment group in the years prior to the merger and in all the five years surrounding the merger for the control group. Standard errors assume clustering at the investor level to account for serial correlation in observing the treatment and control group over multiple years (Bertrand, Duflo, and Mullainathan 2004). The OLS estimates report, for comparison, the coefficients from regressing an investor's decision to hold the acquirer on that of her parent.

The F-statistics of the first stage in Column 1 of Panel B reject the null hypothesis of a weak instrument. The IV estimate equals 3.9 percentage points with a t-value of 20.1. The average ownership propensity in the sample equals 1.3 percentage points, suggesting a 3.9% / 1.3% − 1 = 94.8% increase in the likelihood to hold the acquirer in the aftermath of the events. The IV estimate is larger than the OLS estimate of 2.5 percentage points. This difference in magnitude may arise from the fact that the events that feed into the 2SLS estimate may make the investor more aware of the security and it therefore features more prominently in conversations. Column 2 reports that the increase in the ownership propensity is larger for mothers than for fathers. These findings corroborate the interpretation that the intergenerational correlation in security choice reflects a causal effect.

5.5. Causal effects from adult children to parents

We have so far fixed the direction of causality to run from parents to children. It is conceivable that some adult children may also provide financial advice to their less sophisticated parents. Table

9 addresses this possibility.[8] It uses the merger experiment and analyzes the influence that a child passively becoming a shareholder has on her parent's investment decision.

The table follows the structure of Table 8 but flips the sample selection criteria and the dependent and independent variables. It focuses on the subset of parents who were not shareholders in the target security and then analyzes two sets of parents. The first set is the treatment group in which the child owns the target security whereas the control group consists of parents whose children do not own the target. As in Table 8, we analyze the five years surrounding the event and indicate the treated parents in the years following the event.

Panel A shows that ownership probabilities are similar in the treatment and control groups prior to the event. In the year of the event, fathers whose children are shareholders of the target are 2.3 percentage points more likely to hold the acquirer. The ownership propensity of treated mothers goes up by 3.2 percentage points following the event compared to the control group. Panel B reports the IV estimates that use the indicator for the treatment group in the years following the event as the instrument. The father's coefficient suggests a 3.8 percentage points increase (*t*-value 14.4) in the likelihood to own a security. Mother's estimates are again larger in magnitude whereas the OLS estimates for both parents are smaller than the IV estimates. These regressions suggest that the causality runs not only from parents to children but also in the opposite direction.

6. Conclusion

We find a significant within-family component in the returns investors earn on their financial wealth. Investments in the same set of securities largely drive this intergenerational correlation. Two

[8] Friedman and Mare (2014), Zimmer et al. (2007), and Torssander (2013) find a positive association between child's education and parent's longevity. Using a compulsory schooling reform in Sweden as a natural experiment, Lundborg and Majlesi (2015) find no evidence that the positive association reflect a causal relation.

identification strategies support the interpretation that family members invest in same securities because they causally influence each other.

Our findings inform the modeling efforts that try to rationalize the fat right tail of wealth distributions. The causal interpretation of the correlation also has implications for policy. The influence we document within families suggests the effects of policy initiatives, such as attempts to improve financial literacy, travel up and down in the intergenerational ladder.

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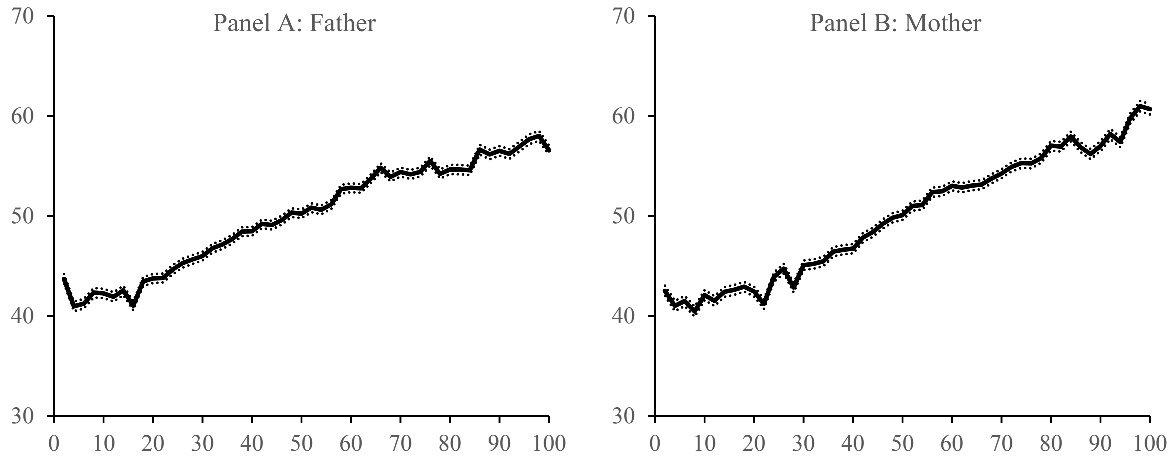

Figure 1. Return on financial wealth as a function of that of an investor's parents

The graph plots an investor's return on her portfolio of stocks and mutual funds as a function of that of her parents. The horizontal axis is the rank transformation of the value-weighted average return on the portfolio of an investor's parent, calculated over a historical 24-month window. The vertical axis depicts the average of the investor's return rank for 20 vigintiles of the parent's return rank. Panel A depicts the intergenerational correlation in returns using the father's return whereas Panel B uses the mother's return. The dotted lines show the 95% confidence intervals.

Table 1

Returns, investor attributes, and asset characteristics as a function of parent's return

This table reports the return investors earn on their financial wealth as a function of their parent's return. The historical return is the value-weighted average portfolio return calculated over the previous 24 months. Factor loadings come from a 4-factor model that includes the market, size, and value factors from Fama-French (1993) and the momentum factor from Carhart (1997). The market factor is the monthly return of the euro-denominated MSCI Europe index less the 12-month Euribor. The euro-denominated SMB, HML, and MOM factors are for the U.S. stock market. The expected return multiplies the estimated factor loadings with the average returns on the factors from 1994 to 2008 assuming zero alphas. Portfolio value is the total value of the portfolio in euros. Labor income is inflation adjusted using the Consumer Price Index from Statistics Finland using 2008 as the base year. The cognitive ability test score is from the enlistment test administered by the Finnish Armed Forces to males enlisted in 1982 or after. School GPA is the average of the individual's grade points from the 9-year comprehensive school for individuals who completed school in 1985 or after. GPA ranges from 4 (lowest) to 10 (highest). Business degree indicates investors with either business or economics degree. Finance professionals work in the finance industry. The asset class 'Other' includes hedge funds and funds investing in alternative asset classes. Retail distribution refers to funds run and distributed by asset management companies affiliated with commercial banks and actively managed funds follow an active management philosophy. Funds of funds are investment vehicles that invest in other mutual funds. The share of each mutual fund type divides the value of holdings in the mutual fund type with the total value of fund and stock holdings.

Panel A: Historical returns

	Father's return quintile (1st = Bottom, 5th = Top)					Mother's return quintile (1st = Bottom, 5th = Top)				
	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Historical return, parent (%)	-8.07	2.32	10.45	16.80	26.39	-8.17	-0.13	7.60	15.06	24.94
Historical return, child (%)	4.72	6.48	8.19	9.64	10.87	4.56	5.81	8.04	9.66	11.46
Historical return rank, child	42.59	47.01	51.70	55.48	58.09	41.94	44.83	50.53	54.52	58.19

Panel B: Expected returns

	Father's return quintile					Mother's return quintile				
	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Expected return, parent (%)	-1.01	1.58	3.48	5.63	9.60	-0.98	1.10	2.85	4.99	9.02
Expected return, child (%)	2.94	3.42	3.85	4.33	4.98	2.96	3.33	3.77	4.30	5.15
Expected return rank, child	43.24	46.72	51.00	54.97	58.47	42.49	45.26	49.53	54.06	58.65
Factor loadings, child										
Market	0.84	0.85	0.92	0.98	0.99	0.82	0.82	0.90	0.99	1.02
Size	0.03	0.01	0.00	-0.03	-0.05	0.03	0.01	0.00	-0.05	-0.07
Value	-0.13	-0.15	-0.17	-0.19	-0.22	-0.13	-0.15	-0.17	-0.18	-0.22
Momentum	-0.01	0.05	0.07	0.11	0.18	0.00	0.05	0.07	0.10	0.19

Panel C: Average investor attributes										
	Father's return quintile					Mother's return quintile				
	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Portfolio value ('000 EUR)	17.98	18.47	22.47	22.38	22.48	17.93	17.58	22.22	23.26	27.11
Labor income ('000 EUR)	31.27	31.32	31.51	32.15	31.59	31.57	31.21	31.66	31.54	31.30
Level of education										
Basic or vocational (%)	44.86	39.63	37.86	40.00	42.04	44.04	41.47	37.62	38.34	40.48
High school (%)	16.82	19.12	19.88	19.77	19.11	17.37	18.41	20.55	20.47	20.93
Bachelor's degree (%)	15.73	15.95	15.69	15.02	15.26	15.79	16.13	15.46	15.44	14.73
Master's degree or higher (%)	22.59	25.30	26.58	25.22	23.60	22.80	23.98	26.37	25.76	23.86
Business and economics degree (%)	17.20	17.72	18.24	19.21	18.79	17.89	17.91	18.58	18.65	19.06
Finance professional (%)	4.40	4.41	4.38	4.72	4.63	4.62	4.59	4.68	4.49	4.58
Female (%)	43.74	43.98	44.30	44.96	44.57	44.85	44.93	45.43	45.84	45.77
Married (%)	41.08	40.59	40.83	41.76	41.31	40.86	39.46	40.07	40.59	39.97
Swedish-speaking (%)	7.61	10.01	10.34	8.88	8.80	7.01	8.87	12.00	9.11	9.38
Birth year (yy)	72.10	72.82	72.80	72.13	72.19	72.23	72.91	72.91	72.64	72.49
Cognitive ability (standardized)	0.38	0.45	0.46	0.47	0.43	0.40	0.42	0.46	0.48	0.45
School GPA (4-10)	8.04	8.10	8.11	8.11	8.08	8.04	8.06	8.11	8.11	8.09

Panel D: Average share of portfolio in asset classes and mutual fund types										
	Father's return quintile					Mother's return quintile				
	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Asset classes										
Stock (%)	39.84	44.79	51.09	54.20	51.31	39.98	40.64	49.62	54.71	54.11
Short-term bond fund (%)	11.81	8.42	7.06	7.26	8.28	12.92	9.27	6.83	6.48	7.83
Long-term bond fund (%)	3.95	3.19	2.75	2.90	2.88	4.16	3.40	2.83	2.82	2.83
Balanced fund (%)	20.70	18.93	15.36	14.90	16.11	19.83	21.58	15.70	14.32	14.76
Equity fund (%)	22.14	23.14	22.24	19.26	19.93	21.46	23.57	23.47	20.30	19.00
Other fund (%)	0.71	0.59	0.52	0.54	0.55	0.79	0.65	0.51	0.46	0.57
Mutual fund types										
Retail distribution (%)	59.06	54.00	47.66	44.60	47.48	58.91	58.20	49.04	44.12	44.74
Actively managed (%)	56.52	51.05	44.55	41.58	44.49	56.50	55.58	45.84	41.21	41.66
Fund of fund (%)	23.76	20.91	17.17	16.71	18.22	23.00	23.75	17.07	16.36	16.75

Table 2

Intergenerational regressions of returns

This table reports coefficient estimates and their associated *t*-values from regressions that explain an investor's portfolio return with that of her father (columns 1 to 3) or mother (columns 4 to 6). The unit of observation is an investor *i* in year *t*. Panel A analyzes historical returns calculated over the previous 24 months. Panel B uses an estimate of expected returns derived from multiplying estimated factor loadings with historical factor premia. Specifications 2 and 5 include decile dummies for total value of the fund portfolio and for annual labor income. They also control for dummies for four levels of education, 10 fields of education, and 11 industries (missing categories omitted). The demographic controls are 32 cohort dummies, and indicators for females, native language, and marital status. Specifications 3 and 6 control for six variables that measure the share of portfolio invested in an asset class (short-term bond fund omitted) and six variables that measure the share of portfolio invested with an asset management company (the five largest companies enter separately and the remaining 24 firms serve as the omitted category). Fund characteristics refer to fractions invested in funds of funds and actively managed funds (asset manager dummies capture retail distribution). The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Historical returns						
Dependent variable	Value-weighted average portfolio return					
Specification	Father			Mother		
	1	2	3	4	5	6
Parent's return	0.169	0.163	0.131	0.207	0.200	0.155
	(91.26)	(89.49)	(78.88)	(101.66)	(99.93)	(85.97)
Controls						
Wealth and income	No	Yes	Yes	No	Yes	Yes
Level and field of education	No	Yes	Yes	No	Yes	Yes
Industry of work	No	Yes	Yes	No	Yes	Yes
Demographics	No	Yes	Yes	No	Yes	Yes
Asset classes	No	No	Yes	No	No	Yes
Asset managers	No	No	Yes	No	No	Yes
Fund characteristics	No	No	Yes	No	No	Yes
Mean dependent variable	0.080	0.080	0.080	0.079	0.079	0.079
Adjusted R^2	0.591	0.601	0.652	0.599	0.609	0.659
Number of observations	742,314	742,314	742,314	662,001	662,001	662,001

Panel B: Expected returns						
Dependent variable	Value-weighted average portfolio return					
Specification	Father			Mother		
	1	2	3	4	5	6
Parent's return	0.187	0.186	0.155	0.219	0.218	0.173
	(94.44)	(94.03	(83.25)	(96.00)	(95.62)	(80.37)
Controls						
Wealth and income	No	Yes	Yes	No	Yes	Yes
Level and field of education	No	Yes	Yes	No	Yes	Yes
Industry of work	No	Yes	Yes	No	Yes	Yes
Demographics	No	Yes	Yes	No	Yes	Yes
Asset classes	No	No	Yes	No	No	Yes
Asset managers	No	No	Yes	No	No	Yes
Fund characteristics	No	No	Yes	No	No	Yes
Mean dependent variable	0.039	0.039	0.039	0.039	0.039	0.039
Adjusted R^2	0.080	0.090	0.223	0.086	0.096	0.227
Number of observations	742,314	742,314	742,314	662,001	662,001	662,001

Table 3

Robustness checks

This table reports robustness checks on the regressions reported in Table 2. The specifications correspond to the regression in column 1 of Table 2. Panel A divides the sample according to investor's birth year into six categories. Specifications 1 and 4 in Panel B rank investors according to their father's portfolio return, either across the whole population or within the father's birth cohort. Specifications 3 and 4 use subsamples for which information on cognitive ability and comprehensive school GPA is available. Specification 5 investigates investors who have no asset holdings in the beginning of the sample period but enter the market in later sample years. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Accounting for life-cycle effects						
Investor's birth year bracket	<1960	1960-64	1965-69	1970-74	1975-79	≥1980
Specification	1	2	3	4	5	6
Parent's return	0.162	0.146	0.150	0.157	0.164	0.212
	(25.23)	(28.93)	(33.21)	(35.21)	(39.92)	(56.54)
Mean dependent variable	0.099	0.095	0.091	0.081	0.069	0.066
Adjusted R^2	0.602	0.592	0.589	0.592	0.588	0.598
Number of observations	57,037	94,459	126,761	135,990	148,208	179,859

Panel B: Additional robustness checks					
Robustness check	Rank of returns	Within-cohort rank of returns	Controlling for cognitive ability	Controlling for GPA	New investors only
Specification	1	2	3	4	5
Parent's return	0.179	0.179	0.158	0.178	0.112
	(108.39)	(109.07)	(53.85)	(77.25)	(27.35)
Mean dependent variable	50.00	50.01	0.080	0.080	0.002
Adjusted R^2	0.032	0.032	0.588	0.592	0.540
Number of observations	742,314	742,314	293,023	484,240	118,694

Table 4

Intergenerational correlation in returns as a function of portfolio overlap

This table reports regressions that stratify the sample according to how much the investor's portfolio overlaps with that of her parent. The portfolio overlap indicates the securities in an investor's portfolio held by her parent and calculates the value-weighted fraction of the shared securities in the investor's portfolio. The first subsample includes cases where no asset holdings match in the two portfolios. The three remaining subsamples estimate the return correlation in samples where overlap ranges from >0% to ≤25%, >25% to ≤75%, and >75% to ≤100%, respectively. Panels A and B report estimates based on an investor's father or mother, respectively. 'No controls' use specifications 1 and 4 in Table 2 whereas 'Controls' refers to specifications 3 and 6. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Father								
Dependent variable	Value-weighted average portfolio return							
	No controls				Controls			
Overlap	0%	>0%, ≤25%	>25%, ≤75%	>75%, ≤100%	0%	>0%, ≤25%	>25%, ≤75%	>75%, ≤100%
Specification	1	2	3	4	5	6	7	8
Parent's return	0.005	0.102	0.410	0.713	0.004	0.083	0.345	0.611
	(2.77)	(20.34)	(95.48)	(173.19)	(2.64)	(18.80)	(80.78)	(128.26)
Mean dependent variable	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080
Adjusted R^2	0.536	0.693	0.786	0.752	0.597	0.744	0.807	0.773
Number of observations	449,815	60,795	82,829	148,875	449,815	60,795	82,829	148,875

Panel B: Mother								
Dependent variable	Value-weighted average portfolio return							
	No controls				Controls			
Overlap	0%	>0%, ≤25%	>25%, ≤75%	>75%, ≤100%	0%	>0%, ≤25%	>25%, ≤75%	>75%, ≤100%
Specification	1	2	3	4	5	6	7	8
Parent's return	0.011	0.125	0.452	0.789	0.008	0.090	0.371	0.687
	(5.19)	(24.25)	(105.18)	(217.06)	(4.16)	(19.74)	(84.43)	(155.04)
Mean dependent variable	0.079	0.079	0.079	0.079	0.079	0.079	0.079	0.079
Adjusted R^2	0.544	0.698	0.796	0.793	0.605	0.748	0.817	0.811
Number of observations	401,585	54,095	74,041	132,280	401,585	54,095	74,041	132,280

Table 5

Correlates of portfolio overlap

This table analyzes correlates of overlap between an investor's portfolio and that of her parent. The dependent variable takes the value of one for an investor whose portfolio contains some securities held by her parent. Independent variables include an indicator for an investor and her parent sharing a dwelling unit when the investor was at the age of 15. The indicator variable for a biological parent equals one for a biological parent and zero for an adoptive parent. Dummies for number of siblings count the number of children born to a mother. Specifications 2 and 4 further include controls for the investor attributes employed in Table 2. The samples in columns 3, 4, 7, and 8 include investors for which the identifier for dwelling unit is available at age of 15. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Dependent variable	Portfolio overlap greater than 0%							
Specification	Father				Mother			
	1	2	3	4	5	6	7	8
Number of siblings = 1	-0.005	-0.001	-0.001	0.003	-0.008	-0.008	-0.003	-0.002
	(-1.54)	(-0.43)	(-0.29)	(0.72)	(-2.76)	(-2.73)	(-0.67)	(-0.48)
Number of siblings = 2	-0.007	-0.003	0.006	0.008	-0.008	-0.009	0.009	0.006
	(-2.05)	(-1.08)	(1.46)	(1.93)	(-2.37)	(-2.68)	(2.08)	(1.28)
Number of siblings = 3	-0.023	-0.017	-0.002	-0.001	-0.011	-0.008	0.015	0.011
	(-5.45)	(-4.34)	(-0.40)	(-0.23)	(-2.54)	(-1.84)	(2.47)	(1.79)
Number of siblings ≥ 4	-0.046	-0.029	-0.004	0.009	-0.037	-0.023	0.011	0.018
	(-8.41)	(-5.47)	(-0.53)	(1.20)	(-6.01)	(-3.72)	(1.29)	(2.08)
Biological parent	-0.008	0.003	0.002	0.011	-0.018	-0.003	-0.014	-0.007
	(-1.26)	(0.43)	(0.30)	(1.50)	(-2.59)	(-0.51)	(-1.70)	(-0.89)
Female	0.015	0.020	0.013	0.015	0.041	0.040	0.038	0.036
	(8.30)	(9.50)	(5.43)	(5.60)	(21.10)	(18.04)	(14.73)	(12.62)
Parent present at age 15			0.053	0.046			0.046	0.043
			(12.02)	(10.66)			(5.11)	(4.84)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Mean dependent variable	0.585	0.585	0.585	0.585	0.579	0.579	0.579	0.579
Adjusted R^2	0.179	0.216	0.178	0.217	0.184	0.214	0.173	0.203
Number of observations	742,314	742,314	410,619	410,619	662,001	662,001	373,715	373,715

Table 6

Intergenerational regressions of security choice

This table reports coefficient estimates and their associated *t*-values (in parentheses) from regressions that explain an individual's decision to hold a particular security. The unit of observation is for an individual *i* and security *j* in year *t*. A holding in security *j* by investor *i* is matched to a security the investor has not held during the sample period. Specifications 1 and 6 control for the security's market share by including security-year fixed effects. Specifications 2 and 7 control for an investor's preference for a particular asset class by including investor-asset class fixed effects. Specifications 3 and 8 control for investors paired with asset management firms whereas specifications 4 and 9 add pairings of investors with mutual fund types. Specifications 5 and 10 replace fixed effects for pairings of an investor with asset classes, asset management firms, and mutual fund types with pairings of investors with each security and identify the effect from year-to-year changes in security holdings. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Dependent variable	Investor invested in an asset									
Specification	Father, $N = 2,577,300$					Mother, $N = 2,219,388$				
	1	2	3	4	5	6	7	8	9	10
Parent invested in an asset	0.235	0.206	0.186	0.183	0.107	0.243	0.209	0.182	0.179	0.134
	(139.45)	(120.09)	(107.92)	(106.48)	(45.18)	(139.08)	(112.55)	(97.39)	(95.35)	(47.52)
Fixed effects										
Security × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor × Asset class	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Inv. × Asset manager	No	No	Yes	Yes	No	No	No	Yes	Yes	No
Inv. × Mutual fund type	No	No	No	Yes	No	No	No	No	Yes	No
Inv. × Security	No	No	No	No	Yes	No	No	No	No	Yes
Mean dependent variable	0.402	0.402	0.402	0.402	0.402	0.406	0.406	0.406	0.406	0.406
Adjusted R^2	0.462	0.594	0.613	0.585	0.838	0.469	0.601	0.622	0.594	0.842

Table 7

Identifying intergenerational correlation in security choice using non-overlapping peer groups

This table reports coefficient estimates and their associated *t*-values (in parentheses) from regressions that explain an individual's decision to hold a particular asset. The regressions correspond to those in columns 1 and 5 in Table 5. The 2SLS estimates instrument for a parent's asset ownership with that of the parent's peers. In Columns 1 and 3, peers are investors who live in the same zip code and belong to the same age cohort as the parent. The four cohorts are for investors who are born before 1930, during 1930s, during 1940s, and in or after 1950. Columns 2 and 4 further define peers by whether the parent's native language is Finnish or Swedish. The instrument is the fraction of peers that hold a security, excluding the parent. The regressions include fixed effects for pairing each zip code with each asset to control for any influences that make investors in a neighborhood likely to own a particular asset. The OLS estimates report the corresponding OLS regressions. The 2SLS diagnostics are the partial R^2 and the F-statistic of the instrument in the first stage. The *t*-values reported in parentheses use standard errors that assume clustering at the zip code level.

Dependent variable	Investor invested in an asset			
Specification	Father		Mother	
	1	2	3	4
OLS	0.169	0.163	0.174	0.166
	(52.51)	(48.52)	(54.69)	(49.95)
2SLS	0.248	0.234	0.316	0.297
	(10.37)	(9.21)	(10.24)	(9.16)
1st stage F-statistic	768.6	671.6	475.2	420.2
1st stage partial R^2	0.014	0.014	0.009	0.009
Instrument based on				
Zip code	Yes	Yes	Yes	Yes
Age category	Yes	Yes	Yes	Yes
Native language	No	Yes	No	Yes
Mean dependent variable	0.409	0.409	0.409	0.409
Adjusted R^2	0.444	0.445	0.448	0.448
Number of observations	1,463,887	1,463,887	1,465,407	1,465,407

Table 8

Using mergers to identify intergenerational correlation in security choice

Panel A reports an investor's propensity to own a security as a function of whether the investor's parent received the security based on ownership of another security in a merger or a spinoff. Investors whose either parent was a shareholder in the target security in the year prior to the merger are the treatment group. The control group includes each treated investor in a randomly chosen merger or spinoff in which the investor's parent was not involved. Investors who were shareholders in the target prior to the event do not enter the sample. The unit of observation is an investor-asset-time triplet. Panel A calculates the likelihood an investor holds the received security in each of the five years surrounding a merger, separately for the treatment and control groups. Panel B reports coefficient estimates and their associated *t*-values (in parentheses) from regressions that explain an investor's decision to hold the received security. The OLS results come from regressions that explain an investor's decision to hold the received security with that of her parent. The 2SLS regressions instrument for parental ownership in the received security with the parent's ownership in the target security prior to the merger or spinoff. The 2SLS diagnostics are the partial R^2 and the F-statistic of the instrument in the first stage. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Investor's ownership propensity in acquirer as a function of parent's ownership of target						
Years surrounding merger	Father owns target	Father does not own target	Difference	Mother owns target	Mother does not own target	Difference
$t = -2$	0.005	0.005	0.0005	0.007	0.005	0.002
$t = -1$	0.005	0.006	-0.001	0.007	0.005	0.002
$t = 0$	0.032	0.008	0.024	0.041	0.008	0.033
$t = +1$	0.030	0.008	0.022	0.039	0.009	0.030
$t = +2$	0.027	0.007	0.020	0.036	0.007	0.030

Panel B: IV regressions using mergers as instrument for ownership		
Dependent variable	Investor invested in an asset	
Specification	Father	Mother
	1	2
OLS	0.025	0.030
	(16.40)	(16.74)
2SLS	0.039	0.048
	(20.13)	(20.80)
1st stage F-statistic	32,222.6	31,883.8
1st stage partial R^2	0.491	0.559
Mean dependent variable	0.013	0.016
Adjusted R^2	0.005	0.006
Number of observations	213,533	162,197

Table 9

Influence from adult children to their parents using the merger experiment

Panels A and B report analyses that follow the structure of Table 8 but focus on the relation that runs from children to parents. The sample consists of parents who were not shareholders in the security that granted the right to receive the other security. Treatment group includes parents whose children were target shareholders whereas the control group consists of non-shareholding children. Panel A calculates the likelihood a parent holds the received security in each of the five years surrounding a merger, separately for the treatment and control groups. Panel B reports coefficient estimates and their associated *t*-values (in parentheses) from regressions that explain a parent's decision to hold the received security. The OLS results come from regressions that explain a parent's decision to hold the received security with that of her child. The 2SLS regressions instrument for child's ownership in the received security with the child's ownership in the target security prior to the merger or spinoff. The 2SLS diagnostics are the partial R^2 and the F-statistic of the instrument in the first stage. The *t*-values reported in parentheses use standard errors that assume clustering at the parent level.

Panel A: Parent's ownership in acquirer as a function of child's ownership of target						
Years surrounding merger	Father's ownership propensity			Mother's ownership propensity		
	Child owns target	Child does not own target	Difference	Child owns target	Child does not own target	Difference
$t = -2$	0.006	0.006	-0.00002	0.005	0.006	-0.001
$t = -1$	0.005	0.006	-0.001	0.005	0.007	-0.002
$t = 0$	0.031	0.008	0.023	0.041	0.009	0.032
$t = +1$	0.030	0.008	0.021	0.039	0.009	0.030
$t = +2$	0.027	0.007	0.020	0.036	0.008	0.028

Panel B: IV regressions using mergers as instrument for ownership		
Dependent variable	Parent invested in an asset	
Specification	Father	Mother
	1	2
OLS	0.025	0.034
	(12.14)	(14.12)
2SLS	0.038	0.052
	(14.37)	(17.01)
1st stage F-statistic	19,792.8	19,960.8
1st stage partial R^2	0.487	0.487
Mean dependent variable	0.013	0.016
Adjusted R^2	0.005	0.008
Number of observations	143,008	143,905