Why Does Portfolio Choice Correlate across Generations?*

Samuli Knüpfer
BI Norwegian Business School and IFN

Elias Rantapuska
Aalto University

Matti Sarvimäki
Aalto University and VATT

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Abstract

We find that investors tend to hold the same securities as their parents. Instrumental variables that exploit social networks and a natural experiment based on mergers allow us to attribute the security-choice correlation to social influence within families. This influence runs not only from parents to children, but also in the opposite direction. Security holdings correlate more when family members are more likely to communicate and when they are more susceptible to social influence. The identical security holdings that social influence generates largely explain why risk-return profiles of household portfolios correlate across generations.

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

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1. Introduction

Why do family members hold similar financial portfolios?[1] Do they share genes or environments that make their portfolios correlated? Or do they influence each other directly through social interaction? We show the social channel is a key driver of parent-child correlations in portfolio choice.

We establish the importance of social interaction by studying the intergenerational correlation in the choice of securities that make up household portfolios. This micro-correlation is beneficial to study because it naturally relates to sharing investment ideas through word-of-mouth communication (Shiller and Pound, 1989). Moreover, it lends itself to analyses of causality that take advantage of plausibly exogenous changes in holdings of individual securities. Finally, it has implications for understanding portfolio heterogeneity and wealth accumulation, because identical security holdings translate into intergenerational correlations in risk-return profiles of household portfolios.

Our analysis builds on register-based data that cover the entire investor population in Finland in 2004–2008. Information on each investor's end-of-year holdings of each security originates from the centralized securities depository and asset-management companies. Coupled with the time series of returns, security holdings allow us to accurately calculate measures of risk and return for each investor's portfolio. The investor data map each individual to her parents, and include rich information on investors' socioeconomic and demographic characteristics.

[1] Black et al. (2017), Fagereng, Mogstad, and Rønning (2015), and Charles and Hurst (2003) document parent-child correlations in portfolio choice, whereas Barnea, Cronqvist, and Siegel (2010) and Cesarini et al. (2010) report sibling correlations.

Our analyses of the intergenerational correlation in security choice relates an investor's decision to hold a security to that of her parent. Unconditional estimates show the propensity to hold a security increases by *threefold*, compared to the baseline probability, when an investor's father or mother owns the security. This increase in holding propensity is statistically highly significant.

Isolating social influence from other factors poses a classic identification challenge (Manski, 1993, 2000). In our context, correlated risk aversion may lead family members to shun risky asset classes, whereas shared educational backgrounds and occupations may make them reduce exposure to common sources of background risk. We use several complementary approaches to examine such possibilities. We start by flexibly controlling for preferences an investor may have for specific types of assets. Of particular interest is our analysis that estimates the security-choice correlation from buy and sell decisions of a particular security by including investor-security fixed effects. This way of controlling for *any* time-invariant preferences an investor and her parent have for a security yields a highly significant increase in the likelihood of investing in a security in the year the parent buys the security. In additional analyses, we further show that positive experiences with a security, geographical proximity, and lack of financial literacy make the correlation stronger. These patterns are consistent with the correlation being greater when family members are more likely to communicate with each other and when investors are more susceptible to familial influence.

An interpretation of the investor-security fixed-effects approach alternative to social influence considers unobservable attributes that make family members malleable to time-varying influences. For example, family members may buy the same security as a response to sales efforts of an asset-management company, which would generate a year-to-year correlation in security choice across generations. We tackle this issue using two further identification strategies.

First, we take advantage of rich data that allow us to approximate social networks. We match every parent with her likely peers, and calculate the fraction of the parent's peers that invest in a particular security. Our two proxies for the parent's peer groups are investors of similar age who live in the same zip code and speak the same native language, and colleagues who work in the same establishment. This approach relies on the idea that investors are unlikely to be directly affected by parents' peers, so their influence on investors must run through parents. When this condition holds, investment decisions of parents' peers are a valid instrument for the parent's decision (for similar strategies, 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).

Second, we analyze plausibly exogenous changes in security ownership. These shocks arise from mergers in which the target shareholders become owners in the acquiring security without making an active purchase decision. We identify all shareholders of the target security and analyze how their children alter investment behavior when their parents passively become shareholders in the acquirer.

Both identification approaches strongly support the social-influence hypothesis. In the peer approach, a parent has a much higher likelihood of holding a security when many of her peers hold the asset. The instrumental variable (IV) estimates for the child's holding propensity are strongly positive and highly significant. Similarly, a child is much more likely to invest in a security after her parent has passively become an owner of that security. This evidence on causal social influence allows us to rule out intergenerational transmission of risk preferences, background risks, and other non-social factors as the main driver of the security-choice correlation.

The two identification strategies also allow us to investigate the possibility that in addition to parents affecting their children, children can influence their parents. This mechanism does not typically feature in studies of intergenerational transmission, because the outcome of interest determines the direction of causality. Human capital investments, for example, happen early in life and they thus have a natural causal direction from older to younger generations. Financial investments do not have this feature, because adult children may advise their parents.

We find a significantly positive effect that runs from the choice of an adult child to that of her parents. Comparing the child-to-parent influence with the transmission from older to younger generations, we find it is economically meaningful but smaller. This finding advances our understanding of linkages between family members, by showing children may also influence their parents.

The strong intergenerational influence in security choice has important implications for understanding the origins of portfolio heterogeneity. We first replicate the intergenerational correlations in a variety of portfolio metrics in our data. For example, investors' expected portfolio return—obtained from estimating a four-factor model and multiplying the factor loadings by their historical return premia—yields intergenerational correlations of 0.19 for fathers and 0.22 for mothers (*t*-values 82.5 and 83.9). This correlation implies an intergenerational spread between the top and bottom deciles of annual expected returns of 2.2%. Compounded over time, such a spread would produce substantial differences in wealth accumulation.

We then ask how important social influence is for generating intergenerational correlations in portfolio choice. In the extreme case of family members holding the same securities with the same portfolio weights, the intergenerational correlation in any portfolio metric would equal one. We use this insight to decompose investors' portfolios according to whether a security features in the parent's portfolio. By construction, the part of the portfolio an investor shares with her parent correlates strongly across generations. The non-shared part may also correlate across generations if family members share attributes, such as risk aversion or financial literacy, that lead them to choose similar, but not the same, securities.

We find that intergenerational correlations in portfolio attributes are largely confined to the securities investors share with their parents. The non-shared part of the portfolio displays an economically insignificant correlation across generations. In the case of expected returns, the non-overlapping part yields estimates of −0.001 and 0.003 for fathers and mothers, respectively (t-values −0.7 and 1.4). A placebo exercise that estimates the correlations from matching each investor with a parent of another investor shows the child-parent relation generates identical security holdings in excess of what can be expected based on the characteristics of the investor's actual parent. These results suggest the intergenerational correlations in portfolio attributes hinge crucially on social interaction that leads family members to hold the same securities.

Our paper contributes to four strands of literature. First, it speaks to the literature that documents social influence in investment decisions. Our results show investors acquire investment ideas not only from their co-workers and neighbors (Hong, Kubik, and Stein, 2005; Hvide and Östberg, 2015; Ivković and Weisbenner, 2007; Kaustia and Knüpfer, 2012), but also from their family members. The focus on family members and the identification strategies we use to establish social influence set our paper apart from this literature

Second, we add to the literature on intergenerational correlations in portfolio choice. Studies using the twin methodology (Barnea, Cronqvist, and Siegel, 2010; Cesarini et al., 2010) suggest intergenerational correlations largely reflect genetic factors, whereas studies of adopted children find an important role for non-genetic factors (Black et al., 2017; Fagereng, Mogstad, and Rønning, 2015). The twin and adoption techniques embed different assumptions, which may explain why they arrive at conflicting conclusions.[2] By using a new approach to isolate social influence from other

[2] The twin technique in Barnea, Cronqvist, Siegel (2010) and Cesarini et al. (2010) assumes the genetic make-up of identical twins is more similar than that of fraternal twins, but that the two types of twins share a similar environment.

channels, our findings uniquely show that social forces in adulthood are an important determinant of portfolio-choice correlations across generations.

Third, our findings speak to the emerging literature on understanding the origins of wealth inequality.[3] Previous work by Charles and Hurst (2003), Boserup, Kopczuk, and Kreiner (2014), Black et al. (2015), Fagereng, Mogstad, and Rønning (2015), and Fagereng et al. (2016) suggests wealth and its returns correlate across generations. Such intergenerational linkages may be important in understanding the determinants of wealth distributions. For example, decades of high returns make a family disproportionately wealthy in the long run (for models that feature heterogeneity in returns to wealth, see Benhabib, Bisin, and Luo, 2015; Campbell, 2016; Gabaix et al., 2016; and Lusardi, Michaud, and Mitchell, 2017; for empirical evidence, see Fagereng et al.; 2016, and Bach, Calvet, and Sodini, 2017). We show the intergenerational spread in financial returns largely arises from social influence within families. Modeling efforts aimed at explaining intergenerational transmission of wealth and its returns may benefit from incorporating the social mechanism we find.

Fourth, our paper is also relevant to the literature that documents intergenerational correlations in other settings. Many papers document intergenerational correlations in income and education (for reviews, see Björklund and Salvanes, 2011; Black and Devereux, 2011; Jäntti and Jenkins, 2015; and Solon, 1999). Kreiner, Leth-Petersen, and Willerslev-Olsen (2016) analyze the intergenerational correlation in personal defaults, whereas Dohmen et al. (2011) document

The adoption technique in Black et al. (2017) and Fagereng, Mogstad, and Rønning (2015) assume assignment of adoptees to adoptive families is as good as random. Calvet and Sodini (2014) find the genetic component estimated for pairs of twins correlates with the extent of communication within the pairs.

[3] Benhabib and Bisin (2017), Roine and Waldenström (2015), and Piketty and Zucman (2015) provide reviews of wealth inequality. Recent empirical work in understanding the sources of wealth inequality include Piketty, Postel-Vinay, and Rosenthal (2006), Roine and Waldenström (2009), and Saez and Zucman (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.

intergenerational transmission in risk attitudes and trust. Anderson et al. (2015) find a strong intergenerational correlation in the choice of automobile brands. Our paper suggests a social mechanism that may be relevant for understanding the origins of some of these correlations.

The rest of the paper unfolds as follows. Section 2 presents the data sources and reports descriptive statistics. Section 3 estimates the intergenerational correlation in security choice, and section 4 establishes the role of social influence in generating the correlation. Section 5 discusses implications of the security-choice correlation for intergenerational correlations in the attributes of household portfolios. Section 6 concludes.

2. Data and descriptive statistics

2.1. Data

The bulk of our data originate from administrative registers maintained by various authorities. These data include a scrambled personal identification number that allows a merger of data across different registers. Information from public sources complements register-based data.

Statistics Finland provides us with the population of individuals, their linking to parents (biological or adoptive), and a number of individual attributes. The family links are comprehensively available for individuals born in 1955 or after. We further impose restrictions that address the possibility that investments made on behalf of underage children and transfers related to inheritance drive the results. We focus on individuals who are at least 18 years old in the beginning of our sample period in 2004 (born in 1986 or earlier) and whose parents are both alive at the end of the sample period in 2008. An investor appears in the data if she and her parent have held at least one security (stock or mutual fund) in a given year during our sample period. These criteria give us samples of 212,545 father-child and 193,202 mother-child pairs. We observe the individual's and her parents' 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). In addition, identifiers assign employees to establishments and firms, and individuals to zip codes and municipalities.

Finnish Tax Administration (FTA) records information on security holdings. Ownership of mutual funds originates from asset-management firms that directly report to FTA. At the end of each year, these records indicate the mutual funds in which an individual has invested and the market value of each holding. FTA 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. Because individuals are required to register in their own name, joint accounts only appear in cases of estate divisions triggered by marital dissolution or inheritance.

Mutual Fund Report, an industry publication compiled by Investment Research Finland, includes 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 whether the fund is a fund of funds. Grinblatt et al. (2016) discuss the details of these data.

Helsinki Stock Exchange 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. Portfolio attributes

In addition to standard individual attributes, such as portfolio value, income, and education, we calculate portfolio attributes we later use to establish the role of social influence in generating intergenerational correlations of portfolio choice. We consider the following portfolio attributes:

Historical return. We measure portfolio returns by combining annual security holdings with the time series of total returns (including capital gains, dividends, and distributions) of each security. We calculate the returns on the securities held by an investor in each of the preceding 24 months and weight each security by its share in the investor's beginning-of-year portfolio. The average historical excess return is the annualized average of the monthly portfolio return in the previous 24 months over the one-year Euribor rate.

Expected return. We also use the time series of portfolio returns to estimate factor loadings. Our asset-pricing model is the four-factor model that features 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 toward high-beta securities, small companies, value firms, and securities 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 euro-converted SMB, HML, and MOM returns for the United States from Kenneth French's data library. Combining factor loadings with estimates of factor premia make calculating expected excess returns for each investor possible. 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. Assuming a zero alpha, we multiply the factor premia by the factor loadings estimated for each investor to arrive at estimates of expected returns.

Volatility. The time series of returns for each investor makes calculating the riskiness of the chosen portfolio possible. Our measure of risk is portfolio volatility calculated as the annualized standard deviation of the 24 monthly excess returns.

2.3. *Descriptive statistics*

We perform our analyses on two samples of father-child and mother-child pairs. Each sample requires that the investor and her father or mother participate in the financial asset market in at least one year during our sample period by holding at least one security. Table 1 reports descriptive statistics on the investors and their parents in the two samples (we omit the investor column in the sample of mother-child pairs because the descriptive statistics are practically identical to the father-child sample).

The three leftmost columns in Table 1 Panel A show that investors have a portfolio that contains on average three securities and is valued at 20,800 euros. This portfolio has had an average annual excess return of 8.0% and volatility of 16.1%. The expected excess return, based on the factor loadings of 0.91, –0.01, –0.17, and 0.08 on the market, size, value, and momentum factors, respectively, equals 3.9%. The factor loadings imply the average investor tilts her portfolio toward defensive growth securities whose price has recently increased. The weights in various asset classes reveal an average allocation to directly held stock and equity mutual funds of 48.7% + 21.6% = 70.3%. The next most popular asset classes are balanced funds (17.3%), short-term bond funds (8.6%), long-term bond funds (3.2%), and other funds, such as hedge funds (0.6%). Fifty-one percent are allocated to actively managed funds, 48.0% to retail funds (asset-management arms of the commercial banks with branch networks), and 19.4% to funds of funds. These fractions imply the average fund portfolio, which has a 51.3% weight in the total financial portfolio, largely consists of actively managed retail funds.

The three leftmost columns in Panel B show that investors have an average labor income of 31,600 euros, and 59.1% of them have acquired a degree in excess of basic or vocational education. Business or economics graduates constitute 18.2% of the investors, and 4.5% work in the finance industry. Females, married, and Swedish-speaking investors are minorities with fractions of 44.3%, 41.1%, and 9.1%, respectively. The investors are on average 36 years old at the end of the sample period in 2008.

The three middle columns in Panels A and B report descriptive statistics for the investors' fathers. Panel A shows fathers are substantially wealthier and more diversified than their children. Their historical return and volatility also display higher values than those of their children. These patterns largely reflect idiosyncratic factors as their offsetting exposures to the market and momentum factors leave their expected return similar to that of their children. Fathers have a somewhat higher equity share than their children, and within equities, they are more likely to invest in directly held stock than mutual funds. This pattern is consistent with the cohort effects reported in Keloharju, Knüpfer, and Rantapuska (2012). Panel B reports fathers have a lower level of education and are less likely than their children to have gained a business or economics degree or to work in finance. Given that they have children, it is not surprising they are likely to have married. They are on average 65 years old in 2008.

The remaining rightmost columns in Panels A and B report on the investors' mothers. Many gender differences arise in comparison to fathers. Mothers have much less invested in financial assets and hold fewer securities than fathers. They also have less exposure to the market, growth, and momentum factors, and a lower allocation to equities, which explains why their expected return is somewhat lower than that for fathers or children. Panel B shows mothers have lower levels of income and education but are more likely than fathers to have a business or economics degree and to work in finance. Their average age in 2008 is 63 years.

3. Correlation in security choice across generations

3.1. Baseline results

We analyze how an investor's choice of a particular security associates with that of her parent. We organize the security 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 a security in a year, and zero otherwise. The independent variable is the holding indicator defined for the investor's parent. We use a linear probability model to estimate the intergenerational associations. Standard errors assume clustering at the investor level.

The great number of investors over multiple years coupled with the complete menu of stocks and mutual funds investable in Finland would result in a panel with more than two billion observations. Computational feasibility necessitates a randomization approach that economizes on sample size but does not generate bias. We match each security an investor owned during our sample with a randomly chosen security the investor never held. For these holdings and non-holdings, we retrieve the full time series of investor-security-year triplets, which results into sample sizes of 8.1 and 7.3 million for father and mother samples, respectively. Our regressions use a consistent estimator that reweights each observation with its inverse probability of featuring in our estimation sample (Manski and Lerman, 1977). The securities investors hold enter with a weight of one, whereas the randomly chosen non-holdings obtain a weight of $1 / (1/(N - n)) = N - n$, where N is the total number of securities available to investors in a given year and n equals the number of securities an investor holds in that year.

Table 2 reports results from four regressions that vary the set of control variables. The four leftmost columns display the coefficients for the investor's father, whereas the remaining four columns report on the investor's mother. Columns 1 and 5 report the baseline estimates that condition on fixed effects for each security-year pairing. These controls address the higher likelihood of investing in securities with larger market shares. Columns 2 and 6 report regressions that add fixed effects for pairing an investor with each asset class. This specification controls for family members' shared tendency to invest in a particular asset class that may arise from shared risk preferences or other shared determinants of asset allocation. Intergenerational correlations in occupations, for example, may translate into correlations in labor income profiles, which may influence an investor's willingness to invest in certain asset classes (Cocco, Gomes, and Maenhout, 2005; Heaton and Lucas, 2000; Viceira, 2001).

Columns 3 and 7 add further sets of fixed effects for each mutual fund type (actively managed, retail distribution, and fund of funds) and each asset-management firm paired with each investor.[4] These specifications capture shared preferences for different types of funds, possibly driven by financial literacy, and preferences for investing with the same asset-management firm, perhaps arising from the geographic reach of a firm's distribution channel.

Columns 4 and 8 replace all pairings of investors and observable security characteristics with fixed effects for each investor-security pairing. This specification takes advantage of the within-individual time series of security holdings that allow us to estimate the correlation from instances in which an investor either buys a new security or sells her entire security holding. The focus on changes in holdings enables us to rule out the role of *any* time-invariant preferences an investor and her parent have for a particular security and its characteristics.

The baseline regression in column 1 yields an intergenerational correlation of 0.18 (*t*-value 70.7). The unconditional probability of holding a security in a given year is 0.06 percentage points,

[4] The five largest asset managers enter separately, and the remaining firms serve as the omitted category. Directly held stock, for which asset managers and fund types are not defined, also features in the omitted category.

so the father's holding increases an investor's likelihood of owning the security by 0.18 / 0.06 = 300%.[5] The fixed effects for pairing an investor with asset classes in column 2 and with asset-management firms and mutual fund types in column 3 generate estimates of 0.20 and 0.16 (*t*-values 62.5 and 72.7). These estimates suggest investor preferences for observable security characteristics account for 1 − 0.16/0.18 = 11% of the correlation in security choice.

Column 4 estimates the security-choice correlation from changes in security holdings over time. The coefficient suggests an investor's probability of buying a security goes up by 0.21 percentage points in the year in which the investor's father purchases the security (*t*-value 49.5). Columns 5 to 8 report the corresponding estimates for the investor's mother. These correlations, and the patterns in how coefficients change across specifications, mirror those of the father.

Taken together, Table 2 shows investors are much more likely to hold a security owned by their parents, even when we account for preferences to invest in particular types of securities. The specifications that take advantage of time-series variation in holdings further suggest time-invariant preferences for *any* unobserved asset characteristics do not drive the security-choice correlation.

3.2. Robustness checks

Table 3 reports robustness checks that study life-cycle effects and restrict the data to informative subsamples. The table shows estimates for the investor-father sample; results for mothers are reported in Table IA1.

Life-cycle effects. Panel A of Table 3 reruns the regressions in subsamples stratified by investors' birth year. Investors born before 1960 appear in column 1, whereas investors born after

[5] These numbers use a consistent estimator that weights each observation by its inverse probability of entering the estimation sample. The unweighted mean holding propensity equals 30.6 percentage points, which mechanically reflects the way we sample holdings and non-holdings.

1979 constitute column 6. Columns 2–5 report on four five-year intervals between the two extreme categories. The coefficient estimates are all highly statistically significant. The security-choice correlation is highest, 0.26, for the youngest category of investors who are not more than 24 years old at the start of the sample period in 2004. The other brackets display a monotonically decreasing pattern as a function of age. The oldest category of investors above the age of 44 shows an estimate of 0.10, which implies a 158% increase from the mean holding propensity. This estimate shows the intergenerational influence remains economically meaningful even for the oldest investors in our sample.

Accounting for parents' and grandparents' purchases. Column 1 in Panel B addresses the possibility that the legacy of investment accounts parents manage on behalf of their underage children generate the security-choice correlation. We focus on a subsample of investors who start our sample period with no security holdings, but enter the market in later sample years. For these investors, who are immune to the legacy of their parents' purchases, we find an estimate of 0.16 (*t*-value 33.9). Column 2 addresses an alternative story according to which grandparents may gift securities for their children and grandchildren. The subsample of investors whose grandparents do not own and have not owned any securities yields an estimate of 0.22 (*t*-value 53.0), suggesting the grandparental channel is not instrumental in generating the security-choice correlation.

Excluding potentially influential observations. The remaining columns in Panel B investigate subsamples that exclude potentially influential clusters in the data. Column 3 shows the correlation equals 0.16 (*t*-value 55.5) when we exclude investors who hold securities in only one asset class. Column 4 drops the five most popular securities, and returns a correlation of 0.26 (*t*-value 67.9).

3.3. *Variation in security-choice correlation across families*

Table 4 analyzes how the familial security-choice correlation varies by the likely frequency of communication and susceptibility to social influence. We implement these analyses by interacting the parental holding indicator in Table 2 with variables that likely mediate the security-choice correlation. Column 1 in Table 4 reports estimates for an investor's father (corresponding to column 1 in Table 2), whereas column 2 reports correlations for the mother (as in column 5 in Table 2). The table omits the main effects included in the regressions.

We first investigate the role of positive and negative experiences in mediating the intergenerational correlation. Kaustia and Knüpfer (2012) suggest positive experiences with the stock market make investors more likely to communicate with their peer group. We extend this logic to our setting and interact the parental holding indicator with a dummy that takes the value of one if a security has had a strictly positive return in the previous year, and zero otherwise. In column 1, this interaction attracts a positive coefficient that implies a 0.047/0.102 = 45.9% higher correlation, suggesting the paternal influence is stronger when a security has generated a favorable experience. The maternal specification in column 2 returns a 0.037/0.135 = 27.6% higher correlation.

We also consider a number of factors that relate to family composition and family environment. Motivated by Kalil et al. (2016), Björklund and Chadwick (2003), Gould and Simhon (2015), and Price (2008), we study how parents' proximity and family size affect the security-choice correlation. An interaction of a dummy for the father living in the same zip code in column 1 enters with a significantly positive coefficient. This estimate implies an increase of 0.057/0.102 = 55.3% in the correlation. Column 2 reports an 33.5% increase for mothers. The patterns concerning family size indicate no clear pattern. Families with three or four children generate the highest correlation, whereas the correlations are comparable for only children and families with more than four children.

Inspired by Bowles and Gintis (2002), we study how the correlation varies in parent-child pairs stratified by gender. The positive coefficient for the female indicator in column 1 translates into an increase of 0.013/0.102 = 12.7% in the correlation, suggesting female investors are more susceptible to parental influence than male investors. Comparing the coefficients for father-daughter and mother-daughter pairs in columns 1 and 2 does not support the hypothesis that children would be more affected by the parent of their own gender when choosing securities in their portfolio.

We analyze a potential mediating role of financial literacy by including an indicator for investor-parent pairs in which neither of them holds a business or economics degree. The coefficient is significantly positive in the paternal specification in column 1 but loses significance for mother-child pairings in column 2.

Our final interaction contrasts biological with adopted children. Black et al. (2015) and Fagereng, Mogstad, and Ronning (2015) find lower intergenerational correlations for adopted than biological children, presumably because adoptive parents lack the genetic connection to their children. In addition to addressing genetic transmission of investor preferences, this interaction is informative about an interpretation according to which genetic predispositions make members of the same family more likely to follow lessons they learn through word of mouth. For example, a genetically transmitted risk attitude might make convincing a family member to invest in risky assets easier.[6]

We do not find a statistically significant difference in intergenerational correlation of security choice between biological and adopted children (our data contain 5,478 and 4,315 adopted children of fathers and mothers, respectively). The small point estimates suggest genetic factors do not play a major role in generating the security-choice correlation.

[6] Cunha et al. (2006) and Manuck and McCaffery (2014) discuss the evidence on gene-environment interactions.

4. Establishing role of social influence

4.1. Using peer groups to identify causal effects

The strong intergenerational correlation in the timing of buy and sell decisions, which we document above, is in line with social interaction. However, it could also be reconciled with investors and their parents responding to time-varying influences in the same way. For example, financial advisors may be more successful in selling a product to financially illiterate families.

We use two identification strategies that are immune to time-varying confounding factors. The first approach takes advantage of information that allows an approximation of social networks. We reconstruct a parent's social network and create an instrumental variable that relates the parent's investment decision to that of her peers. If these peers affect the parent but not her child, the IV strategy yields an estimate of causal parent-to-child influence (for similar strategies, 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 use two alternative definitions of a parent's peers. First, we match the parent with investors who live in the same zip code and belong to the same age cohort. In additional specifications, we also use information on whether the parent's native language is either of the two official languages, Finnish or Swedish. These peer groups stem from people being likely to interact with geographically proximate people of the same age and native language. Our data have in total 2,995 zip codes, and cohorts are 10-year intervals of the parent's age so that the top and bottom categories include parents born before 1930 and after 1950.

We also consider an alternative peer group that consists of parent's colleagues at work. A subsample of our data has information on identifiers that tag the establishment of work for each individual.[7] These 20,988 establishments represent a factory, office, or other physical location and thus define people who likely interact with each other on a regular basis.

We define the instrument for the parental holding indicator as the fraction of a parent's peers who invest in a security. This instrument excludes the parent herself to avoid the mechanical relation that arises from correlating a parent's decision with a variable that contains that same decision. We include fixed effects for each pairing of a security with either a zip code for neighbors or a firm for co-workers. These fixed effects absorb all unobservable reasons for why people living in a given zip code or working in the same firm tend to hold certain securities.

Table 5 Panel A reports the results of regressions that correspond to columns 1 and 5 in Table 2.[8] The three leftmost columns report the results for the investor's father, whereas the mother's estimates appear in the remaining three columns. Columns 1 and 4 define peers according to zip codes and cohorts. Peer groups that use native language in addition to zip codes and cohorts feature in columns 2 and 5. Columns 3 and 6 report the work-based peer group.

The IV estimate in column 1 equals 0.12 (*t*-value 34.1). The instrument's impressive *F*-statistic indicates the regression does not suffer from the weak-instrument problem. The more refined instrument that takes advantage of native language as an additional dimension of peer groups in column 2 generates an equally strong first stage and an IV estimate of 0.11 (*t*-value 31.5). The instrument based on co-workers in column 3 yields an IV estimate of 0.17 (*t*-value 10.2). The regressions for the investor's mother in columns 4-6 yield coefficient estimates that are larger in

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[7] The codes are missing for public sector employees and individuals who are not in the labor force.

[8] Table IA2 shows the OLS estimates for the samples in Table 5, which are subsets of those in Table 2, because a zip code or establishment identifier used to define the peer group is missing. With the exception of work-based peer groups, for which the loss of observations is the largest, estimates in Panel A of Table IA2 are similar to those in Table 2. Panel B is not comparable to Table 2, because its sampling design builds on investors instead of parents.

magnitude than the father's estimates in columns 1-3. These results are consistent with the interpretation that the intergenerational correlation in security choice does not arise from time-varying confounding factors, but that parents influence their offspring.

Table 5 Panel B addresses the possibility that adult children provide their parents with investment ideas.[9] It explains the parent's security choice with that of her child, and uses instruments that calculate the fraction of the child's peers invested in a security. We define peer groups in the same manner as in Panel A, except that cohorts are born in 1955-1964, 1965-1974, and 1975-1986. The larger number of securities held by fathers (4.6) and mothers (3.4) compared to children (3.1) explains why Panel B includes more observations than Panel A.

The first-stage *F*-statistics in Panel B are well above critical thresholds of weak-instrument tests. The IV estimate of 0.035 in column 1 (*t*-value 12.4) indicates ownership probability increases by 53.1% when a child holds a security compared to the mean holding propensity of 0.06 percentage points. This relative increase amounts to 53.1% / (0.12/0.06) = 26.7% of the parent-to-child effect in Panel A. Column 2, which stratifies the peer groups by native language in addition to age and zip code, yields similar results. The workplace peers in column 3 generate a larger child-to-parent influence that equals 58.8% of the corresponding parent-to-child effect in Panel A. Columns 4-6 report somewhat smaller relative effects for mothers compared to fathers. Overall, these results suggest children also affect their parents' investment decisions and that the magnitude of this effect is at most three-fifths of that in the opposite direction.

[9] 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 reflects a causal relation. Cronqvist and Yu (2017) find CEOs who have a daughter manage companies that score higher on social responsibility rankings, consistent with female socialization. Washington (2008) and Oswald and Powdthavee (2010) report on female socialization in the context of political views.

4.2. Natural experiment based on mergers

The second identification approach considers mergers in which the target shareholding of an investor's parent passively converts to a holding in the acquirer. We track an investor's likelihood of purchasing the acquirer in 14 mergers for which we have holding data in the five years surrounding the merger. Our sample consists of all investors with a parent who is a target shareholder in the beginning of the year the merger is completed. For each of these treated investor-merger pairs, we consider control observations that represent mergers in which the investor's parent is not a target shareholder. We exclude investors who are shareholders in the target entity to avoid the mechanical increase in the likelihood to hold the acquirer. These criteria give us 4,241 father-child and 4,054 mother-child pairings from the base line samples used in Table 2.

Table 6 Panel A reports the results of difference-in-differences regressions that include the treatment dummy, indicators for the five years surrounding the merger ($t = -1$ omitted), and their interactions. 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). Columns 1 and 2 report the treatment effect for an investor's father passively becoming a shareholder, whereas columns 3 and 4 report the effect for the mother. The regressions in columns 2 and 4 include fixed effects for pairing each security with each year, which controls for secular trends in ownership of a security. These fixed effects subsume the time indicators that drop out of the regressions.

Column 1 reports a coefficient of 0.042 for interacting the treatment dummy with the indicator for the year in which the merger was completed (t-value 12.7). This effect suggests an investor whose father passively became an acquirer shareholder is 4.2 percentage points more likely to hold the acquirer than other investors. Column 2, which includes security-year fixed effects, reports a smaller increase of 2.8 percentage points (t-value 9.3). Mothers in columns 3 and 4 generate larger effects than fathers, with increases of 5.5 and 3.7 percentage points, respectively (t-values 14.3 and 10.8). These effects are economically large as the average holding propensity in the samples of fathers and mothers equal 1.4 and 1.3 percentage points, respectively.

Across all specifications, the treatment-time interactions decrease as time passes, but they remain statistically and economically significant. The interactions for $t - 2$ are marginally significant in one of out of the four specifications and are small in magnitude. This result shows the treatment and control groups are on parallel trends prior to treatment. The main effects for the treatment group are significantly positive in three specifications, suggesting the investors whose fathers passively became acquirer shareholders had a higher overall tendency to hold the acquirer. These findings corroborate the interpretation that the intergenerational correlation in security choice reflects social interaction between parents and their children.

As in Table 5, Panel B in Table 6 analyzes the influence of adult children on their parents. It flips the sample-selection criteria and the dependent and independent variables and focuses on the subset of parents who were not shareholders in the target security. The treatment group consists of parents whose children hold the target, whereas the control group includes all the other parents. This sample has 4,892 investor-parent pairings. As in Panel A, we analyze the five years surrounding the merger and indicate the treated parents in the years following the merger.

For the treated fathers in columns 1 and 2, the propensity to own the acquirer in the merger-completion year is 3.0 and 1.8 percentage points higher, respectively (t-values 11.3 and 7.5). The corresponding estimates for mothers are again higher than for fathers, at 4.9 and 3.0 percentage points (t-values 14.5 and 10.6). The average holding propensities of 1.2 and 1.3 percentage points in the two samples suggest economically meaningful treatment effects. As in Panel A, the effects monotonically decrease as a function of time. The three t – 2 interactions that are significantly positive imply the parallel-trend assumption does not hold in these samples. However, the weak pretrends suggest decreasing pre-merger holding propensities for the treatment group, making them unlikely to account for the much larger increases in the year the merger is completed. With the exception of column 4, the main effects for the treatment group are insignificant. These results corroborate the child-to-parent influence we find in Table 5 Panel B.

5. Implications of social influence for portfolio heterogeneity

5.1. Intergenerational correlations in portfolio attributes

Because social influence leads family members to hold identical securities, it likely contributes to intergenerational correlations in the attributes of household portfolios. We estimate these correlations in our data and examine how much of them can be attributed to holdings of the same securities.

We first report both nonparametric and regression-based estimates of intergenerational correlations of portfolio attributes. Figure 1 plots an investor's historical and expected return as well as volatility on those of her father (Panel A) and mother (Panel B). The horizontal axis is the rank transformation of a parent's portfolio attribute. The vertical axis depicts the average rank of the investor's portfolio attribute for each of the 20 vigintiles of the parent's rank. The graph also reports the average expected portfolio return at the 10th and 90th percentiles of parent's return distribution.

Panel A shows a close-to-linear rank-rank relationship for historical return. The bottom and top vigintiles of the fathers' distribution place investors at the 44th and 57th percentiles in their own return distribution. The corresponding numbers for mothers in Panel B are at the 42nd and 61st percentiles. The two other portfolio attributes in Panels A and B also display a positive and close-to-linear relation. The results on forward-looking expected returns show the intergenerational correlations do not solely stem from transitory shocks to returns during our sample period, but also reflect systematic differences in investment styles family members adopt in their portfolios. The intergenerational spread between the top and bottom decile of expected return equals 2.2% and 2.1% for fathers and mothers, respectively, implying sizable differences in wealth accumulation over time.

Table 7 reports regression-based estimates from models that explain an investor's portfolio attribute in a given year with that of her father or mother. The regressions control for year fixed effects.[10] Standard errors that assume clustering at the investor level take into account the multiple years we observe an investor, and the year-to-year overlap in the 24-month historical return window.

The coefficient estimate of 0.17, reported in Column 1 in Panel A, implies a 1.7-percentage-point higher historical return for every 10-percentage-point increase in the father's return. The estimate is highly significant with a *t*-value of 81.1. The bottom rows of the panel report that the explanatory power increases from 0.58 to 0.59 when we add the father's return to the model (year fixed effects explain a large fraction of historical return variation). The corresponding regression for an investor's mother in column 4 yields an estimate of 0.21 (*t*-value 90.1). The remaining columns in Panel A report the intergenerational correlations for volatility and expected return. These estimates are close to those obtained for historical returns, and they tend to be somewhat higher for mothers than for fathers. They also are qualitatively similar to estimates reported in previous literature. For example, Barnea et al. (2010) and Fagereng et al. (2015) report positive intergenerational correlations for stock market participation in Sweden and Norway, respectively.

Table IA4 reports intergenerational correlations in alternative portfolio attributes. We analyze the components of the four-factor regressions we use to compute expected returns to retrieve the

[10] Table IA3 reports conditional correlations that control for observable attributes of the individual, such as wealth, income, and education, and portfolio characteristics, such as allocation to various asset classes. These correlations are typically lower than those that obtain in Table 7. This pattern is not surprising, because allocation to various asset classes is a strong driver of all of the portfolio metrics we consider.

factor loadings, idiosyncratic residual variance, and alpha. The correlations for factor loadings are similar to the estimates for expected returns. Idiosyncratic variance and alpha yield somewhat lower correlations, presumably because of the added noise in their estimation. All in all, the intergenerational correlations are robust to the choice of portfolio metrics.

5.2. Role of social influence

How much of the intergenerational correlations in portfolio attributes are due to social influence within families? We approach this question in Table 7 Panel B by decomposing the intergenerational correlations into two parts. The first component consists of the correlation that arises from investors holding the same securities as their parents. This correlation deviates from unity only because the security weights in investors' and their parents' portfolios are not necessarily the same.

The second, perhaps more interesting, component is the correlation in the non-shared securities. The attributes of these securities, and their combination in the portfolio, may correlate even in the absence of any intra-family communication if shared genetic or environmental factors lead family members to choose similar but not the same securities. If intergenerational correlations in portfolio choice are primarily due to social interaction concerning individual securities, we would expect to find little correlation in the attributes of the non-shared portfolio.

We analyze the contribution of the shared and non-shared components by analyzing a subsample of investors who hold at least one shared and one non-shared security (representing 30.9% and 28.2% of the total samples of fathers and mothers, respectively). This restriction enables us to identify the shared and non-shared correlations from variation within families, and ensures different types of families do not contribute to the estimation (e.g., family members with no overlapping securities may refrain from communicating with each other).

Table 7 Panel B reports the intergenerational correlation separately for the shared and non-shared parts. It follows the structure of Panel A but splits the parent's portfolio according to whether a security appears in the investor's portfolio. The shared and non-shared securities determine the two independent variables in the regressions by weighting each security by their fraction of the portfolio.

The three leftmost columns in Panel B report the results for fathers. Column 1 shows the historical returns of the shared portfolio strongly correlates across generations. This mechanical correlation does not equal one, because security weights tend to differ in the father's and child's portfolio. More interestingly, the non-shared portfolio yields an intergenerational correlation that is small in magnitude. The 0.015 correlation (*t*-value 8.4) implies very little intergenerational similarity in the non-shared portfolios. Column 4 reports a small correlation also for mothers.

Columns 2 and 5 report the shared and non-shared components for volatility, whereas columns 3 and 6 display results for expected returns. Again, we find practically no intergenerational correlation beyond the securities family members share with each other. The non-shared component becomes statistically insignificant in the specifications for expected returns (*t*-values −0.7 and 1.4).

The analysis of shared and non-shared securities gives us an upper bound of the role of social interaction, because identical holdings may also arise from non-social influences, such as preferences for local firms and employer stock, and funds offered by a local financial advisor (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Benartzi, 2001; Foerster et al., 2017). We develop a placebo exercise that allows us to investigate the role of non-familial factors. For each investor-parent-year triplet, we scramble the parents so that each investor matches not with her own parent but with another randomly chosen "placebo" parent. We perform this randomization within blocks of parents to address likely non-social channels. The actual and placebo parents are either residents of the same municipality, employees of the same firm, or clients of the same asset manager.[11] We then run regressions of an investor's portfolio attribute against that of her placebo parents.

Table 8 Panel A reports the correlations of an investor's portfolio attribute with that of her placebo parent, estimated separately for each of the three matching criteria (municipality, firm, or asset manager). All of the estimates, each coming from a separate regression, are substantially smaller than those based on actual parent-child linkages in Table 7 Panel A. The largest correlations for placebo fathers in columns 1-3 obtain for the matching within employees of a firm. However, compared to the 0.17 we report in column 1 of Table 7 Panel A, the 0.04 estimate for historical return (*t*-value 25.6) represents a fraction of only 20.5%. Matches based on municipalities and firms yield even smaller correlations, and patterns for mothers are similar to those we observe for fathers.

Does the variation in portfolio correlations across actual and placebo parents arise from variation in the degree of identical security holdings? We explore this relation in Table 8 Panel B, where we document the overlap in the security holdings of investors and either their actual or randomly chosen parents. The panel reports the value-weighted fraction of the investor's security holdings that also feature in the portfolio of the actual or the placebo parent as a function of the investor's total portfolio value. The table reports an average portfolio overlap for actual fathers and mothers of 18.8% and 18.5%, respectively. The placebo parents have substantially lower overlap. The overlap for placebo fathers is at its highest at 11.9% for same-firm matches, whereas the lowest overlap at 10.0% obtains for residents of a municipality. This ordering mirrors the magnitudes of portfolio correlations in Panel A.

[11] We identify the clients of each asset manager from their mutual fund holdings. As earlier, we consider the five largest asset managers and a residual category. Parents who are identified as clients of many asset managers are assigned one client relation based on the largest fraction of portfolio value held at an asset manager and parents with no mutual funds do not enter the asset-manager sample.

Table IA5 repeats the analyses in Panels A and B in Table 8 by randomly choosing a placebo parent from among all parents instead of stratifying within zip codes, establishments, or asset managers. Panel A reports insignificant and small correlations in all three portfolio attributes we consider. Panel B reports portfolio overlap of 0.08 and 0.07 for randomly chosen fathers and mothers, respectively. Overlap does not equal zero here, because two randomly chosen investors likely end up investing in highly popular securities. The non-zero overlap can result in insignificant correlations in Panel A, because a large fraction of shared securities in a child's portfolio does not necessarily translate into a large fraction in her parent's portfolio.

The results on placebo parents highlight the unique role of the parent-child link in leading to holdings of identical securities and driving the correlations in portfolio attributes. Taken together, familial interaction contributes substantially to the intergenerational correlations in portfolio choice.

6. Conclusion

Our findings suggest the investment ideas family members share with each other contribute substantially to intergenerational correlations in portfolio choice. This evidence adds to the literature on social influence by showing investors learn from their family members. It also provides a new account of why family members tend to hold similar portfolios. The importance of the social channel implies intergenerational correlations of investor attributes alone—through genes, nurture, or environments—is unlikely to drive intergenerational transmission of portfolio choice. Yet shared attributes, such as risk aversion or financial literacy, may make it easier for an investor to convince her family member to invest in a security. Such influence still crucially hinges on social interaction, suggesting a limited independent role for transmission of investor attributes.

The social influence we document has a number of implications. The identical security holdings result in family members not only experiencing similar returns, but also having similar exposure to idiosyncratic shocks. These patterns inform modeling efforts aimed at explaining observed wealth distributions. Our results also suggest the effects of policy initiatives, such as attempts to improve financial literacy, get amplified in the familial transmission process. Conversely, mistaken investment beliefs and fraudulent practices may also travel in the intergenerational network.

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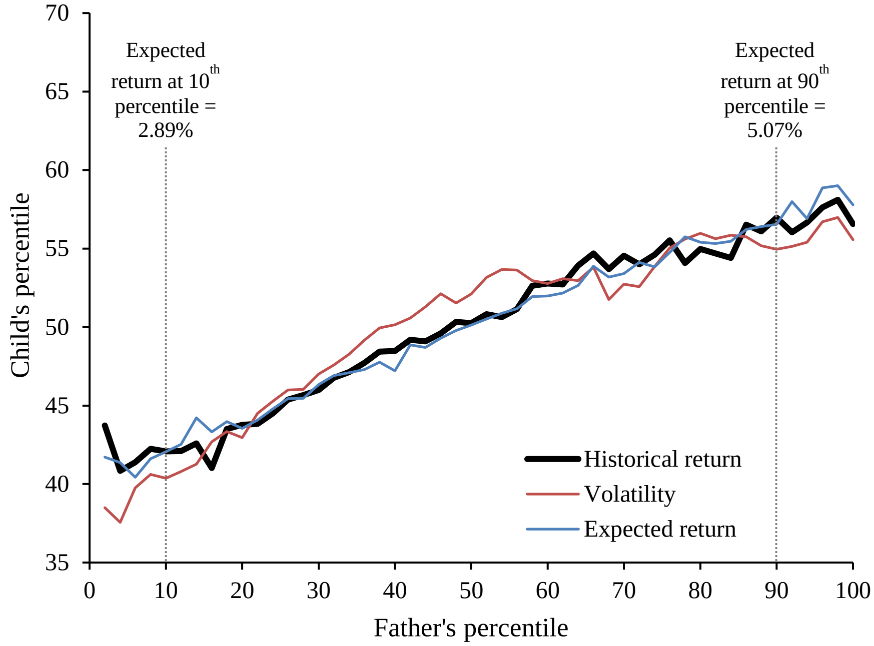
Panel A: Investor's portfolio attribute as a function of her father's



Panel B: Investor's portfolio attribute as a function of her mother's

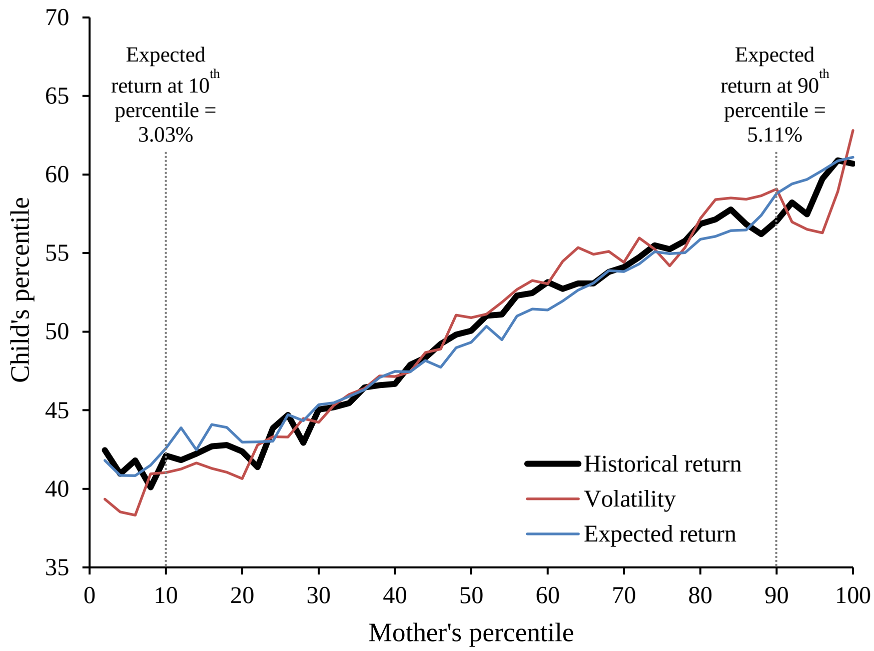


Figure 1. Intergenerational correlations in portfolio attributes

The graph plots investors' portfolio attributes as a function of her parents'. Portfolio attributes include annualized historical and expected excess returns and annualized volatility. The horizontal axis is the rank transformation of a given portfolio attribute of an investor's parent. The vertical axis depicts the average rank of the investor's portfolio attribute for 20 vigintiles of the parent's attribute. Panels A and B depict the rank-rank correlations for the investor's father and mother, respectively.

Table 1

Portfolio characteristics and investor attributes

This table reports descriptive statistics of the investor and parent samples. The unit of observation is investor-year. The historical return is the value-weighted average portfolio return calculated over the previous 24 months. Factor loadings come from a four-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 US stock market. The expected return multiplies the estimated factor loadings by the average returns on the factors from 1994 to 2008 assuming zero alphas. Portfolio value is the total value of the portfolio in euros. Retail distribution refers to funds distributed through bank branch networks. These fund-related fractions assign directly held stock to the unreported omitted category. Labor income is inflation adjusted using the Consumer Price Index from Statistics Finland using 2008 as the base year. Business and economics degree refers to individuals who have graduated with a degree in those fields. Finance professionals work in the finance industry. Panel B omits the medians and standard deviations of the dummy variables because they directly follow from the mean. The columns for investors in Panels A and B report the statistics for the sample of father-child pairs.

Panel A: Portfolio characteristics

	Investor, N = 742,314			Father, N = 742,314			Mother, N = 662,001		
	Mean	Median	Sd	Mean	Median	Sd	Mean	Median	Sd
Portfolio value ('000 EUR)	20.8	3.0	235.2	84.3	10.4	1316.2	38.7	6.8	366.7
Number of securities	3.0	2.0	3.6	4.6	3.0	5.6	3.4	2.0	3.9
Historical return	8.0	10.1	20.9	9.6	12.7	20.9	7.9	8.7	19.4
Volatility	16.1	15.4	10.7	16.5	15.9	9.8	14.3	13.6	9.9
Expected return	3.9	3.3	4.5	3.9	3.4	4.2	3.4	2.7	4.0
Factor loadings									
Market	0.91	0.92	0.59	0.94	0.96	0.54	0.84	0.83	0.55
Size	−0.01	0.01	0.51	0.04	0.02	0.45	0.00	0.01	0.43
Value	−0.17	−0.11	0.58	−0.18	−0.12	0.55	−0.14	−0.07	0.50
Momentum	0.08	0.02	0.50	0.06	0.02	0.49	0.05	0.01	0.44
Share invested in asset class									
Stock (%)	48.7	43.0	46.5	60.6	87.1	43.7	47.8	39.2	45.5
Short-term bond fund (%)	8.6	0.0	25.6	8.2	0.0	24.0	11.5	0.0	28.6
Long-term bond fund (%)	3.2	0.0	15.1	3.1	0.0	14.3	4.2	0.0	17.0
Balanced fund (%)	17.3	0.0	33.8	12.9	0.0	28.3	19.3	0.0	34.0
Equity fund (%)	21.6	0.0	36.1	14.7	0.0	29.0	16.4	0.0	31.1
Other fund (%)	0.6	0.0	6.4	0.5	0.0	5.6	0.7	0.0	7.0
Share invested in fund types									
Actively managed (%)	51.0	55.5	46.5	39.3	12.7	43.6	52.1	60.4	45.5
Retail distribution (%)	48.0	38.0	46.6	37.4	6.3	43.3	50.5	53.1	45.6
Fund of fund (%)	19.4	0.0	35.6	14.7	0.0	30.2	21.1	0.0	35.5

Panel B: Investor attributes									
	Investor, N = 742,314			Father, N = 742,314			Mother, N = 662,001		
	Mean	Median	Sd	Mean	Median	Sd	Mean	Median	Sd
Labor income ('000 EUR)	31.6	27.3	33.9	39.0	28.9	56.1	24.2	21.0	21.6
Level of education									
Basic or vocational (%)	40.9			67.0			76.5		
High school (%)	18.9			1.8			3.2		
Bachelor's (%)	15.5			12.4			8.9		
Master's or higher (%)	24.7			18.8			11.4		
Business or econ. degree (%)	18.2			9.9			20.2		
Finance professional (%)	4.5			1.7			4.7		
Female (%)	44.3			0.0			100.0		
Married (%)	41.1			90.3			85.2		
Swedish-speaking (%)	9.1			9.1			8.9		
Birth year	1972	1973	8	1943	1944	8	1945	1946	8

Table 2

Intergenerational correlation in security choice

This table reports coefficient estimates and their associated *t*-values (in parentheses) from regressions that explain an investor's decision to hold a particular security. The unit of observation is for an investor *i* and security *j* in year *t*. A holding in security *j* by investor *i* is matched to a randomly chosen security the investor has not held during the sample period. Each observation is weighted with its inverse probability of featuring in the estimation sample in order to obtain consistent estimates. The securities investors hold enter with a weight of one, whereas the randomly chosen non-holdings obtain a weight of $1 / (1/(N - n)) = N - n$, where N is the total number of securities available to investors in a given year and n equals the number of securities an investor holds in that year. Specifications 1 and 5 control for the security's market share by including security-year fixed effects. Specifications 2 and 6 condition on investors' preferences for a particular asset class, whereas specifications 3 and 7 also control for asset-management firm and fund type. In these specifications, each investor is paired with each observable security characteristic. The five largest asset managers enter separately, and the remaining firms serve as the omitted category. Specifications 4 and 8 replace fixed effects for pairing an investor with observable security characteristics with pairing investors with each security. The mean dependent variable and coefficients are multiplied by 100. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level. Specifications 1-4 have 212,545 unique father-child pairs, whereas columns 5-8 have 193,202 unique mother-child pairs.

Dependent variable	Investor invested in a security							
Specification	Father, N = 8,065,922				Mother, N = 7,348,276			
	1	2	3	4	5	6	7	8
Parent invested in a security	0.180	0.202	0.160	0.213	0.177	0.203	0.150	0.238
	(70.73)	(62.50)	(72.71)	(49.46)	(60.97)	(52.35)	(65.98)	(47.00)
Fixed effects								
Security × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investor × Asset class	No	Yes	Yes	No	No	Yes	Yes	No
Investor × Asset manager	No	No	Yes	No	No	No	Yes	No
Investor × Fund type	No	No	Yes	No	No	No	Yes	No
Investor × Security	No	No	No	Yes	No	No	No	Yes
Mean dependent variable	0.059	0.059	0.059	0.059	0.060	0.060	0.060	0.060
Adjusted R^2	0.098	0.318	0.409	0.648	0.099	0.319	0.412	0.650

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 the investor's birth year into six categories. Specification 1 in Panel B investigates investors who have no security holdings in the beginning of the sample period but enter the market in later sample years. Specification 2 considers investors whose grandparents do not participate in the financial asset market. Specification 3 includes investors who have holdings in multiple asset classes, and specification 4 excludes the top five most common securities held by individual securities. The mean dependent variable and coefficients are multiplied by 100. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level. All results in the table are for fathers; results for mothers are in the Internet Appendix.

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 invested in a security	0.103	0.126	0.144	0.180	0.222	0.263
	(28.94)	(29.99)	(32.32)	(36.21)	(42.65)	(47.02)
Mean dependent variable	0.065	0.063	0.062	0.060	0.058	0.062
Adjusted R^2	0.159	0.126	0.121	0.122	0.120	0.138
Number of observations	686,224	1,108,732	1,464,422	1,554,334	1,620,302	1,631,908

Panel B: Additional robustness checks				
Robustness check	New investors only	Investors whose grandparents are not investors	Investors with securities from various asset classes	Excluding top five securities
Specification	1	2	3	4
Parent invested in a security	0.162	0.221	0.159	0.255
	(33.85)	(53.03)	(55.49)	(67.93)
Mean dependent variable	0.066	0.058	0.071	0.049
Adjusted R^2	0.132	0.103	0.093	0.101
Number of observations	770,890	3,123,394	4,015,206	7,381,543

Table 4

Heterogeneity

This table reports regressions that interact the parental holding indicator with investor and security attributes that may moderate the intergenerational correlation in security choice. The interactions include an indicator for a security's positive return in the previous 12 months. The dummy for living in the same zip code equals one for parents and children whose registered address is in the same zip code. An indicator for not having a business or economics degree takes the value of one if the investor and her parent do not have a degree in business or economics. 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 less one, capped at four or more. The table omits the coefficients on the main effects of the variables that interact with the parental holding indicator. The mean dependent variable and coefficients are multiplied by 100. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level. Specification 1 has 212,545 unique father-child pairs, whereas specification 2 has 193,202 unique mother-child pairs.

Dependent variable	Investor invested in a security	
Specification	Father	Mother
	1	2
Parent invested in a security	0.102	0.135
	(4.43)	(4.71)
× Positive return in past 12 months	0.047	0.037
	(19.84)	(14.82)
× Live in same zip code	0.057	0.045
	(12.65)	(9.24)
× No business or economics degree	0.017	0.001
	(2.76)	(0.21)
× Female	0.013	0.010
	(2.36)	(1.64)
× Biological parent	0.0002	0.003
	(0.01)	(0.13)
× Number of siblings = 1	0.011	−0.008
	(1.34)	(−0.87)
× Number of siblings = 2	0.022	−0.008
	(2.48)	(−0.89)
× Number of siblings = 3	0.024	0.032
	(1.97)	(2.04)
× Number of siblings ≥ 4	0.008	−0.008
	(0.66)	(−0.63)
Mean dependent variable	0.059	0.060
Adjusted R^2	0.098	0.099
Number of observations	8,065,922	7,348,276

Table 5

Identifying social influence using partially overlapping peer groups

Panel A reports coefficient estimates and their associated *t*-values (in parentheses) from regressions that explain an investor's decision to hold a particular security. The regressions correspond to those in columns 1 and 5 in Table 2. The 2SLS regressions instrument for a parent's ownership with that of her peers. In columns 1 and 4, peers are investors who live in the same zip code and belong to the same age cohort as the parent. The four cohorts for parents' peers are investors born before 1930, during the 1930s, during the 1940s, and in or after 1950. Columns 2 and 5 further stratify peers by whether the parent's native language is Finnish or Swedish. Columns 3 and 6 use the parent's work establishment, available for a subset of parents, to define the peer group. The instrument is the fraction of peers that hold a security, excluding the parent herself. The regressions include fixed effects for pairing each zip code (columns 1, 2, 4, and 5) or firm (columns 3 and 6) with each security. The 2SLS diagnostics are the partial R^2 and the F-statistic of the instrument in the first stage. The mean dependent variable and coefficients are multiplied by 100. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level. Panel B reports analyses that follow the structure of Panel A but focus on the influence that runs from adult children to parents. Peer groups are defined in the same way as for parents except that the cohorts for the child's peers are investors born in 1955-1964, 1965-1974, and 1975-1986.

Panel A: Impact of parent on child						
Dependent variable	Investor invested in a security					
Specification	Father			Mother		
	1	2	3	4	5	6
Parent invested in a security	0.117	0.107	0.173	0.177	0.161	0.188
	(34.08)	(31.50)	(10.20)	(31.16)	(29.11)	(10.82)
1st stage F-statistic	4,806.6	4,572.6	514.6	2,379.8	2,237.6	548.5
1st stage partial R^2	0.021	0.021	0.042	0.011	0.011	0.041
Instrument based on						
Zip code	Yes	Yes	No	Yes	Yes	No
Age category	Yes	Yes	No	Yes	Yes	No
Native language	No	Yes	No	No	Yes	No
Work establishment	No	No	Yes	No	No	Yes
Mean dependent variable	0.059	0.059	0.052	0.059	0.059	0.053
Adjusted R^2	0.375	0.388	0.426	0.378	0.391	0.429
Number of observations	7,975,713	7,975,713	1,905,347	7,275,869	7,275,869	1,910,335

Panel B: Impact of adult child on parent						
Dependent variable	Parent invested in a security					
Specification	Father			Mother		
	1	2	3	4	5	6
Investor invested in a security	0.035	0.032	0.118	0.023	0.021	0.095
	(12.38)	(11.19)	(8.74)	(7.15)	(6.42)	(9.46)
1st stage F-statistic	4,463.1	4,260.3	442.4	2,922.2	2,805.8	637.4
1st stage partial R^2	0.013	0.013	0.010	0.012	0.012	0.012
Instrument based on						
Zip code	Yes	Yes	No	Yes	Yes	No
Age category	Yes	Yes	No	Yes	Yes	No
Native language	No	Yes	No	No	Yes	No
Work establishment	No	No	Yes	No	No	Yes
Mean dependent variable	0.066	0.066	0.060	0.071	0.071	0.064
Adjusted R^2	0.526	0.544	0.725	0.576	0.593	0.659
Number of observations	11,984,288	11,984,288	3,211,493	7,428,134	7,428,134	2,241,269

Table 6

Using mergers to identify social influence

Panel A reports an investor's propensity to hold a security as a function of her parent becoming a shareholder of the acquirer through ownership in the target. The treatment group consists of investors whose parent is a target shareholder, whereas the control group includes all the other investors. Investors who are target shareholders prior to the merger do not enter the sample. The unit of observation is an investor-merger-time triplet in which time refers to two years before and after the merger. The difference-in-differences regression relates an indicator for an investor holding the acquirer to indicators for treatment, time, and their interactions. Panel B reports analyses that follow the structure of Panel A but focus on the influence that runs from children to parents. The treatment group includes parents whose children are target shareholders, whereas the control group consists of all the other parents. Parents who are target shareholders prior to the merger are excluded from the sample. In both panels, specifications 2 and 4 add fixed effects for pairing each security with each year in the regression. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Impact of parent on child				
Dependent variable	Investor invested in acquirer			
Specification	Father		Mother	
	1	2	3	4
Parent owns target × $t = -2$	0.001	−0.0003	−0.0002	−0.002
	(1.77)	(−0.52)	(−0.27)	(−1.98)
Parent owns target × $t = 0$	0.042	0.028	0.055	0.037
	(12.72)	(9.34)	(14.28)	(10.78)
Parent owns target × $t = 1$	0.032	0.023	0.042	0.031
	(9.03)	(7.11)	(10.04)	(8.17)
Parent owns target × $t = 2$	0.027	0.018	0.037	0.026
	(8.19)	(6.10)	(9.30)	(7.42)
Parent owns target	0.0002	0.0033	0.0048	0.0065
	(0.12)	(2.09)	(2.35)	(3.71)
$t = -2$	−0.002		−0.001	
	(−6.33)		(−5.26)	
$t = 0$	0.002		0.002	
	(7.09)		(7.82)	
$t = 1$	0.003		0.003	
	(6.46)		(7.28)	
$t = 2$	0.001		0.001	
	(1.53)		(2.48)	
Security × year fixed effects	No	Yes	No	Yes
Mean dependent variable	0.014	0.014	0.013	0.013
Adjusted R^2	0.004	0.029	0.008	0.031
Number of observations	294,710	294,710	281,385	281,385

Panel B: Impact of child on parent				
Dependent variable	Parent invested in acquirer			
Specification	Father		Mother	
	1	2	3	4
Child owns target × t = −2	0.003	0.002	0.002	0.0002
	(5.74)	(3.47)	(3.56)	(0.41)
Child owns target × t = 0	0.030	0.018	0.049	0.030
	(11.33)	(7.53)	(14.46)	(10.64)
Child owns target × t = 1	0.022	0.016	0.038	0.024
	(7.65)	(6.04)	(10.84)	(8.18)
Child owns target × t = 2	0.021	0.015	0.035	0.023
	(7.80)	(5.82)	(10.27)	(7.86)
Child owns target	−0.0008	0.000004	0.002	0.006
	(−0.51)	(0.003)	(1.44)	(4.59)
t = −2	−0.0019		−0.002	
	(−7.51)		(−6.53)	
t = 0	0.0020		0.0019	
	(6.95)		(7.63)	
t = 1	0.0030		0.0034	
	(7.45)		(9.85)	
t = 2	0.00005		0.00041	
	(0.11)		(1.07)	
Security × year fixed effects	No	Yes	No	Yes
Mean dependent variable	0.012	0.012	0.013	0.013
Adjusted R^2	0.002	0.025	0.006	0.034
Number of observations	340,200	340,200	340,065	340,065

Table 7

Intergenerational correlations in portfolio attributes

Panel A reports coefficient estimates and their associated *t*-values from regressions that explain an investor's portfolio attribute 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*. Columns 1 and 4 analyze historical returns, whereas columns 2 and 5 investigate volatility, both calculated over the previous 24 months. Columns 3 and 6 use an estimate of expected returns derived from multiplying estimated factor loadings by historical factor premia. The regressions include year fixed effects. Panel B splits the parent's portfolio into the parts shared and not shared with the investor. The shared part includes securities an investor and her parent hold, whereas the remaining securities define the non-shared part. Portfolio metrics for the two parts are calculated by weighting each security according to its value in the portfolio. Investors who have at least one shared and at least one non-shared security enter the sample in Panel B. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level. Panel A has 205,295 father-child and 185,916 mother-child pairs, whereas the corresponding numbers for Panel B are 67,012 and 54,972.

Panel A: Total portfolio, all investors

Specification	Father			Mother		
	Historical return	Volatility	Expected return	Historical return	Volatility	Expected return
	1	2	3	4	5	6
Parent's portfolio attribute	0.169	0.187	0.187	0.207	0.222	0.219
	(81.07)	(70.61)	(82.54)	(90.06)	(83.95)	(83.91)
Mean dependent variable	0.080	0.161	0.039	0.079	0.159	0.039
Adjusted R^2	0.591	0.108	0.080	0.599	0.124	0.086
Adjusted R^2 with controls only	0.580	0.081	0.052	0.584	0.084	0.050
Number of observations	742,314	742,314	742,314	662,001	662,001	662,001

Panel B: Portfolio shared and not shared with parent, investors with some overlap with parent

Specification	Father			Mother		
	Historical return	Volatility	Expected return	Historical return	Volatility	Expected return
	1	2	3	4	5	6
Parent's portfolio attribute, shared	0.583	0.609	0.553	0.581	0.619	0.538
	(183.57)	(133.37)	(147.61)	(161.52)	(137.36)	(124.44)
Parent's portfolio attribute, not shared	0.015	0.018	−0.001	0.029	0.021	0.003
	(8.37)	(7.40)	(−0.70)	(14.96)	(8.49)	(1.39)
Mean dep. Variable	0.104	0.179	0.044	0.099	0.169	0.043
Adjusted R^2	0.828	0.557	0.530	0.826	0.583	0.504
Number of observations	229,603	229,603	229,603	186,968	186,968	186,968

Table 8

Matching investors with randomly chosen parents

This table replaces an investor's actual parent with another randomly chosen "placebo" parent, and estimates correlations in portfolio attributes of the investor and the placebo parent, in a manner similar to Table 7 Panel A. Placebo parents are chosen from among subsets of parents according to the actual parent's characteristics. The subsets are either residents of a municipality, employees of a firm, or clients of an asset manager. Clients of each asset manager are identified by their mutual fund holdings. The five largest asset managers and a residual category containing all the other asset managers define the client relation. Parents identified as clients of many asset managers are assigned one client relation based on the largest fraction of portfolio value held at an asset manager, and parents with no mutual funds do not enter the asset-manager sample. Panel A estimates regressions of an investor's portfolio attribute on that of the placebo parent. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level. Panel B calculates the overlap in security holdings of an investor and her actual parent, or her placebo parent using the four matching criteria. Portfolio overlap, which can vary between zero and one, is defined as the value-weighted fraction of the investor's holdings of securities that feature in the actual or placebo parent's portfolio. The panel reports means and standard deviations of the portfolio overlap measure. Samples for fathers (mothers) have 742,314 (662,001) observations, except for the asset-manager sample, in which the corresponding number is 289,401 (354,910).

Panel A: Correlations in portfolio attributes

Specification	Father			Mother		
	Historical return	Volatility	Expected return	Historical return	Volatility	Expected return
	1	2	3	4	5	6
Randomly chosen parent within:						
Residents of a municipality	0.015	0.019	0.023	0.018	0.022	0.023
	(11.77)	(14.16)	(17.03)	(13.19)	(15.84)	(15.24)
Employees of a firm	0.035	0.039	0.044	0.039	0.044	0.048
	(25.64)	(26.34)	(30.25)	(26.53)	(27.96)	(28.66)
Clients of an asset manager	0.023	0.023	0.014	0.007	0.006	0.005
	(9.79)	(8.09)	(4.99)	(3.76)	(3.24)	(2.25)

Panel B: Descriptive statistics of portfolio overlap

	Father		Mother	
	Mean	Sd	Mean	Sd
Actual parent	0.188	0.353	0.185	0.350
Randomly chosen parent within:				
Residents of a municipality	0.100	0.268	0.086	0.250
Employees of a firm	0.119	0.290	0.106	0.277
Clients of an asset manager	0.108	0.274	0.073	0.233

Internet Appendix to

Why Does Portfolio Choice Correlate across Generations?*

Samuli Knüpfer
BI Norwegian Business School and IFN

Elias Rantapuska
Aalto University

Matti Sarvimäki
Aalto University and VATT

January 30, 2018

* E-mails: samuli.knupfer@bi.no, elias.rantapuska@aalto.fi, matti.sarvimaki@aalto.fi.

Table IA1

Robustness checks for investor-mother sample

This table reports analyses in Table 3 for the sample that pairs the investor with her mother. 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 invested in a security	0.110	0.138	0.149	0.176	0.207	0.231
	(25.35)	(25.98)	(29.69)	(33.71)	(32.44)	(45.18)
Mean dependent variable	0.063	0.062	0.060	0.059	0.056	0.060
Adjusted R^2	0.137	0.116	0.111	0.113	0.114	0.131
Number of observations	591,724	986,758	1,333,082	1,439,198	1,486,880	1,510,634

Panel B: Additional robustness checks				
Robustness check	New investors only	Investors whose grandparents are not investors	Investors with securities from various asset classes	Excluding top five securities
Specification	1	2	3	4
Parent invested in a security	0.133	0.203	0.156	0.250
	(29.70)	(48.06)	(49.09)	(58.00)
Mean dependent variable	0.067	0.058	0.071	0.049
Adjusted R^2	0.139	0.105	0.095	0.102
Number of observations	675,430	2,871,650	3,696,272	6,721,270

Table IA2

OLS estimates in the peer-group analyses

This table reports OLS estimates for the samples in Panels A and B in Table 5. These samples are subsets of those in Table 2, because an identifier used to define the peer group is missing. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Impact of parent on child

Dependent variable	Investor invested in a security					
Specification	Father			Mother		
	1	2	3	4	5	6
Parent invested in a security	0.179	0.179	0.231	0.177	0.177	0.203
	(69.28)	(69.28)	(43.32)	(59.65)	(59.65)	(47.36)
Mean dependent variable	0.059	0.059	0.052	0.059	0.059	0.053
Adjusted R^2	0.098	0.098	0.111	0.099	0.099	0.112
Number of observations	7,975,713	7,975,713	1,905,347	7,275,869	7,275,869	1,910,335

Panel B: Impact of child on parent

Dependent variable	Parent invested in a security					
Specification	Father			Mother		
	1	2	3	4	5	6
Child invested in a security	0.154	0.154	0.175	0.171	0.171	0.178
	(44.18)	(44.18)	(29.52)	(42.88)	(42.88)	(34.21)
Mean dependent variable	0.066	0.066	0.060	0.071	0.071	0.064
Adjusted R^2	0.117	0.117	0.122	0.124	0.124	0.141
Number of observations	11,984,288	11,984,288	3,211,493	7,428,134	7,428,134	2,241,269

Table IA3

Intergenerational correlations in portfolio attributes conditional on observables

This table repeats regressions in Panel A of Table 7 by adding controls for observable investor attributes and portfolio composition. These include decile dummies for total value of financial assets and for annual labor income. It also controls for dummies for four levels of education, 10 fields of education, and 11 industries (missing categories omitted). The demographic controls are 31 cohort dummies, and indicators for females, native language, and marital status. Portfolio characteristics include six variables that measure the fraction of portfolio invested in an asset class (short-term bond fund omitted) and six variables that measure the fraction of portfolio invested with an asset-management company (the five largest companies enter separately, and the remaining firms serve as the omitted category). It further includes fractions invested in funds of funds and actively managed funds (asset-manager controls capture retail distribution). The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Specification	Father			Mother		
	Historical return	Volatility	Expected return	Historical return	Volatility	Expected return
	1	2	3	4	5	6
Parent's portfolio attribute	0.131	0.060	0.155	0.155	0.050	0.173
	(69.61)	(34.90)	(72.16)	(75.93)	(30.19)	(70.01)
Mean dependent variable	0.080	0.161	0.039	0.079	0.159	0.039
Adjusted R^2	0.652	0.648	0.223	0.659	0.653	0.227
Number of observations	742,314	742,314	742,314	662,001	662,001	662,001

Table IA4

Alternative portfolio attributes

This table repeats the regressions in Panel A of Table 7 for alternative portfolio attributes. Idiosyncratic variance is the residual variance from the factor regressions used to compute expected returns in Table 7; estimates of factor loadings and alpha come from these regressions as well. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Father

Specification	Four-factor loadings				Idiosync. variance	Four-factor alpha
	Market	HML	SMB	MOM		
	1	2	3	4	5	6
Parent's portfolio attribute	0.188	0.178	0.178	0.188	0.144	0.144
	(96.67)	(72.21)	(68.99)	(75.06)	(14.75)	(66.19)
Mean dependent variable	0.914	−0.172	−0.010	0.083	0.002	0.003
Adjusted R^2	0.050	0.053	0.042	0.078	0.028	0.109
Adjusted R^2 with controls only	0.021	0.026	0.017	0.047	0.017	0.093
Number of observations	742,314	742,314	742,314	742,314	742,314	742,314

Panel B: Mother

Specification	Four-factor loadings				Idiosync. variance	Four-factor alpha
	Market	HML	SMB	MOM		
	1	2	3	4	5	6
Parent's portfolio attribute	0.219	0.213	0.213	0.226	0.176	0.180
	(107.56)	(75.09)	(78.63)	(74.98)	(13.23)	(73.13)
Mean dependent variable	0.914	−0.169	−0.017	0.082	0.002	0.003
Adjusted R^2	0.062	0.059	0.048	0.083	0.031	0.114
Adjusted R^2 with controls only	0.022	0.027	0.016	0.047	0.018	0.094
Number of observations	662,001	662,001	662,001	662,001	662,001	662,001

Table IA5

Randomly choosing placebo parents from among all parents

This table repeats the analyses in Panels A and B of Table 8 by randomly choosing a placebo parent from among all parents instead of within zip codes, firms, or asset managers. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Correlations in portfolio attributes

Specification	Father			Mother		
	Historical return	Volatility	Expected return	Historical return	Volatility	Expected return
	1	2	3	4	5	6
Randomly chosen parent	0.0002	-0.001	0.001	0.001	-0.002	-0.002
	(0.13)	(-0.44)	(0.53)	(0.55)	(-1.40)	(-1.04)

Panel B: Descriptive statistics of portfolio overlap

	Father		Mother	
	Mean	Sd	Mean	Sd
Randomly chosen parent	0.079	0.239	0.067	0.223