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Why Does Portfolio Choice Correlate across Generations?*

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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, and is stronger when family members are more likely to communicate with each other. 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

A puzzlingly high degree of heterogeneity emerges in virtually all domains of household financial decision-making (Campbell, 2006; Campbell, Calvet, and Sodini, 2007; and Guiso and Sodini, 2013). Recent work convincingly shows such heterogeneity can be traced back to familial origins.[1] But why does family matter so much? Do family members share genes or environments that make their decisions 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 the context of household 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 informative to study because it naturally relates to sharing investment ideas through word-of-mouth communication (Shiller and Pound, 1989). Moreover, it has implications for understanding portfolio heterogeneity and wealth accumulation, because identical security holdings mechanically translate into intergenerational correlations in risk-return profiles of household portfolios. Finally, it lends itself to analyses of causality that take advantage of plausibly exogenous changes in holdings of individual securities.

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

[1] Black et al. (2017a), Fagereng, Mogstad, and Rønning (2018), 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.

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

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 about 150% compared to the baseline probability of 6-7 percentage points, when an investor's parent 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, smaller family size, and being of the same gender make the correlation stronger. These patterns are consistent with the correlation being greater when family members are more likely to communicate with each other.

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

First, we use an instrumental variable approach that takes advantage of rich data allowing us to approximate social networks. We match every parent with her neighbors and co-workers, and calculate the fraction of them investing in a particular security. If an investor does not directly communicate and does not share unobservables with her parents' peers, their investment decisions serve as a valid instrument for the parent's decision.[2] To guard against the possibility of direct influence, we focus our analysis on investors who do not live in the same area or do not work in the same establishment as their parents. We also include fixed effects that absorb unobservables common to neighborhoods or firms.

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 employ a difference-in-differences approach that tells us how children of the target shareholders 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

[2] 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), and Nicoletti, Salvanes, and Tominey (2018).

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 provide their parents with financial advice.

We find a significantly positive effect that runs from the choice of an adult child to that of her parents. This child-to-parent influence is economically meaningful but somewhat smaller than the effect in the opposite direction. This finding advances our understanding of linkages between family members, by showing adult 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 a 2.2% intergenerational spread between the top and bottom deciles of annual expected return. Compounded over time, such a spread would produce substantial differences in wealth accumulation.

We then ask how important familial 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 −0.6 and 1.3). 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., 2017a; Fagereng, Mogstad, and Rønning, 2018). The twin and adoption techniques embed different assumptions, which may explain why they arrive at conflicting conclusions.[3] Consistent with the important role of assumptions, Calvet and Sodini (2014) find the genetic component estimated for pairs of twins correlates with the extent of communication within the pairs. By using a new approach to isolate social influence from other 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.[4] Previous work by Charles and Hurst (2003), Boserup, Kopczuk, and Kreiner (2014), Black et al. (2017b), Fagereng, Mogstad, and Rønning (2018), and Fagereng et al. (2018) 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 can 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.; 2018, and Bach, Calvet, and Sodini, 2018). We show the intergenerational spread in returns on financial assets 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.

[3] 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. The adoption technique in Black et al. (2017a) and Fagereng, Mogstad, and Rønning (2018) assume assignment of adoptees to adoptive families is as good as random.

[4] 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.

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 intergenerational transmission of risk attitudes and trust. Anderson et al. (2015) find an 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 212,544 father-child and 193,199 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, municipalities, and provinces.

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.[5] 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.

[5] The large fraction of business and economics graduates stems from such degrees ranging from secondary degrees in business administration to doctoral studies in economics.

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 and cluster standard errors at the parent level.

The great number of investors and the complete menu of stocks and mutual funds investable in Finland observed over multiple years would result in a panel with more than two billion observations. Computational feasibility thus necessitates a randomization approach that economizes on sample size but does not generate bias. We first pick each security an investor's parent owned during our sample period and then randomly choose another security the parent never held. The probability of a security being randomly drawn obtains from the observed holdings of each security in the aggregate portfolio of all individual investors.[6] For the holdings and non-holdings, we retrieve the full time series of investor-security-year triplets, which results into sample sizes of 12.4 and 7.7 million for the samples of fathers and mothers, respectively.

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, which may affect 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.[7] 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.

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[6] An alternative sampling scheme would start from an investor's holdings instead of those her parent. We do not use this approach, because outcome-based sampling (i.e. choosing the sample based on the investor's holdings) is known to result in estimation bias (Manski and Lerman, 1977).

[7] 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.

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 0.083 (t-value 145.9). In our sample of holdings and non-holdings, the mean probability of owning a security in a given year is 5.7 percentage points, so the father holding a security increases an investor's likelihood of owning the same security by 0.083 / 0.057 = 147%. 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 0.071 and 0.069 (t-values 129.7 and 122.0). These estimates suggest investor preferences for observable security characteristics account for $1 - 0.07/0.08 = 17\%$ 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 2.4 percentage points in the year in which the investor's father purchases the security (t-value 53.9). 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 security 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 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, 0.091, for the youngest category of investors who are not more than 24 years old at the start of the sample period in 2004. Scaled by the mean dependent variable reported at the bottom of the table, the relative increase in the holding propensity monotonically decreases by age. The oldest category of investors above the age of 44 shows a relative effect of 0.083 / 0.072 = 114%, which shows the intergenerational correlation 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 0.057 (*t*-value 36.5). 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 0.085 (*t*-value 96.7), 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 115.5) 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 0.069 (*t*-value 119.8).

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 between family members. 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 0.017/0.095 = 18% higher correlation, suggesting the paternal correlation is stronger when a security has generated a favorable experience. The maternal specification in column 2 returns a 0.016/0.116 = 13% 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 0.038/0.095 = 40% in the correlation. Column 2 reports a 39% increase for mothers. The patterns concerning family size indicate a clear pattern of larger families displaying a smaller correlation.

Inspired by Bowles and Gintis (2002), we study how the correlation varies in parent-child pairs stratified by gender. The negative father-daughter coefficient in column 1 translates into a 0.009/0.095 = 10% lower correlation whereas the corresponding effect for the mother-daughter pairs in column 2 is a 0.014 / 0.116 = 12% larger correlation. These patterns are consistent with the idea that children are more likely to communicate with the parent of their own gender when choosing securities in their portfolio.

Our final interaction contrasts biological with adopted children. Black et al. (2017b) and Fagereng, Mogstad, and Rønning (2018) 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 willingness to take risks might make it easier to convince a family member to invest in risky assets.[8]

We do not find a statistically significant difference in the 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 estimates suggest genetic factors do not play a major role in generating the security-choice correlation.

[8] 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 documented in Table 2, 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. This IV strategy yields an estimate of causal parent-to-child influence under the assumption that the parent's peers affect the child only through their influence on her parents and that the parent's peers and the child do not share unobservables not captured by the observable controls (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, 2018).

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. These peer groups stem from people being likely to interact with their neighbors of the same age. The cohorts are 10-year intervals of each parent's age so that, for example, a parent aged 50 matches with her neighbors of the age of 45-54.

Two design features guard against the possibility that parent's peers directly affect children or that omitted factors common to the constellation of the investor, her parent, and the parent's peers make them invest in the same security. First, we require that the parent and child live in a different municipality to make it unlikely that the parent and child share the same peers. Second, we include fixed effects for pairing each zip code with each security. These fixed effects absorb all unobservable reasons for people living in the same zip code to hold certain securities (for example, listed firms having an establishment or an asset management company marketing its products in a zip code.)

Our second definition of peers considers parent's colleagues at work. A subsample of our data has information on identifiers that tag the establishment of work for each individual and that also uniquely link each establishment to each firm. These establishments represent a factory, office, or other physical location and thus define co-workers who likely interact with each other on a regular basis. Analogously to the neighbor instrument, we allay concerns of direct influence by focusing on investors whose parents do not work at their establishment. We also include fixed effects for pairing each firm to which an establishment belongs with each security to account for unobservable factors that make investors in the same firm hold the same securities (employee ownership of listed firms and financial advisory perks provided by the company are examples of such factors.)

For both neighbors and co-workers, 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, and enters the first stage nonparametrically as four quartile indicators to account for possible nonlinearities.[9] To make sure peer groups of meaningful size enter the sample, we require that they contain at least 30 investors. This requirement, combined with the 22% participation rate in stocks and mutual funds (Keloharju, Knüpfer, and Rantapuska, 2012),

[9] The nonlinearities arise from peer groups having either a zero or unusually high holding propensity. The peer groups with zero holding propensity are assigned to the first quartile and the remaining strictly positive values define the remaining three quartiles.

translates into our samples having about 30,000 peer groups in the analyses of neighbors whereas the corresponding number is about 3,200 for co-workers. The average peer groups have about 600 and 300 investors, respectively.

Table 5 Panel A reports the results of regressions that correspond to columns 1 and 5 in Table 2. 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 analyze parent's neighbors whereas columns 2 and 4 report the results for parent's co-workers.

The IV estimate in column 1 equals 0.166 (t-value 42.4). The instrument's impressive F-statistic indicates the regression does not suffer from the weak-instrument problem. The co-workers in column 2 yields an IV estimate of 0.165 (t-value 9.5). The regressions for the investor's mother in columns 3 and 4 yield coefficient estimates that are larger in magnitude than the father's estimates 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, but that parents influence their offspring.

The IV estimates in Table 5 Panel A are larger than the OLS estimates in Table 2. Table IA2 shows that the larger IV estimates do not stem from differences in the samples we use to generate the IV estimates. For example, the OLS estimate for the sample in the first column of Table 5 Panel A equals 0.070, which amounts to 42% of the IV estimate. Two reasons may explain why the IV regressions return estimates larger than OLS.

The less plausible explanation considers violations of the exclusion restriction that could overstate the causal effect. Although testing for these violations is not possible, they are unlikely in our setup that deliberately chooses a sample of geographically or professionally distant family members to guard against direct influence, and conservatively controls for any confounding factors affecting investors in the same neighborhood or the same firm.

The more plausible explanation entertains the possibility that the local average treatment effect returned by the IV regression is larger than the average effect uncovered by the OLS regression (Imbens and Angrist, 1994). The IV estimate obtains from the subset of complying sociable parents who are susceptible to peer influence. If sociability correlates across generations, the parents who act on their peers' advice may also be more successful in altering their children's behavior. When families of varying degrees of sociability are averaged in the OLS estimation, the estimate becomes smaller.

Table 5 Panel B addresses the possibility that adult children may also provide their parents with investment ideas.[10] It explains the parent's security choice with that of her child, and uses instruments similar to Panel A but now calculates them as the fraction of the child's peers invested in a security. The sampling design is also reversed compared to Panel A so that each holding by a child is assigned a randomly chosen non-holding that the child never held during the sample period. The smaller number of securities held by children (3.1) compared to fathers (4.6) and mothers (3.4) explains why Panel B includes less observations than Panel A.

The first-stage *F*-statistics in Panel B are well above critical thresholds of weak-instrument tests. Across all specifications, the IV estimates scaled by the mean dependent variable are smaller than those in Panel A. For example, the estimate of 0.154 in column 1 (*t*-value 7.9) shows ownership probability increases by 171% when a child holds a security compared to the mean holding propensity of 9 percentage points. This relative increase amounts to 171% / (0.166/0.052) = 79% of

[10] 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.

the parent-to-child effect in Panel A. These results suggest children affect their parents' investment decisions although to a lesser extent than in the opposite direction.

Table IA3 provides a number of checks that assess the robustness of the IV results. The table follows the same structure as Table 5 but modifies the definition of the instrument or analyzes alternative samples. Motivated by the two official languages in Finland (Finnish and Swedish) that define social networks ranging from educational institutions to recreational activities, column 1 further stratifies the parent's neighbors by native language. Column 2 stratifies the co-workers in an establishment further by age to capture the idea that co-workers of the same age are more likely to interact with each other.

Column 3 in Table IA3 uses the neighbor instrument, but focuses on a subsample of investors who live in a province different from their parents' place of residence. The provinces are 19 administrative units that are much larger than the municipalities we use in Table 5, making it even less likely children interact with the parent's peers on a regular basis. Column 4 applies a similarly motivated sample restriction to the co-worker instrument by analyzing a sample of children who work at a firm different from that of their parents.

Across all the specifications in columns 1-4, the coefficient estimates remain highly significant and imply large magnitudes. Columns 5-8 repeat the robustness checks for the investor's mother and finds estimates similar to those for the father. Panel B in Table IA3 repeats all the regressions investigating child-to-parent influence and reports statistically significant and sizable estimates.

4.2. Natural experiment based on mergers

Our 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. We start from a sample that 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 as control observations all the other 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 pre-trends 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.[11] Standard errors are clustered at the parent level to take into account the multiple years we observe a parent, and the year-to-year overlap in the 24-month historical return window.

The coefficient estimate of 0.169, 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 81.0. 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 0.207 (*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. (2018) report positive intergenerational correlations for stock market participation in Sweden and Norway, respectively.

Table IA5 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 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

[11] Table IA4 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.

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

Does social influence within families help to explain the intergenerational correlations in portfolio attributes? 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 examine 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 that display some portfolio overlap, 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).[12]

Table 7 Panel B 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 return 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 7.7) 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 return (t-values −0.6 and 1.3).

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

[12] Table IA6 performs a complementary analysis of families whose members have varying degrees of portfolio overlap. This exercise delivers results similar to our main approach. The differences in signs in columns 1 and 4 of Table IA6 arise from Panels A and B capturing total return variation whereas Panel C focuses on systematic variation only.

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.[13] 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 municipalities. However, compared to the 0.187 we report in column 1 of Table 7 Panel A, the 0.021 estimate for expected return (t-value 9.1) represents a fraction of only 11%. Matches based on firms and asset managers yield even smaller correlations, and patterns for mothers are similar to those we observe for fathers.

Table 8 Panel B documents 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. The table reports an average portfolio overlap for actual fathers and mothers of 0.172 and 0.169, respectively. The placebo parents have substantially lower overlap that ranges from 0.075 to 0.107, which mirrors the low correlations in Panel A.

[13] 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.

To further validate the placebo exercise, Table IA7 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 confirms the expectation that the correlations should be insignificant in all the three portfolio attributes we consider. Panel B reports portfolio overlap of 0.071 and 0.066 for randomly chosen fathers and mothers, respectively. Perhaps contrary to first-pass intuition, overlap does not equal zero here, because two randomly chosen investors likely end up investing in the same highly popular securities. The non-zero overlap can, however, 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.

Although we have chosen the three factors we use in sampling the placebo parents on the basis of known empirical determinants of security choice, Table 8 may miss some important characteristics. We assess this possibility in Table IA8 that further stratifies the placebo parents according to their wealth and education. To keep the bins from which we draw the placebo parents large enough, we first divide them into categories by whether the parent's financial wealth is above or below the median, and then also by whether the parent has an education above or below a high school degree. Across all the different ways to stratify the sample, the correlations in Panel A remain a small fraction (8%-19%) of the real correlations in Table 7. Panel B reports similarly small portfolio overlap. Based on this robustness check, it is highly unlikely further stratifications would produce a substantially larger placebo correlation.

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, the findings in this section strongly suggest 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—are 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 role for transmission of investor attributes as the sole driver of portfolio-choice correlations across generations.

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, misguided beliefs may also travel in the intergenerational network.

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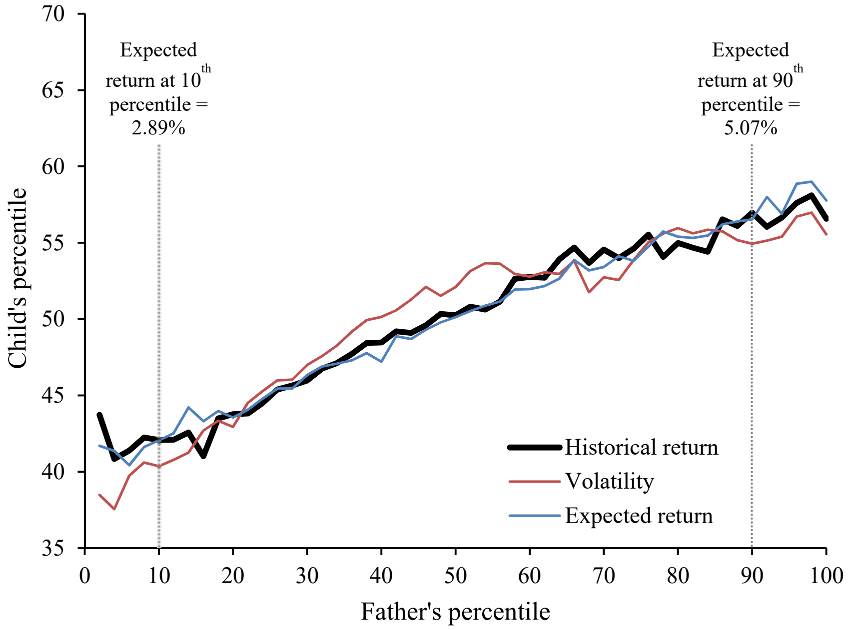
Panel A: Investor's portfolio attribute as a function of her father's



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

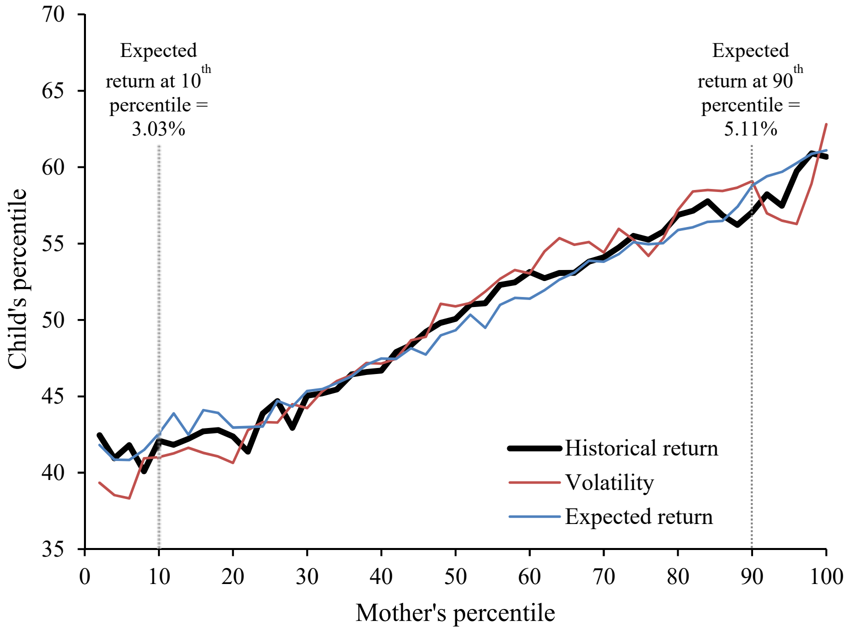


Figure 1. Intergenerational correlations in portfolio attributes

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 any level of 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. The table has 212,544 unique father-child pairs and 193,199 unique mother-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's parent is assigned a randomly chosen non-holding the parent has not held during the sample period. 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 t-values reported in parentheses use standard errors that assume clustering at the parent level. Specifications 1-4 have 212,544 unique father-child pairs, whereas columns 5-8 have 193,199 unique mother-child pairs.

Dependent variable	Investor invested in a security							
Specification	Father, N = 12,431,835				Mother, N = 7,721,974			
	1	2	3	4	5	6	7	8
Parent invested in a security	0.083	0.071	0.069	0.024	0.113	0.097	0.094	0.038
	(145.89)	(129.72)	(122.04)	(53.94)	(148.16)	(125.39)	(115.45)	(55.59)
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	0.057	0.057	0.057	0.057	0.074	0.074	0.074	0.074
Adjusted R^2	0.074	0.234	0.205	0.799	0.092	0.285	0.242	0.807

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 *t*-values reported in parentheses use standard errors that assume clustering at the parent level. All results in the table are for fathers; results for mothers appear in Table IA1.

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	0.083	0.075	0.079	0.079	0.080	0.091
	(40.21)	(52.10)	(67.42)	(69.79)	(73.40)	(86.92)
Mean dependent variable	0.072	0.064	0.060	0.056	0.052	0.053
Adjusted R^2	0.117	0.100	0.088	0.076	0.069	0.076
Number of observations	689,952	1,301,180	1,950,590	2,303,913	2,675,226	3,510,974

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	0.057	0.085	0.157	0.069
	(36.47)	(96.66)	(115.52)	(119.80)
Mean dependent variable	0.046	0.053	0.112	0.039
Adjusted R^2	0.038	0.069	0.118	0.040
Number of observations	292,714	5,507,818	1,680,625	10,740,540

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. 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 *t*-values reported in parentheses use standard errors that assume clustering at the parent level. Specification 1 has 212,544 unique father-child pairs, whereas specification 2 has 193,199 unique mother-child pairs.

Dependent variable	Investor invested in a security	
Specification	Father	Mother
	1	2
Parent invested in a security	0.095	0.116
	(52.06)	(52.99)
× Positive return in past 12 months	0.017	0.016
	(31.33)	(21.18)
× Live in same zip code	0.038	0.045
	(28.94)	(27.22)
× Female	−0.009	0.014
	(−8.88)	(9.98)
× Biological parent	−0.002	−0.003
	(−0.66)	(−0.72)
× Number of siblings = 1	−0.013	−0.015
	(−6.81)	(−6.51)
× Number of siblings = 2	−0.018	−0.018
	(−8.12)	(−6.54)
× Number of siblings = 3	−0.024	−0.018
	(−7.82)	(−4.72)
× Number of siblings ≥ 4	−0.036	−0.033
	(−8.92)	(−5.50)
Mean dependent variable	0.057	0.074
Adjusted R^2	0.091	0.110
Number of observations	10,259,783	6,420,350

Table 5

Identifying social influence using neighbors and co-workers

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 3, the neighbors are investors who live in the same zip code and belong to the same age cohort as the parent. Each parent's cohort comprises investors who are born in the 10-year period surrounding the parent's birth year. Investors living in the same municipality as their parent are excluded from the sample. Columns 2 and 4 use a parent's work establishment, available for a subset of parents, to define the parent's co-workers. Investors working at the same establishment as their parent are excluded from the sample. All the samples include peer groups with at least 30 investors. The instrument is the fraction of parent's peers that hold a security, excluding the parent herself, broken down into quintile dummies. The regressions include fixed effects for pairing each zip code (columns 1 and 3) or firm (columns 2 and 4) with each security. 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 B reports analyses that follow the structure of Panel A but focus on the influence that runs from children to parents. Peer groups are defined in the same way as for parents.

Panel A: Impact of parent on child				
Dependent variable	Child invested in a security			
Specification	Father		Mother	
	1	2	3	4
Parent invested in a security	0.166	0.165	0.186	0.194
	(42.35)	(9.45)	(39.74)	(9.98)
Instrument based on				
Zip code	Yes	No	Yes	No
Age category	Yes	No	Yes	No
Work establishment	No	Yes	No	Yes
Fixed effects				
Zip code × Security	Yes	No	Yes	No
Firm × Security	No	Yes	No	Yes
1st stage F-statistic	4,356.4	237.0	3,888.1	251.8
1st stage partial R^2	0.019	0.012	0.026	0.019
Mean dependent variable	0.052	0.050	0.069	0.068
Number of observations	5,873,582	1,260,188	3,610,084	891,292

Panel B: Impact of child on parent				
Dependent variable	Parent invested in a security			
Specification	Father		Mother	
	1	2	3	4
Child invested in a security	0.154	0.307	0.152	0.227
	(7.94)	(5.73)	(7.53)	(6.80)
Instrument based on				
Zip code	Yes	No	Yes	No
Age category	Yes	No	Yes	No
Work establishment	No	Yes	No	Yes
Fixed effects				
Zip code × Security	Yes	No	Yes	No
Firm × Security	No	Yes	No	Yes
1st stage F-statistic	381.3	58.2	311.2	136.5
1st stage partial R^2	0.003	0.004	0.003	0.004
Mean dependent variable	0.090	0.094	0.078	0.082
Number of observations	2,285,576	1,091,264	2,049,938	1,118,502

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 parent 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 parent level. Panel A has 187,029 father-child and 165,969 mother-child pairs, whereas the corresponding numbers for Panel B are 52,163 and 42,415.

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
	(80.98)	(70.23)	(82.45)	(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
	(173.02)	(128.87)	(135.18)	(147.65)	(134.30)	(113.79)
Parent's portfolio attribute, not shared	0.015	0.018	−0.001	0.029	0.021	0.003
	(7.65)	(6.94)	(−0.64)	(13.67)	(7.88)	(1.25)
Mean dependent 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. The sample is restricted to cases in which the bins from which the placebo parent is drawn have at least 30 observations. 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 three 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 214,402 (256,493) observations, except for the asset-manager sample, in which the corresponding number is 134,750 (158,981).

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	0.018	0.018	0.021	0.020	0.020	0.024
	(8.11)	(7.51)	(9.05)	(9.48)	(8.74)	(10.44)
Employees of a firm	0.006	0.010	0.012	0.004	0.005	0.007
	(2.86)	(4.13)	(5.16)	(1.87)	(2.31)	(2.85)
Clients of an asset manager	0.018	0.030	0.008	−0.001	0.007	0.004
	(5.35)	(7.48)	(1.80)	(−0.43)	(2.55)	(1.14)

Panel B: Descriptive statistics of portfolio overlap

	Father		Mother	
	Mean	Sd	Mean	Sd
Actual parent	0.172	0.338	0.169	0.340
Randomly chosen parent within:				
Residents of a municipality	0.089	0.252	0.082	0.247
Employees of a firm	0.083	0.244	0.075	0.237
Clients of an asset manager	0.107	0.271	0.075	0.235

Internet Appendix to

Why Does Portfolio Choice Correlate across Generations?*

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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 parent 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	0.097	0.095	0.099	0.108	0.115	0.134
	(36.30)	(50.84)	(65.79)	(72.78)	(78.61)	(93.19)
Mean dependent variable	0.082	0.076	0.073	0.072	0.070	0.076
Adjusted R^2	0.113	0.110	0.102	0.092	0.092	0.105
Number of observations	446,852	838,926	1,268,934	1,451,324	1,642,610	2,073,328

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	0.075	0.120	0.205	0.095
	(38.64)	(99.94)	(123.76)	(122.28)
Mean dependent variable	0.059	0.072	0.145	0.053
Adjusted R^2	0.049	0.092	0.144	0.057
Number of observations	242,964	3,357,072	1,109,110	6,528,880

Table IA2

OLS estimates in samples used for 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 parent level.

Panel A: Impact of parent on child

Dependent variable	Child invested in a security			
Specification	Father		Mother	
	1	2	3	4
Parent invested in a security	0.070	0.077	0.100	0.111
	(101.63)	(57.73)	(102.89)	(63.22)
Mean dependent variable	0.052	0.050	0.069	0.068
Adjusted R^2	0.069	0.065	0.086	0.086
Number of observations	5,873,582	1,260,188	3,610,084	891,292

Panel B: Impact of child on parent

Dependent variable	Parent invested in a security			
Specification	Father		Mother	
	1	2	3	4
Child invested in a security	0.108	0.128	0.110	0.129
	(81.18)	(73.17)	(81.34)	(76.93)
Mean dependent variable	0.090	0.094	0.078	0.082
Adjusted R^2	0.115	0.116	0.104	0.103
Number of observations	2,285,576	1,091,264	2,049,938	1,118,502

Table IA3

Robustness checks on IV results

This table reports robustness checks on the IV regressions in Table 5 by modifying the definition of the instrument or analyzing alternative samples. Column 1 in Panel A adds native language (Finnish or Swedish) to zip code and age to define the geographic peer group. Column 2 stratifies co-workers in an establishment further by age. Column 3 restrict the sample used for the geographic instrument to investors who live in a province different from their parents' place of residence (there are 19 provinces in our data). Column 4 applies a sample restriction to the co-worker instrument by analyzing a sample of children who work at a firm different from that of their parents. Columns 5-8 repeat these checks for the investor's mother and Panel B reports them for the child-to-parent influence. The *t*-values reported in parentheses use standard errors that assume clustering at the parent level.

Panel A: Impact of parent on child								
Dependent variable	Child invested in a security							
Specification	Father				Mother			
	Zip code × age × native language	Estab-lishment × age	Parent and child live in different province	Parent and child work for different firm	Zip code × age × native language	Estab-lishment × age	Parent and child live in different province	Parent and child work for different firm
	1	2	3	4	5	6	7	8
Parent invested	0.165	0.173	0.168	0.168	0.184	0.162	0.185	0.193
	(38.69)	(6.85)	(31.51)	(9.48)	(35.61)	(5.27)	(28.64)	(9.92)
Fixed effects								
Zip code × Security	Yes	No	Yes	No	Yes	No	Yes	No
Firm × Security	No	Yes	No	Yes	No	Yes	No	Yes
1st stage *F*-statistic	3,840.8	122.0	2,445.6	228.2	3,221.0	104.6	2,077.8	246.8
1st stage partial R^2	0.018	0.012	0.020	0.012	0.024	0.014	0.026	0.020
Mean dependent variable	0.052	0.049	0.051	0.050	0.069	0.069	0.068	0.068
N of observations	5,873,582	754,346	3,310,040	1,240,522	3,610,084	587,412	1,996,802	875,828

Panel B: Impact of child on parent								
Dependent variable	Parent invested in a security							
Specification	Father				Mother			
	Zip code × age × native language	Estab-lishment × age	Parent and child live in different province	Parent and child work for different firm	Zip code × age × native language	Estab-lishment × age	Parent and child live in different province	Parent and child work for different firm
	1	2	3	4	5	6	7	8
Child invested	0.139	0.316	0.144	0.304	0.148	0.235	0.147	0.231
	(6.50)	(3.72)	(6.56)	(5.65)	(7.18)	(4.17)	(4.90)	(6.95)
Fixed effects								
Zip code × Security	Yes	No	Yes	No	Yes	No	Yes	No
Firm × Security	No	Yes	No	Yes	No	Yes	No	Yes
1st stage *F*-statistic	326.5	23.8	290.2	56.2	293.4	43.3	136.3	136.1
1st stage partial R^2	0.003	0.006	0.003	0.004	0.003	0.005	0.002	0.004
Mean dep. variable	0.090	0.091	0.083	0.094	0.078	0.080	0.071	0.081
N of observations	2,285,576	458,886	1,785,682	1,075,666	2,049,938	475,062	1,226,982	1,101,448

Table IA4

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 parent 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	0.059	0.155	0.155	0.049	0.173
	(69.56)	(34.40)	(72.11)	(75.94)	(30.12)	(70.00)
Mean dependent variable	0.080	0.161	0.039	0.079	0.159	0.039
Adjusted R^2	0.652	0.651	0.223	0.659	0.656	0.227
Number of observations	742,314	742,314	742,314	662,001	662,001	662,001

Table IA5

Intergenerational correlations in 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 parent level.

Panel A: Father

Specification	Four-factor loadings				Idiosyn-cratic 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
	(87.86)	(62.33)	(58.61)	(64.41)	(12.79)	(57.37)
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				Idiosyn-cratic 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
	(97.86)	(63.51)	(66.76)	(63.79)	(12.71)	(63.49)
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 IA6

Splitting sample according to portfolio overlap

This table repeats the analyses in Panel A of Table 7 by splitting the sample by the degree of overlap in the portfolios of the investor and her parent (0%, >0% and ≤50%, and >50% and ≤100%). Panels A, B, and C report regressions whose dependent variables are historical return, volatility, and expected return, respectively. The *t*-values reported in parentheses use standard errors that assume clustering at the parent level.

Panel A: Historical return

Sample	Father			Mother		
Portfolio overlap	0	>0%,≤50%	>50%,≤100%	0	>0%,≤50%	>50%,≤100%
Specification	1	2	3	4	5	6
Parent's attribute	0.005	0.192	0.675	0.011	0.222	0.744
	(2.77)	(48.23)	(184.05)	(5.19)	(54.29)	(229.02)
Mean dependent variable	0.062	0.092	0.117	0.065	0.091	0.105
Adjusted R^2	0.536	0.724	0.759	0.544	0.728	0.795
Number of observations	449,815	106,140	186,359	401,585	94,693	165,723

Panel B: Volatility

Sample	Father			Mother		
Portfolio overlap	0	>0%,≤50%	>50%,≤100%	0	>0%,≤50%	>50%,≤100%
Specification	1	2	3	4	5	6
Parent's portfolio attribute	0.032	0.210	0.712	0.043	0.224	0.776
	(13.12)	(50.29)	(172.50)	(15.56)	(51.41)	(215.47)
Mean dependent variable	0.148	0.154	0.195	0.153	0.152	0.177
Adjusted R^2	0.065	0.188	0.469	0.070	0.198	0.552
Number of observations	449,815	106,140	186,359	401,585	94,693	165,723

Panel C: Expected return

Sample	Father			Mother		
Portfolio overlap	0	>0%,≤50%	>50%,≤100%	0	>0%,≤50%	>50%,≤100%
Specification	1	2	3	4	5	6
Parent's portfolio attribute	−0.015	0.159	0.748	−0.017	0.169	0.794
	(−8.23)	(44.98)	(199.20)	(−7.87)	(44.46)	(225.18)
Mean dependent variable	0.036	0.041	0.045	0.037	0.041	0.043
Adjusted R^2	0.036	0.143	0.417	0.041	0.139	0.480
Number of observations	449,815	106,140	186,359	401,585	94,693	165,723

Table IA7

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	0.003	−0.001	−0.001	−0.003	−0.002	0.001
	(1.19)	(−0.23)	(−0.25)	(−1.60)	(−0.85)	(0.59)

Panel B: Descriptive statistics of portfolio overlap

	Father		Mother	
	Mean	Sd	Mean	Sd
Randomly chosen parent	0.071	0.227	0.066	0.222

Table IA8

Choosing placebo parents using more characteristics

This table repeats the analyses concerning expected return in Panels A and B of Table 8 by adding wealth and education to the variables that stratify the bins from which we randomly choose placebo parents. Each row in Column 1 in Panel A stratify the sample according to the variable in the row and whether the parent's financial wealth is above or below the median. Column 2 repeats the same exercise by further splitting the sample by whether the parent's level of education is above or below a high school degree. The cells report the placebo correlation in expected return. Panel B reports mean portfolio overlap. The *t*-values reported in parentheses use standard errors that assume clustering at the investor level.

Panel A: Correlations in expected return				
Specification	Father		Mother	
	Wealth	Wealth and education	Wealth	Wealth and education
	1	2	3	4
Randomly chosen parent within:				
Residents of a municipality	0.026	0.028	0.034	0.037
	(11.43)	(12.06)	(15.23)	(16.54)
Employees of a firm	0.025	0.035	0.025	0.036
	(10.85)	(15.13)	(11.39)	(16.08)
Clients of an asset manager	0.026	0.027	0.017	0.021
	(7.46)	(7.74)	(6.04)	(7.29)

Panel B: Mean portfolio overlap				
	Father		Mother	
	Expected return		Expected return	
	Wealth	Wealth and education	Wealth	Wealth and education
Randomly chosen parent within:				
Residents of a municipality	0.098	0.101	0.090	0.095
Employees of a firm	0.096	0.103	0.087	0.094
Clients of an asset manager	0.114	0.115	0.083	0.084

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