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Social Interaction in the Family:
Evidence from Investors' Security Holdings*

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Abstract

We show investors tend to hold the same securities as their parents. This intergenerational correlation is stronger for mothers and family members who are more likely to communicate with each other. An instrumental variables estimation and a natural experiment suggest the correlation reflects social influence. This influence runs not only from parents to children, but also vice versa. The resulting holdings of identical securities increase intergenerational correlations in portfolio choice, exacerbate wealth inequality, and amplify the consequences of behavioral biases.

Keywords: Social interaction, portfolio choice, wealth inequality, behavioral bias

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1. Introduction

This paper documents a new intergenerational correlation in the choice of securities that make up household portfolios, investigates its drivers, and analyzes its implications for portfolio choice, wealth inequality, and behavioral biases. Figure 1 presents the starting point of our study by showing an investor is much more likely to own a stock or mutual fund held by her parent. In our comprehensive data of investors and securities in Finland, the conditional ownership probability equals 12.2% and 15.8% for securities held by an investor's father or mother, respectively. This probability is only 0.3% for the remaining securities.

Why are investors so much more likely to own the securities held by their parents? We argue that social interaction within the family is the primary reason family members hold the same securities. This interpretation is consistent with earlier evidence showing investors acquire investment ideas from their co-workers and neighbors (Hong, Kubik, and Stein, 2005; Hvide and Östberg, 2015; Ivković and Weisbenner, 2007; Kaustia and Knüpfer, 2012; Ouimet and Tate, 2020). The hypothesis that such social interactions also take place in the family is especially appealing in our context, because individual securities are a more natural topic for investment-related discussions than abstract risk-return concepts (Shiller and Pound, 1989).[1]

Alternatively, the security-choice correlation across generations can reflect channels that do not involve family members causally influencing each other (Manski, 1993, 2000). 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

[1] This social mechanism may also be important in explaining intergenerational correlations in other contexts. Björklund and Salvanes (2011), Black and Devereux (2011), Jäntti and Jenkins (2015), and Solon (1999) review these correlations. Anderson et al. (2015) find an intergenerational correlation in the choice of automobile brands.

risk. However, many of these preferences naturally operate at the level of an individual's portfolio and do not necessarily explain why family members would hold an identical security. For example, shared willingness to bear financial risk can explain why an investor and her parent hold stocks, but does not necessarily tell us which security family members pick for implementing their shared risk preference. Nevertheless, we empirically address this and other alternative explanations.

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

Our analysis of the intergenerational correlation in security choice relates an investor's decision to hold a security to that of her parent. To understand whether this correlation reflects causal influence, we flexibly control 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. We also find sizable and significant security-choice correlations in analyses that explicitly control for an array of observable investor attributes and security preferences revealed by the investor's portfolio holdings.

The security-choice correlations vary in the population in interesting ways. They decrease in geographical distance, family size, and differences in gender, which is consistent with these family members communicating less with each other. Mothers display larger correlations, which suggests they are a more potent source of investment-related information.

We further investigate the social-influence hypothesis by accounting for unobservable attributes that may make family members susceptible to time-varying influences. For example, members of the same family may buy the same security in response to sales efforts of an asset-management company, which would generate the year-to-year correlation we find using the investor-security fixed-effects approach. Although we find family members who do not share an investment advisor display security-choice correlations similar to the full sample, we also tackle this issue using two identification strategies.

First, we use an instrumental variable (IV) 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 these peers 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 and correlated unobservables, we focus our analysis on investors who do not live in the same neighborhood or do not work in the same firm as their parents, and include fixed effects that absorb preferences for securities 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

[2] For similar strategies, see Bramoullé, Diebbari, and Fortin (2009), De Giorgi, Frederiksen, and Pistaferri (2020), De Giorgi, Pellizzari, and Redaelli (2010), Lee, Liu, and Lin (2010), and Nicoletti, Salvanes, and Tominey (2018).

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, we have a strong first stage; namely, a parent has a much higher likelihood of holding a security when many of her peers do so. The IV estimates for the child's holding propensity as a function of her parent's holding 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 speaks in favor of social interaction in the family being an important 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 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.

The strong intergenerational influence in security choice has important implications for understanding portfolio choice, wealth inequality, and behavioral biases, because the holdings of identical securities make investment decisions correlated across generations.

We study the implications for portfolio choice by decomposing intergenerational correlations in portfolio attributes, such as expected portfolio return and portfolio volatility, according to the overlap of security holdings in the family members' portfolios. We find intergenerational correlations in portfolio attributes are largely confined to the securities investors share with their parents. A placebo exercise corroborates this finding by showing the correlations in portfolio attributes are small when an investor is matched to a comparable parent of another investor. These results are consistent with social forces in adulthood significantly contributing to intergenerational correlations of portfolio choice. Narratives solely emphasizing genetic transmission, nurturing in childhood, and other early-life factors (Barnea, Cronqvist, and Siegel, 2010; Cesarini et al., 2010; Calvet and Sodini (2014); Black et al., 2017; Fagereng, Mogstad, and Rønning, 2018) thus leave an important part of the story untold.

The shared security holdings also have implications for dynamics of wealth inequality, because identical security holdings expose family members to the same sources of return dispersion. We quantify this effect by analyzing the cross-sectional variation in portfolio values across families and its evolution over time under two scenarios. The first scenario combines the investor's portfolio with that of her actual parent, whereas the second counterfactual scenario uses randomly chosen comparable parents. Comparing the growth in the cross-sectional variation of family wealth in the two scenarios shows the shared security holdings exacerbate wealth inequality by increasing the dispersion in the families' returns on wealth. This dispersion is important for understanding wealth inequality, as has been shown in theoretical work by Benhabib, Bisin, and Luo (2019), Campbell (2016), Gabaix et al. (2016), and Lusardi, Michaud, and Mitchell (2017) and in the data by Campbell, Ramadorai, and Ranish (2019), Fagereng et al. (2020), and Bach, Calvet, and Sodini (2020).[3]

[3] Benhabib and Bisin (2018), Roine and Waldenström (2015), Piketty (2014), and Piketty and Zucman (2015) provide reviews of wealth inequality.

The identical security holdings are also relevant for understanding the importance of behavioral biases, because the security-choice correlation may make an investor's biases spill over to her family members. We study this implication by analyzing the preference for familiar investments across generations (Coval and Moskowitz, 1999; Benartzi, 2001; Grinblatt and Keloharju, 2001; Huberman, 2001, Keloharju, Knüpfer, and Linnainmaa, 2012). We find a parent's security holdings in her industry of work are a strong predictor of her child's investment in the industry, even after controlling for the child's own industry. This result suggests the aggregate impact of behavioral biases is larger than that expected in the absence of familial spillovers.

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 portfolio choice, wealth inequality, and behavioral biases. 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 linkage to parents (biological or adoptive), and several 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 the 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. The 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 increased 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 US 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 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 investors have an average labor income of 31,600 euros, and 59.1% of them have acquired a degree higher than basic or vocational education. Business or economics graduates constitute 18.2% of the investors, and 4.5% work in the finance industry.[4] Female, 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, because 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 shows fathers have a lower level of education and are less likely than their children to have received a business or economics degree or to work in finance. Given that they have children, the finding that they are likely to be married is not surprising. They are, on average, 65 years old in 2008.

[4] 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 is associated 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 1 if an investor holds a security in a year, and 0 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. We cluster standard errors at the parent and security levels to account for parents having more than one child and investors making correlated investment decisions within securities.

Although we can calculate the simple ownership probabilities in Figure 1 using the security holdings of investors and their parents supplemented with information on the number of investors and securities each year, computational constraints make using the full panel of investor-security-year triplets in subsequent analysis impossible. We employ a sampling design that retains all the investors but randomizes the securities featuring in the estimation sample. 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.[5] For the holdings and non-holdings, we retrieve the full time series of investor-security-year triplets, which results into computationally feasible sample sizes of 12.4 million and 7.7 million for the samples of fathers and mothers, respectively.

Table 2 Panel A 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 family members investing in securities with larger market shares. They also help in dealing with discrepancies in a security's weight in the market portfolio and its free float. 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.[6]

[5] An alternative scheme would start from an investor's holdings instead of those of 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).

[6] 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.

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 the manager's distribution channel.

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

The baseline regression in column 1 shows the probability of holding a security increases by 8.3 percentage points if the investor's father holds the security (t-value 26.1). 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 28.2 and 24.2). These estimates suggest investor preferences for observable security characteristics can account for $1 - 0.069/0.083 = 17\%$ of the intergenerational association in security choice.

Column 4 estimates the intergenerational 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 38.2). In the full sample of holdings and non-holdings in Figure 1, the mean probability of owning a security is 0.3 percentage points, so the father holding a security makes the investor's conditional probability of owning the security eight times higher than the unconditional probability. This result suggests time-invariant preferences for any unobserved security characteristics do not drive the security-choice correlation.

Columns 5 to 8 report the corresponding estimates for the investor's mother. The patterns of these estimates across specifications mirror those of the father. However, the mother's coefficients are larger than those of the father in all the specifications. Table 2 Panel B further investigates this result by running regressions that jointly account for the ownership of the father, the mother, or both. This analysis allows us to address the possibility that mothers spuriously display larger coefficients because they are more likely to hold securities also appearing in the fathers' portfolios.

Across all the specifications in Panel B, the coefficient for the mother remains larger than that of the father, even when the regression explicitly accounts for the securities co-held by the father and the mother. The specification including investor-security fixed effects in column 4 yields statistically significant coefficients of 0.019, 0.031, and 0.023 for the father, the mother, and their joint ownership, respectively. These estimates show the mother's larger coefficient is not an artifact of co-held securities. Instead, they are consistent with mother-child interactions being a more important determinant of investment decisions than father-child interactions. A potential reason for this stronger association is that mothers and children discuss investments more or those discussions are more influential in translating into actions.

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. Table 3 Panel A reruns the regressions in subsamples stratified by investors' birth year. Investors born before 1960 appear in column 1, and investors born after 1979 constitute column 6. Columns 2–5 report on four five-year intervals between the oldest and youngest age categories. The coefficient estimates are all highly statistically significant and they decrease monotonically with age. The security-choice correlation is highest, 0.032, for the youngest category of investors who are 24 years old or younger. However, the estimate remains economically and statistically significant at 0.015 even for the oldest investors.

Parents' and grandparents' purchases. Column 1 in Panel B addresses the possibility that the legacy of investment accounts that 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 0.023 (t-value 14.6). Column 2 addresses an alternative possibility, according to which grandparents may gift securities to their children and grandchildren. The subsample of investors whose grandparents do not own and have not owned any securities yields an estimate of 0.027 (t-value 32.8), suggesting the grandparent channel does not generate the security-choice correlation.

Investment advisors. Column 3 analyzes a subsample of investors who do not share an investment advisor and thus are not jointly influenced by the same advisor. The market for financial advice in Finland largely operates through retail banks that sell mutual funds managed by their own asset-management arms, most often in their local bank branch. We use this feature to infer the lack of common advisors from the information on the asset managers of the mutual funds held by an investor and her parent. If these asset managers are different, the investor and her parent are unlikely to share an advisor. We estimate the security-choice correlation in the holdings of directly held stock as the mutual fund holdings in this sample are mechanically unrelated. The coefficient of 0.024 (t-value 37.9) shows the security-choice correlation survives this sample restriction, which is consistent with shared financial advisors not being the intergenerational correlation's primary driver.

Insider trading. Columns 4 and 5 focus on subsamples that estimate the security-choice correlation for mutual funds and for investors whose parents work in the public sector. These samples allow us to address the possibility an investor attempts to hide insider trading by directing her family members to make the trades on her behalf. Because insider trading most naturally pertains to shares in individual firms and parents working in the public sector likely do not have access to a firm's insider information, the subsamples of mutual funds and public-sector workers are informative about the role of insider information in generating the security-choice correlation. The significantly positive estimate of 0.025 in both specifications (t-values 31.8 and 19.0) suggest a limited role for this channel.

Potentially influential observations. Columns 6 and 7 investigate subsamples that exclude potentially influential clusters of the data. The estimate of 0.049 (t-value 30.7) in column 6 shows the correlation is not confined to investors who hold securities in just one asset class. Column 7 drops the five most popular securities and returns an estimate of 0.023 (t-value 38.8).

Alternative sampling design. Column 8 chooses a 20% random subsample of investors in Table 2 and uses all the securities in lieu of the randomly chosen securities in populating the non-holdings. This sample of 159 million observations yields a coefficient of 0.027 (t-value 23.2). This estimate is close to our baseline estimate of 0.024 reported in Table 2 Panel A.

Randomly matched parents. Column 9 performs a placebo analysis that randomly scrambles the identity of each investor's parent and estimates the security-choice correlation. This exercise generates a reassuringly insignificant estimate suggesting biases in randomizing the sample of securities or selecting investors and parents into the sample do not generate our results.

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 4 in Table 2), whereas column 2 reports correlations for the mother (as in column 8 in Table 2).

We consider several factors that relate to family composition and family environment. Motivated by Björklund and Chadwick (2003), Gould and Simhon (2020), Kalil et al. (2016), 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 0.009/0.034 = 27% in the correlation. Column 2 reports a 32% increase for mothers. The interactions 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 0.013/0.034 = 37% lower correlation, whereas the corresponding number for the mother-daughter pairs in column 2 is only 17%. This pattern is consistent with the idea that children are more likely to communicate with the parent of their own gender.

Our final interaction contrasts biological with adopted children. Black et al. (2020) and Fagereng, Mogstad, and Rønning (2021) find lower intergenerational correlations for adopted than for 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 convincing a family member to invest in risky assets easier.[7]

We do not find a statistically or economically 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.

4. Establishing role of social influence

4.1. Using peer groups to identify social influence

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 simultaneously selling a product to several members of a financially illiterate family.

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 two assumptions. First, the parent's peers can only affect the child through their influence on the child's parents. Second, the parent's peers and the child cannot share

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

unobservable characteristics not captured by the observable control variables (for similar strategies, see Bramoullé, Diebbari, and Fortin, 2009; De Giorgi, Frederiksen, and Pistaferri, 2020; 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 ages 45–54.

Two design features guard against the possibility that parents' 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, the inclusion of investor-security fixed effects captures all unobservable reasons for people living in the same neighborhood to hold certain securities (e.g., listed firms having an establishment or an asset-management company marketing its products in a certain location.)

Our second definition of peers considers parents' 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-parent pairs that work at different firms. Investor-security fixed effects account for unobservable factors that make investors in the same establishment hold the same securities (e.g., employee ownership of listed firms and financial advisory perks provided by the company).

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 variable 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. To ensure peer groups are of meaningful size, we require they contain at least 30 investors. This requirement, combined with the 22% participation rate in stocks and mutual funds (Keloharju, Knüpfer, and Rantapuska, 2012), translates into 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 4 and 8 in Table 2. The two leftmost columns report the results for the investor's father, and the mother's estimates appear in the remaining two columns. Columns 1 and 3 analyze parents' neighbors, and columns 2 and 4 report the results for parents' co-workers.

The IV estimate based on neighbors in column 1 equals 0.119 (t-value 13.3), whereas the use of co-workers in column 2 yields an estimate of 0.105 (t-value 4.9). The large first-stage F-statistic for the instruments indicates the regression does not suffer from the weak-instrument problem. The regressions for the investor's mother in columns 3 and 4 yield estimates that are similar in magnitude to those of the father. 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 0.019, which amounts to 16% of the IV estimate.[8]

The larger IV estimate likely arises from the local average treatment effect underlying the IV estimates being larger than the average effect identified by the OLS regression (Imbens and Angrist, 1994). The IV estimate obtains from the subset of "compliers," that is, sociable parents who discuss investment ideas with their peers. These parents may also be more likely to discuss investments with their children. When OLS regressions average the sociable parents together with all the other parents, the estimate of social influence becomes smaller.

Table IA3 provides checks that assess the robustness of the IV results. These analyses stratify the sample further to create more tightly defined peer groups. The table follows the same structure as Table 5 but modifies the definition of the instrument.

Motivated by the two official languages (Finnish and Swedish) that define social networks ranging from educational institutions to recreational activities in Finland, column 1 of Table IA2 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. The resulting estimates are similar to those reported in Table 5.

Table 5 Panel B addresses the possibility that adult children may also provide their parents with investment ideas.[9] 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 investing

[8] Jiang (2017) reports the IV estimate is, on average, about nine times the OLS estimate in studies published in the three major finance journals.

[9] Friedman and Mare (2014), Zimmer et al. (2007), and Torssander (2013) find a positive association between a child's education and the parent's longevity. Using a compulsory schooling reform in Sweden as a natural experiment, Lundborg and Majlesi (2018) 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.

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 (3.0) compared to fathers (4.6) and mothers (3.4) explains why Panel B includes fewer observations than Panel A.

The first-stage *F*-statistics in Panel B show the instruments are strong. The IV estimates are all statistically significant and slightly smaller than those in Panel A. Table IA3 Panel B assesses the robustness of child-to-parent influence and reports all the coefficients are statistically significant at the 10% level. The fact that the IV estimates identify the effects only for the "compliers" prevents us from characterizing how the two directions of causality aggregate into the OLS estimates reported in Table 2. Nevertheless, these results suggest children affect their parents' investment decisions.

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 mutual fund mergers for which we have holding data in the five years surrounding the merger (this criterion is not satisfied by any merger involving publicly listed stocks in our data). These mutual fund mergers entailed asset-management firms streamlining their product offerings by combining two of their mutual funds within their fund families. These events were not connected with any organizational changes at the level of the asset manager, such as mergers of two asset-management companies, and they involved two mutual funds from the same asset manager. The target shareholders were informed about the event without generating much attention in media, which makes them ideal for studying information transmission within families.

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 baseline 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. In the absence of social transmission of information regarding the acquirer, we would expect the interactions of the treatment dummy and the dummies for years 0 through 2 to be statistically indistinguishable from zero. Standard errors assume clustering at the parent level to account for serial correlation in observing the treatment and control group over multiple years (Bertrand, Duflo, and Mullainathan, 2004).

Column 1 reports the treatment effect for an investor's father passively becoming a shareholder, whereas column 2 reports the effect for the mother. 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 than the other investors to hold the acquirer. Mothers in column 2 generate larger effects than fathers, with an increase of 5.5 percentage points (t-value 14.3). These effects are economically large because the average holding propensity in the samples of fathers and mothers equals 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 small in magnitude, which suggests the treatment and control groups are on parallel trends prior to treatment. 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 column 1, the propensity to own the acquirer in the merger-completion year is 3.0 percentage points higher (t-value 11.3). The corresponding estimate for mothers is again higher than for fathers, at 4.9 percentage points (t-value 14.5). 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 significant $t - 2$ interactions imply the parallel-trends assumption does not fully hold in these samples. However, the small magnitude of the pre-trends makes them unlikely to account for the much larger increases in the year the merger is completed. These results corroborate the child-to-parent influence we find in Table 5 Panel B.

5. Implications of intergenerational correlations in security choice

5.1. Portfolio choice

This section studies the implications of family members holding the same securities for understanding portfolio choice, wealth inequality, and behavioral biases. We first estimate intergenerational correlations in the attributes of household portfolios and examine how much of them can be attributed to holdings of the same securities. Earlier work attributes intergenerational correlations in portfolio attributes to genetic and non-genetic early-life factors (Barnea, Cronqvist, and Siegel, 2010; Cesarini et al., 2010; Black et al., 2017; Fagereng, Mogstad, and Rønning, 2018). The identical security holdings we examine here emphasize a new channel related to social interaction in adulthood.

Table 7 Panel A reports estimates from regressions that explain a portfolio attribute of an investor with that of her parents. The regressions control for year and investor fixed effects, thus identifying the associations from annual changes within an investor.[10] The clustering of standard errors at the parent level takes into account the multiple years we observe a parent, and the year-to-year overlap in the 24-month historical return window.

For each portfolio attribute, the regression uses three samples of parent-child pairs. The first sample includes all the pairs, whereas the two remaining subsamples divide the pairs by the extent of their overlapping security holdings. This decomposition allows us to understand how much the identical security holdings contribute to intergenerational correlations in portfolio choice. To enable precise estimation of these regressions with investor fixed effects, we split the sample based on the within-investor average of portfolio overlap over the sample period.

For the full sample, the coefficient estimate of 0.171, reported in column 1 in Panel A, implies a 1.7% higher historical return for every 10% increase in the father's return. The estimate is highly significant with a *t*-value of 20.5. This full-sample estimate reflects the combination of two associations emanating from the two subsamples by portfolio overlap. When the investor and her parent share no security holdings, the estimate is indistinguishable from zero, whereas it is 0.494

[10] Figure IA1 plots an investor's portfolio attribute against that of her father and mother. All the attributes display close-to-linear parent-child correlations. Table IA4 reports correlations that replace the portfolio attribute with its percentile rank in a year. These correlations are similar to those in Table 7 Panel A.

(*t*-value 47.8) for the investor-parent pairs with some portfolio overlap. Columns 2 and 3 repeat this pattern for volatility and expected returns, and it extends to mothers in columns 4–6. Because these results show minimal intergenerational association beyond the securities family members share with each other, the holdings of identical securities appear to substantially contribute to the portfolio-choice correlations across generations.

Table 7 Panel B addresses the possibility of identical security holdings arising from non-social influences, such as shared preferences for local firms and employer stock, and funds offered by a shared financial advisor (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Benartzi, 2001; Foerster et al., 2017). 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 both within all parents and blocks of parents to address likely non-familial channels. These blocks include residents of the same municipality, employees of the same firm, or clients of the same asset manager.[11] We repeat regressions of an investor's portfolio attribute against that of the placebo parent by drawing the parent 1,000 times, and we report the average point estimate and *t*-value across the draws.

All the estimates in the panel are substantially smaller than those based on actual parent-child links. Compared to the smallest estimate of 0.171 in Table 7 Panel A, the largest estimate of 0.026 in Panel B represents a fraction of only 15%.[12] These results on placebo parents highlight the unique role of the parent-child link in leading to holdings of identical securities. To the extent the placebo analysis captures the effect of non-social determinants of correlated security holdings, the

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

[12] Table IA5 further stratifies the placebo parents according to their wealth and education. The placebo correlations remain a small fraction of the correlations in Table 7 Panel A.

results also suggest familial interaction concerning individual securities substantially contributes to the intergenerational correlations in portfolio choice.

5.2. Portfolio diversification and wealth inequality

Because any portfolio inherits the return properties of its securities, family members holding identical securities are exposed to the same sources of return dispersion. This dispersion can matter for the accumulation of family wealth and its distribution over the long run (Benhabib, Bisin, and Luo, 2019). Bach, Calvet, and Sodini (2020), Campbell, Ramadorai, and Ranish (2019), and Fagereng et al. (2020) show the return to household wealth varies considerably in the population and explains the dynamics of wealth inequality.

We quantify the importance of identical security holdings for wealth inequality by analyzing the cross-sectional variation in portfolio values and its evolution over time. We combine the portfolios of each investor with those of her parents and study how the cross-sectional variation in their logged values change in 2004–2017. This measure quantifies inequality growth from log returns, which captures the effects of both mean returns and portfolio diversification through the well-known impact of variance on log returns (Campbell, Ramadorai, and Ranish, 2019).

We consider two scenarios to quantify the impact of identical security holdings. The first scenario combines the investor's portfolio with that of her actual parents, whereas the second scenario uses placebo parents randomly chosen in the same way as in Table 7 Panel B. We then analyze the change in the variance of logged portfolio values in 2004–2017 and its difference between the two scenarios. We abstract from the impact of trading and portfolio flows between these two dates by using buy-and-hold returns on the securities held in 2004. Disappearing securities earn the risk-free rate from the delisting date.

Table 8 reports the variance of logged portfolio values in 2004 and 2017 and their difference. The third column in the first row reports the variance increased by 0.11 in 2004–2017 for the investors matched to their actual parents. The remaining rows show the changes for matching investors with randomly chosen parents within the four blocks of parents used in Table 7 Panel A. These hypothetical changes range from 0.04 to 0.06, which amount to at most 52.9% of the corresponding change in actual family wealth, as shown in the fourth column.

These results show breaking the parent-child link while preserving its observable characteristics leads to a decrease in wealth inequality over time. To the extent the observable characteristics capture non-social determinants of shared security holdings well, the results further suggest familial interaction exacerbates wealth inequality.

5.3. Investment biases

The identical security holdings are also relevant for understanding the importance of behavioral biases, because the security-choice correlation can exacerbate the impact of any investment biases by making them spill over to an investor's family members. We study this implication by analyzing the preference for familiar investments (Coval and Moskowitz, 1999; Benartzi, 2001; Grinblatt and Keloharju, 2001; Huberman, 2001; Keloharju, Knüpfer, and Linnainmaa, 2012).

Table 9 studies an investor's portfolio allocation across industries and its connection with the investor's and her parent's industry of work. Availability of data dictates the focus on industries, whereas the industry focus requires us to restrict the sample to directly held stock, because we cannot link mutual funds or their holdings to industries. For each investor, the table calculates the portfolio weight in an industry based on the market values of the security holdings in the investor's portfolio and regresses it against the investor's and her parent's industry of work.

Column 1 replicates the well-known finding of investors overweighting the stocks with which they are familiar: the portfolio weight is significantly higher in the investor's industry of work. The estimate suggests the weight is higher by 0.009/0.021 = 42% compared with the mean portfolio weight across the 45 industries in our sample. More interestingly, we also find the father's industry of work generates an incremental portfolio tilt of the same order of magnitude.

Column 2 adds the father's portfolio weight in an industry to understand how much of the investor's portfolio weight in her father's industry can be attributed to the father's holdings in that industry. This estimate is strongly positive and highly significant, and it subsumes the explanatory power of the father's industry indicator. Here, a one-standard-deviation increase in the father's portfolio weight increases that of the investor by $0.444 \times 0.108 = 0.048$. Columns 3 and 4 find qualitatively similar results for mothers.

These results are consistent with behavioral biases spilling over to an investor's family members and suggest their aggregate consequences are larger than those expected in the absence of familial interaction.

6. Conclusion

We find social interaction leads family members to hold the same securities. This evidence adds to the literature on social interaction by showing investors acquire investment ideas from their family members. It also has important implications for understanding investment decisions and their consequences. We show the identical security holdings increase intergenerational correlations in portfolio choice, exacerbate wealth inequality, and amplify the consequences of behavioral biases.

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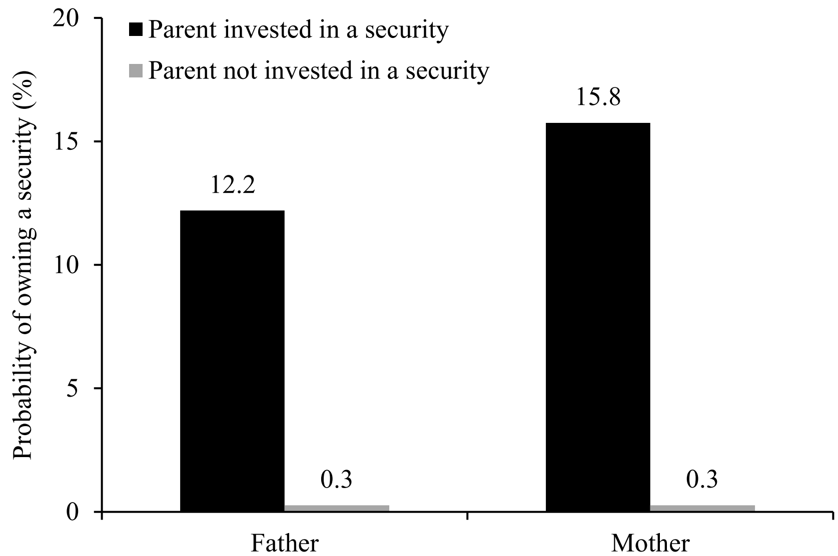

Figure 1. Security choice across generations

This graph plots the probability that investor *i* holds security *j* in year *t* as a function of her father's or mother's ownership of that security. The number of investor-security-year triplets is 758 million for fathers and 680 million for mothers. The sample includes, on average, 718 securities each year.

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 two-way clustering at the parent and security levels.

Panel A: Father and mother separately								
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
	(26.08)	(28.24)	(24.27)	(38.20)	(26.33)	(29.78)	(25.02)	(39.37)
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
Adjusted R^2	0.074	0.234	0.205	0.799	0.092	0.285	0.242	0.807

Panel B: Father and mother jointly				
Dependent variable	Investor invested in a security			
Specification	N = 13,450,281			
	1	2	3	4
Father invested in a security	0.060	0.052	0.050	0.019
	(26.46)	(29.01)	(24.17)	(36.30)
Mother invested in a security	0.083	0.072	0.069	0.031
	(29.84)	(31.33)	(25.02)	(38.80)
Father and mother invested in a security	0.077	0.072	0.076	0.023
	(15.02)	(18.80)	(19.00)	(15.31)
Fixed effects				
Security × Year	Yes	Yes	Yes	Yes
Investor × Asset class	No	Yes	Yes	No
Investor × Asset manager	No	No	Yes	No
Investor × Fund type	No	No	Yes	No
Investor × Security	No	No	No	Yes
Adjusted R^2	0.098	0.253	0.268	0.800

Table 3

Robustness checks

This table reports robustness checks on the regressions reported in Table 2. The specifications correspond to the regression including investor-security fixed effects in column 4 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 two-way clustering at the parent and security levels. 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	0.015	0.016	0.019	0.022	0.025	0.032
	(8.59)	(11.97)	(18.37)	(21.16)	(25.73)	(30.79)
Adjusted R^2	0.841	0.824	0.809	0.795	0.780	0.791
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	Grand-parents not investors	Different investment advisors	Mutual funds	Parents in public sector	Investors with various asset classes	Excluding top 5 securities	20% random sub-sample	Ran-domly matched parents
Specification	1	2	3	4	5	6	7	8	9
Parent invested	0.023	0.027	0.024	0.025	0.025	0.049	0.023	0.027	−0.0001
	(14.56)	(32.83)	(37.91)	(31.80)	(19.01)	(30.71)	(38.78)	(23.16)	(−0.66)
Adjusted R^2	0.709	0.787	0.800	0.686	0.800	0.852	0.752	0.709	0.808
Number of obs.	292,714	5,535,630	12,287,875	5,628,897	1,385,090	1,680,625	10,740,540	159 mil.	1,541,392

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 specifications correspond to the regressions including investor-security fixed effects in columns 4 and 8 of Table 2. The dummy for living in the same zip code equals 1 for parents and children whose registered address is in the same zip code. The indicator variable for a biological parent equals 1 for a biological parent, and 0 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 *t*-values reported in parentheses use standard errors that assume two-way clustering at the parent and security levels.

Dependent variable	Investor invested in a security	
Specification	Father	Mother
	1	2
Parent invested in a security	0.034	0.046
	(20.20)	(19.90)
× Live in same zip code	0.009	0.015
	(11.09)	(11.99)
× Female	−0.013	−0.008
	(−10.10)	(−5.02)
× Biological parent	0.001	0.0002
	(0.38)	(0.05)
× Number of siblings = 1	−0.005	−0.009
	(−3.09)	(−3.90)
× Number of siblings = 2	−0.008	−0.013
	(−4.11)	(−4.93)
× Number of siblings = 3	−0.010	−0.014
	(−3.38)	(−2.94)
× Number of siblings ≥ 4	−0.017	−0.018
	(−5.76)	(−3.42)
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 4 and 8 in Table 2, and they include fixed effects for pairing each investor with each security. The 2SLS regressions instrument for a parent's ownership with that of her peers. In columns 1 and 3, peers are investors who live in the same zip code and belong to the same age cohort as the parent. 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 parents 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 firm 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 a parent's peers that hold a security, excluding the parent herself. 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 two-way clustering at the parent and security levels. 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	0.119	0.105	0.125	0.095
	(13.33)	(4.89)	(13.15)	(3.10)
Instrument based on				
Zip code	Yes	No	Yes	No
Age category	Yes	No	Yes	No
Work establishment	No	Yes	No	Yes
1st stage F-statistic	71.0	59.5	44.3	41.3
1st stage partial R^2	0.002	0.002	0.004	0.003
Number of observations	5,873,582	1,183,166	3,610,084	854,344

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	0.121	0.073	0.107	0.056
	(2.21)	(3.36)	(2.90)	(2.39)
Instrument based on				
Zip code	Yes	No	Yes	No
Age category	Yes	No	Yes	No
Work establishment	No	Yes	No	Yes
1st stage *F*-statistic	114.3	61.1	110.4	52.1
1st stage partial R^2	0.0004	0.002	0.0004	0.002
Number of observations	2,285,576	1,058,096	2,049,938	1,082,960

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
Parent owns target × t = -2	0.001	−0.0002
	(1.77)	(−0.27)
Parent owns target × t = 0	0.042	0.055
	(12.72)	(14.28)
Parent owns target × t = 1	0.032	0.042
	(9.03)	(10.04)
Parent owns target × t = 2	0.027	0.037
	(8.19)	(9.30)
Parent owns target	0.0002	0.0048
	(0.12)	(2.35)
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)
Mean dependent variable	0.014	0.013
Adjusted R^2	0.004	0.008
Number of observations	294,710	281,385

Panel B: Impact of child on parent		
Dependent variable	Parent invested in acquirer	
Specification	Father	Mother
	1	2
Child owns target × t = -2	0.003	0.002
	(5.74)	(3.56)
Child owns target × t = 0	0.030	0.049
	(11.33)	(14.46)
Child owns target × t = 1	0.022	0.038
	(7.65)	(10.84)
Child owns target × t = 2	0.021	0.035
	(7.80)	(10.27)
Child owns target	−0.0008	0.002
	(−0.51)	(1.44)
t = -2	−0.002	−0.002
	(−7.51)	(−6.53)
t = 0	0.002	0.002
	(6.95)	(7.63)
t = 1	0.003	0.003
	(7.45)	(9.85)
t = 2	0.00005	0.0004
	(0.11)	(1.07)
Mean dependent variable	0.012	0.013
Adjusted R^2	0.002	0.006
Number of observations	340,200	340,065

Table 7

Implications for 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 and investor fixed effects, and they are reported for all investors and by splitting the sample based on the within-investor average of the overlap of the investor's and her parent's security holdings. The *t*-values reported in parentheses use standard errors that assume clustering at the parent level. Panel B replaces an investor's actual parent with a randomly chosen "placebo" parent and estimates correlations in portfolio attributes of the investor and the placebo parent, in the same way as Panel A. Placebo parents are chosen from among blocks of parents according to the actual parent's characteristics. The blocks are either all parents, residents of a municipality, employees of a firm, or clients of an asset manager. The panel repeats the draw 1,000 times and reports the mean coefficient and *t*-value. The sample is restricted to cases in which the bin from which the placebo parent is drawn has 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 has the same number of father-child and mother-child pairs as Table 1, whereas Panel B has 241,995 (295,267) observations for fathers (mothers).

Panel A: Intergenerational associations in portfolio attributes by portfolio overlap

Specification	Father				Mother			
	Historical return	Volatility	Expected return	*N*	Historical return	Volatility	Expected return	*N*
	1	2	3		4	5	6	
All investors	0.171	0.195	0.193	713,899	0.212	0.228	0.223	635,611
	(20.51)	(29.91)	(21.59)		(26.52)	(49.78)	(22.62)	
No overlap	−0.0003	0.029	−0.012	419,127	0.006	0.043	−0.015	373,708
	(−0.05)	(3.66)	(−1.55)		(0.77)	(4.51)	(−1.44)	
Some overlap	0.494	0.539	0.543	278,156	0.554	0.583	0.576	248,140
	(47.79)	(75.79)	(54.85)		(72.56)	(80.48)	(64.03)	

Panel B: Replacing actual parents with randomly chosen parents

Specification	Father			Mother		
	Historical return	Volatility	Expected return	Historical return	Volatility	Expected return
	1	2	3	4	5	6
Randomly chosen parent within:						
All parents	−0.00002	−0.0001	0.00002	−0.0001	−0.0001	−0.0001
	(0.02)	(−0.05)	(0.06)	(−0.09)	(−0.47)	(−0.02)
Residents of a municipality	0.009	0.010	0.009	0.016	0.018	0.017
	(3.39)	(2.52)	(2.48)	(3.18)	(2.91)	(2.46)
Employees of a firm	0.004	0.0003	0.005	0.004	0.007	0.007
	(1.35)	(0.09)	(1.50)	(1.26)	(3.76)	(2.23)
Clients of an asset manager	0.024	0.026	0.003	0.005	0.007	0.003
	(3.50)	(9.14)	(1.82)	(1.94)	(3.76)	(1.82)

Table 8

Implications for portfolio diversification and wealth inequality

This table analyzes how the intergenerational correlation in security choice contributes to portfolio diversification and wealth inequality. Returns and corresponding portfolio values are based on value-weighted buy-and-hold returns assuming portfolio weights at the end of 2004. Disappearing securities earn the risk-free rate (12-month Euribor). The variance of logged portfolio value is calculated in 2004 and 2017 across all investors, and its difference measures the change in wealth concentration in 2004–2017. All the statistics aggregate the investor's portfolio with that of her actual parents or randomly chosen parents from among subsets of parents according to the investor's characteristics. The panel repeats the random draw 1,000 times and reports the mean estimate.

	Variance of logged portfolio value			
	2004	2017	Change 2004–2017	Change relative to investor and actual parent
Actual parents	2.601	2.711	0.110	
Randomly chosen parents within:				
All parents	2.213	2.260	0.048	43.3 %
Residents of municipality	2.222	2.281	0.058	52.9 %
Employees of a firm	2.220	2.265	0.045	41.2 %
Clients of an asset manager	2.277	2.313	0.036	32.7 %

Table 9

Implications for investment biases

This table reports intergenerational correlations in the industry bias of investors and their parents. The dependent variable is an investor's portfolio weight in an industry in a year. The independent variables are indicators for the investor and the parent working in an industry, and the portfolio weight defined for the investor's parent. Industries consist of 45 codes based on the two-digit industry classification by Statistics Finland. The portfolios only contain directly held stock because mutual funds or their holdings cannot be assigned to industries. The sample is restricted to investors and parents for which the industry code of their employer is known (60,799 and 51,728 investor-parent pairs in the samples for fathers and mothers, respectively). The *t*-values reported in parentheses use standard errors that assume two-way clustering at the parent and industry levels.

Dependent variable	Investor's portfolio weight in an industry			
Specification	Father		Mother	
	1	2	3	4
Investor works in industry	0.009	0.008	0.009	0.009
	(5.93)	(5.93)	(4.67)	(4.78)
Parent works in industry	0.008	−0.0003	0.006	0.001
	(3.36)	(−0.28)	(2.12)	(0.78)
Parent's portfolio weight in industry		0.444		0.450
		(73.63)		(73.26)
Mean dependent variable	0.021	0.021	0.021	0.021
Adjusted R^2	0.176	0.308	0.191	0.346
Number of observations	3,475,576	3,475,576	3,370,834	3,370,834

Internet Appendix to

Social Interaction in the Family: Evidence from Investors' Security Holdings*

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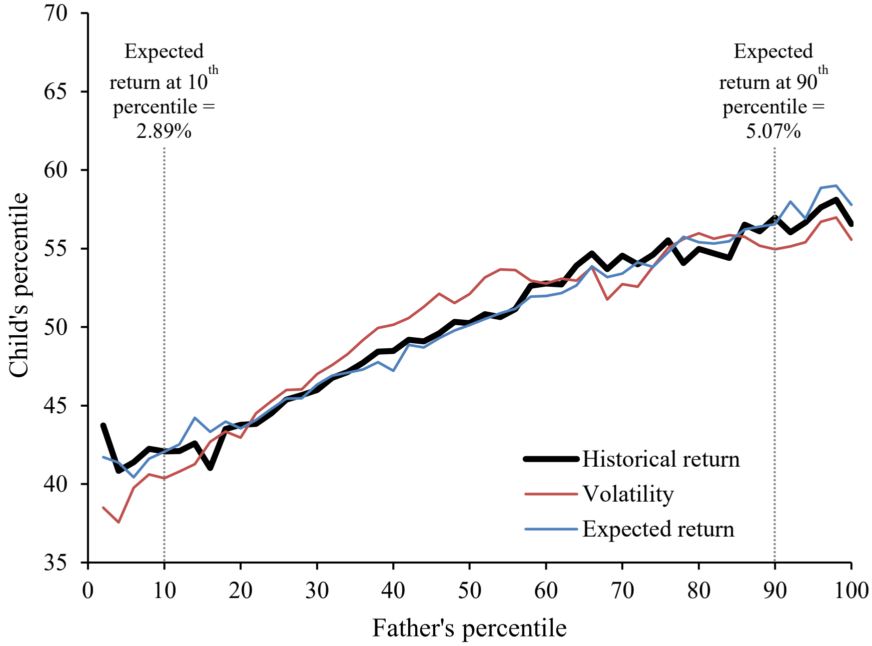
Panel A: Investor's portfolio attribute as a function of her father's



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

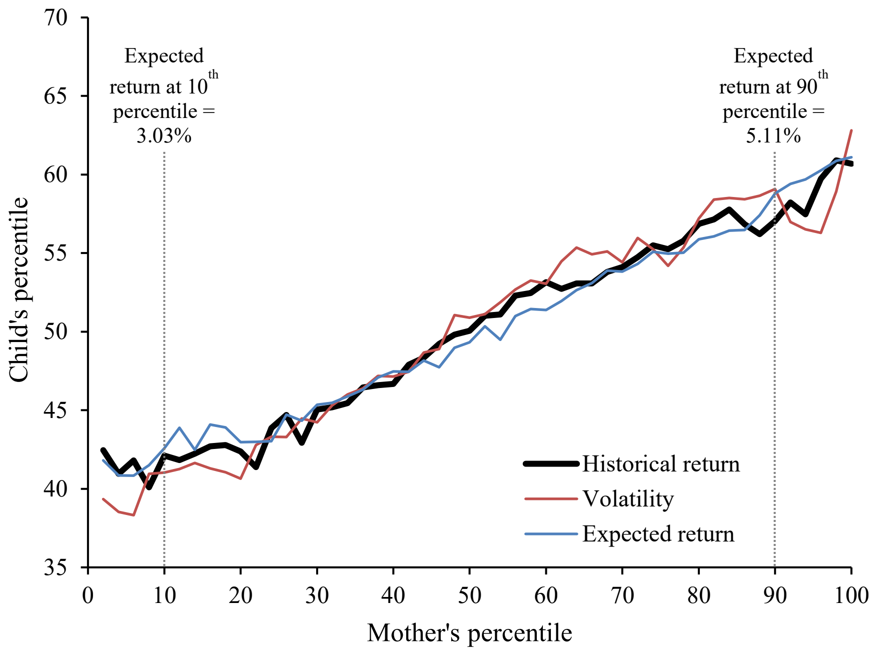


Figure IA1. Intergenerational correlations in portfolio attributes

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 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	0.024	0.024	0.028	0.033	0.037	0.054
	(9.91)	(12.81)	(20.07)	(20.98)	(28.84)	(31.32)
Mean dependent variable	0.082	0.076	0.073	0.072	0.070	0.076
Adjusted R^2	0.839	0.833	0.818	0.806	0.792	0.795
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	Grand-parents not investors	Different investment advisors	Mutual funds	Parents in public sector	Investors with various asset classes	Excluding top 5 securities	20% random subsample	Ran-domly matched parents
Specification	1	2	3	4	5	6	7	8	9
Parent invested	0.035	0.043	0.037	0.033	0.041	0.069	0.036	0.041	−0.0002
	(16.53)	(33.81)	(39.05)	(36.11)	(24.96)	(30.70)	(40.67)	(25.30)	(−1.80)
Adjusted R^2	0.720	0.794	0.807	0.697	0.798	0.865	0.759	0.710	0.808
Number of obs.	242,964	3,371,452	7,541,954	3,895,373	1,654,182	1,109,110	6,528,880	144 mil.	7,721,974

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. The estimate in each panel and column correspond to those in Table 5. 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	0.019	0.023	0.030	0.037
	(28.90)	(17.47)	(28.30)	(18.83)
Adjusted R^2	0.797	0.797	0.808	0.796
Number of observations	5,873,582	1,183,166	3,610,084	854,344

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	0.026	0.032	0.026	0.030
	(23.41)	(20.15)	(24.93)	(20.67)
Adjusted R^2	0.828	0.824	0.852	0.843
Number of observations	2,285,576	1,058,096	2,049,938	1,082,960

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/other or Swedish) to zip code and age to define the geographic peer group. Column 2 stratifies co-workers in an establishment further by age. Columns 3 and 4 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	Establishment × age	Zip code × age × native language	Establishment × age
	1	2	3	4
Parent invested in a security	0.117	0.093	0.126	0.051
	(13.45)	(3.19)	(13.56)	(1.75)
Fixed effects				
Zip code × Security	Yes	No	Yes	No
Firm × Security	No	Yes	No	Yes
1st stage F-statistic	72.7	45.6	45.7	29.0
1st stage partial R^2	0.002	0.002	0.004	0.002
Number of observations	5,735,060	693,114	3,528,480	561,854

Panel B: Impact of child on parent

Dependent variable	Parent invested in a security			
Specification	Father		Mother	
	Zip code × age × native language	Establishment × age	Zip code × age × native language	Establishment × age
	1	2	3	4
Child invested in a security	0.116	0.053	0.093	0.038
	(2.17)	(1.73)	(2.76)	(1.74)
Fixed effects				
Zip code × Security	Yes	No	Yes	No
Firm × Security	No	Yes	No	Yes
1st stage F-statistic	116.8	66.3	101.4	46.0
1st stage partial R^2	0.0004	0.003	0.0004	0.003
Number of observations	2,050,528	445,878	1,838,568	461,714

Table IA4

Using percentile ranks to estimate intergenerational correlations in portfolio attributes

This table repeats regressions in Panel A of Table 7 by replacing the portfolio attribute with its percentile rank in a year. 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	0.180	0.192	0.188	0.215	0.235	0.211
	(36.34)	(40.88)	(18.66)	(28.40)	(56.13)	(22.36)
Number of observations	713,899	713,899	713,899	635,611	635,611	635,611

Table IA5

Choosing placebo parents using more characteristics

This table repeats the analyses concerning expected return in Panel B of Table 7 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 panel repeats the draw 1,000 times and reports the mean coefficient and its *t*-value.

Specification	Father		Mother	
	Wealth	Wealth and education	Wealth	Wealth and education
	1	2	3	4
Randomly chosen parent within:				
Residents of a municipality	0.009	0.009	0.016	0.016
	(3.45)	(3.74)	(3.03)	(3.23)
Employees of a firm	0.004	0.004	0.004	0.003
	(1.34)	(1.34)	(1.24)	(1.17)
Clients of an asset manager	0.027	0.028	0.007	0.009
	(4.59)	(4.18)	(3.33)	(3.32)

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