The Banker in Your Social Network*

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Abstract

We study how bankers affect financial decisions of their social connections. Comprehensive register data from Finland allow us to use a within-individual identification strategy that leverages changes in financial market participation surrounding job switches to the banking industry. This research design reveals a large positive effect of bankers on their family members' financial decisions. This banker effect declines in social distance, is more pronounced for nonparticipating individuals, and is greater for riskier assets. Our results collectively suggest bankers' sales skills are more influential in effecting change than their financial knowledge alone. These insights are relevant for understanding the efficacy of financial literacy initiatives, the impact and value of financial advice, and the nature of expertise in financial markets.

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1 Introduction

This study analyzes how bankers affect the personal finances of their social connections. We study bankers because they can be a potent social source of financial information. They possess expert financial knowledge (Philippon and Reshef, 2012; Boustanifar, Grant, and Reshef, 2018; Böhm, Metzger, and Strömberg, 2018; Célérier and Vallée, 2019) that they can impart to other people. Their adeptness in client interactions can also make them effective in persuading others to overcome suspicions about financial matters (Gennaioli, Shleifer, and Vishny, 2015). These qualities make bankers ideal for understanding whether and how financial knowledge travels in social networks. We investigate how large the social spillovers of financial knowledge are and how they vary by social distance, professional role, investment types, and individual characteristics. These analyses inform us about the environments conducive and the conditions necessary for social spillovers in the financial context.

We study the effect of bankers on their social connections by using comprehensive and reliable register data from Finland in 2004-2016. Information on occupations allows us to accurately identify bankers. These roles encompass advisors, analysts, brokers, and asset managers. Detailed family links make it possible to construct an important part of a banker's social network.[1] Our focus is on the banker's family members' decision to participate in the financial market by investing in stocks and mutual funds. This choice of outcome variable aligns with the earlier literature that extensively analyzes the puzzlingly low willingness of households to invest in risky assets (e.g., Vissing-Jørgensen, 2002; Calvet, Campbell, and Sodini, 2007).

This research design has many advantages. Transitions into banker roles allow us to identify the effects from variation within an individual. They also lend themselves to additional robustness checks that address potential confounding effects associated with job switches. Our focus on family members alleviates the problem of people selecting

[1] Our research design does not lend itself to studying other social networks. Nevertheless, we study co-workers of the family members in an extension to our baseline results.

into a particular social network because the close family members we consider are predetermined by forces likely not driving career moves (fertility or household formation). Furthermore, the Finnish institutional setting that virtually never involves sales commissions for financial products rules out the possibility of bankers benefiting financially from persuading their family members.

We first establish bankers are more likely to participate in financial markets compared to the population and to themselves prior to moving to banking. Taking advantage of this variation by including individual fixed effects and controlling for observable individual characteristics, we find a substantial increase in financial market participation for bankers themselves. This result suggests bankers personally benefit from their new professional role, which validates the use of banking job switches as a shock to financial expertise.

We next show the bankers' better expertise spills over to their family members. Panel regressions that control for individual fixed effects and observable characteristics show large and significant positive effects on the family member's financial market participation. Importantly, these analyses control for the individual's own banker status and are thus immune to concerns related to within-family correlations in occupations.

Although the within-individual estimation strategy is a powerful way to identify the banker effects, we address several possible confounders. The job switches in general may advance an individual's career and make her more likely to gain access to company-sponsored financial advice that spills over to her family members. The high-skill nature of the banker's jobs may also improve general skills useful for understanding financial matters, leaving no special role for the switch to finance per se.

We address these alternative explanations by employing a difference-in-differences strategy that compares switches to banking to those to other industries. If job switches in general improved the workers' access to financial advice or job transitions to high-skill occupations endowed the workers with skills useful for financial matters, we would find no effects in this empirical design. Contrary to these expectations, the difference-in-differences setup delivers results comparable to the earlier results, suggesting the switch to banking uniquely generates the effects.

The largest effects obtain for partners who benefit from daily interactions and shared financial responsibilities with the banker. For these individuals, we find a 4.1 percentage point (pp) increase in participation ($t = 11.85$), which compares favorably to the 25.7% mean rate of financial market participation. The effect is smaller, but significant for individuals whose children move to finance. Here the effect equals 2.0 pp ($t = 7.57$). The effect on siblings declines further, but remains positive and statistically significant (0.6 pp, $t = 2.29$). These results suggest the spillovers in social networks decay with social distance. The significantly positive banker effects for parents and siblings also rule out the possibility that our results are solely driven by delegation of financial decisions within a shared household, potentially arising from differences in knowledge (Banerjee et al., 2021) or bargaining power (Addoum, 2017) between household members.

Our rich data further allows us to decompose the banker effects by the family member's characteristics. We find largest effects for individuals who do not participate in financial markets at the beginning of our sample period. The insignificant effects for financial market participants suggest their connection to a banker does not deter them from exiting the market (over a three-year horizon, about 10% of participants exit the market). Other individual characteristics seem to matter little. Formal education, income, and gender do not generate reliably different banker effects. Relatedly, we find that various portfolio attributes, such as expected returns, volatility, and investment costs, appear unaffected by knowing a banker, conditional on being a financial market participant. Overall, these patterns are consistent with bankers mostly affecting individuals with no prior investing experience regardless of their socioeconomic status.

What drives the social spillovers in our setting? The banker may pass some of her newly acquired financial knowledge to her family member. Several results speak against this channel as the sole driver of our results. We only observe banker effects on non-participating individuals, although learning about finance should also pertain to avoiding exits. Better financial knowledge should also generate an effect on safer assets and improved portfolio attributes for financial market participants, which we do not find. Moreover, financial knowledge alone should generate effects across various banker roles. Our effect appears confined to bankers in client-facing front office roles.

An alternative explanation that can collectively rationalize our findings involves the sales skills that bankers acquire in their jobs. Gennaioli, Shleifer, and Vishny (2015) describe investors as "too nervous or anxious to make risky investments on their own, and hence hire money managers and advisors to help them invest". A banker in the family can naturally fill this role by reducing investment anxiety. The larger effects that obtain for non-participants, front office bankers trained to deal with clients, and risky assets more prone to inducing anxiety are consistent with this interpretation. The primary role of bankers in their family thus appears to make participation more palatable.

In an extension to our baseline results, we study how the banker effect spreads in the wider social network by linking banker's family members to their co-workers. For this second-degree social network, we find precisely estimated zeros. These null results suggest the banker effect does not travel further in the family members' social networks. The social spillovers thus appear to be limited to individuals fluent in both financial knowledge and skills in effecting change.

We contribute to the following literatures. First, our results are relevant for the work that studies financial literacy. The level of financial literacy is low around the world, and it positively correlates with better financial decision-making (for a review, see Lusardi and Mitchell, 2014). Our paper adds to this work by showing causal evidence on how financial knowledge travels in social networks. Although we find such spillovers in our setting, they are largely driven by how effective the bankers are in persuading their social connections, rather than them simply transmitting their financial knowledge. This observation is important for evaluating financial education initiatives aimed at improving financial literacy.[2]. Haliassos, Jansson, and Karabulut (2020) report evidence on social

[2]The empirical case for such initiatives is mixed (Hastings, Madrian, and Skimmyhorn, 2013) and a meta-

spillovers in the context of how refugees to Sweden were placed to neighborhoods differing in proxies of financial literacy. We study a setting with a more powerful social source of financial information and use empirical designs that address various identification concerns. We also provide a detailed account of how the effect varies in the population and what this tells us about the nature of social spillovers.

Second, we contribute to the analysis of social interactions in finance (for reviews, see Hirshleifer, 2020; Kuchler and Stroebel, 2020). Earlier work shows peer effects play an important role in various financial decisions by households (Duflo and Saez, 2003; Hong, Kubik, and Stein, 2004; Kaustia and Knüpfer, 2012; Beshears et al., 2015; Hvide and Östberg, 2015; Ouimet and Tate, 2020). Our context allows us to show that individuals' personal finances benefit from having access to a banker. In other settings, social interaction appears to adversely affect the quality of decision-making (Bailey et al., 2018; Rantala, 2019). We also document patterns that suggest substantial heterogeneity in how financial knowledge travels in social networks.

Third, our results speak to work understanding the market for financial advice (Bergstresser, Chalmers, and Tufano, 2008; Bhattacharya et al., 2012; Foerster et al., 2017; Hoechle et al., 2018; Linnainmaa et al., 2020). Self-selection of clients to seeking advice makes it challenging to establish the impact and value of financial advisors. Our results suggest bankers have a beneficial impact on their social connections by increasing financial market participation, but likely only when the bankers are fluent in dealing with clients.

Finally, our paper relates to the work that studies the impact of expertise on financial decision-making. These studies document how expertise affects the personal financial decisions of real estate agents (Rutherford, Springer, and Yavas, 2005; Levitt and Syverson, 2008), mutual fund managers (Bodnaruk and Simonov, 2015), economics graduates (Guiso and Jappelli, 2005; Christiansen, Joensen, and Rangvid, 2008), and finance professionals (Grinblatt, Keloharju, and Linnainmaa, 2011). Our paper differs from this work

analysis of published policy evaluations finds small effects (Fernandes, Lynch, and Netemeyer, 2014). More recent studies display larger effects (Kaiser et al., 2022) by studying the social spillovers of expertise.

The rest of the paper unfolds as follows. Section 2 introduces the data and provides descriptive statistics. Section 3 reports baseline results. Section 4 investigates channels, heterogeneity, and intensive margin. Section 5 studies spillover effects beyond family members. Section 6 concludes.

2 Data, definitions, and descriptive statistics

2.1 Data

Our data combines information on occupations, industry of work, family relations, and asset holdings from administrative registers maintained by various Finnish authorities. These data include a scrambled personal identification number that makes it possible to merge across different registers. Information from public sources complements the register-based data.

Statistics Finland provides us with the population of individuals, their links to their parents and partners, and many individual attributes. We observe individuals and their attributes in 2004-2016. The parental links are comprehensively available for individuals born in 1955 or after. Our sample includes the population of individuals at least 18 years old at the beginning of the sample period in 2004 (born in 1986 or earlier). We observe the individual's industry of work (corresponding to the NACE Rev. 2 classification), occupational codes (corresponding to the ISCO-88 and ISCO-08 classifications), occupational status (self-employed, employee, and out-of-labor force), annual income, level of education (basic, high school, bachelor, and master or higher), year of birth, and marital status (single, divorced, and married).

Finnish Tax Administration (FTA) records information on asset 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 holdings in each publicly listed stock 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 temporarily 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 the characteristics of all mutual funds available to Finnish investors. We use these data to assign each mutual fund to an asset class (short-term bonds, long-term bonds, balanced, equity, and alternative), to calculate portfolio returns, and for fund fees. 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 calculate the year-end market value of annual holdings in all publicly listed stocks and portfolio returns.

2.2 Definitions and institutional setting

We define a banker as an individual who works in the banking industry (NACE: 641: Monetary intermediation, 663: Fund management activities) and is in a finance occupation. The following ISCO-08 codes are our finance occupations: 1211: Finance manager, 1346: Financial institution branch manager, 2412: Financial and investment advisers, 2413: Financial analysts, 3311: Securities and finance dealers and brokers, 3312: Credit and loans officers, 4211: Bank tellers and related clerks, and 4312: Statistical, finance, and insurance clerks.

This combination of industry and occupation, and the fact that it excludes workers holding only administrative or support roles, ensures we correctly identify individuals who likely possess substantial financial knowledge. The Finnish institutional setting also means our results cannot be driven by the bankers' professional incentives to sell bank products. In Finnish retail banks, such sales commissions rarely exist. When they do, they only amount to public recognition or small nominal rewards.

Data availability dictates the family members we can analyze. We use the parental links to assign each individual her parents (mother, father, or both) and we classify individuals as siblings if they share the same mother. Because our identification strategy uses job switches to banking and such transitions are rare for older-age individuals in our data, we focus on the cases in which an individual's child switches to banking. The data set also tags the individual's partner by marriage or cohabitation. These partners can vary over time so we fix the partner of an individual at the time of the job switch. Our family members thus include an individual's partner, children, and siblings.

2.3 Descriptive statistics

Panel A in Table 1 reports that we classify 1.1% of the sample subjects as bankers whereas the corresponding number for the subjects' family members varies from 0.3% to 1.8% depending on the family relation. This core sample of all the individuals entering the sample over the sample years of 2004-2016 has 2.2 million individuals and 26.9 million observations. Relaxing the restriction of having a finance occupation would result in a 1.5% fraction of the sample working in banking. This overall worker share is comparable to other Nordic countries, but lower than in the U.S. (Böhm, Metzger, and Strömberg, 2018). Each individual in our data has on average 1.9 parents, 0.8 children, and 0.7 partners.

Panels B and C in Table 1 reports the characteristics of the core sample. The sample subjects earn on average 32,500 euros per year, typically have either basic, high school, or vocational education, and are in employment. Only 26% of them hold stocks and/or mutual funds. Directly held stock, balanced funds combining equities and bonds, and equity funds account for the bulk of this participation in financial markets. This lack of participation suggests substantial room for improving the individual's financial outcomes.

Panel A in Table 2 reports more details on the distribution of bankers by their professional skill level. About 10% of the bankers hold managerial positions and 15% are professionals. Income, fraction of men, age, and level of education increase in banker skill levels. Financial market participation is high across all the skill levels among the bankers. Even bankers belonging to the clerical worker category, representing 45% of the bankers, have a high financial market participation rate of 65%. This high participation suggests that bankers are much more likely to participate in financial markets compared to what would be predicted by their observable characteristics.

3 Results

3.1 Panel regressions utilizing within-individual variation

To get the first perspective on the financial market participation of the banker's family members, we report estimates from linear probability regressions in Table 3 using our full panel. The unit of observation is an individual in a year, the dependent variable is an indicator for financial market participation, and the explanatory variables include one banker dummy for the individual herself and another for her family members. These two banker indicators allow us to estimate the marginal effects of an individual being a banker herself and her having a banker in the family. We run these regressions separately in samples in which we can link an individual to her partner, children, and siblings. These estimates should naturally be considered correlational rather than causal.

Panel A displays the results of regressions that only include year fixed effects. Panel B adds indicators for birth year, gender, four levels of education, income deciles, months in unemployment, four occupational statuses, and three marital statuses. These observable controls address the correlation of the banker dummies with various known determinants of financial market participation. Panel C further adds individual fixed effects and birth year indicators interacted with year. These additional controls identify the coefficients from within-individual variation and address the possibility the banker dummies correlate with the individual's stage in the lifecycle (Cocco, Gomes, and Maenhout (2005) and Fagereng, Gottlieb, and Guiso (2017) find a strong life-cycle profile in stock market participation).

Column 1 in Panel A shows bankers are 38.5 pp more likely to hold stocks or mutual funds. Controls in Panel B reduce this effect to 31.2 pp and individual fixed effects and birth year time trends in Panel C to 16.2 pp. As the data include the entire population born in 1955-1986, the t-value of 39.54 in Column 1 is not surprisingly large. The estimates also are economically sizeable compared to the average financial market participation rate of 25.7%. The coefficients thus imply at least a 63% (16.2/25.7) higher participation rate for bankers than for the average individual. The fixed-effects specification further suggests bankers are much more likely to participate in financial markets not only compared to non-bankers, but also to themselves before the job switch to banking.

Columns 2 to 4 in Table 3 shift the focus from an individual to her family members. These regressions retain the banker indicator for the individual, which allows us to isolate the effect attributable to the family member while keeping the individual's banker status fixed. Column 2 in Panels A to C shows that an individual having a banker in her family significantly increases financial market participation. For partners in Panel A without controls, the participation rate is 17.7 pp higher. This estimate corresponds to 17.7/37.5 = 47.2% of the effect of an individual herself being a banker.

Controls in Panel B cut the estimate to 11.5 pp, or 36% of the individual banker effect. The most conservative fixed-effects estimates in Panel C correspond to a 4.1 pp increase, representing 25.3% of the individual banker effect. This decrease in the relative effect from Panel A to C likely reflects similarity in the characteristics of family members that the controls and fixed effects capture. These characteristics can include socioeconomic status, cognitive and noncognitive skills, beliefs, and preferences.

Columns 3 and 4 in Table 3 increase the social distance between the individual and her family member. The coefficient is smaller for the individual's children in Column 3 than for partners in Column 2 and smallest for siblings in Column 4. The point estimates for partners (4.1 pp), parents (2.0 pp), and siblings (0.6 pp) are sizeable given the conservative nature of the fixed-effects specification in Panel C[3]. This monotonic decrease likely reflects the degree of social interaction between the individual and her family member and shows the banker effect declines in social distance. Furthermore, the significant effects for parents and siblings suggest delegated portfolio management within a shared household, which would rarely include parents or siblings, cannot entirely explain the findings.

3.2 Difference-in-differences regressions

The panel regression approach in Table 3 allows us to control for any confounding effects arising from observable time-varying characteristics and unobservable time-invariant characteristics. Nevertheless, these regressions do not necessarily allow us to separate the effect of becoming a banker from the general effect of job switches. Workers switching their jobs may become more likely to participate in financial markets due to their higher income or lower background risk, and they may also get access to employer-sponsored financial advice.

We address these and related concerns by developing a difference-in-differences design around job switches. This setup compares individuals whose family members become bankers (treatment) to those whose family members switch to an industry other than finance (control). Our sample includes these two sets of individuals before and after their family member's job switches, which allows us to isolate the effect of moving to banking from the effect of switching a job.

We focus on individuals for which we observe financial market participation status in the five years before (from $t-5$ to $t-1$) and five years after (from t until $t+4$) the job switch. This restriction, including job switches in years 2009-2011, makes it possible to

[3]The individual banker coefficient in Column 3 is significantly smaller in Panel B than Panel C. This result likely emanates from the sample in this specification only including individuals who have at least one child. These older individuals have had plenty of time to potentially learn about financial markets. Their participation status may thus not be particularly responsive to new information acquired in the job switch to banking

construct a matched sample and analyze heterogeneity based on pre-treatment ($t = -6$) characteristics. To rule out any effects emanating from the individual herself switching her job, we exclude individuals who themselves become bankers during the follow-up period.

We estimate the treatment effects using the following difference-in-differences regression:

$$y_{i,t} = \beta \times Post_t \times Treat_i + \gamma_i + \gamma_t + \gamma_\tau + Birthyear_i \times \gamma_t + \epsilon_{i,t} \quad (1)$$

where $y_{i,t}$ is an indicator for financial market participation of an individual i in year t, $Treat_i$ equals one for individuals whose family member switches jobs to banking, $Post_t$ equals one for the five years after the family member's job switch, γ_i, γ_t, and γ_τ are individual, calendar year, and event time fixed effects. $Birthyear_i \times \gamma_t$ capture time trends by birth year. We cluster standard errors by the family member that switches jobs.

We use three different samples in the difference-in-differences regressions. The first is the full sample whereas the second sample restricts job switches in the control group to industries with skill requirements similar to the banking industry. These industries include Information and Communication (NACE: 58-63), Real Estate (NACE: 68), Professional, Scientific and Technical Activities (NACE: 69-74), and Administrative and Support Activities (NACE 77, 78, 82).

The third sample is a matched sample that uses coarsened exact matching based on observables at $t = -6$. This technique finds an exact match for each treatment individual by using marital status, months in unemployment, level of education, annual income deciles, occupational status, and five-year birth year bins. We weight multiple exact matches by the inverse of their frequency.

Table 4 compares characteristics of individuals in the treatment and control groups for the three samples (full, related industries, and matched sample). We measure these characteristics six years before the job switch ($t-6$). The table reports the differences between the treatment and control groups using robust standard errors.

In the full sample, the individuals whose family members move to banking are more likely to participate in financial markets, are more educated, and are more likely to be self-employed. These unsurprising level differences are not necessarily an issue for our identification strategy if they do not generate differential pre-trends in financial market participation. The related industry sample displays smaller differences in financial market participation and socioeconomic status whereas differences in age, labor income, gender, and education somewhat increase. The treatment and control groups in the matched sample are by design similar, except for the small differences in age and labor income that we match by income decile and five-year age bins.

Table 5 reports the results from estimating model (1) on the three alternative samples. The full sample in Panel A yields a 5.5 pp interaction of the treatment and post indicators for partners in the first column whereas the two remaining columns report estimates of 1.8 pp and 1.4 pp, respectively. These coefficients are statistically significant, and they are somewhat larger for partners and siblings compared to the linear probability models in Table 3. Panels B and C restrict the control group to related industries and matched individuals, respectively, and yield results that are similar to Panel A and Table 3. These results convincingly show the increase in participation we observe at the time an individual's family member becomes a banker does not emanate from job switches in general or from career moves to high-skill industries. Rather, the effect appears to be uniquely attributable to switches to banking.

Figure 1 extends regression (1) by replacing the interaction of the post and treatment dummies with interactions for the event time dummies and the treatment dummy. This figure uses the full sample; Figure IA3 displays the results for the two alternative samples. Despite the differences in observables we report in Table 4, no differences in the pre-trends between treatment and control groups in the five years before the family member's job switches obtain in Figure 1. The coefficients following the job switch show financial market participation steadily increases after a family member becomes a banker. This pattern likely reflects the gradual social propagation of financial expertise and the time it takes for an individual to accumulate savings.

Figure IA2 reports the unconditional averages of participation for the treatment and control groups. The three leftmost panels show the average participation in event time whereas the three rightmost panels display the average relative to the time of treatment. All the panels clearly show the banker effect emanates from the treatment group increasing participation following treatment.

We revisit the effects on the bankers themselves in Figure IA1. It plots regression coefficients for regressing financial market participation on event time dummies interacted with the treatment indicator. In all the three samples of the bankers who are either partners, children, or siblings of our treated individuals, we find a relative increase of about 20 pp in financial market participation around the role change to a banker.

4 Channels

4.1 Two potential channels and roadmap for analyses

Our results so far show individuals experience a significant increase in financial market participation when their family member becomes a banker. We now evaluate potential channels that can drive the banker effect. Earlier we have refuted two potential channels: financial incentives are practically nonexistent in our setting and delegation within a household likely does not extend to family members living outside the household.

The remaining channels can involve the newly appointed bankers transferring their new *financial knowledge* to their family members by educating them about risk, return, and costs. This channel would result in higher financial literacy among family members and improved decision-making. Alternatively, bankers may use their newly acquired *sales skills* to help their family members to overcome their initial anxiety to enter financial markets. This channel suggests bankers would serve as “money doctors” in their family by providing comfort and peace of mind, increasing trust in financial markets, and lowering perceived risks (Gennaioli, Shleifer, and Vishny, 2015).

Because our data does not detail the interactions between bankers and their family members, we rely on a collage of evidence that collectively speaks to the two channels. We explore treatment heterogeneity by individual characteristics, extensive margin effects across asset classes, treatment intensity by banker characteristics, and intensive margin effects on market participants.

4.2 Heterogeneity by individual characteristics

Table 6 estimates, for each type of family member, the difference-in-differences regressions in Panel A of Table 5 by including triple interactions for characteristics of the family member. These characteristics are prior financial market participation, i.e., whether the individual already participated in financial markets at the beginning of our sample period ($t-6$), and the individual's level of education, income, and gender.

The first insight in Table 6 arises from the coefficients in the first two rows in the three columns. The estimates for non-participants are 8.8 pp, 2.4 pp, and 2.2 pp for partners, parents, and siblings, respectively. The triple interactions with prior participation status in the second row reveals the estimates for participants only amount to 3.1 pp, -0.5 pp and 0.1 pp, respectively. These differences between non-participants and participants are statistically significant for partners and parents. Bankers thus appear to help family members to enter financial markets whereas they are less effective in preventing participating family members from exiting.

The lack of any other consistent interactions is the second insight in Table 6. Out of the nine triple interactions reporting on heterogeneity along education, income, and gender, only one is statistically significant. Because earlier evidence indicates that these characteristics strongly correlate with financial literacy (Almenberg and Dreber, 2015; Bottazzi and Lusardi, 2021; Cole, Paulson, and Shastry, 2014; Grinblatt, Keloharju, and

Linnainmaa, 2011; Guiso and Jappelli, 2005; Lusardi and Mitchell, 2014), our results suggest the banker effects are not moderated by these proxies for financial literacy. We have verified this result does not arise from the prior participation status capturing the bulk of the variation in financial literacy. If we exclude this variable from the regressions, the estimates remain statistically insignificant. In IA2, we re-estimate the results of Table 6 using the two alternative samples using related industries and matched controls. These settings deliver results comparable to the baseline sample.

4.3 Extensive margin effects across asset classes

Table 7 analyzes the banker effects across different asset classes. These effects are estimated separately for risky and safe assets by defining the dependent variable as an indicator for holding any security in the respective asset class. We define risky assets as direct equity, equity mutual funds, balanced funds, and alternative funds whereas safe assets are short-term and long-term bond funds.

Table 7 reports the risky and safe asset coefficients for the three types of family members. Columns 1, 3, and 5 show the coefficients range from 1.7 pp to 5.5 pp for risky assets and they are all statistically significant. The estimates for safe assets in the remaining three columns are small in magnitude and statistically indistinguishable from zero. These results show the banker effect emanates solely from risky assets and the bankers do not materially affect participation in safe assets. Table IA3 shows this conclusion also holds in the two alternative samples.

4.4 Intensive margin effects on market participants

Table 8 studies the portfolio attributes of the individuals that participate in financial markets. These analyses reveal whether bankers affect the quality of the portfolio chosen by individuals who already have made the decision to participate in financial markets. We calculate portfolio attributes that capture diversification, return moments, and investment costs. These metrics include number of stocks and number of mutual funds held, expected portfolio return based on a four-factor model, portfolio volatility, average management fees of the mutual funds held by an individual, and an indicator for holding index funds.

Panels A, B, and C report the effects for the three types of family members. Diversification measures appear in the first two columns, return moments in the next two columns and investment costs in the last two. Across all the panels and columns, the only estimates that are statistically significant are volatility for partners, number of stocks for parents, and number of funds for siblings. These estimates suggest increases in the number of securities and decreases in portfolio volatility.

Although these results suggest bankers may improve portfolio diversification for some of their family members, the general lack of significance across all the estimates in the table indicates a participating individual does not typically gain much from having a newly appointed banker in their family.

4.5 Treatment intensity by banker's characteristics

Some of the bankers act in a front office sales role in which they directly interact with clients. Other bankers hold back office positions that involve less client interactions. Given these two types of roles differently involve the acquisition of sales skills, studying their effects separately can inform us about the channels driving the banker effects.

Panel A in Table 9 studies this difference in treatment intensity by singling out bankers in front-office and other roles. The descriptions in detailed occupation codes make it possible to identify occupations that clearly involve client interactions. All the other occupations that are more difficult to classify fall into the other category. Front-office roles are branch managers, financial and investment advisors, securities and finance dealers and brokers, and bank tellers and related clerks. The other roles are finance managers, financial analysts, credit and loan officers, and statistical, finance and insurance clerks.

The regressions in Panel A of Table 9 follow regression specification (1) but break down the banker indicator into the front-office and other roles and interact these two indicators with the post indicator. Columns 2 and 3 show the estimates are only significant for the front-office roles in our samples of parents and siblings. The estimates for partners in Column 1 are both significant, but their difference is not statistically significant ($p-value = 0.65$). These results support the view that bankers in front-office roles are most effective in influencing their family members, particularly those with whom they do not interact on a day-to-day basis.

Panel B of Table 9 provides another way of assessing the impact of the banker's professional role. Here we add two groups of finance professionals whose positions do not involve client-facing interactions related to personal investments. In our Finnish setting, people receive financial advice predominantly from commercial banks and their asset-management arms whereas other types of financial advisors are rare. This institutional feature suggests finance professionals working outside the banking industry are less accustomed to providing financial advice to individual clients.

We thus separately indicate finance professionals working in non-banking financial institutions in the financial industry (holding companies, trusts, funds and other financial entities, and other credit-granting institutions). We also indicate finance professionals working outside the finance industry (a CFO of a non-financial firm would be an example).

Using the same regression setup as in Panel A, we find these two additional groups of finance professionals have virtually no effect on their family members. The lack of effects outside the banking industry suggests bankers are more effective in convincing their family members than other finance professionals.

4.6 Taking stock

Our collage of evidence shows the banker effects are limited to market entries whereas the portfolios of participating individuals remain unaffected. Beyond prior participation status, we find the banker effect does not reliably vary by individuals' socioeconomic status nor by gender. Furthermore, the effect is only present in risky assets and it is driven by bankers that occupy sales roles in the banking industry.

These results are difficult to reconcile with the view that bankers solely transmit their newly acquired financial knowledge to their family members. Participating individuals would benefit from not exiting the market and improving their portfolios' risk-return profile, which we do not find. For non-participants, we would expect the largest effects for the low-education and low-income individuals that lack financial literacy, but our results do not reveal such heterogeneity.

Furthermore, transmission of financial knowledge should also matter for investment in safe assets, but we fail to find such an effect. Finally, new finance professionals in non-sales roles and outside the banking industry likely learn new financial knowledge that they could transmit to their family members, which we do not detect in the data.

Our results are thus more consistent with the view that bankers acquire skills beyond financial knowledge and these skills help them in improving their family members' personal finances. Such sales skills can increase the family member's trust in investing and lower its perceived riskiness (Gennaioli, Shleifer, and Vishny, 2015). This trust is naturally important for entering the market, but matters less for the participating individuals who have already overcome their initial anxiety. Such trust-building should also matter more for risky than safe assets. This channel can also explain why the largest effect obtains for bankers in sales roles and why the effect does not extend to finance professionals outside the banking industry.

All in all, our results suggest that financial knowledge does not travel easily in social networks unless accompanied by the message coming from an individual possessing the means to persuade others.

5 Spillover effects in the wider social network

Our results so far show that bankers are effective in improving the personal finances of their family members. We now ask how this banker effect travels further in social networks. The financial knowledge an individual acquires from the newly appointed banker in her family may trickle down to the individual's own peers. In light of the evidence in the previous section highlighting the likely role of sales skills in the propagation of financial knowledge, it is also possible that an individual lacking the banker's skill set is less effective in persuading her own peers.

We analyze these effects by leveraging data on the workplaces of the individuals. This information tags individuals working in the same physical location at the same organization (office, factory, warehouse, shop, and others) and thus makes it possible to identify the co-workers of an individual.

Table 10, Panel A, presents the results of difference-in-differences regressions similar to regression (1), but replacing the individuals populating the sample with their co-workers. The focus on workplaces necessarily restricts the sample to individuals who are employed in the baseline sample in Table 5. We impose this employment restriction in the year of the job switch and retain the co-workers in all sample years. For example, one observation from one individual employed in the year of the family member's job switch in the original sample is replaced with n observations for each of the n co-workers of an individual in the year of the job switch. Because the replacement of one individual with her co-workers results in more observations for larger establishments, but the treatment still involves the family member of just one individual, we weight each observation by the inverse number of workers in the establishment. This weighting effectively gives each individual equal weight, as in Table 5.

Panel A in Table 10 reports precisely estimated zeros for all the three types of family members. The 95% confidence intervals for the largest coefficients, obtaining for partners, rule out effects larger than 0.8 pp. Panel B further studies whether establishment size matters for the estimates. On one hand, small establishments likely feature tighter social connections that facilitate social interaction. On the other hand, large establishments have more potential connections that can lead to larger spillovers.

Focusing on establishments employing less than 100 or less than 25 coworkers, Panel

B shows the estimates remain insignificant and small in magnitude. These results show the banker's influence on her family members does not appear to travel further in the family members' own networks. This lack of social transmission in the wider network is consistent with the view that the bankers' combination of financial and sales skills makes them particularly effective in spreading good financial practices.

6 Conclusion

We find that bankers affect the financial decisions of their family members. Our evidence collectively suggests that this banker effect is not solely driven by transmission of financial knowledge. Rather, it appears the skills bankers have in dealing with clients help them to persuade their family members in financial matters. Consistent with this notion, the banker effect does not appear to travel further in the family members' own social networks. The bankers thus seem to play the role of money doctors in their family.

Our results suggest financial education initiatives aimed at improving financial literacy should not only focus on the subject matter but also ensure its effective delivery. They should also account for the heterogeneity in how financial knowledge travels in social networks. Our findings that emphasize the important role of the banker's sales skills in the propagation of financial knowledge reinforce the view that one of the main roles of financial advisors is to make investing more palatable.

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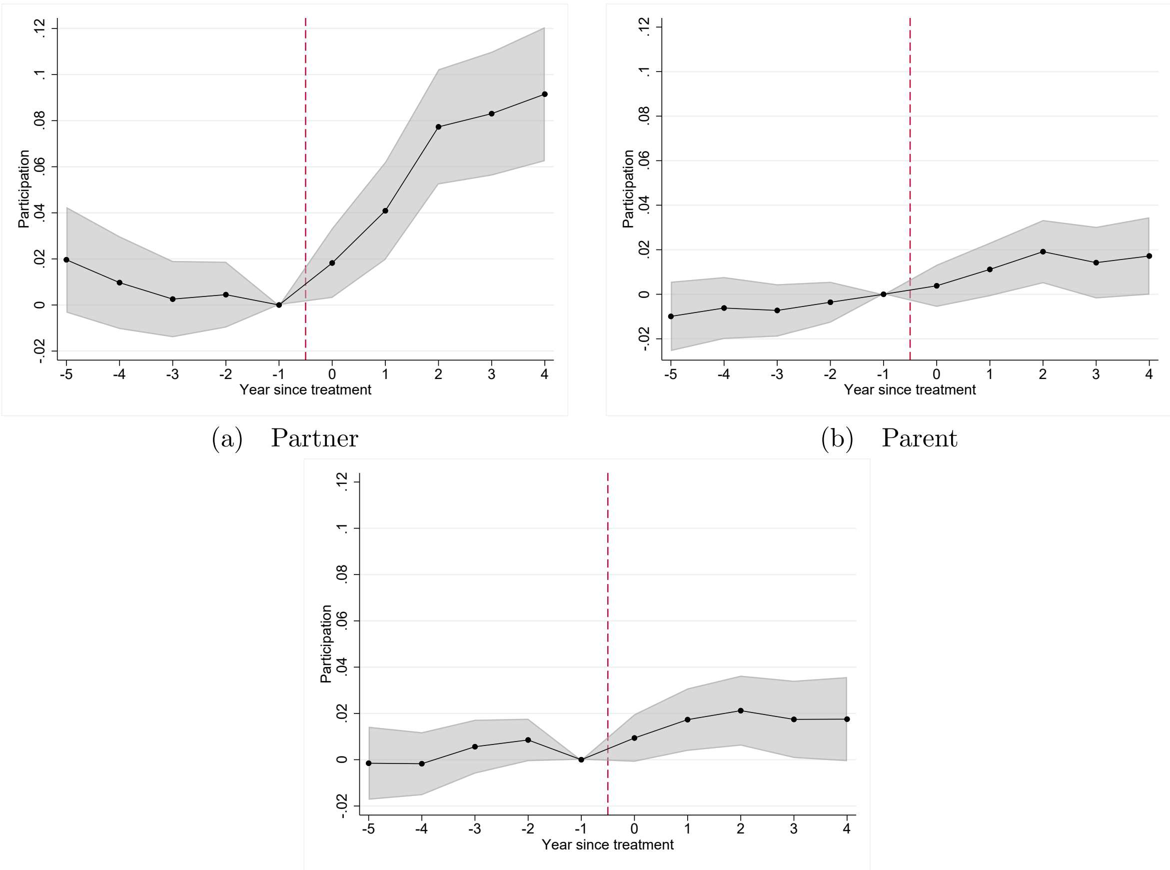

(a) Partner

(b) Parent

(c) Sibling

Figure (1) Financial market participation of family members around the banker's job switch

This figure displays coefficients from a linear probability model that explains financial market participation with event time dummies interacted with the treatment indicator. The treatment group includes individuals whose family members become bankers (i.e., a finance occupation in the banking industry) whereas the control group includes individuals whose family members switch to other jobs. The first year in which a family member works in the new job is $t = 0$ and the omitted year is $t = -1$. The three panels display effects for the bankers' partners (a), parents (b), and siblings (c). The regressions include individual and year fixed effects and fixed effects for interacting each birth cohort with year. Standard errors are clustered by the individual who switches jobs. The shaded area around the point estimates displays the 95% confidence intervals.

Table (1) Descriptive statistics of sample individuals

This table reports descriptive statistics for individuals in our sample that includes 2,211,276 individuals and 26,911,698 observations. The portfolio value and labor income are adjusted using the consumer price index from Statistics Finland with 2016 as the base year. The "other" category in socioeconomic status contains students, conscripts in the national military or civilian service, and other individuals outside the labor force.

	Mean	Median	Standard deviation
	Panel A: Fraction of bankers and number of family members		
	Mean	Median	Standard deviation
Individual is banker [%]	1.1	-	10.6
Partner is banker [%]	0.9	-	9.2
Child is banker [%]	0.3	-	5.4
Sibling is banker [%]	1.8	-	13.2
Nr. of siblings per individual	1.93	2.00	1.73
Nr. of parents per individual	0.82	0.00	1.18
Nr. of partners per individual	0.69	1.00	0.46
	Panel B: Financial market participation		
	Mean	Median	Standard deviation
Fin. market part. [%]	25.7	-	43.7
Direct equity [%]	12.7	-	33.3
Short-term bond fund [%]	2.8	-	16.4
Long-term bond fund [%]	2.1	-	14.3
Balanced fund [%]	9.4	-	29.2
Equity fund [%]	9.5	-	29.3
Alternative fund [%]	0.5	-	6.9
Tot. financial hold. ['000 EUR]	6.25	0.00	249.54
... conditional on part. ['000 EUR]	24.32	2.91	491.76
	Panel C: Individual characteristics		
	Mean	Median	Standard deviation
Age	40.55	41.00	9.73
Labor income ['000 EUR]	32.49	29.84	30.20
Month unemployed	0.93	0.00	2.60
Male [%]	50.3	-	50.0
Socioeconomic status [%]			
Self-employed	8.6	-	28.0
Worker	72.3	-	44.8
Unemployed	6.5	-	24.6
Out of labor force	4.2	-	20.0
Other socioeconomic status	8.6		28.0
Marital status [%]			
Married	50.8	-	50.0
Divorced	11.7	-	32.2
Single	37.5	-	48.4
Education [%]			
Basic or missing	15.0	-	35.7
High school or vocational	59.8	-	49.0
Bachelor degree	12.5	-	33.0
Master degree or higher	12.8	-	33.4

Table (2) Descriptive statistics of bankers

This table reports average characteristics of bankers in our sample. Panel A splits bankers by professional skill level whereas Panel B compares bankers to non-bankers in the population. "Fin. part." is an indicator for participation in financial markets. Labor income is inflation adjusted using the consumer price index from Statistics Finland with 2016 as base year and reported in thousand euros. "Not defined" includes individuals who have worked as bankers in the past but do not hold the position currently. All indicator variables (Fin. part., male and all education variables) are displayed in percentage points.

	Panel A: Professional skill								
	Fin. part.	Income	Male	Age	Basic educ.	High school	Bachelor	Master	Obs.
Manager	77.3	125.82	65.7	44.89	1.2	29.4	9.9	59.5	28,500
Professional	67.7	67.02	44.9	42.07	1.4	28.0	17.5	53.0	46,023
Assoc. professional	64.5	56.44	34.4	41.87	3.1	47.5	22.1	27.2	61,144
Clerical worker	64.9	35.58	11.6	41.86	6.5	65.4	22.1	6.0	139,695
Other or missing	45.0	26.02	22.0	44.51	9.8	59.8	16.5	13.9	33,243
	Panel B: Bankers and non-bankers								
Bankers	64.2	51.71	27.2	42.46	4.9	52.4	19.7	23.0	308,605
Non-bankers	25.3	32.27	50.5	40.53	15.1	59.9	12.4	12.6	26,603,093

Table (3) Having a banker in the family and financial market participation

This table presents results from linear probability models that explain the financial market participation of an individual with the individual being a banker and the individual having a banker in the family. The banker indicators classify an individual as a banker from the first year in a finance job in the banking industry onwards. Column (1) contains all individuals who have at least one of the family members in columns (2)-(4) available. Columns (2)-(4) restrict the sample to individuals who have a partner, a child, or a sibling. Panel A presents results including year fixed effects ("T"), Panel B adds controls for gender, marital status (married, divorced, single), number of months unemployed, dummies for four levels of education (basic, high school, bachelor, master or higher), dummies for annual income deciles, dummies for occupational status (self-employed, employee, retired, other), and birth year dummies. Panel C adds individual fixed effects ("I") and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by individual. Column titles indicate the banker's family member whose financial market participation the column studies.

	Panel A: No controls, year fixed effects			
	(1) Individual	(2) Partner	(3) Parent	(4) Sibling
Individual is banker	0.385***	0.375***	0.383***	0.376***
	(157.96)	(140.13)	(102.47)	(144.10)
Family member is banker		0.177***	0.106***	0.079***
		(60.08)	(25.98)	(38.08)
Constant	0.253***	0.264***	0.243***	0.255***
	(983.26)	(865.77)	(595.58)	(909.99)
Obs.	26,911,698	18,516,770	10,809,549	23,282,773
Number of individuals	2,211,276	1,876,424	849,498	1,829,422
R-squared	0.014	0.017	0.015	0.015
Fixed effects	T	T	T	T
Time trends	No	No	No	No
Controls	No	No	No	No

	Panel B: Controls, year fixed effects			
	(1) Individual	(2) Partner	(3) Parent	(4) Sibling
Individual is banker	0.312***	0.318***	0.324***	0.309***
	(130.16)	(119.61)	(88.35)	(120.48)
Family member is banker		0.115***	0.063***	0.048***
		(40.02)	(16.20)	(24.40)
Constant	0.201***	0.206***	0.196***	0.198***
	(199.01)	(155.41)	(110.90)	(176.13)
Obs.	26,911,698	18,516,770	10,809,549	23,282,773
Number of individuals	2,211,276	1,876,424	849,498	1,829,422
R-squared	0.098	0.094	0.094	0.095
Fixed effects	T	T	T	T
Time trends	No	No	No	No
Controls	Yes	Yes	Yes	Yes

	Panel C: Controls and fixed effects for year, individual, and birth year interacted with year			
	(1) Individual	(2) Partner	(3) Parent	(4) Sibling
Individual is banker	0.162***	0.162***	0.093***	0.163***
	(39.54)	(32.39)	(9.65)	(38.09)
Family member is banker		0.041***	0.020***	0.006**
		(11.85)	(7.57)	(2.29)
Constant	0.273***	0.327***	0.263***	0.277***
	(13.63)	(8.00)	(8.87)	(12.61)
Obs.	26,884,316	18,441,278	10,807,493	23,277,745
Number of individuals	2,183,894	1,800,932	847,444	1,824,394
R-squared	0.715	0.733	0.730	0.712
Fixed effects	I,T	I,T	I,T	I,T
Time trends	BC	BC	BC	BC
Controls	Yes	Yes	Yes	Yes

Table (4) Covariate balance in treatment and control groups

This table presents average characteristics of individuals in the treatment and control group prior to treatment at $t = -6$. The table reports the statistics for the full sample, a sample restricted to individuals whose relatives change job into related industries (information and communication, finance and insurance, real estate, professional, scientific and technical activities, and administrative and support activities), and a matched sample based on a coarsened exact match on the following pre-treatment ($t = -6$) characteristics: marital status (married, divorced, single), number of months unemployed, level of education (basic, high school, bachelor, master or higher), annual income deciles, occupational status (self-employed, employee, retired, other) and five-year birth year bins. The t-values are from a linear probability model regressing a particular variable on the treatment dummy and are based on robust standard errors.

	Panel A: Portfolio characteristics								
	Full sample			Only related industries			Matched sample		
	Treat.	Control	t	Treat.	Control	t	Treat.	Control	t
Financial market part. [%]	32.3	27.6	6.9	32.3	30.7	2.0	32.3	27.8	6.5
Direct equity [%]	16.8	13.3	6.6	16.8	15.8	1.6	16.8	13.7	5.7
Short-term bond fund [%]	3.5	3.0	1.9	3.5	3.2	0.8	3.5	3.0	1.7
Long-term bond fund [%]	2.8	2.2	2.4	2.7	2.6	0.4	2.8	2.2	2.4
Balanced fund [%]	10.8	10.0	1.8	10.8	10.6	0.2	10.8	9.9	2.0
Equity fund [%]	13.1	10.3	5.9	13.1	11.8	2.2	13.1	10.3	5.8
Alternative fund [%]	0.8	0.4	2.9	0.8	0.5	1.9	0.8	0.4	2.9
Portfolio value [‘000 EUR]	7.32	5.79	1.8	7.33	9.02	-0.7	7.32	6.87	0.4
... conditional on part. [‘000 EUR]	22.67	20.95	0.6	22.71	29.39	-0.8	22.67	24.69	-0.6
	Panel B: Individual characteristics								
	Full sample			Only related industries			Matched sample		
	Treat.	Control	t	Treat.	Control	t	Treat.	Control	t
Age	40.85	40.73	0.8	40.86	39.92	5.1	40.85	40.81	0.3
Labor income [‘000 EUR]	37.19	37.28	-0.2	37.16	39.10	-3.8	37.19	36.34	2.1
Month unemployed	0.46	0.12	12.7	0.46	0.10	12.6	0.46	0.46	0.0
Male [%]	53.00	49.45	4.9	53.08	48.50	5.2	53.00	53.00	0.0
Socioeconomic status [%]									
Self-employed	10.2	7.3	6.8	10.2	6.3	7.9	10.2	10.2	0.0
Worker	78.3	85.1	-11.6	78.2	85.2	-10.0	78.3	78.3	0.0
Out of labor force	2.3	1.9	2.1	2.4	1.8	2.3	2.3	2.3	0.0
Other	6.2	4.9	3.7	6.1	6.0	0.2	6.2	6.2	0.0
Marital status [%]									
Married	57.9	60.5	-3.7	57.8	59.1	-1.4	57.9	57.9	0.0
Divorced	11.0	9.0	4.3	11.0	8.6	4.7	11.0	11.0	0.0
Single	31.1	30.5	1.0	31.1	32.4	-1.5	31.1	31.1	0.0
Education [%]									
Basic or missing	9.8	7.4	5.7	9.9	6.2	7.5	9.8	9.8	0.0
High school or vocational	62.5	67.4	-7.0	62.5	62.4	0.1	62.5	62.5	0.0
Bachelor	13.9	12.5	2.9	13.9	13.9	-0.1	13.9	13.9	0.0
Master or higher	13.8	12.8	2.1	13.7	17.4	-5.9	13.8	13.8	0.0
Obs.	4,878	278,313		4,836	9,988		4,878	278,313	

Table (5) Difference-in-differences regressions

This table presents the results of a difference-in-differences regression in which the dependent variable is an indicator for financial market participation in a year. The sample consists of individuals whose family members switched jobs across industries and for which the data include five years around the job switch. The treatment group includes individuals whose family members become bankers and the control group includes all the other individuals. Post indicates all years since the job switch ($t = 0$ to $t = 4$). The regressions include individual ("I") and year ("T") fixed effects and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs. Panel A presents results using the full sample. Panel B restricts the sample to individuals whose relatives switch jobs into related industries (information and communication, finance and insurance, real estate, professional, scientific and technical activities, and administrative and support activities). Panel C uses a matched sample based on a coarsened exact match on the following pre-treatment ($t = -6$) characteristics: marital status (married, divorced, single), number of months unemployed, level of education (basic, high school, bachelor, master or higher), annual income deciles, occupational status (self-employed, employee, retired, other) and five-year birth year bins. Column titles indicate the banker's family member whose financial market participation the column studies.

	Panel A: Full sample		
	(1) Partner	(2) Parent	(3) Sibling
Post × Treat	0.055***	0.018***	0.014**
	(5.32)	(3.00)	(2.16)
Obs.	1,240,630	1,126,040	1,741,750
Number of individuals	124,063	112,604	174,175
Number of treated individuals	1,029	2,242	1,979
R-squared	0.77	0.80	0.77
Fixed effects	I, T	I, T	I, T
Time trends	BC	BC	BC
	Panel B: Only related industries		
	(1) Partner	(2) Parent	(3) Sibling
Post × Treat	0.052***	0.020***	0.015**
	(5.01)	(3.15)	(2.14)
Obs.	290,710	266,380	399,870
Number of individuals	29,071	26,638	39,987
Number of treated individuals	1,029	2,242	1,979
R-squared	0.77	0.80	0.77
Fixed effects	I, T	I, T	I, T
Time trends	BC	BC	BC
	Panel C: Matched sample		
	(1) Partner	(2) Parent	(3) Sibling
Post × Treat	0.051***	0.018***	0.009
	(4.84)	(2.87)	(1.37)
Obs.	689,380	808,340	1,085,090
Number of individuals	68,938	80,834	108,509
Number of treated individuals	1,016	2,180	1,930
R-squared	0.74	0.80	0.75
Fixed effects	I, T	I, T	I, T
Time trends	BC	BC	BC

Table (6) Treatment heterogeneity by individual characteristics

This table presents the results of difference-in-differences regressions corresponding to Table 5, Panel A, interacting the interaction of the treatment and post indicators with individual pre-treatment ($t = -6$) characteristics. Participants are individuals who participate in financial markets whereas high education refers to holding a university degree and high income refers to having above-median income. The regressions include individual ("I") and year ("T") fixed effects and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs. Column titles indicate the banker's family member whose financial market participation the column studies.

	(1) Partner	(2) Parent	(3) Sibling
Treat × Post	0.088***	0.024**	0.022**
	(3.89)	(2.41)	(2.19)
Treat × Post × Participant	-0.057***	-0.029**	-0.012
	(-2.64)	(-2.20)	(-0.76)
Treat × Post × High education	-0.003	0.016	-0.009
	(-0.11)	(1.06)	(-0.50)
Treat × Post × High income	-0.054***	0.016	-0.008
	(-2.68)	(1.33)	(-0.61)
Treat × Post × Male	0.026	-0.009	0.013
	(1.16)	(-0.86)	(1.05)
Post × Participant	-0.176***	-0.169***	-0.175***
	(-90.72)	(-80.62)	(-99.06)
Post × High education	0.038***	0.035***	0.037***
	(18.87)	(14.61)	(19.98)
Post × High income	0.008***	0.026***	0.019***
	(4.56)	(16.13)	(13.50)
Post × Male	0.025***	0.001	0.017***
	(16.32)	(0.96)	(12.95)
Obs.	1,240,630	1,126,040	1,741,750
Number of individuals	124,063	112,604	174,175
Number of treated individuals	1,029	2,242	1,979
R-squared	0.77	0.80	0.78
Fixed effects	I, T	I, T	I, T
Time trends	BC	BC	BC

Table (7) Participation in risky and safe asset classes

This table presents difference-in-differences regressions similar to Table 5, Panel A, but changing the definition of the dependent variable to include either risky or safe assets. Risky assets are direct stock holdings, equity funds, balanced funds, and alternative funds whereas safe assets include long-term and short-term bond funds. The regressions include individual ("I") and year ("T") fixed effects and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs. Column titles indicate the banker's family member whose financial market participation the column studies.

	Partner		Parent		Sibling	
	(1) Risky	(2) Safe	(3) Risky	(4) Safe	(5) Risky	(6) Safe
Post × Treat	0.0551***	0.0044	0.0175***	0.0012	0.0166**	0.0003
	(5.36)	(0.82)	(2.84)	(0.31)	(2.54)	(0.08)
Obs.	1,240,630	1,240,630	1,126,040	1,126,040	1,741,750	1,741,750
Number of individuals	124,063	124,063	112,604	112,604	174,175	174,175
Number of treated individuals	1,029	1,029	2,242	2,242	1,979	1,979
R-squared	0.77	0.66	0.80	0.67	0.77	0.66
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC

Table (8) Effects on portfolios of individuals who participate in financial markets

This table presents difference-in-differences regressions similar to Table 5, Panel A, but restricting the sample to individuals who are participants during the entire sample period. Columns (5) and (6) further restrict the sample to mutual fund investors. The dependent variables are the number of stocks or funds held, expected return and portfolio volatility, average equally-weighted fund fees, and an indicator for holding index funds. Expected returns emanate from a four-factor model that includes the market, size, value, and momentum factors. 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 in 1994-2008. Expected return, volatility, and fund fees are displayed in percent. Panels A-C presents results for partners, parents, and siblings, respectively. The regressions include individual ("I") and year ("T") fixed effects and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs.

	Panel A: Partner					
	Diversification		Return Moments		Investment Costs	
	(1) Nr. stocks	(2) Nr. funds	(3) Exp. ret.	(4) Vola	(5) Fund Fees	(6) Index Funds
Post × Treat	0.185	-0.040	0.198	-1.541*	-2.020	0.041
	(1.52)	(-0.64)	(0.37)	(-1.84)	(-0.52)	(1.41)
Obs.	101,250	101,250	101,250	101,250	87,730	87,730
Number of individuals	10,125	10,125	10,125	10,125	8,772	8,772
Number of treated indiv.	73	73	73	73	81	81
R-squared	0.82	0.79	0.25	0.59	0.85	0.59
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC

	Panel B: Parents					
	Diversification		Return Moments		Investment Costs	
	(1) Nr. stocks	(2) Nr. funds	(3) Exp. ret.	(4) Vola	(5) Fund Fees	(6) Index Funds
Post × Treat	0.125*	0.042	0.009	-0.090	2.230	0.007
	(1.84)	(0.87)	(0.04)	(-0.15)	(1.00)	(0.67)
Obs.	100,770	100,770	100,770	100,770	78,460	78,460
Number of individuals	11,913	11,913	11,913	11,913	9,083	9,083
Number of treated indiv.	231	231	231	231	202	202
R-squared	0.84	0.79	0.24	0.60	0.86	0.52
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC

	Panel C: Siblings					
	Diversification		Return Moments		Investment Costs	
	(1) Nr. stocks	(2) Nr. funds	(3) Exp. ret.	(4) Vola	(5) Fund Fees	(6) Index Funds
Post × Treat	-0.026	0.111*	0.085	-0.376	-3.486	0.001
	(-0.30)	(1.78)	(0.36)	(-0.64)	(-1.37)	(0.06)
Obs.	129,910	129,910	129,910	129,910	115,520	115,520
Number of individuals	13,754	13,754	13,754	13,754	12,343	12,343
Number of treated indiv.	171	171	171	171	163	163
R-squared	0.80	0.78	0.25	0.61	0.86	0.58
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC

Table (9) Treatment intensity by banker characteristics

This table presents the results of difference-in-differences regressions similar to Table 5, Panel A, but splitting the treatment group by banker characteristics. Panel A splits the treatment group by whether the banker holds a front-office sales role or other roles. The front-office roles are finance and insurance branch manager (ISCO-08: 1346), financial and investment advisor (2412), securities and finance dealer and broker (3311), and bank teller and related clerk (4211). The other roles are finance manager (1211), financial analyst (2413), credit and loan officer (3312), and statistical, finance and insurance clerk (4312). Panel B includes separate treatment dummies for bankers in the banking industry (NACE: 641, 663), finance professionals in other financial institutions (642: Activities of holdings, 643: Trust, funds, and other financial entities, 649: Financial leasing and other credit granting), and finance professionals outside the finance industry (i.e., employees in finance occupations (ISCO-08 codes: 1211, 1346, 2412, 2413, 3311, 3312, 4211, 4312) working in companies outside the finance industry such as CFOs, risk managers, and their support staff). The regressions include individual ("I") and year ("T") fixed effects and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs. Column titles indicate the banker's family member whose financial market participation the column studies.

	Panel A: Bankers' professional role		
	(1) Partner	(2) Parent	(3) Sibling
Post × Treat (Front office)	0.053***	0.023***	0.016**
	(4.63)	(3.36)	(2.12)
Post × Treat (Other roles)	0.065***	-0.002	0.009
	(2.67)	(-0.13)	(0.62)
Obs.	1,240,630	1,126,040	1,741,750
Number of individuals	124,063	112,604	174,175
Number of treated individuals	.	.	.
... front office	840	1,870	1,550
... other role	189	372	429
R-squared	0.77	0.80	0.77
Fixed effects	I, T	I, T	I, T
Time trends	BC	BC	BC

	Panel B: Bankers' industry		
	(1) Partner	(2) Parent	(3) Sibling
Post × Treat (Working in banking)	0.055***	0.018***	0.014**
	(5.33)	(2.97)	(2.14)
Post × Treat (Working in other finance)	0.003	-0.001	-0.004
	(0.28)	(-0.06)	(-0.50)
Post × Treat (Working outside finance)	0.002	-0.006	-0.003
	(0.63)	(-0.91)	(-0.95)
Obs.	1,240,630	1,126,040	1,741,750
Number of individuals	124,063	112,604	174,175
Number of individuals treated by bankers	.	.	.
... working in banking	1,029	2,242	1,979
... working in other finance	681	480	1,174
... working outside finance	6,968	1,982	8,705
R-squared	0.77	0.80	0.77
Fixed effects	I, T	I, T	I, T
Time trends	BC	BC	BC

Table (10) Spillover effects on co-workers of banker's family members

This table presents difference-in-differences regressions similar to Table 5, Panel A, but replacing the dependent variable with financial market participation of the co-workers of the family members. The treatment group includes individuals working in the same establishment as the banker's family members at the time of treatment. The control group is defined in the same way as the treatment group, except for using the non-bankers' family members. Panel A analyzes all co-workers whereas Panel B restrict the sample to establishments with less than 100 or 25 employees. To reduce the influence of large establishments, all regressions weight observations by the inverse number of co-workers in an establishment. The regressions include individual ("I") and year ("T") fixed effects and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs. Column titles indicate the banker's family member whose financial market participation the column studies.

	Panel A: Baseline		
	(1) Partner	(2) Parent	(3) Sibling
Post × Treat	0.0006 (0.16)	-0.0005 (-0.17)	0.0002 (0.07)
Obs.	11,337,820	10,744,620	12,109,040
Number of individuals	1,133,782	1,074,462	1,210,904
Number of treated individuals	78,232	92,678	120,040
R-squared	0.77	0.78	0.77
Fixed effects	I, T	I, T	I, T
Time trends	BC	BC	BC

	Panel B: Excluding large establishments					
	Less than 100 coworkers			Less than 25 coworkers		
	(1) Partner	(2) Parent	(3) Sibling	(4) Partner	(5) Parent	(6) Sibling
Post × Treat	-0.002 (-0.31)	-0.001 (-0.45)	-0.002 (-0.67)	-0.007 (-0.91)	-0.0041 (-0.88)	-0.0023 (-0.50)
Obs.	6,729,520	6,149,370	7,538,210	2,686,610	2,371,690	3,231,200
Number of individuals	672,952	614,937	753,821	268,661	237,169	323,120
Number of treated individuals	9,927	18,637	20,837	2,889	5,620	5,774
R-squared	0.77	0.78	0.77	0.77	0.78	0.77
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC

Internet Appendix: The Banker in Your Social Network

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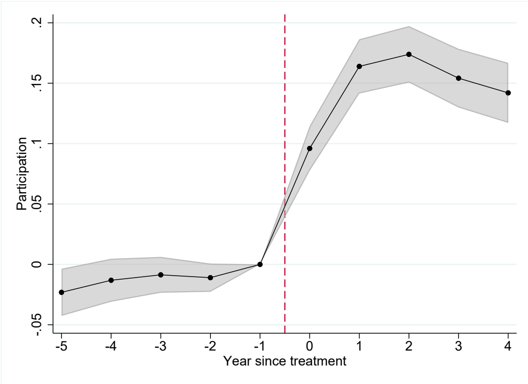
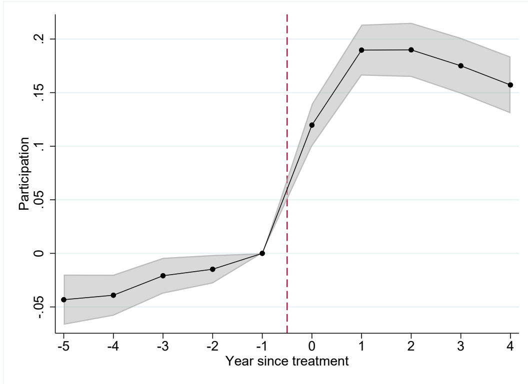
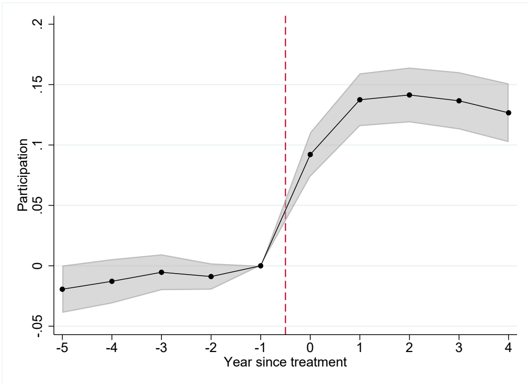
June 1, 2023



(a) Partner



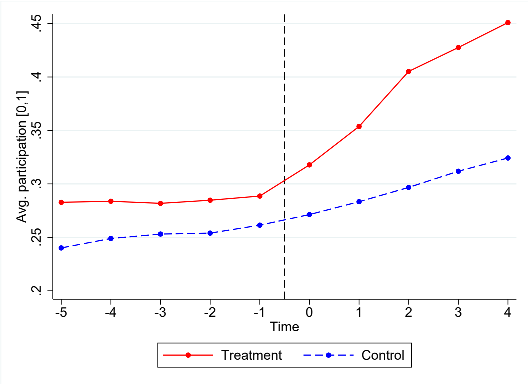
(b) Child



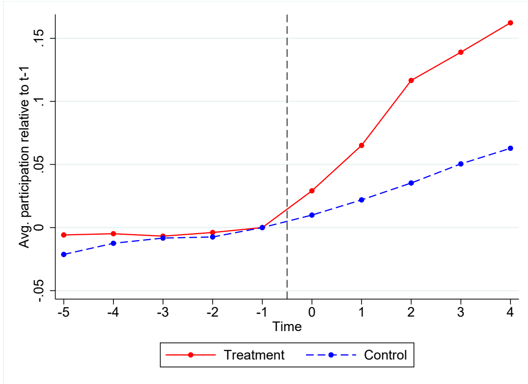
(c) Sibling

Figure (IA1) Financial market participation of bankers around their job switch

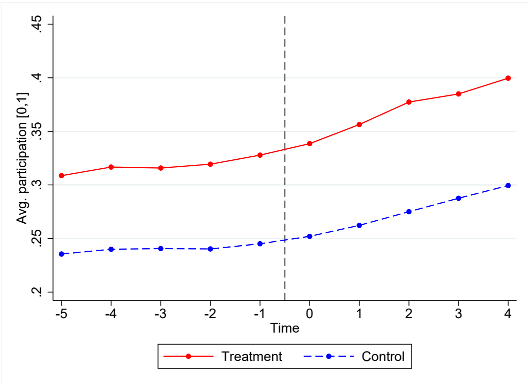
This figure displays coefficients from a linear probability model that explains financial market participation with event time dummies interacted with the treatment indicator. The sample consists of individuals who switched jobs across industries. The first year in which an individual works in the new job is t=0 and the omitted year is $t = -1$. The three panels display effects for the banker's partners (a), parents (b), and siblings (c). The regressions include individual and year fixed effects and fixed effects for interacting each birth year with year. Standard errors are clustered by the individual who switches jobs. The shaded area around the point estimates displays the 95% confidence intervals.



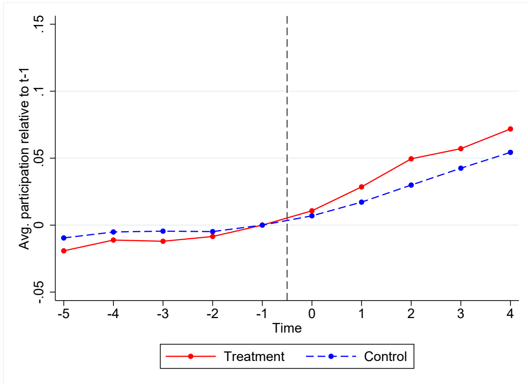
(a) Partner



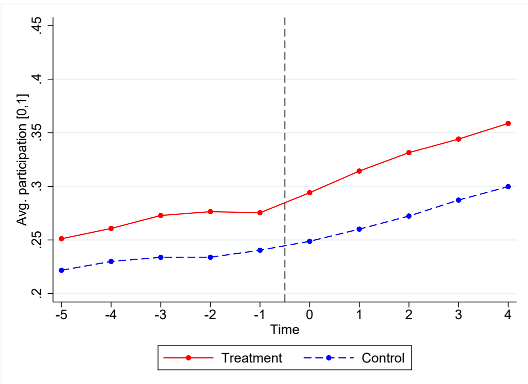
(b) Partner



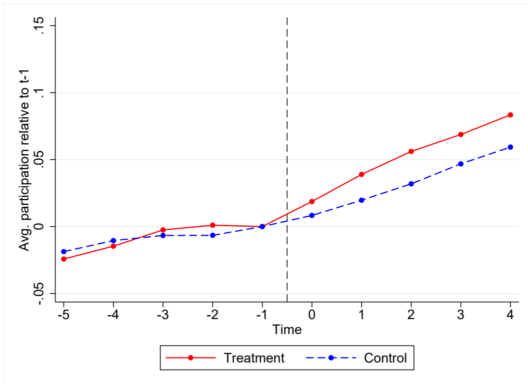
(c) Parent



(d) Parent



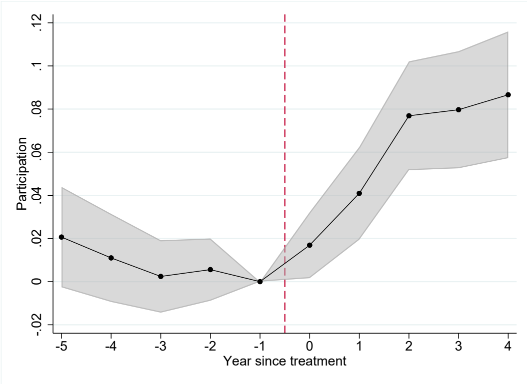
(e) Sibling



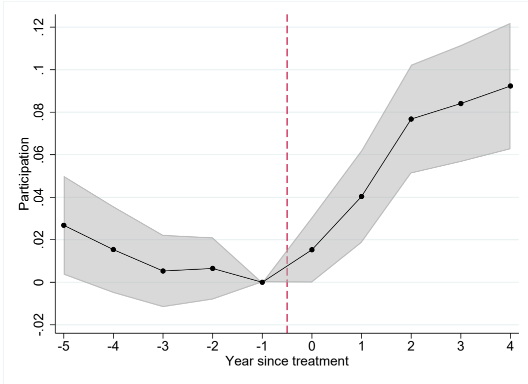
(f) Sibling

Figure (IA2) Average financial market participation of family members around the banker's job switch

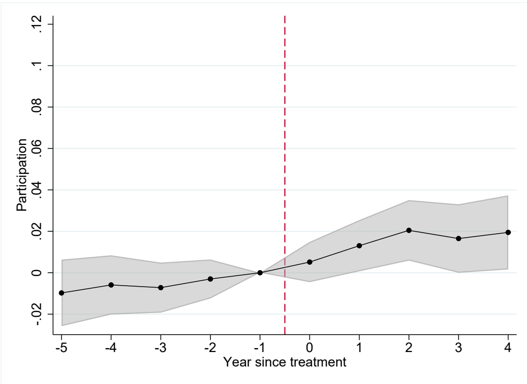
This figure displays the average financial market participation of individuals whose relatives changed jobs across industries. The treatment group consists of individuals whose family members become bankers whereas the control group includes all other job switchers. The first year in which an individual works in the new job is $t = 0$ and the omitted year is $t = -1$. Panels (a), (c), and (e) present the average participation of individuals in the treatment and control group whereas panels (b), (d), and (f) present the average participation relative to $t = -1$. The six panels display effects for job switchers' partners (a, b), parents (c, d), and siblings (e, f).



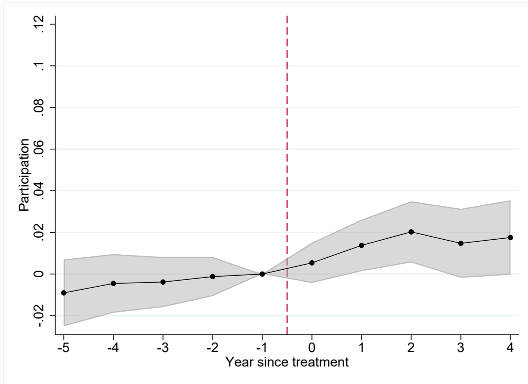
(a) Partner - Related industry sample



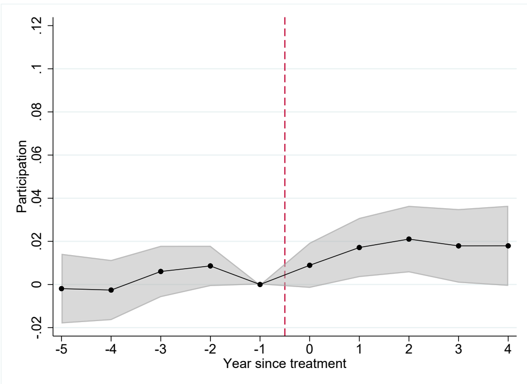
(b) Partner - Matched sample



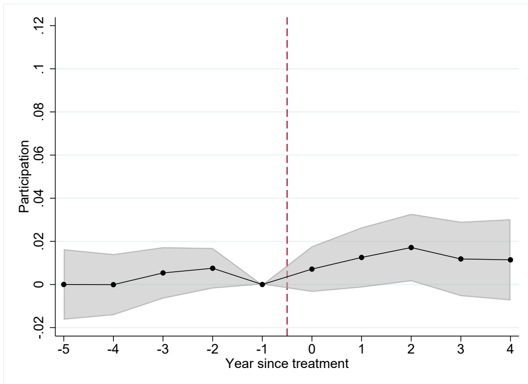
(c) Parent - Related industry sample



(d) Parent - Matched sample



(e) Sibling - Related industry sample



(f) Sibling - Matched sample

Figure (IA3) Financial market participation of family members around the banker's job switch in alternative samples

This figure displays coefficients from a linear probability model that explains financial market participation with event time dummies interacted with the treatment indicator similar to Figure 1, but estimated in the two additional samples in Table 5. Panels (a), (c), and (e) restrict the sample to individuals whose family members switch jobs into related industries (information and communication, finance and insurance, real estate, professional, scientific and technical activities, and administrative and support activities). Panels (b), (d), and (f) use a matched sample based on a coarsened exact match on the following pre-treatment ($t = -6$) characteristics: marital status (married, divorced, single), number of months unemployed, level of education (basic, high school, bachelor, master or higher), annual income deciles, occupational status (self-employed, employee, retired, other) and five-year birth year bins. The panels display effects for the banker's partners (a, b), parents (c, d), and siblings (e, f). The first year in which an individual works in the new job is $t = 0$ and the omitted year is $t = -1$. The regressions include individual and year fixed effects and fixed effects for interacting each birth year with year. Standard errors are clustered by the individual who switches jobs. The shaded area around the point estimates displays the 95% confidence intervals.

Table (IA1) Pooling all family members to one banker indicator

This table presents results from linear probability models similar to Table 3, but pooling all family members (partners, parents, siblings) into one banker indicator. This indicator takes the value of one if at least one of the family members is a banker. Column (1) presents results including year fixed effects ("T") and Column (2) adds controls for gender, marital status (married, divorced, single), number of months unemployed, dummies for four levels of education (basic, high school, bachelor, master or higher), dummies for annual income deciles, dummies for occupational status (self-employed, employee, retired, other), and birth year dummies. Column (3) adds individual fixed effects ("I") and birth year dummies interacted with year dummies ("BC"). Standard errors are clustered by individual.

	(1)	(2)	(3)
Individual is banker	0.374***	0.335***	0.096***
	(86.09)	(77.77)	(8.48)
Family member is banker	0.099***	0.062***	0.021***
	(39.00)	(25.26)	(7.86)
Constant	0.257***	0.205***	0.273***
	(494.06)	(78.65)	(98.38)
Obs.	6,866,763	6,866,763	6,866,763
Number of individuals	625,191	625,191	625,191
R-squared	0.018	0.084	0.743
Fixed effects	T	T	I,T
Time trends	No	No	BC
Controls	No	Yes	Yes

Table (IA2) Treatment heterogeneity in alternative samples

This table presents the results of difference-in-differences regressions similar to Table 6, but estimated in the two additional samples in Table 5. Panel A restricts the sample to individuals whose family members switch jobs into related industries (information and communication, finance and insurance, real estate, professional, scientific and technical activities, and administrative and support activities). Panel B uses a matched sample based on a coarsened exact match on the following pre-treatment ($t = -6$) characteristics: marital status (married, divorced, single), number of months unemployed, level of education (basic, high school, bachelor, master or higher), annual income deciles, occupational status (self-employed, employee, retired, other) and five-year birth year bins. The regressions include individual ("I") and year ("T") fixed effects and birth year dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs. Column titles indicate the banker's family member whose financial market participation the column studies.

	Panel A: Only related industries			Panel B: Matched sample		
	(1) Partner	(2) Parent	(3) Sibling	(4) Partner	(5) Parent	(6) Sibling
Treat × Post	0.077***	0.027**	0.016	0.086***	0.026**	0.014
	(3.38)	(2.56)	(1.56)	(3.74)	(2.53)	(1.29)
Treat × Post × Participant	-0.056**	-0.035**	-0.006	-0.054**	-0.022	-0.002
	(-2.54)	(-2.55)	(-0.41)	(-2.39)	(-1.58)	(-0.12)
Treat × Post × High education	-0.004	0.015	-0.008	0.005	0.008	-0.014
	(-0.15)	(0.95)	(-0.44)	(0.17)	(0.53)	(-0.75)
Treat × Post × High income	-0.048**	0.016	-0.007	-0.049**	0.014	0.002
	(-2.31)	(1.26)	(-0.54)	(-2.35)	(1.09)	(0.16)
Treat × Post × Male	0.026	-0.011	0.013	0.020	-0.014	0.004
	(1.17)	(-0.98)	(0.98)	(0.87)	(-1.28)	(0.31)
Post × Participant	-0.177***	-0.163***	-0.180***	-0.182***	-0.173***	-0.184***
	(-45.25)	(-38.30)	(-49.97)	(-35.67)	(-47.71)	(-50.81)
Post × High education	0.040***	0.036***	0.037***	0.030***	0.043***	0.037***
	(10.09)	(7.60)	(9.92)	(6.06)	(8.52)	(6.70)
Post × High income	0.002	0.026***	0.021***	0.003	0.025***	0.006
	(0.47)	(7.55)	(6.83)	(0.58)	(6.83)	(1.27)
Post × Male	0.025***	0.003	0.017***	0.030***	0.003	0.025***
	(7.32)	(0.89)	(6.16)	(8.45)	(1.16)	(7.72)
Obs.	290,710	266,380	399,870	689,380	808,340	1,085,090
Number of individuals	29,071	26,638	39,987	68,938	80,834	108,509
Number of treated individuals	1,029	2,242	1,979	1,016	2,180	1,930
R-squared	0.77	0.81	0.78	0.75	0.81	0.76
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC

Table (IA3) Participation in risky and safe asset classes in alternative samples

This table presents the results of difference-in-differences regressions similar to Table 7, but estimated in the two additional samples in Table 5. Panel A restricts the sample to individuals whose family members switch jobs into related industries (information and communication, finance and insurance, real estate, professional, scientific and technical activities, and administrative and support activities). Panel B uses a matched sample based on a coarsened exact match on the following pre-treatment ($t = -6$) characteristics: marital status (married, divorced, single), number of months unemployed, level of education (basic, high school, bachelor, master or higher), annual income deciles, occupational status (self-employed, employee, retired, other) and five-year birth year bins. The dependent variable indicates financial market participation via either risky or safe assets. Risky assets are direct stock holdings, equity funds, balanced funds, and alternative funds whereas safe assets include long-term and short-term bond funds. The regressions include individual ("I") and year ("T") fixed effects and birth cohort dummies interacted with year dummies ("BC"). Standard errors are clustered by the family member who switches jobs. Column titles indicate the banker's family member whose financial market participation the column studies.

	Panel A: Only related industries					
	Partner		Parent		Sibling	
	(1) Risky	(2) Safe	(3) Risky	(4) Safe	(5) Risky	(6) Safe
Post × Treat	0.052***	0.004	0.019***	0.002	0.016**	0.001
	(4.98)	(0.67)	(2.99)	(0.47)	(2.33)	(0.30)
Obs.	290,710	290,710	266,380	266,380	399,870	399,870
Number of individuals	29,071	29,071	26,638	26,638	39,987	39,987
Number of treated individuals	1,029	1,029	2,242	2,242	1,979	1,979
R-squared	0.77	0.66	0.81	0.66	0.78	0.66
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC
	Panel B: Matched sample					
	Partner		Parent		Sibling	
	(1) Risky	(2) Safe	(3) Risky	(4) Safe	(5) Risky	(6) Safe
Post × Treat	0.051***	0.004	0.017***	0.003	0.012*	-0.001
	(4.91)	(0.77)	(2.65)	(0.63)	(1.74)	(-0.20)
Obs.	689,380	689,380	808,340	808,340	1,085,090	1,085,090
Number of individuals	68,938	68,938	80,834	80,834	108,509	108,509
Number of treated individuals	1,016	1,016	2,180	2,180	1,930	1,930
R-squared	0.75	0.64	0.80	0.67	0.75	0.66
Fixed effects	I, T	I, T	I, T	I, T	I, T	I, T
Time trends	BC	BC	BC	BC	BC	BC