Till Death (or Divorce) Do Us Part:
Early-life Family Disruption and Investment Behavior

André Betzer
BUW - Schumpeter School of Business and Economics

Peter Limbach
University of Cologne and Centre for Financial Research (CFR)

P. Raghavendra Rau
University of Cambridge
(Corresponding author)

Henrik Schürmann
BUW - Schumpeter School of Business and Economics

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Abstract

We document a long-lasting association between a common societal phenomenon, early-life family disruption, and investment behavior. Controlling for socioeconomic status and family background, we find fund managers who experienced the death or divorce of their parents during childhood exhibit a stronger disposition effect, take lower risk, and are more likely to sell their holdings following risk-increasing firm events. The results are consistent with persistent symptoms of post-traumatic stress and strengthen as treatment intensifies. The evidence adds to our understanding of the role of social factors and "nurture" in finance as well as the origin of investment biases.

Keywords: Disposition effect, Family disruption, Feelings, Formative experience, Investor behavior, Risk-taking, Social finance

JEL codes: G11, G23, G41

Betzer and Schürmann: University of Wuppertal, Schumpeter School of Business and Economics, Gaußstr. 20, 42119 Wuppertal, Germany (e-mail: betzer@wiwi.uni-wuppertal.de and henrik.schuermann@gmail.com); Limbach: University of Cologne and the Centre for Financial Research (CFR), Albertus-Magnus-Platz, 50923 Cologne, Germany (e-mail: plimbach@wiso.uni-koeln.de). Rau: Cambridge Judge Business School, Trumpington Street, Cambridge CB2 1AG, United Kingdom (email: r.rau@jbs.cam.ac.uk). We would like to thank Mike Anderson, Vineet Bhagwat, Robert Campbell, Jay Choi, Martijn Cremers, Henrik Cronqvist, Qingjie Du, Chris P. Duk, Oguzhan Karakas, Matti Keloharju, Alessandro Previtero, Stefan Trautmann, and seminar participants at Cambridge University, the Centre for Financial Research, the 2019 FMA Asian meetings, the 2020 FMA meetings, the 2019 German Finance Association meetings, and the 2020 Western Finance Association meetings for helpful comments. We are also grateful to our editor, Geert Bekaert, and two anonymous referees for their comments.

1. Introduction

"I had a very nice childhood, certainly. […] And then he [her father] died at the age of 38, which I'm sure had a profound effect on me, because I was then 12."

– Judith Lawrie, principal and portfolio manager at HLM Venture Partners (Boston, MA)[1]

The emerging field of social finance examines how societal issues affect economic behavior (Hirshleifer, 2015; Cronqvist, 2018).[2] This literature has only recently begun to study the financial-economic consequences of broad societal developments, such as anti-discrimination movements (e.g., Lins et al., 2020), climate change (e.g., Krueger, Sautner, and Starks, 2020), and terrorism (e.g., Dai et al., 2020). We contribute to this literature by showing that a common societal issue, *early-life family disruption*, is associated with long-lasting differences in investment behavior.

Understanding how financial decisions relate to early-life family disruption is important because family disruption affects children across virtually all societies. According to 1998 data from the U.S. Bureau of the Census and demographer estimates for the period from World War II to the early 1990s, half of first marriages in the U.S. end up voluntarily dissolved and slightly more than half of all divorces involve children under the age of 18 (see Amato, 2000). The proportion of marriages ending in divorce in the U.S. has also historically been high, equaling at least 30% since the 1960s (Schoen et al., 1985). Furthermore, in 2008, one out of every 20 children in the U.S. aged 15 or younger suffers the loss of one or both parents (Owens, 2008). Hence, given their prevalence and documented impact, it is important to examine whether and how these experiences relate to investment decisions that can affect the allocation of capital in financial markets.

In this paper, we examine investment behavior by mutual fund managers, i.e., professional investors who perform standardized professional tasks and share a comparable socioeconomic status. Mutual fund investments constitute a substantial portion of financial wealth for the average U.S. household and mutual fund managers play an important societal role as delegated investors

[1] Interview on May 17, 2000, Schlesinger Library, Radcliffe Institute Records of the Harvard-Radcliffe Program in Business Administration Oral History Project, 1945-2015.

[2] Social factors include aspects of socialization (e.g., Cronqvist and Yu, 2017; Duchin, Simutin, and Sosyura, 2020), social interactions (e.g., Hong, Kubik, and Stein, 2004; Kaustia and Knüpfer, 2012; Huang, Hwang, and Lou, 2019), as well as ideologies and religions (e.g., Kumar, Page, and Spalt, 2011; Hong and Kostovetsky, 2012), among others.

of household wealth. However, while existing evidence indicates that fund managers are subject to behavioral biases such as the disposition effect[3] (e.g., Frazzini, 2006), we still know very little about where these investment biases originate (Hirshleifer, 2015).

Using unique hand-collected data, we show that fund managers who experienced the death or divorce of their parents during their childhoods exhibit stronger disposition effects and take less risk, even after accounting for various socioeconomic and family factors. We also examine moderators of the relation between family disruption and investment behavior, specifically social support, the age at which a manager experienced family disruption, and family wealth.

Our results are consistent with the literature in social psychology and medicine that shows that deep personality traits can be molded by early childhood experiences. The social psychology literature, based on seminal work by Freud (1953) and Bronfenbrenner (1979), suggests that an individual's early-life family environment plays an essential role in forming his or her personality and preferences. Black et al. (2017) show that environmental factors, such as the labor market risk of the parents, substantially determine the intergenerational transmission of risk-taking behavior. Barnea, Cronqvist, and Siegel (2010) and Cesarini et al. (2010) show that genetic factors explain at most one-third of the cross-sectional variation in risk-taking, leaving significant variation to be explained by environmental factors. Recent evidence suggests that environmental treatments, such as cultural heritage or experience of recessions or natural disasters, can have persistent effects on highly educated and experienced CEOs (e.g., Pan, Siegel, and Wang, 2020; Bernile, Bhagwat, and Rau, 2017; Malmendier, Tate, and Yan, 2011). However, the evidence on lasting early-life shocks to the family of the professional is limited. The few existing studies on the role of the manager's family examine short-term economic effects of changes to either the *family of choice* (the family created by choice of partner) (e.g., Roussanov and Savor, 2014; Cronqvist and Yu, 2017) or the *family of origin* (the family the subject is born into) (e.g., Liu et al., 2019). The lack of evidence on the long-term effects arising from the family of origin is surprising given that it is the "*most important and enduring of all human social groupings*" (Smith et al., 2009, p.5). We provide some of the first pieces of evidence on the lasting role that specific early-life family factors can play for the investment behavior of finance professionals.

[3] The disposition effect describes the greater propensity of individuals to sell stocks when they are at a gain than when they are at a loss (Shefrin and Statman, 1985).

Laudenbach, Malmendier, and Niessen-Ruenzi (2019) argue that long-lasting effects of imprinting experiences are likely to have deep biological foundations. The medical literature corroborates this argument, suggesting that these experiences may create deep-seated cognitive effects that cannot simply be undone with education or training. Medical studies provide evidence that both parental death and divorce in childhood have a long-lasting influence on the hypothalamic-pituitary-adrenal (HPA) axis, a major neuroendocrine system in our body that controls reactions to stress. As a result, early-life family disruption can lead to syndromes of *post-traumatic stress* in adulthood, particularly vulnerability to future loss (e.g., Mireault and Bond, 1992), lower self-esteem (e.g., Lutzke et al., 1997), and an increased level of anxiety (e.g., Kendler et al., 1992). Anxiety, in turn, increases individuals' risk aversions (e.g., Loewenstein et al., 2001; Kuhnen and Knutson, 2005), while lower self-esteem has been related to the disposition effect (Hirshleifer, 2015). Hence, relative to their untreated cohorts, we expect investors who experienced early-life family disruption to exhibit a stronger disposition effect and take less risk.

Following the procedure described in Chuprinin and Sosyura (2018), we hand-collect information on fund managers' family backgrounds and their parents' deaths and marital status from various sources, such as the U.S. census, other federal and state records, and historical newspaper articles. We find that the investment behavior of fund managers who experienced early-life family disruption, defined as the death or divorce of the parent(s) before the age of 20, indeed differs significantly from their untreated cohorts, in a manner consistent with the symptoms of long-seated traumatic childhood stress. Specifically, we find that treated managers exhibit a significantly stronger disposition effect. They also reduce total fund risk by up to 20 percent (relative to the mean) after assuming office. The reduction in fund risk manifests in less idiosyncratic and market risk and a lower tracking error of the funds they manage. Treated managers are also significantly more likely to sell their holdings following risk-increasing firm events, i.e., exogenous CEO turnover and M&A transactions.

Our results are based on regressions including various fixed effects, such as fund (and/or fund family) fixed effects as well as manager birth cohort and birth state fixed effects. The latter two account for managers who grew up during different times or in different U.S. states and might have been subject to different factors influencing their investment behavior, such as different economic conditions (Malmendier and Nagel, 2011), different crime rates, and different likelihoods of family disruption.

Our results persist when we additionally control for a broad set of socioeconomic and family background measures, including the parents' age and country of birth, home owner status, and occupation (e.g., whether the parents were both working, were blue-collar workers or self-employed) as well as the fund manager's number of siblings and whether she is a first-born. In contrast to our family disruption measure, none of these measures consistently explains variation in fund manager investment behavior. Our results are robust to the use of both coarsened exact matching and propensity score matching methodologies and various controls for socioeconomic effects to further address concerns of omitted variable bias. We also find no indication that the effect of family disruption is moderated by the wealth of the fund manager's family or that our results are driven by fund managers providing (financial) support for their bereaved parent.

To address further concerns regarding identification, we exploit heterogeneity in disruption events. Specifically, we separately examine parental deaths and divorces as well as unexpected deaths and deaths of non-working mothers. Difficult parental relations might, for example, cause a divorce and simultaneously affect children's investment behavior later in life. However, our results remain significant for each of the four event types. These tests also provide evidence that a wealth shock caused by a parental death is unlikely to drive our results given that deaths of non-working mothers arguably do not constitute significant shocks to family wealth or socioeconomic status. This conclusion is also supported when we restrict the sample to those deaths that involve children of school age and bereaved parents who had at least the same level of education as their deceased spouses. In these cases, the bereaved parent is arguably more likely to compensate for the financial loss induced by a parental death. Overall, the evidence supports the view that the trauma of family disruption relates to investment behavior later in life.

We additionally investigate moderators that potentially cause variations in treatment intensity across treated managers and may affect the strength of the link between family disruption and investment behavior. We compare fund managers who experienced family disruption during their formative years, i.e., age 5-15 (Bernile, Bhagwat, and Rau, 2017), to managers who had similar experiences during their non-formative years (0-4 or 16-19 years). We also exploit variation in social support and welfare using the fraction of people with a religious denomination in the county where a manager's family lived at the time of the parental death or divorce. We find a significantly stronger association between family disruption and fund risk when the disruption occurred during managers' formative years or when the manager's family had less social support.

The disposition effect is also stronger in case of less social support, while we find a similar association for formative and non-formative years. The results mitigate possible endogeneity concerns as any omitted variable would have to show similar patterns.

Finally, we investigate whether the existence of a skill gap between managers who experienced early-life family disruption and those who did not might explain our results. We examine active share as a measure of manager skill, as suggested by Cremers and Petajisto (2009), as well as risk-adjusted performance. Our tests provide no indication of a skill gap. Treated managers are not less active, nor do they perform better or worse than their untreated cohorts. The performance result is consistent with evidence suggesting that the disposition effect does not relate to fund performance (Cici, 2012).

Our study is broadly related to two papers, which are also concerned with fund managers' *family of origin*. Chuprinin and Sosyura (2018) establish a socioeconomic link between family descent and subsequent performance of mutual fund managers. Using a similar data source to ours, they find that fund managers born from poor families outperform managers born from rich families, arguing that unlike managers from rich families, managers born poor are promoted only if they outperform, as they lack the network that rich family managers can draw upon. Their study contributes to the literature on the labor market in the fund management industry. In contrast, we study a traumatic and common societal phenomenon experienced by fund managers during their childhood. Our paper contrasts with theirs in that we show evidence that early-life family conditions affect deep-seated personality traits that, in turn, affect investment behavior, even after accounting for the family's socioeconomic status. In a concurrent working paper, Liu et al. (2019) exploit deaths of managers' parents to study whether bereavement has a direct immediate impact on investment decisions. We address a fundamentally different research question from Liu et al. (2019). Instead of asking whether bereavement events *during* managers' tenures have short-term effects on investment behavior, we ask whether there is a long-term association between investment behavior and early-life traumatic events.

Our study contributes to two strands of the literature. First, we contribute to the emerging literature on social finance, particularly to the recent literature on the financial consequences of societal phenomena. Hirshleifer (2015, p. 151) argues that *"there is a need to move from behavioral to social finance"* and calls for more research on how social aspects relate to financial behavior. We document that an early-life disruption of the family of origin, an event that many children are subject to, is associated with investors' behavior later in life. Second, our study contributes to the literature on the role that environmental treatments, particularly "nurture", play in explaining differences in individuals' investment behavior (e.g., Barnea, Cronqvist, and Siegel, 2010; Cesarini et al., 2010). In contrast with existing studies, we unravel investors' family backgrounds using comprehensive data on fund managers' families of origin to enhance our understanding of the factors of "nurture" and relate them not only to financial risk-taking but also to the disposition effect. Our results suggest that the (in)stability of the family, rather than specific features of the family environment, consistently relates to investment behavior later in life.

2. Motivation and Theoretical Underpinning

Psychological research posits that early-life family background plays an essential role in forming individuals' personality and preferences (e.g., Freud, 1953; Bronfenbrenner, 1979; Bornstein, 2015). In this context, attachment theory (Bowlby, 1969, 1973, 1980) focuses on the role that early attachments play in the development of the individual. Central to this theory is the idea that a disruption of the bond between a child and his or her attachment figures has important implications for the child's subsequent development. It is thus not surprising that psychologists rank parental deaths and parental divorces among the most severe experiences that children can make (e.g., Monoghan, Robinson, and Dodge, 1979), and the causes of family disruption are often seen as traumatic turning points in children's lives (Rutter, 1996).

Evidence from developmental psychology indicates that experiencing early-life family disruption has extremely long-lasting effects on personality and well-being (Amato and Keith, 1991; Tennant, 1991; Parsons, 2011; Ellis, Dowrick, and Lloyd-Williams, 2013; Flèche, Lekfuangfu, and Clark, 2019). Medical research suggests channels that drive these long-term effects: Parental death and divorce in childhood increase psychological distress in adulthood due to a dysregulation of the hypothalamic-pituitary-adrenal (HPA) axis, which increases individuals' cortisol levels (e.g., Nicolson, 2004; Bloch et al., 2007). Further, Meinlschmidt and Heim (2007) show altered central sensitivity to the effects of oxytocin (relevant to protection against stress) after early parental separation, and Luecken and Appelhans (2005) find that parental loss or divorce increases the risk of affective disorder into adulthood. Accordingly, early-life family disruptions act as chronic stressors for individuals (Vezzetti, 2008), often leading to symptoms of post-traumatic stress (see also Stoppelbein and Greening, 2000).

As a result, individuals who experienced early-life family disruption show greater perceived vulnerability to future loss (e.g., Mireault and Bond, 1992)[4], lower self-esteem (e.g., Lutzke et al., 1997; Ellis, Dowrick, and Lloyd-Williams, 2013), and higher levels of anxiety (e.g., Bifulco et al., 1992; Kendler et al., 1992; Tyrka et al. 2008). Background emotions, such as general anxiety, in turn, affect people's long-term behavior (e.g., Engelmann et al., 2015). Specifically, anxiety has been shown to increase risk aversion (e.g., Loewenstein et al., 2001; Kuhnen and Knutson, 2005; Maner and Schmidt, 2006; Maner et al., 2007), even after controlling for beliefs (Kuhnen and Knutson, 2011). Consequently, investors who experienced early-life family disruption can be expected to take less risk.

Apart from risk-taking, enhanced vulnerability to future loss and lower self-esteem can be expected to relate to individuals' reluctance to realize losses and hence to the disposition effect. While several studies provide evidence that even investment professionals are subject to this investment bias (e.g., Frazzini, 2006), Hirshleifer (2015) notes that the origins of the disposition effect are relatively unexplored. Hirshleifer also argues that the reversal of the disposition effect when investors can assign blame to others (Chang, Solomon, and Westerfield, 2016) indicates that people's urge to maintain self-esteem is a key driver of the effect. Hence, we expect investors to be more prone to the disposition effect if they experienced early-life family disruption, leading to reduced self-esteem and increased vulnerability to future loss.

We note that the literature also provides some evidence for personal growth following trauma (Tedeschi and Calhoun, 2004). In the case of parental divorce, children may develop competencies and grow personally as they undertake divorce-related challenges (Bernstein and Robey, 1962; Gately and Schwebel, 1992). Mack (2001) reports that adults who experienced parental divorce in childhood have higher levels of self-confidence than adults raised in intact families. Similarly, Maier and Lachman (2000) find that the early death of a parent can cause men to have more confidence in their own opinion. Individuals with high self-confidence, in turn, believe more in themselves and are not easily swayed by risk, which makes them more likely to make riskier choices (Chuang et al., 2013). Thus, post-traumatic growth may also affect investment

[4] Mireault and Bond (1992) find that bereaved survey participants worry significantly more about future losses than non-bereaved participants.

behavior by fostering risk-taking and by mitigating the disposition effect via enhanced self-confidence.

It is thus an open empirical question whether early-life family disruption has a long-term influence on investors' risk-taking behavior and the disposition effect later in life. Addressing this question to provide an understanding of how family disruption relates to investment behavior is important, even beyond just the finance literature.

3. Data, Methodology, and Summary Statistics

3.1. Data

3.1.1. Mutual fund and manager data

To construct our initial sample, we obtain information on fund managers from Morningstar Direct for the period from 1980 to 2017.[5] Morningstar reports the name of each manager of a fund and provides information on the manager's education, employment history, and the start and end date with a fund. We limit our sample to U.S.-domiciled equity funds (active and defunct) by filtering the U.S. Category Group for "US Equity". We exclude index, sector, and specialty funds. A fund share class is only included in our sample if its Morningstar style and CUSIP are available. We obtain fund characteristics and returns from the Center for Research in Security Prices (CRSP) Survivor Bias-Free Mutual Fund Database. We use the fund's CUSIP to match Morningstar and CRSP data and combine share classes using MFLINKS. We obtain fund return data and fund characteristics from CRSP. These data include the fund's expense ratio, turnover ratio, total net assets (TNA), fund family size, and a fund's first offer date. Return, expense ratio, and turnover ratio are the TNA-weighted average across all fund share classes.[6] We obtain portfolio holdings data from the Thomson Reuters Mutual Fund Holdings database, which we merge with the CRSP mutual fund data using MFLINKS. To establish a clean correspondence between fund manager family background and mutual fund risk, we exclude team-managed fund years and years in which

[5] We choose Morningstar Direct as the source for fund manager information as it is more accurate than CRSP (Patel and Sarkissian, 2017).
[6] If fund characteristics are available at a higher frequency, such as monthly or quarterly, we use the last available data point in a year to construct our annual sample.

a single-managed fund is managed by more than one manager due to manager turnover. We obtain a sample of 2,139 managers who pass these initial criteria.

Next, we obtain the most complete version of a manager's name, including the full middle name and name suffixes, using the Financial Industry Regulatory Authority (FINRA) investment adviser registration records. We use the employment history provided in FINRA to confirm the accuracy of a match. We then complement our data on managers' education with information from Bloomberg, Capital IQ, funds' SEC filings, employer websites, managers' LinkedIn profiles, and Marquis Who's Who records. We manually search for a manager in each of these sources and only add information to our sample if we verify a match using a manager's full name and employment history. Sometimes we are also able to obtain the names of a fund manager's parents, e.g., from Marquis Who's Who.

Finally, we gather information on the manager's birth year. For managers without information on age or birth year from the above sources, we search in the 1992 edition of Nelson's Directory of Investment Managers. For a minority of managers for whom we cannot detect the birth year, we follow Chevalier and Ellison (1999) and approximate it using the graduation year.

3.1.2. Family background data

Our main source of data for information on fund managers' family backgrounds are federal and state records. For the collection of family background data, we limit our sample to managers born in 1949 or earlier. There are two reasons for this restriction. First, we require that the latest available U.S. decennial census - the main data source for family control variables - accurately reflects a manager's familial situation. The U.S. government does not release personally identifiable information about individuals until 72 years after it was collected for the decennial census ("72-Year Rule", 92 Stat. 915; Public Law 95-416; October 5, 1978). Thus, the latest decennial census with personally identifiable information available is the 1940 federal census. Second, by restricting our sample to fund managers born in 1949 or earlier, we ensure that (most of) the managers' parents have died, so that we can identify the parents' death years. This filter restricts the sample to 615 managers. Investigating managers' backgrounds, we find that 36 managers were raised outside the U.S. and, as a result, their families were not covered in the U.S. census. After eliminating these cases, we end up with 579 fund managers with potential census records.

To identify personal census records for the households in which fund managers grew up, we apply the data collection procedure described in Chuprinin and Sosyura (2018) with some minor modifications. We provide a detailed description of our data collection methodology in Internet Appendix A. We are able to find the households' census records for 538 (93%) of our 579 fund managers.[7] This share is essentially the same as in Chuprinin and Sosyura (2018). In terms of the number of fund managers, our sample compares favorably with extant studies on (older) fund managers, e.g., Chevalier and Ellison (1999) (492 managers), Chuprinin and Sosyura (2018) (387), Hong and Kostovetsky (2012) (600), and Liu et al. (2019) (471).[8]

The decennial federal census provides information on the home value or rent of each household, the number of household members, their age, class of work (employee, self-employed, government worker, etc.), education, income, occupation, state of birth, and their relation to the household's head. We use this information to search for the manager's parents in state and federal databases maintained by the genealogy research service Ancestry.com. We identify the mother's and father's year of death by screening death records using their full name, birth state, birth year, and place of residence obtained from the census. When we find a match, we search for the person's obituary in local and state newspapers on Newspaper.com (the world's largest online newspaper archive) and on Legacy.com (the largest commercial provider of online memorials) to obtain additional information about the deceased parents. Obituaries typically mention the deceased parent's spouses and other family members. To verify a potential match, we require the obituary to mention the name of the fund manager and the names of other relatives listed in the household's census record. This procedure nearly eliminates the possibility of a spurious match as the identified obituary contains the unique combination of a parent's name, birth state, birth year, name of spouse, children as well as other relatives mentioned in the census. We are able to identify the death years of 1,025 manager parents (502 mothers and 523 fathers). The fact that we obtain death years for nearly all parents in our sample mitigates the concern that our data collection is biased, since newspapers and other public sources might, for instance, be more likely to report deaths of parents from wealthier or more well-known families. We do not remove managers from the sample

[7] In our analyses, we have to rely on a smaller number of fund managers due to a lack of data on fund risk-taking and other fund characteristics.
[8] Our sample is larger than the sample in Chuprinin and Sosyura (2018) since we choose 1949 as the cutoff birth year for fund managers, whereas fund managers in their sample are born in or before 1945.

if we are unable to identify the death records of both parents (given that some parents might still be alive).

To identify parental divorces, we screen death records and obituaries of managers' parents for the following signals: a name of a parent's spouse that is different from the name reported in the census, a reference to a divorce, separation or new marriage, a reference to a step-child, or a male child with a different last name. Our (almost) complete set of parents' death records and obituaries again mitigates the concern that our data collection is biased toward wealthier or more well-known families. If we find an indication for a divorce, we search for a divorce record on Ancestry.com and screen local newspapers for a notification about a divorce, a custody or a maintenance dispute. We verify matches using the names of all relatives and the locations mentioned in these documents. In some cases, we can directly identify a divorce from the U.S. census if the marital status of a manager's parents in the census is "divorced".

We obtain further data from several sources. First, we complement and verify information on fund managers' education using college yearbooks. Second, we extend our information on parental occupations to years after the census using historical U.S. city directories from the locations of the parents' census records. We identify parents in the city directories using their names and addresses from the census record. College yearbooks and city directories are accessible via Ancestry.com. Third, to compare fund managers' parents to other U.S. households, we retrieve anonymized household census data from the Integrated Public Use Microdata Series (IPUMS). Using the IPUMS data, we construct state-level medians for male income, rent, and home value. Fourth, we obtain county-level data on the membership in religious bodies throughout the United States for the year 1952 from the American Religion Data Archive (ARDA).

Overall, our final sample comprises 484 fund managers, 569 funds, and 4,839 fund years for which we have information on whether a fund manager experienced an early-life family disruption or not and for which we have data on funds' total risk.[9] Our sample is economically important given that it accounts for 25% of all assets of single-managed domestic equity funds in the median

[9] A fund can leave the sample for several reasons: (i) it was closed or merged with another fund; (ii) its new fund manager was born after 1949; (ii) its new fund manager was born in or before 1949, but data on his family background is missing; (iv) it switched from a single-managed to a team-managed fund. A fund manager can leave the sample for several reasons such as death or retirement, or because his or her fund becomes team-managed or because the fund manager switches to a team-managed fund. As a result, we do not observe all funds or fund managers every year.

sample year, i.e., 1998. This share is significantly higher in earlier years (up to 73%) and decreases over the more recent years of the sample (e.g., 15% in the 2008 financial crisis). Because we are not able to obtain information on all fund and manager characteristics for all these fund years, most of our empirical analyses on fund-year level are based on fewer observations.

3.2. Methodology and key variables

To examine whether a long-term association between early-life family disruption and fund manager investment behavior exists, we conduct regressions using the baseline model shown in equation (1):

$$\begin{aligned} Investment\ Behavior_{jt} \;=\; & \alpha + \beta \times Family\ Disruption_{jt} + \Gamma_1 \times Fund\ Controls_{jt-1} \\ & + \Gamma_2 \times Manager\ Controls_{jt-1} + \delta + \varepsilon_{jt} \end{aligned} \tag{1}$$

where *j* and *t* index funds and years (or quarters), respectively; δ stands for fixed effects.

Our dependent variables relate to the disposition effect and fund risk. To assess the extent to which funds exhibit a disposition effect, we follow prior studies (e.g., Odean, 1998; Frazzini, 2006; Cici, 2012) and calculate the variable *Disposition Effect* as the difference between the proportion of realized gains and realized losses for each fund in each quarter. We use the average purchase price as the cost basis. A fund that is prone to the disposition effect will disproportionately realize more gains than losses, and the variable *Disposition Effect* will take on larger and positive values. We use four measures of fund risk. The primary risk measure, *Total Risk*, is the standard deviation of monthly gross returns during the year. We decompose *Total Risk* into its idiosyncratic component, i.e., the variable *Idiosyncratic Risk*, and its systematic component, i.e., the variable *Market Risk*, by estimating a market model using a fund's monthly gross returns and the value-weighted return on all NYSE, AMEX, and NASDAQ stocks. *Market Risk* is the estimated β from this model, while *Idiosyncratic Risk* is the standard deviation of the estimated residuals, i.e., the root-mean-squared error. Finally, because the tracking error is an important metric of portfolio risk in the mutual fund industry, we retrieve quarterly data on a fund's tracking error from Antti Petajisto's website for the period 1980-2009. *Tracking Error* is defined as the volatility of the difference between the fund's portfolio return and the return of its benchmark index (Cremers and Petajisto, 2009). The Appendix provides detailed definitions of all variables used in this study.

Our main explanatory variable of interest is *Family Disruption*. This indicator variable equals one if a fund manager experienced either the death of a parent or the divorce of his or her parents before the age of 20, and zero otherwise. We use parental deaths and divorces as the two events that mark the disruption of a manager's family as both are viewed by psychologists as the most severe events that can happen in an individual's childhood and adolescence (e.g., Monoghan, Robinson, and Dodge, 1979; Rutter, 1996). We choose the age of 0-19 years for two reasons: first, to measure the influence of family disruption throughout a manager's entire childhood and teenage years and, second, because children typically leave their parents' households at the age of 19 or younger to attend college or, generally, to gain greater independence from their parents.

Our baseline regression model includes two standard sets of control variables covering fund and manager characteristics that have been used in the prior literature (see for example, Chevalier and Ellison, 1999, Chuprinin and Sosyura, 2018, and Pool et al., 2019, among others). Fund characteristics include the variables *Fund Age*, *Fund Size*, *Fund Family Size*, *Avg. Monthly Return*, *Expense Ratio*, and *Turnover Ratio*. Manager characteristics include the variables *Manager Age* and *Manager Tenure* and the indicator variables *Female*, *Ivy League*, *MBA*, and *PhD*. It is plausible that some of these variables may have confounding effects with the family disruption variable. For example, younger fund managers, who are likely to hold smaller tenures at the fund, are more likely to have experienced family disruption as divorce rates have increased over time. The prior literature (e.g., Chevalier and Ellison, 1999) suggests that age and tenure are important determinants of fund managers' investment behavior. Hence, it is important to control for the manager's age and his tenure with the fund.

Manager characteristics also include controls for a manager's family background, i.e., *Parental Education* and *Family Wealth*, as social class relates to managerial risk-taking (Kish-Gephart and Campbell, 2015). For the former, we follow Chuprinin and Sosyura (2018) and measure the parents' education as their average education attainment score, defined as follows: education attainment equals 3 if the parent attended college, 2 if the parent attended high school but not college, 1 if the parent attended elementary school but not high school, and 0 if the parent has no formal education. We construct *Family Wealth* as a measure for the socioeconomic status of a manager's family during his childhood/adolescence. It is defined as the income of a manager's father reported in the census record, if the record is available and if the father worked for at least 20 full-time equivalent weeks during the previous year. If not, it is defined as the father's home value or rent. Imposing a minimum of 20 full-time equivalent weeks effectively excludes part-time or irregular jobs. In a small number of cases in which neither income nor rent or home value are available for the father, we use the mother's home value or rent. As in Chuprinin and Sosyura (2018), income is expressed in multiples of the state median male income in the state of the household and rent and home values are expressed in multiples of the state median.

All continuous (dependent and explanatory) fund variables are winsorized at the 1st and 99th percentiles. Time-varying explanatory variables enter the regressions with one lag. Further, all regressions include time fixed effects and are complemented with varying other fixed effects (FE), i.e., fund FE, fund family FE, investment style FE (based on Morningstar fund styles), manager birth cohort FE (based on decades), and manager birth state FE. We explain the specific use of different fixed effects in Section 4. Standard errors are clustered at the fund manager level to allow for serial correlation resulting from unobservable managerial characteristics, as in Chuprinin and Sosyura (2018).

For robustness purposes and to compare the importance of family disruption to measures of socioeconomic status and family background, we conduct further regressions based on an extended regression model. Specifically, we complement the regression model in equation (1) by two sets of additional variables that may be related to both family disruption and investment behavior.

The first set of additional variables are indicators related to the occupation of a manager's parents: (i) *Parent Self-employed* equals one if at least one of the fund manager's parents worked on his or her own account or was an employer according to the "class of worker" item in the census, (ii) *Parent Worked in Finance* equals one if at least one of the manager's parents worked in the finance industry, i.e., banking, insurance, investment, or real estate, (iii) *Father Blue-collar Worker*, which equals one if the father's job involved manual labor, e.g., in the manufacturing, mining, or farming industry, and (iv) *Both Parents Working*, which equals one if both parents were employed according to their census records.

The second set of variables is related to the manager's life at home during his or her childhood: (v) *Firstborn* is an indicator equal to one if a manager is the firstborn child, (vi) *Number of Siblings* indicates a manager's number of siblings, (vii) *Avg. Parental Age at Manager's Birth* measures the average age of the parents at the time of the fund manager's birth, (viii) *Parents' Age Difference* measures the absolute age difference between the father and the mother, (ix) *Parent Born Outside U.S.* is an indicator equaling one if at least one parent migrated to the U.S., and (x)

Parent Homeowner equals one if a parent lived in a home that was not rented but owned by the residents according to the parents' census records. Finally, we add the indicator variable *Manager Works for Home State Fund*, which equals one if a fund is managed by a fund manager whose home state is the state in which the fund firm is located.

We also use the baseline regression model to examine whether family disruption relates to fund manager skill using different dependent variables. Specifically, instead of the measures discussed above, we use the following variables on the left-hand side of equation (1): *Active Share* (Cremers and Petajisto, 2009) as well as measures of risk-adjusted performance, i.e., *Alpha* (i.e., one-factor alpha) and *Sharpe Ratio*. We define these variables in the Appendix and discuss the regressions in Section 5.

3.3. Summary statistics

Table 1 presents the summary statistics for our sample. We provide statistics for the total sample as well as for the two subsamples of treated and untreated fund managers (i.e., *Family Disruption* = 1 vs. 0) and report t-statistics for tests of mean differences between the two subsamples. In 15.1% (or 732) of all fund years, a fund is managed by a manager who experienced early-life family disruption (see Panel B). About 70% of family disruptions are early parental deaths and 30% are early divorces. Table IA-A1 in Internet Appendix A provides an overview of the types of parental deaths that caused early-life family disruption. These deaths occurred between 1927 and 1964. We are able to identify the cause of death for more than 70% of all deaths. Only a few parents died during military service (4.7%) or because they suffered from a long-term disease such as hypertension or skin cancer (18.6%). Most parents died suddenly, either due to an accident (2.3%) or due to sudden illness (e.g. pneumonia or stroke) (23.3%) or because of another unknown reason reported to be sudden (23.3%). Hence, the majority of all deaths for which we can identify a cause of death can be classified as sudden and unexpected and are plausibly exogenous.

Panel A shows the statistics for time-invariant fund manager characteristics, including the manager's birth year, education (i.e., *Ivy League*, *MBA*, *PhD*) and gender, as well as his or her family background. Treated and untreated managers do not significantly differ in terms of most of these characteristics. The typical treated and untreated managers were born around the same time (1940 vs. 1941), and have comparable levels of education (54% and 7% of both groups have an MBA and a PhD, respectively). Moreover, their parents also have similar educational backgrounds

(2.3 vs. 2.4), occupations (e.g., 15% vs. 17% worked in finance; 27% vs. 26% of fathers had a blue-collar job), and wealth (3.1 vs. 2.7). Statistically significant differences only exist for three characteristics: treated managers are less likely to be firstborns (42% vs. 56%), the age difference of their parents is, on average, slightly larger (6 vs. 4 years), and their parents are marginally older at the manager's birth (32 vs. 30 years).

Panel B reports summary statistics for time-varying manager and fund characteristics at the fund-year level. Treated managers are marginally older (56 vs. 54.5 years) and have marginally longer tenures (8 vs. 7.5 years). There are significant differences across a number of dimensions for fund characteristics. Specifically, treated and untreated managers differ in terms of the age of the funds they manage (17 vs. 15 years) and the funds' expense ratios (0.013 vs. 0.012). The (family) size, performance, and turnover ratios of the funds are not significantly different across the two groups. Importantly, treated managers are associated with significantly lower total fund risk (0.043 vs. 0.046) and lower market risk (0.932 vs. 0.987). Hence, managers who experienced early-life family disruption appear to be associated with less risky funds. Panel C reports summary statistics at the fund-quarter level. Consistent with Panel B, treated managers' portfolios have a significantly lower *Tracking Error*. The mean *Disposition Effect* is negative indicating that mutual funds realize, on average, more losses than gains, which is consistent with prior findings by Sialm and Starks (2012). Interestingly, funds managed by treated fund managers have, on average, a positive *Disposition Effect* suggesting that they realize disproportionately more gains than losses. The difference in the *Disposition Effect* between treated and untreated managers is significant.

Finally, to illustrate fund managers' backgrounds and locations, Figure IA-A1 in Internet Appendix A depicts the distribution of manager birth states and fund locations. The figure provides no indication of any unusual clustering of birth states or fund locations. As expected, funds are located in states with larger populations and these states are also more likely to be manager birth states, e.g., New York (80 managers in total, 9 treated managers), Massachusetts (48, 3), Pennsylvania (44, 6), Ohio (33, 6), Illinois (31, 2), and California (23, 2).

4. Early-life Family Disruption, the Disposition Effect, and Risk-taking

In this section, we examine the association of early-life family disruption with the disposition effect and risk-taking of fund managers. Section 4.1 presents evidence on the disposition effect, Section 4.2 discusses results on risk-taking behavior, and Section 4.3 provides evidence on fund managers' trading behavior in reaction to events that increase the risk and uncertainty of their investee firms. In Section 4.4, we consider various socioeconomic and family background factors and present evidence from two matching approaches. Sections 4.5 and 4.6, respectively, present evidence on different events and moderators of family disruption.

4.1. Early-life family disruption and the disposition effect

The disposition effect describes the greater propensity of individuals to sell stocks when they are at a gain than when they are at a loss (Shefrin and Statman, 1985). To analyze the prevalence of this investment behavior, we use the variable *Disposition Effect*, which is the difference between the proportion of realized gains and losses for each fund in each quarter (Odean, 1998).

We expect treated fund managers to show a greater tendency for the disposition effect. Individuals who experienced early-life family disruption tend to have less self-esteem, which has been argued to be a key driver of the disposition effect (Hirshleifer, 2015). Furthermore, fund managers who experienced the loss of their parents due to death or divorce, and who are thus more vulnerable to future loss, may also be more likely to avoid the realization of losses in their portfolios and realize gains more quickly.

We regress the variable *Disposition Effect* on the variable *Family Disruption*, along with fund and manager controls and time fixed effects (FE) as described in Section 3.2. We additionally include varying combinations of other fixed effects to control for unobserved heterogeneity across funds and fund managers as well as fund families and investment styles. The results are shown in Table 2.

In specification (1), we include fund family and investment style FE as well as fixed effects for managers' birth cohorts and birth states. Birth cohort and birth state FE allow us to control for the possibility that fund managers who grew up during different times or in different U.S. states might have been differentially likely to have witnessed family disruption (e.g., as divorce rates have increased) and might have been subject to different factors that influence their investment behavior. For example, managers growing up in different periods and in different states are likely to have experienced different (macro)economic and social conditions (e.g., different economic growth, different state-level policy, or different crime rates) and different events, such as natural disasters, which have been shown to affect people's economic behavior (e.g., Malmendier and Nagel, 2011; Bernile, Bhagwat, and Rau, 2017). In specification (2), we use fund FE, instead of fund family and style FE, to account for unobserved time-invariant heterogeneity across funds, while in specification (3), we additionally include fund family and investment style FE. Fund family and investment style FE, in conjunction with fund FE, address the concern that funds change their trading strategy and, simultaneously, hire (fire) treated fund managers as they switch their investment objectives or fund families (typically as the result of fund family mergers). In specification (4), we use fund, birth cohort, and birth state FE. We refer to this specification as our baseline regression model.

Over all four specifications, the coefficient on *Family Disruption* is positive and significant at the 1% level. This finding indicates that fund managers who experienced early-life family disruption exhibit a significantly stronger disposition effect than their untreated cohorts. In particular, the magnitude of the coefficient on the variable *Disposition Effect* in specification (4) of Table 2 amounts to 71% of the variable's standard deviation (= 0.117/0.165). These untreated cohorts were, for example, born in the same decade and state and work for the same fund family or fund. In untabulated robustness tests, we also estimate several other regression specifications using other combinations of fixed effects and find the coefficient on *Family Disruption* to remain statistically significant with comparable coefficient size.[10] Our results also remain qualitatively similar when we measure the disposition effect via the disposition ratio (instead of the spread) (e.g., Odean, 1998; Cici, 2012).

4.2. Early-life family disruption and risk-taking

To examine whether and how early-life family disruption relates to fund manager risk-taking, we next regress different measures of fund risk on our variable of interest, *Family Disruption*. We again include varying combinations of fixed effects to control for unobserved heterogeneity across funds and fund managers as well as fund families and investment styles. The results are shown in Table 3.

Panel A of Table 3 presents the results for *Total Risk*, our main risk measure, and parallels the regression specifications shown in Table 2. The coefficient on *Family Disruption* is negative

[10] The coefficient on *Family Disruption* remains statistically significant when we use fund investment style × time fixed effects, birth cohort × birth state fixed effects, fund family but no fund investment style fixed effects, as well as no fixed effects (except for time). The results also remain statistically significant when we cluster standard errors on fund level instead of fund manager level.

and significant at the 5% level in specification (1) and at the 1% level in specifications (2) to (4), indicating that fund managers who experienced early-life family disruption take significantly less risk than their untreated cohorts. Indeed, our estimates suggest that treated managers reduce total fund risk by up to 20% relative to the sample mean. The magnitude of the coefficient on *Total Risk* in specification (4) of Table 3 equals 41% of the variable's standard deviation (= -0.009/0.022). The coefficient on *Family Disruption* is also important on a relative basis given that it is almost as large as that for fund manager gender (i.e., females) and one magnitude larger than that of a one-decade increase in manager age.

As before, we estimate several other regression specifications in untabulated robustness tests. Across all these untabulated tests, the coefficient on *Family Disruption* continues to remain statistically significant and the size of the regression coefficient remains virtually unchanged.[11]

In Panel B of Table 3, we examine the components of the fund's total risk, i.e., *Idiosyncratic Risk*, *Market Risk*, and the fund's *Tracking Error*. The specifications in Panel B parallel the one presented in specification (4) of Panel A, which includes fund, birth cohort, birth state, and year FE. Over all the specifications, the coefficient on *Family Disruption* is negative and significant at the 5% level or better.[12] Hence, the reduction in total fund risk appears to reflect a reduction in all three components of risk.

4.3. Reactions to risk/uncertainty-increasing events of investee firms

We next investigate how fund managers who experienced early-life family disruption trade in reaction to idiosyncratic increases in risk and uncertainty of their investee firms. This analysis, which is motivated by the approach in Pool et al. (2019), is econometrically important for two reasons. First, it allows us to examine how managers react to arguably unexpected firm events *after* the fund manager-fund matching took place. Second, it enables us to control for fund manager-stock fixed effects, which account for managers' endogenous selection of stocks. We can hence mitigate potential concerns of endogenous fund manager-fund matching, i.e., treated fund

[11] We use fixed effects similar to those mentioned in the previous footnote. Again, the results also remain statistically significant when we cluster standard errors on fund level instead of fund manager level.

[12] In untabulated tests, we re-estimate our fund risk regression model shown in specification 4 of Panel A of Table 3 with semi-deviation and upside beta (Whaley, 2002) as the dependent variables. We find the coefficient on *Family Disruption* to be negative and significant for both measures. Treated fund managers hence appear to reduce both upside and downside potential.

managers preferring to manage less risky funds or fund boards hiring managers to simply execute their plans of reducing fund risk (via selecting lower risk stocks).[13] Importantly, fund manager-stock fixed effects also account for any time-invariant manager characteristics, which rules out that unobserved (early-life) fund manager experiences or differences in innate talent explain our results. Therefore, we are not only able to provide additional insights into the investment behavior of treated managers, but we also strengthen the causal link between early-life family disruption and investment behavior.

To examine this trading behavior, we consider two corporate events, exogenous CEO turnover and takeover announcements, which are difficult to foresee (consistent with the significant stock price reactions to these events). Exogenous CEO turnover is arguably unrelated to prior firm performance and increases firms' risk and uncertainty with regard to subsequent CEO-firm match quality and corporate strategy. Takeovers are major corporate investments, often with long-term impact on the acquiring firm, which are risky in the sense that they can lead to either considerable value creation or value destruction. If fund managers who experienced family disruption indeed take lower risk, we expect them to be more likely to sell their holdings in firms following exogenous CEO turnover or takeover announcements. We examine fund managers' reactions to these two types of events using the regression model in equation (2) below:

$$\begin{aligned} Sell_{jst} = {} & \alpha + \beta_1 \times Family\ Disruption_{jt} \times Event_{jst} + \beta_2 \times Event_{jst} \\ & + \Gamma \times Controls_{jt-1} + \delta + \varepsilon_{jst} \end{aligned} \quad (2)$$

where j, s, and t index funds, stocks, and holding periods, respectively; δ stands for fixed effects.

[13] Internet Appendix D provides an additional test that addresses the concern of endogenous fund manager-fund matching more directly. Specifically, we restrict our sample to those years in which a fund manager takes office in order to examine whether a fund's risk in the previous year has explanatory power for the match between the treated fund manager and the fund. The number of observations in these regressions is relatively small because we are unable to obtain information on (lagged) fund characteristics when the fund manager-fund match occurred before the start of our sample period or when the funds were set up for the first time. We regress the variable *Family Disruption* on $Total\ Risk_{t-1}$, i.e., fund risk in the year before the matching took place, and controls for fund characteristics (i.e., fund age and size, fund family size, performance, turnover and expense ratios), which also enter the regressions with one lag. We further control for year and investment style fixed effects. Specifications (1) and (2) show the results from OLS regressions, while specifications (3) and (4) show the results based on Logit regressions. The coefficient on $Total\ Risk_{t-1}$ is statistically insignificant in all four specifications suggesting that treated fund managers are not more likely to match to lower-risk funds. In untabulated regressions, we also find no indication that the likelihood of fund manager departure differs across treated and untreated fund managers.

We use *Sell* and, alternatively, *Terminating Sell* as the dependent variable. *Sell* is an indicator variable that equals one if a fund sells (as opposed to holds or buys) at least some of the shares it holds in the investee firm from the previous holdings report date to the current holdings report date. The indicator variable *Terminating Sell* is identical to the variable *Sell* except that it only equals one if a fund sells all the shares it holds in the investee firm. The regressions include the same (time-varying) fund and fund manager controls as used in our baseline regression model shown in specification (4) of Table 2 as well as fund manager-stock fixed effects and time fixed effects. We cluster standard errors on fund-stock level.

In equation (2), *Event* is a placeholder that stands for the variables *Exogenous CEO Turnover* and *M&A*. The indicator variable *Exogenous CEO Turnover* equals one if a firm in the fund's portfolio experienced an exogenous CEO turnover in year *t*. Exogenous CEO turnover data are classified and provided, on an annual level, by Eisfeldt and Kuhnen (2013) for the years 1992-2006, which limits our analysis to this period. *M&A* is an indicator variable equal to one if a firm in the fund's portfolio announces an M&A transaction (as the bidder) between the previous holdings report date and the current holdings report date. Data on M&A are obtained from the SDC Platinum M&A database for the period 1980-2017. These data also allow us to examine potentially riskier and more uncertain M&A transactions, namely cross-border M&A (variable *Cross-border M&A*) and M&A involving non-public targets (variable *Non-public M&A*).

The regression results for fund managers' trading behavior in reaction to the risk-increasing events of investee firms are shown Table 4. The results for the dependent variable *Sell* are shown in specifications with odd numbers, while the results for *Terminating Sell* are shown in specifications with even numbers. Specifications (1) and (2) present the results for exogenous CEO turnover and specifications (3) to (8) present the results for M&A announcements. The estimates suggest that treated managers are significantly more likely to sell their shareholdings when these firms exhibit risk-increasing events. Specifically, for both dependent variables, *Sell* and *Terminating Sell*, the coefficients on *Family Disruption* × *Exogenous CEO Turnover* and *Family Disruption* × *M&A* are positive and statistically significant at the 1% level and the 5% level in specifications (1) to (3) and (4), respectively. Furthermore, consistent with treated managers taking less risk, the results for takeovers are more pronounced for riskier transactions, particularly those involving non-public targets that fund managers arguably find harder to evaluate. In sum, Table 4 provides significant support for the notion that fund managers who experienced family disruption early in their life exhibit different investment behavioral patterns and take less risk.[14]

4.4. Accounting for socioeconomic and family background measures

The results in the previous sections suggest that early-life family disruption exhibits a significant long-term association with the disposition effect and risk-taking by fund managers. Hence, the (in)stability of the family environment during childhood helps explain differences in fund manager investment behavior. In this section, we provide additional evidence to support this conclusion.

Our detailed data on fund managers' families allow us to compare how early-life family disruption relates to investment behavior relative to various measures of socioeconomic status and family background. We can thus address several alternative explanations for our results by controlling for potential confounding features of early-life family disruption and provide a better understanding of the relative importance of the (in)stability of the family environment. To the best of our knowledge, this analysis provides the first comprehensive picture of the long-term association between early-life family environment and investment behavior, which also fosters our understanding of how "nurture" relates to financial decisions later in life.

We re-estimate our baseline regression model (see specification 4 of Table 2) including the variable *Family Disruption* together with a broad set of additional control variables. To construct these variables, we hand-collect data from the U.S. Census, obituaries, and city directories. Panel A of Table 5 shows the results from regressions with *Disposition Effect* and *Total Risk* as dependent variables. The regressions include fewer observations than our models in Tables 2 and 3 since we are not able to obtain the additional socioeconomic and family background data for all managers.

We augment our baseline model by including the following additional variables, which are defined in Section 3.2, and which are intended to measure differences in socioeconomic status and

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[14] In an untabulated robustness test, we estimate the regression model shown in equation (2) relying on a market-wide measure of risk and uncertainty instead of certain corporate events. Specifically, we interact *Family Disruption* with the variable *VIX*, which is the average of the daily Chicago Board Options Exchange (CBOE) Volatility Index (VIX) over the period between the previous holdings report date and the current holdings report date of the fund. Data are obtained from the CBOE for the period 1990-2017. The VIX measures the implied volatility of the S&P 500 index anticipated on the derivative market and is thus a measure of perceived stock market risk or simply a "fear gauge" (see, e.g., Bloom, 2009). For the dependent variable *Terminating Sell*, we find treated fund managers are more likely to sell stocks in reaction to increased market-wide risk and uncertainty as measured by higher VIX values.

wealth as well as parenting. The first set of variables is related to the occupations of managers' parents. Generally, the use of occupation-related variables is motivated by the economics literature, which shows that occupation and employment status provide valuable information about people's preferences to take risks (Ekelund et al., 2005; Bonin et al. 2007). We use the indicator variables *Father Blue-collar Worker* and *Both Parents Working*. Blue-collar jobs are arguably more dangerous and may thus relate to an individual's risk aversion as well as the likelihood of parental deaths, while a household in which both parents are employed may be affected differently, both financially and in terms of parenting, by the death or divorce of the parent(s). We also use the indicator variables *Parent Self-employed* and *Parent Worked in Finance* as having self-employed parents or parents who work in the finance industry may influence one's investment style and ability to invest due to, e.g., different perceptions of risk and a "kitchen table" education.[15]

The second set of variables comprises six controls that are related to the fund manager's life at home during his or her childhood. We use the variable *Number of Siblings* (i.e., the manager's number of siblings) and the indicator variable *Firstborn* as Campbell, Jeong, and Graffin (2019) provide recent evidence that managers' strategic risk-taking is related to their birth order. We use three variables to capture differences in parenting. *Avg. Parental Age at Manager's Birth* measures the average age of the parents at the time of the fund manager's birth, which has been shown to shape the offspring's behavior as adults (e.g., Belsky et al., 2012). *Parents' Age Difference* is the absolute age difference between father and mother, which may relate to conflicts between parents and the likelihood of parental divorces and deaths (Francis-Tan and Mialon, 2015). The indicator variable *Parent Born Outside U.S.* captures whether at least one of the fund manager's parents migrated to the U.S., which may relate to different parenting habits but also captures differences in socioeconomic status. Such differences are also captured by the indicator variable *Parent Homeowner*, which equals one if a parent lived in a home that was not rented but owned. Homeowners may have higher or lower financial burdens, which could affect their willingness take financial risks.

[15] For treated fund managers, i.e., those who experienced family disruption during their childhood, all variables that are related to the occupations of their parents are measured prior to the disruption to ensure that they do not pick up the effect of the family disruption itself.

Finally, we add the indicator variable *Manager Works for Home State Fund* because fund managers who experienced family disruption may be more likely to stay in their home state to take care of their bereaved parent, perhaps providing them with an informational advantage on or an uninformed bias for local firms (Pool, Stoffman, and Yonker, 2012), which could affect their investment behavior.

Even after adding the eleven controls above to our regression model, the coefficient on *Family Disruption* remains significant at the 1% level and economically comparable to the baseline results for both *Disposition Effect* and *Total Risk*. This evidence suggests the following. First, the long-term association of early-life family disruption with both risk-taking and the disposition effect is robust to controlling for various measures capturing socioeconomic status and wealth as well as family background and parenting. The robustness of our results to the inclusion of these measures indicates that post-traumatic stress is more likely to explain the results than a straightforward socioeconomic explanation. Second, in both regressions, *Family Disruption* ranks among the most significant variables. Specifically, no other variable, except for *Both Parents Working*, does explain both risk-taking *and* the disposition effect. Hence, we conclude that the (in)stability rather than other specific features of the family environment relate to investment behavior later in life. Our evidence extends previous research on the explanatory power of "nurture" for differences in individuals' investment behavior (e.g., Barnea, Cronqvist, and Siegel, 2010; Cesarini et al., 2010).

Panel B of Table 5 shows results from re-estimating our baseline regression model (specification 4 of Table 2), additionally including the interaction term *Family Disruption* × *Family Wealth*. If the observed relation between early-life family disruption and investment behavior is caused by a socioeconomic/wealth channel, we would expect it to vary with family wealth. In contrast, if the relation is driven by an effect on personality traits, we should find an insignificant coefficient on the above interaction term. Our results are in line with the latter channel. The coefficient on *Family Disruption* × *Family Wealth* is statistically insignificant while the coefficient on *Family Disruption* remains significant for both dependent variables, *Disposition Effect* and *Total Risk*. The results also suggest that the association between early-life family disruption and investment behavior is unlikely to be caused by wealth shocks induced by family disruption, particularly parental deaths. We further address this concern in the next section.

A related concern is that early-life family disruption may only relate to the investment behavior of fund managers because treated managers need to take care of and financially support their bereaved parent. Simply put, the need to (financially) support someone else might cause less risk-taking. To address this concern, we re-estimate our baseline regression and limit the treated fund years to those years after which a manager's last parent died, assuming that (financial) support ends with the remaining parent's death. We report the results in Panel C of Table 5. The coefficient on Family Disruption is significant at the 1% level when using *Disposition Effect* and *Total Risk* as dependent variable, indicating that (financial) support for the bereaved parent does not explain our results.

To further address concerns of omitted variables and inappropriate counterfactuals, we also provide additional evidence from two matching approaches – propensity score matching (PSM) (Rosenbaum and Rubin, 1983) and coarsened exact matching (CEM) (Iacus, King, and Porro, 2012) – in Internet Appendix C. Our results using either approach are qualitatively similar to the baseline regression results shown in Tables 2 and 3.

4.5. Do different causes of family disruption affect investment behavior differently?

In this section, we examine whether different causes of family disruption show different long-term associations with investment behavior. Examining the heterogeneity in family disruption factors is not only important as it provides a more nuanced understanding of this prevalent societal phenomenon, but also because it addresses several endogeneity concerns, which cause threats to identification.

Panels A to Panel E of Table 6 each show results from estimations of our baseline regression model (specification 4 of Table 2) for the dependent variables *Disposition Effect* (in specification 1) and *Total Risk* (in specification 2). We regress the dependent variables on four different variables of interest, which measure the cause of family disruption, along with the same controls as used in the baseline regression model. These variables of interest are: (1) *Parental Death*, which is an indicator variable that equals one if family disruption is caused by the death of a parent, (2) *Parental Divorce*, which is an indicator variable that equals one if family disruption is caused by the divorce of the parents, (3) *Unexpected Death*, which is an indicator variable that equals one if family disruption is caused by the death of a parent that is not due to a long-term disease or occurred during military service, and (4) *Maternal Death*, which is an indicator variable that equals one if family disruption is caused by the death of the mother, where we focus on non-working mothers only. As before, all cases of family disruption must have taken place before the fund manager was 20 years old.

As the first test, we distinguish between the two components of family disruption, i.e., parental death and parental divorce. It is unclear whether we should expect to find a stronger relation to investment behavior in case of parental death or in case of parental divorce. While the former is arguably the more severe form of family disruption in the sense that it causes a complete, irreversible break of the parent-child relationship (whereas parental contact is still possible after a divorce), the latter may lead to an ongoing conflict and feeling of disruption that the child has to cope with as it grows up. However, Mack (2001) finds that relative to adults who experienced parental death during childhood or adolescence, adults who experienced parental divorce report higher levels of confidence. Hence, it is an open empirical question which form of family disruption has a stronger long-term impact on children and whether the impact is even the same. Second, it is plausible that parental divorce is endogenous to the pre-divorce structure of family life. Simply put, difficult parental relations might cause the divorce of the parents and simultaneously affect the investment behavior of the child later in life.

Panels A and B of Table 6 report the results from this test. We consider the two variables *Parental Death* and *Parental Divorce* separately in Panel A and Panel B, respectively, to see if both have explanatory power for fund manager risk-taking and the disposition effect when compared to the counterfactual of an intact family background. In Panel A, we find that the coefficient on *Parental Death* has the expected sign, i.e., it is positive in specification (1) and negative in specification (2), and is statistically significant at the 1% level in both specifications. In Panel B, the coefficient on *Parental Divorce* also has the expected sign and is also statistically significant (at the 5% level or better). We conclude that both components of family disruption significantly relate to fund managers' investment behavior later in life, and that our results are not driven by parental divorces, which might be endogenous.

Analogous to parental divorces, some parental deaths may also be endogenous to investment behavior later in life and might drive our results, for example, a parent who suffered from a cardiac defect or diabetes potentially differed in his parenting and risk-taking behavior, which may, in turn, have a long-lasting influence on the investment behavior of his children. Panel C of Table 5 provides evidence that our results for parental deaths are robust to focusing on unexpected deaths by excluding deaths that were caused by long-term illness or occurred during military service according to death records and obituaries. The respective variable of interest, *Unexpected Death*, has the expected sign in both specifications and is statistically significant at the 1% level for *Disposition Effect* and the 5% level for *Total Risk*.

Lastly, we investigate whether potential wealth implications of family disruption are the main reason why treated fund managers show a different investment behavior later in life. In the earlier years during which treatment took place, the father was typically the main income earner in the family. Hence, our results could be driven by paternal deaths reflecting shocks to family wealth that might affect children's attitudes toward financial risk.[16] To test this, we examine only those cases of parental deaths caused by deaths of non-working mothers. Such deaths are unlikely to have significant financial implications and thus allow us to disentangle wealth and personality implications of family disruption. Panel D of Table 5 shows the results from regressions that use *Maternal Death* as the variable of interest. The coefficient on this variable is negative and significant at the 5% level or better in both specifications. As an alternative test, shown in Panel E of Table 5, we examine only those cases of deaths involving bereaved parents who have at least the same level of education as their deceased spouses as well as children of school age (6 years or older). The idea is that any potential wealth shock should at least be weaker if the bereaved parent has at least a similar level of education allowing him or her to compensate the wealth shock by starting to work (or working more), which is more feasible when children already go to school. Again, our results remain statistically significant. Overall, both tests provide corroborating evidence for the hypothesis that the trauma of early-life family disruption itself, and not just a potential wealth shock induced by parental deaths or divorces, relates to fund managers' investment behavior later in life.[17]

[16] Koudijs and Voth (2016) find that the risk of a wealth shock (even without ex-post real consequences) affects subsequent risk-taking behavior of financial experts, whereas Brunnermeier and Nagel (2008) suggest that plausibly exogenous wealth fluctuations play no role in explaining changes in households' wealth allocation to risky assets.

[17] Given that the vast majority of all fund managers are male, the evidence in Panel D further suggests that parental deaths do not just matter to investment behavior because male children lose their (male) role models.

4.6. What factors moderate the effect of early-life family disruption?

In this section, we investigate what factors moderate the long-term association between early-life family disruption and investment behavior. To this end, we exploit different sources of exogenous variation in treatment intensity across treated fund managers. These variations in treatment intensity also provide further support for the hypothesis that family disruption affects personality and help address endogeneity concerns as any omitted variable would have to generate the same patterns as the moderators in order to explain our results.

Our first test is motivated by prior research, which suggests that imprinting events have a particularly strong impact on individuals' risk-taking behavior later in life when experienced during their formative years, i.e., the ages 5 to 15 (see Bernile, Bhagwat, and Rau, 2017, and the literature therein). Thus, we explore whether fund managers are more prone to the disposition effect and take on fewer risks if an early-life family disruption occurred during their formative years as opposed to their non-formative years. We re-estimate our baseline regression model (shown in specification 4 of Table 2) and replace the variable *Family Disruption* by the two indicator variables *Family Disruption - Formative Years* and *Family Disruption - Non-formative Years*. The former variable equals one if family disruption took place during a fund manager's formative years, whereas the latter equals one for family disruption taking place during the non-formative years of a manager's early life (i.e., ages 0-4 or ages 16-19). Panel A of Table 7 presents the results from regressions of *Disposition Effect* (specification 1) and *Total Risk* (specification 2) on the two above variables.

Specification (1) shows that family disruption during formative and non-formative years are related to an equally large increase in the disposition effect. However, specification (2) shows that the reduction in total fund risk can be attributed mainly to those treated fund managers who experienced a family disruption during their formative years. Specifically, while the regression coefficients on both variables have the expected negative sign, only the coefficient on *Family Disruption - Formative Years* is significant at the 1% level and the difference between the two coefficients is statistically significant. This evidence implies that treatment in non-formative years has only a limited impact on risk-taking, but a considerable effect in formative years.

In our second test, we exploit county-level variation in social support and welfare as provided by members of religious denominations. This analysis is motivated by the idea that a family disruption constitutes an arguably less severe shock (i.e., treatment intensity is weaker) when social support and welfare is higher. Support for this idea is provided by the evidence in Ellis, Dowrick, and Lloyd-Williams (2013) who find that social support (from friends, religious organizations, and schools) reduces the distress associated with parental death. In this context, the literature regards religious communities as a main source of social support and welfare for individuals in need (e.g., Cnaan et al., 2002) and as an informal insurance mechanism protecting individuals against certain idiosyncratic risks (Ager and Ciccone, 2017). There is also evidence on facilitated coping through spirituality among grieving children (Andrews and Moratta, 2005). However, in case of parental divorces, it is not entirely clear whether religious people indeed provide social support to disrupted families or whether they instead ignore or even scorn them.

To measure social support and welfare, we take the county where a fund manager and his or her family lived around the time that the family disruption event took place and proxy the level of religiosity in that county by the variable *Religiosity Ratio*. We define this variable as the fraction of people in the county who are members of religious denominations. Religious membership statistics and county population data are obtained from the Association of Religion Data Archives for 1952 as this year lies in the middle of our family disruption period and as religiosity ratios tend to be relatively stable over time. For managers who experienced a family disruption, *Religiosity Ratio* equals the number of members of all religious denominations in the home county divided by the county's total population. We set the value of this variable to zero for all managers who did not experience family disruption.

To test whether higher levels of religious support lessen the impact of family disruption on investment behavior, we again re-estimate our baseline regression model including an additional interaction term, *Family Disruption* × *Religiosity Ratio*. If treatment intensity is lower when religious communities offer more social support and welfare, we expect the coefficient on the interaction term to be significantly negative for the disposition effect and positive for the risk effect, reducing the baseline effect of *Family Disruption*. We regress the same two dependent variables as in Panel A on *Family Disruption*, the interaction term *Family Disruption* × *Religiosity Ratio*, and controls. Panel B of Table 7 reports the results. Consistent with the notion that more social support and welfare lessen the relation between family disruption and fund manager risk taking, we find the coefficient on the interaction term *Family Disruption* × *Religiosity Ratio* to be negative and significant at the 10% level when used to explain *Disposition Effect* in specification (1). In specification (2), the coefficient is positive and significant at the 5% level indicating that social support and welfare also lessens the long-term relation between *Family Disruption* and *Total Risk*.

In an additional untabulated test, we find that the association between early-life family disruption and investment behavior lingers over time, consistent with the notion that family disruption is an imprinting experience with long-term consequences caused by persistent post-traumatic symptoms. We test this by interacting *Family Disruption* with an indicator for whether a manager's age is above the median manager age in the sample. When we add this interaction term to our regressions, the coefficient is not statistically significant.

5. Early-life Family Disruption and Manager Skill

As a last step, we investigate whether a skill gap exists between fund managers who experienced early-life family disruption and those who did not. Such a skill gap, which may exist, for example, due to differences in parenting across treated and untreated fund managers, could potentially explain some of our results presented in Section 4. To test for differences in fund manager skills, we follow Cremers and Petajisto (2009) and Petajisto (2013) and examine whether treated fund managers differ in terms of the variable *Active Share*, which measures the fraction of the fund's portfolio holdings that deviate from the holdings of the benchmark index.[18] According to Cremers and Petajisto (2009), the fund's active share is a proxy for stock selection, i.e., picking individual stocks expected to outperform their peers, and thus serves as a measure of fund manager skill. We also test whether disruptions of managers' families in their early life are associated with differences in risk-adjusted fund performance. We use two performance measures, *Alpha* and *Sharpe Ratio*. We regress the three aforementioned variables on *Family Disruption*, along with the same controls as used in our baseline regressions (see specification 4 of Table 2). The results of these regressions are shown in Table 8. We find the coefficient on *Family Disruption* to be statistically insignificant in all regressions, i.e., for *Active Share* in specification (1), as well as for *Alpha* and *Sharpe Ratio* in specifications (2) and (3). In untabulated regressions, we find similar results for multi-factor alphas. Thus, our results provide no indication of a skill gap between treated and untreated managers.

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[18] We retrieve quarterly data on active share from Antti Petajisto's website. As these data are only available for the years 1980-2009, the respective regressions are based on fewer observations.

This evidence is in line with and complements our results from Section 4: While fund managers who experienced early-life family disruption tend to make fewer risky investments, they do not seem to differ in terms of skills. The performance results are also consistent with evidence suggesting that the disposition effect does not relate to fund performance (Cici, 2012).

6. Conclusion

This paper contributes to the emerging literature on social finance by documenting the potential long-term financial consequences of a prevalent societal phenomenon, early-life family disruption. Specifically, we show that the death or divorce of the parent(s) during childhood relates to risk-taking and the extent to which professional investors exhibit a disposition effect later in life. Our results are consistent with well documented long-lasting symptoms of post-traumatic stress caused by family disruption. Specifically, we find that treated managers exhibit a stronger disposition effect and reduce idiosyncratic and market risk as well as a fund's tracking error when taking office. Consistently, treated managers are also more likely to sell their holdings in reaction to risk-increasing corporate events. Our results are robust to a large set of controls for socioeconomic and family background measures and do not appear to be driven by a wealth shock caused by family disruption. The age at which the fund manager experienced family disruption as well as the social support the manager received around this time seem to be an important moderators of the relation between family disruption and investment behavior.

The evidence in this study suggests that the stability of an individual's early-life family environment is a potential source of variation that helps explain the behavior of professional investors. Thus, our study extends the limited literature on the role that "nurture", the family of origin in particular, can play for investor behavior. It thus has potential implications for the allocation of capital in financial markets.

We note a final caveat to our results. Our paper compares the risk behavior of individuals who end up as managers of actively managed mutual funds. If active fund management is a relatively high-risk occupation, it is plausible that, relative to individuals without family disruption, individuals entering the active fund management industry will be less likely to grow up with experience of family disruption. Therefore, our sample will be biased towards individuals who are less likely to experience family disruption, implying that all our results here are biased towards zero. In the absence of this selection bias, for example, if individuals coming from both disrupted and undisrupted family backgrounds were forced equally to become active fund managers, the coefficients estimated here would likely be even larger in absolute size.

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Table 1
Summary Statistics

Panel A: Time-invariant manager characteristics (on manager level)

		(1) Total			(2) Family Disruption = 1			(3) Family Disruption = 0		Difference in means (2-3)
Variable	**N**	**Mean**	**SD**		**Mean**	**SD**		**Mean**	**SD**	**t-statistic**
Avg. Parental Age at Manager's Birth	484	30.459	5.131	59	32.153	7.004	425	30.224	4.777	**2.05**
Birth Year of Manager	484	1941	6.258	59	1940	7.769	425	1941	6.022	-0.85
Both Parents Working	484	0.190	0.393	59	0.136	0.345	425	0.198	0.399	-1.27
Family Wealth	483	2.705	3.103	59	3.096	3.302	424	2.650	3.075	0.98
Father Blue-collar Worker	423	0.270	0.444	51	0.255	0.440	372	0.272	0.445	-0.25
Female	484	0.048	0.213	59	0.034	0.183	425	0.049	0.217	-0.60
Firstborn	463	0.546	0.498	57	0.421	0.498	406	0.564	0.496	**-2.03**
Ivy League	484	0.312	0.464	59	0.271	0.448	425	0.318	0.466	-0.74
MBA	484	0.545	0.498	59	0.542	0.502	425	0.546	0.498	-0.05
PhD	484	0.068	0.252	59	0.068	0.254	425	0.068	0.252	-0.01
Number of Siblings	444	1.782	1.489	57	1.667	1.528	387	1.798	1.484	-0.61
Parents Age Difference	481	4.005	3.722	57	5.542	5.200	424	3.805	3.456	**2.13**
Parental Education	479	2.373	0.613	59	2.305	0.695	420	2.382	0.601	-0.81
Parent Born Outside U.S.	474	0.127	0.333	55	0.145	0.356	419	0.124	0.330	0.42
Parent Homeowner	484	0.558	0.497	59	0.559	0.501	425	0.558	0.497	0.02
Parents Self-employed	484	0.143	0.350	59	0.203	0.406	425	0.134	0.341	1.25
Parents Worked in Finance	484	0.167	0.374	59	0.153	0.363	425	0.169	0.376	-0.33

Panel B: Family disruption, time-varying manager and fund characteristics (on fund-year level)

	(1) Total				(2) Family Disruption = 1			(3) Family Disruption = 0			Difference in means (2-3)
Variable	**N**	**Mean**	**P50**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**t-statistic**
Manager characteristics											
Family Disruption	4,839	0.151		0.358	732		0.000	4,107		0.000	
Manager Age	4,839	54.799	55.000	8.858	732	56.148	9.614	4,107	54.558	8.696	**4.18**
Manager Tenure	4,839	7.579	5.083	7.487	732	8.241	8.093	4,107	7.461	7.369	**2.44**
Fund characteristics											
Total Risk	4,839	0.045	0.041	0.022	732	0.043	0.020	4,107	0.046	0.022	**-3.13**
Idiosyncratic Risk	4,837	0.020	0.016	0.013	731	0.020	0.012	4,106	0.020	0.013	0.14
Market Risk	4,839	0.979	0.955	0.337	732	0.932	0.328	4,107	0.987	0.338	**-4.20**
Avg. Monthly Return	4,742	0.009	0.011	0.015	718	0.009	0.014	4,024	0.009	0.015	-0.04
Expense Ratio	4,742	0.012	0.012	0.006	718	0.013	0.008	4,024	0.012	0.006	**3.75**
Fund Age	4,836	15.469	10.167	15.533	729	17.105	17.934	4,107	15.178	15.050	**2.74**
Fund Size	4,796	4.680	4.671	1.862	726	4.718	2.007	4,070	4.673	1.835	0.55
Fund Family Size	4,796	6.172	6.924	3.499	726	6.080	3.463	4,070	6.188	3.505	-0.78
Turnover Ratio	4,000	0.744	0.480	0.857	609	0.704	0.927	3,391	0.751	0.843	-1.15

Panel C: Portfolio activities (on fund-quarter level)

	(1) Total				(2) Family Disruption = 1			(3) Family Disruption = 0			Difference in means (2-3)
Variable	**N**	**Mean**	**P50**	**SD**	**N**	**Mean**	**SD**	**N**	**Mean**	**SD**	**t-statistic**
Active Share	9,482	0.849	0.878	0.122	1,335	0.846	0.109	8,147	0.850	0.124	-1.10
Disposition Effect	15,256	-0.016	0.000	0.165	2,341	0.008	0.155	12,915	-0.021	0.166	**8.19**
Tracking Error	9,479	0.077	0.064	0.045	1,332	0.074	0.037	8,147	0.077	0.046	**-3.31**

This table presents summary statistics for the variables used in this study. The sample period is 1980-2017. Panel A reports summary statistics on manager level for time-invariant manager characteristics. Panel B reports summary statistics on fund-year level for family disruption as well as time-varying manager and fund characteristics. Panel C reports summary statistics on fund-quarter level for variables of portfolio activity. Fund characteristics, except for fund age, and measures of portfolio activities are winsorized at the 1st and 99th percentiles. Summary statistics are shown for the total sample and for the subsamples of managers who did and did not experience early-life family disruption (Family Disruption = 1 vs. 0). The last column reports the t-statistics for difference-in-means tests between the two subsamples. T-statistics significant at the 5% level are bolded. Panel D provides an overview of the causes of parental deaths that lead to family disruption. In case both parents died, the cause of death for the first parent who died is reported.

Table 2
Early-life Family Disruption and the Disposition Effect

Dependent variable	*Disposition Effect*			
	(1)	(2)	(3)	(4)
Family Disruption	**0.051*****	**0.071*****	**0.076*****	**0.117*****
	(3.45)	**(2.78)**	**(3.14)**	**(5.12)**
Female	-0.001	0.038*	0.034	0.003
	(-0.04)	(1.80)	(1.60)	(0.10)
(Manager Age) / 100	0.129	0.080	0.116	0.405*
	(1.06)	(0.50)	(0.73)	(1.76)
(Manager Tenure) / 100	-0.014	-0.001	-0.007	-0.097
	(-0.21)	(-0.00)	(-0.05)	(-0.66)
Ivy League	-0.003	-0.022	-0.022	0.003
	(-0.35)	(-1.14)	(-1.19)	(0.16)
MBA	0.012	-0.009	-0.008	-0.010
	(0.99)	(-0.50)	(-0.48)	(-0.57)
PhD	-0.028	-0.008	-0.007	0.021
	(-1.50)	(-0.26)	(-0.24)	(0.37)
Parental Education	0.014*	0.025*	0.025*	0.036***
	(1.85)	(1.86)	(1.82)	(2.59)
Family Wealth	-0.004*	-0.007**	-0.008**	-0.020***
	(-1.85)	(-2.28)	(-2.52)	(-4.38)
Fund Age	0.000	-0.018***	-0.019***	-0.021***
	(0.09)	(-3.56)	(-3.66)	(-3.57)
Fund Size	0.000	0.007**	0.007**	0.005*
	(0.04)	(2.47)	(2.27)	(1.70)
Fund Family Size	-0.002	-0.005**	-0.004*	-0.005*
	(-0.96)	(-2.20)	(-1.73)	(-1.92)
Avg. Monthly Return	-0.213	-0.199	-0.178	-0.205
	(-1.22)	(-1.15)	(-1.01)	(-1.17)
Expense Ratio	-0.823	-1.170	-1.168	-0.982
	(-1.01)	(-1.06)	(-1.08)	(-0.91)
Turnover Ratio	-0.015**	0.001	-0.001	-0.001
	(-2.52)	(0.26)	(-0.28)	(-0.11)
Fund FE	No	Yes	Yes	Yes
Fund Family FE	Yes	No	Yes	No
Investment Style FE	Yes	No	Yes	No
Birth Cohort FE	Yes	No	No	Yes
Birth State FE	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	13,290	13,290	13,290	13,290
Adjusted R-squared	0.158	0.195	0.198	0.204

This table reports coefficients from regressions of *Disposition Effect* on *Family Disruption* with controls for manager and fund characteristics (for the previous period). All specifications include year fixed effects. Additional fixed effects (FE) include fund family FE and fund investment style FE (specifications 1 and 3), fund FE (specifications 2 to 4), as well as manager birth cohort FE and manager birth state FE (specifications 1 and 4). All variables are defined in the Appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 3
Early-life Family Disruption and Risk-taking

Panel A: Family disruption and total fund risk

Dependent variable	***Total Risk***			
	(1)	(2)	(3)	(4)
Family Disruption	**-0.002****	**-0.008*****	**-0.007*****	**-0.009*****
	(-2.10)	**(-2.87)**	**(-2.73)**	**(-3.23)**
Female	-0.006***	-0.009*	-0.010**	-0.011***
	(-2.96)	(-1.86)	(-2.08)	(-3.57)
(Manager Age) / 100	0.012	-0.045***	-0.039***	-0.030
	(0.69)	(-3.33)	(-2.93)	(-1.23)
(Manager Tenure) / 100	-0.017**	0.006	0.005	-0.019
	(-2.07)	(0.50)	(0.39)	(-1.26)
Ivy League	0.000	0.003	0.003	0.002
	(0.12)	(1.52)	(1.56)	(1.05)
MBA	0.000	-0.003*	-0.004**	-0.004**
	(0.19)	(-1.82)	(-2.14)	(-2.10)
PhD	-0.002	-0.009**	-0.008**	-0.006
	(-1.25)	(-2.12)	(-2.15)	(-1.09)
Parental Education	0.001	-0.001	-0.001	-0.000
	(1.28)	(-0.67)	(-0.36)	(-0.37)
Family Wealth	-0.000	0.001*	0.001*	0.001*
	(-0.72)	(1.89)	(1.92)	(1.66)
Fund Age	0.000	0.613	-7.623	-0.022
	(0.26)	(0.00)	(-0.00)	(-0.00)
Fund Size	0.000	0.000	0.000	0.000
	(1.31)	(0.91)	(1.03)	(0.81)
Fund Family Size	0.000	0.000	0.000	0.000
	(0.63)	(0.38)	(0.43)	(0.34)
Avg. Monthly Return	0.067	0.105**	0.102**	0.105**
	(1.29)	(2.26)	(2.20)	(2.20)
Expense Ratio	0.068	0.250	0.213	0.272
	(0.61)	(1.51)	(1.38)	(1.61)
Turnover Ratio	0.001*	-0.001	-0.001	-0.001
	(1.65)	(-0.74)	(-1.05)	(-1.07)
Fund FE	No	Yes	Yes	Yes
Fund Family FE	Yes	No	Yes	No
Investment Style FE	Yes	No	Yes	No
Birth Cohort FE	Yes	No	No	Yes
Birth State FE	Yes	No	No	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	3,929	3,929	3,929	3,929
Adjusted R-squared	0.729	0.764	0.767	0.769

Panel B: Family disruption and other risk measures

Dependent variables	***Idiosyncratic Risk***	***Market Risk***	***Tracking Error***
	(1)	(2)	(3)
Family Disruption	**-0.006***** **(-3.19)**	**-0.199***** **(-3.01)**	**-0.030**** **(-2.53)**
All controls as in Panel A	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Birth Cohort FE	Yes	Yes	Yes
Birth State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	3,929	3,929	8,219
Adjusted R-squared	0.696	0.502	0.618

This table explores the difference in risk-taking between managers who grew up in disrupted families compared to managers from intact families of origin. Panel A reports results from regressions of Total Risk on Family Disruption along with controls for manager and fund characteristics (for the previous year). All specifications include year fixed effects. Additional fixed effects (FE) include fund family FE and fund investment style FE (specifications 1 and 3), manager birth cohort FE and manager birth state FE (specifications 1 and 4) as well as fund FE (specification 2 to 4). Panel B reports results from regressions of Idiosyncratic Risk (specification 1), Market Risk (specification 2), and Tracking Error (specification 3) on Family Disruption along with controls for manager and fund characteristics (for the previous year). All specifications include fund FE, manager birth cohort FE and manager birth state FE, as well as year FE. All variables are defined in the Appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 4
Early-life Family Disruption and Reactions to Increased Firm-level Risk and Uncertainty

Firm event	**Exogenous CEO Turnover**		**M&A announcement**					
Dependent variables	***Sell***	***Terminating Sell***	***Sell***	***Terminating Sell***	***Sell***	***Terminating Sell***	***Sell***	***Terminating Sell***
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Family Disruption × Exogenous CEO Turnover	**0.027*****	**0.026*****						
	(2.90)	**(3.51)**						
Family Disruption × M&A			**0.014*****	**0.008****	0.011**	0.004	-0.013	-0.017**
			(3.08)	**(2.19)**	(2.23)	(0.83)	(-1.51)	(-2.31)
Family Disruption × Cross-border M&A					**0.010**	**0.019****		
					(1.02)	**(2.29)**		
Family Disruption × Non-public M&A							**0.035*****	**0.033*****
							(3.60)	**(3.98)**
Exogenous CEO Turnover	-0.010**	-0.013***						
	(-2.21)	(-3.32)						
M&A			-0.015***	-0.016***	-0.015***	-0.016***	-0.009**	-0.010***
			(-7.31)	(-8.88)	(-6.34)	(-7.57)	(-2.33)	(-2.88)
Cross-border M&A					-0.001	-0.002		
					(-0.24)	(-0.52)		
Non-public M&A							-0.008*	-0.008**
							(-1.80)	(-2.11)
(Manager Age) / 100	13.970***	10.834***	13.854***	10.702***	13.853***	10.701***	13.847***	10.695***
	(22.14)	(19.38)	(22.01)	(19.21)	(22.01)	(19.21)	(22.01)	(19.21)
(Manager Tenure) / 100	-0.133***	-0.018	-0.133***	-0.019	-0.133***	-0.019	-0.133***	-0.019
	(-6.42)	(-1.25)	(-6.45)	(-1.29)	(-6.45)	(-1.29)	(-6.44)	(-1.29)
Fund Age	0.000***	0.001***	0.000***	0.001***	0.000***	0.001***	0.000***	0.001***
	(6.86)	(9.80)	(6.86)	(9.80)	(6.86)	(9.81)	(6.86)	(9.81)
Fund Size	0.003***	-0.002***	0.003***	-0.002***	0.003***	-0.002***	0.003***	-0.002***
	(4.41)	(-2.92)	(4.42)	(-2.91)	(4.42)	(-2.91)	(4.42)	(-2.90)
Fund Family Size	-0.002***	0.004***	-0.002***	0.004***	-0.002***	0.004***	-0.002***	0.004***
	(-3.64)	(9.35)	(-3.64)	(9.36)	(-3.64)	(9.36)	(-3.64)	(9.36)
Avg. Monthly Return	-2.334***	-1.480***	-2.325***	-1.471***	-2.325***	-1.471***	-2.325***	-1.471***
	(-37.91)	(-28.36)	(-37.77)	(-28.18)	(-37.77)	(-28.18)	(-37.77)	(-28.18)
Expense Ratio	-1.955***	-1.864***	-1.959***	-1.868***	-1.958***	-1.867***	-1.957***	-1.867***
	(-7.80)	(-8.92)	(-7.82)	(-8.94)	(-7.82)	(-8.94)	(-7.81)	(-8.94)

Turnover Ratio	-0.007***	-0.004***	-0.007***	-0.004***	-0.007***	-0.004***	-0.007***	-0.004***
	(-4.98)	(-3.69)	(-4.99)	(-3.71)	(-4.99)	(-3.71)	(-4.99)	(-3.71)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,233,462	1,233,462	1,233,462	1,233,462	1,233,462	1,233,462	1,233,462	1,233,462
Adjusted R-squared	0.029	0.063	0.029	0.063	0.029	0.063	0.029	0.063

This table reports results from tests exploiting variation in risk/uncertainty regarding the firms that mutual funds are invested in. Exogenous CEO turnover (based on annual data provided by Eisfeldt and Kuhnen, 2013) and mergers and acquisitions (M&As) (retrieved from SDC) are used as risk/uncertainty-increasing firm-specific events. The tests are conducted on stock level based on the stock holdings reported by mutual funds. Regression results are from OLS regressions of stock selling measures, i.e., Sell and Terminating Sell, on different variables of interest along with controls for fund and time-varying manager characteristics (for the previous holdings report date) as well as fund manager-stock and year fixed effects. Sell is an indicator variable that equals one if a fund reduced the number of shares of a stock from the previous to the current holdings report date (as opposed to increasing the number of shares or holding it constant) and Terminating Sell is an indicator that equals one if the number of shares was reduced to zero. Specifications (1) and (2) present results for exogenous CEO turnovers based on regressions of the two stock selling measures on the variables Family Disruption × Exogenous CEO Turnover and Exogenous CEO Turnover along with controls. Exogenous CEO Turnover is an indicator variable that equals one if a company in a fund's portfolio experienced an exogenous CEO turnover in year t. Specifications (3) to (8) present results for M&As based on regressions of the two stock selling measures on the variables Family Disruption × M&A and M&A (specifications 3 and 4), or on the variables Family Disruption × Cross-border M&A and Cross-border M&A (specifications 5 and 6), or on the variables Family Disruption × Non-public M&A and Non-public M&A (specifications 7 and 8) along with controls. M&A is an indicator variable that equals one if a company in a fund's portfolio announced an M&A between the previous holding report date and the current holding report date. Cross-border M&A and Non-public M&A are indicator variables that equal one if the M&A target company is not located in the U.S. and if the M&A target company is not publicly listed, respectively. All variables are defined in the Appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by fund-stock. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 5
Early-life Family Disruption, Family Background, and Investment Behavior

Panel A: Importance of family disruption relative to other family background measures

Dependent variables	***Disposition Effect***	***Total Risk***
	(1)	(2)
Family Disruption	**0.155*****	**-0.006*****
	(4.37)	**(-3.03)**
Firstborn	0.054	0.008*
	(0.69)	(1.86)
Number of Siblings	0.001	-0.003***
	(0.15)	(-4.02)
Parent Self-employed	-0.041	0.002
	(-1.12)	(0.80)
Parent Worked in Finance	0.083*	-0.005
	(1.72)	(-1.39)
Father Blue-collar Worker	-0.113**	-0.001
	(-2.24)	(-0.56)
Both Parents Working	0.092**	-0.008***
	(1.97)	(-3.07)
Avg. Parental Age at Manager's Birth	0.000	0.000
	(0.09)	(0.69)
Parents Age Difference	-0.000	0.000
	(-0.05)	(0.46)
Parent Born Outside U.S.	0.110*	0.008*
	(1.89)	(1.72)
Parent Homeowner	-0.122	-0.001
	(-1.47)	(-0.27)
Manager Works for Home State Fund	0.318***	0.001
	(3.73)	(0.21)
Controls as in Table 2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	9,813	2,913
Adjusted R-squared	0.200	0.769

Panel B: Can families' socioeconomic status explain our results?

Dependent variables	***Disposition Effect***	***Total Risk***
	(1)	(2)
Family Disruption × Family Wealth	**0.008**	**-0.000**
	(0.89)	**(-0.40)**
Family Disruption	0.093**	-0.008**
	(2.54)	(-2.14)
Controls as in Table 2	Yes	Yes
Fund FE	Yes	Yes

Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	13,290	3,929
Adjusted R-squared	0.204	0.768

Panel C: Does (financial) support for the bereaved parent explain our results?

Dependent variables	***Disposition Effect***	***Total Risk***
	Only treated fund years after both parents died	
	(1)	(2)
Family Disruption	**0.103***** **(3.04)**	**-0.016***** **(-5.00)**
Controls as in Table 2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	12,655	3,744
Adjusted R-squared	0.205	0.770

This table reports how Family Disruption relates to other family background measures in terms of economic and statistical magnitude. Panel A shows results from regressions of fund investment measures, i.e., Disposition Effect (specification 1) and Total Risk (specification 2) on Family Disruption along with controls for manager and fund characteristics (for the previous period) as well as fund and year fixed effects and manager birth cohort and birth state fixed effects. All regressions include additional controls for fund managers' family background, i.e., Firstborn, Number of Siblings, Parent Self-employed, Parent Worked in Finance, Avg. Parental Age at Manager's Birth, Father blue-collar Worker, Both Parents working, Parents Age difference, Parent born outside U.S., Parent Homeowner as well as for fund managers' home state employment measured by the indicator variable Manager Works for Home State Fund. Panel B presents estimates from regressions of Disposition Effect and Total Risk on the two variables Family Disruption and Family Disruption × Family Wealth along with controls for manager and fund characteristics (for the previous year) as in Table 2 as well as fund and year fixed effects and manager birth cohort and birth state fixed effects. Panel C reports the results from regressions of Disposition Effect and Total Risk on Family Disruption based on the sample that (besides all untreated fund years) includes only those treated fund years after both of a manager's parents died. Both specifications again include controls for manager and fund characteristics (for the previous year) as in Table 2 as well as fund and year fixed effects and manager birth cohort and birth state fixed effects. All variables are defined in the Appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 6
Heterogeneity in Early-life Family Disruption Factors

Dependent variables	***Disposition Effect***	***Total Risk***
	(1)	(2)
Panel A: Disruption due to parental death		
Parental Death	**0.092*****	**-0.010*****
	(3.67)	**(-3.17)**
Observations	12,719	3,765
Adj. R-squared	0.196	0.770
Panel B: Disruption due to parental divorce		
Parental Divorce	**0.193*****	**-0.010****
	(3.30)	**(-1.98)**
Observations	11,785	3,489
Adj. R-squared	0.203	0.773
Panel C: Disruption due to unexpected death		
Unexpected Death	**0.080*****	**-0.009****
	(2.97)	**(-2.59)**
Observations	12,334	3,653
Adj. R-squared	0.197	0.770

This table reports results on how different types of family disruption affect investment behavior. All panels report results from regressions of fund investment measures, i.e., *Disposition Effect* (specification 1) and *Total Risk* (specification 2) on different variables of interest along with controls for manager and fund characteristics (for the previous period) as well as fund and year fixed effects and manager birth cohort and birth state fixed effects. Panel A and Panel B report the results from separate regressions of fund investment measures on either the variable *Parental Death* or the variable *Parental Divorce*, i.e., the two components of the variable *Family Disruption*, along with controls. We use separate regressions for the two variables to test whether each has explanatory power for fund investment measures when tested against the counterfactual of an intact family. Panel C reports the results from regressions of fund investment measures on the variable *Unexpected Death*, defined as those early parental deaths that were not caused by a long-term disease or occurred during military service, along with controls. Panel D reports the results from regressions of fund investment measures on the variable *Maternal Death*, defined as only those cases of early-life family disruption in which a fund manager's mother died, along with controls. Panel E reports the results from regressions of fund investment measures on the variable *Parental Death*, defined as only those cases of early parental death in which a fund manager's bereaved parent has at least the same level of education as her deceased spouse and the fund manager reached at least school age (6 years or older). All variables are defined in the Appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Panel D: Disruption due to maternal death (non-working mothers only)		
Maternal Death	**0.094****	**-0.019*****
	(2.17)	**(-4.33)**
Observations	11,908	3,516
Adj. R-squared	0.199	0.774
Panel E: Parental deaths involving bereaved parents with an education level ≥ the deceased's education level and children aged ≥ 6 years		
Parental Death	**0.074*****	**-0.008****
	(2.65)	**(-2.30)**
Observations	12,112	3,594
Adj. R-squared	0.193	0.770
Controls as in Table 2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes

Table 7
Moderators of Early-life Family Disruption

Panel A: Family disruption during formative vs. non-formative years

Dependent variables	*Disposition Effect*	*Total Risk*
	(1)	(2)
Family Disruption - Formative Years	**0.086***	**-0.025*****
	(1.96)	**(-4.18)**
Family Disruption - Non-formative Years	**0.127*****	**-0.005**
	(4.56)	**(-1.60)**
Difference in Family Disruption coefficients	**-0.0403**	**-0.0209*****
p-value of difference	**0.468**	**0.00107**
Female	-0.001	-0.013***
	(-0.03)	(-4.82)
(Manager Age) / 100	0.386*	-0.052**
	(1.66)	(-2.22)
(Manager Tenure) / 100	-0.104	-0.023
	(-0.71)	(-1.54)
Ivy League	0.003	0.002
	(0.13)	(1.06)
MBA	-0.008	-0.004*
	(-0.44)	(-1.79)
PhD	0.012	-0.009*
	(0.21)	(-1.94)
Parental Education	0.035**	-0.001
	(2.56)	(-1.20)
Family Wealth	-0.020***	0.001***
	(-4.34)	(2.81)
Fund Age	-0.021***	-0.022
	(-3.51)	(-0.00)
Fund Size	0.005*	0.000
	(1.70)	(0.82)
Fund Family Size	-0.005*	0.000
	(-1.91)	(0.36)
Avg. Monthly Return	-0.206	0.104**
	(-1.18)	(2.18)
Expense Ratio	-0.978	0.275
	(-0.91)	(1.63)
Turnover Ratio	-0.000	-0.001
	(-0.08)	(-1.03)
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	13,290	3,929
Adjusted R-squared	0.203	0.769

Panel B: Social support and welfare around family disruption

Dependent variables	***Disposition Effect***	***Total Risk***
	(1)	(2)
Family Disruption × Religiosity Ratio	**-0.469***	**0.048****
	(-1.88)	**(2.34)**
Family Disruption	0.373***	-0.036***
	(2.60)	(-2.96)
Controls and fixed effects as in Panel A	Yes	Yes
Observations	13,276	3,925
Adjusted R-squared	0.204	0.769

This table reports regression coefficients from regressions on factors that moderate the effect of family disruption affect investment behavior. All panels report coefficients for regressions on fund investment measures, i.e., *Disposition Effect* (specification 1) and *Total Risk* (specification 2) on different variables of interest along with controls for manager and fund characteristics (for the previous period) as well as fund and year fixed effects and manager birth cohort and birth state fixed effects. Panel A reports the results from regressions of risk measures on the two variables *Family Disruption_Formative Years* and *Family Disruption_Non-formative Years* along with controls. *Family Disruption_Formative Years* and *Family Disruption_Non-formative Years* are indicator variables, which equal one if a fund manager experienced family disruption during his or her formative years (age 5-15) and non-formative years (age 0-4 or 16-19), respectively. Panel B reports the results from regressions of fund investment measures on the two variables *Family Disruption* and *Family Disruption × Religiosity Ratio* along with controls. *Religiosity Ratio* is the fraction of members of all religious denominations in the home county of a manager's family around the time that family disruption took place. Mean (median) *Religiosity Ratio* is 0.55 (0.51). All variables are defined in the Appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table 8
Family Disruption and Risk-adjusted Fund Performance

Dependent variables	*Active Share*	*Alpha*	*Sharpe Ratio*
	(1)	(2)	(3)
Family Disruption	**-0.022**	**0.027**	**0.162**
	(-0.59)	**(1.54)**	**(1.20)**
Female	0.015***	-0.001	-0.005
	(2.95)	(-0.17)	(-0.13)
(Manager Age) / 100	-0.091	0.312*	2.900**
	(-0.30)	(1.75)	(2.03)
(Manager Tenure) /100	0.322**	0.026	-0.302
	(2.26)	(0.22)	(-0.35)
Ivy League	-0.007	-0.010	-0.042
	(-0.49)	(-0.94)	(-0.58)
MBA	-0.022	0.014	0.670***
	(-0.68)	(0.44)	(2.83)
PhD	0.018	0.030**	0.134
	(1.42)	(2.13)	(1.49)
Parental Education	0.022	0.013	0.009
	(1.21)	(1.42)	(0.13)
Family Wealth	0.004	-0.005*	-0.054*
	(1.61)	(-1.74)	(-1.77)
Fund Age	-0.006**	-0.110	-0.673
	(-2.25)	(-0.00)	(-0.00)
Fund Size	-0.015***	-0.034***	-0.245***
	(-4.62)	(-11.15)	(-9.98)
Fund Family Size	-0.000	0.008***	0.063***
	(-0.04)	(3.39)	(3.34)
Avg. Monthly Return	-0.018		
	(-0.31)		
Expense Ratio	0.003**	0.000	-0.003
	(2.50)	(0.22)	(-0.35)
Turnover Ratio	0.316	-1.333	-8.280
	(0.29)	(-1.24)	(-0.96)
Fund FE	Yes	Yes	Yes
Birth Cohort and Birth State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	8,220	3,929	3,929
Adjusted R-squared	0.876	0.223	0.753

This table reports results from regressions of *Active Share* (specification 1), *Alpha* (specification 2), and *Sharpe Ratio* (specification 3) on *Family Disruption* and controls for manager and fund characteristics (for the previous period). All specifications also include fund fixed effects, year fixed effects, and manager birth cohort and birth state fixed effects. All variables are defined in the Appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Appendix A

This appendix provides the definitions of all variables and terms used in this study. Data on fund manager characteristics are gathered from Morningstar Direct as well as from Bloomberg, Capital IQ, Marquis Who's who, and SEC filings, among other sources. Data on fund managers' family background are gathered from the U.S. census as well as from Ancestry.com, Legacy.com, and Newspaper.com, among other sources. Data on fund characteristics are obtained from CRSP.

Table A.1
Variable definitions

Variable	**Definition**
Manager characteristics	
Family Disruption	Indicator variable for a manager's early-life family disruption that is equal to one for a manager who experienced either the death of a parent or the divorce of her parents before the age of 20, and zero otherwise.
Female	Indicator variable equal to one for a female fund manager, and zero otherwise.
Manager Age	Age of fund manager in years.
Manager Tenure	Number of years since a fund manager's start date with a fund.
Ivy League	Indicator variable equal to one for a manager who attended an Ivy League university, and zero otherwise.
MBA	Indicator variable equal to one for a manager who holds an MBA degree, and zero otherwise.
PhD	Indicator variable equal to one for a manager who holds a PhD or JD degree, and zero otherwise.
Parental Education	Average education attainment score for a manager's parents as in Chuprinin and Sosyura (2018). The education attainment score is equal to 3 if the person attended college, 2 if the parent attended high school but not college, 1 if the parent attended elementary school but not high school, and 0 if the parent has no school education.
Family Wealth	Income of a manager's father from his census record, if available and if the father worked for at least 20 weeks during the previous year, and if not the father's home value or rent. If neither income nor home value or rent are available for a manager's father, the mother's home value or rent is used. Income is expressed in multiples of the state median male income in the state of the household and rent and home value are expressed in multiples of the state median.
Religiosity Ratio	Fraction of members of all religious denominations in the home county of a manager's family around the time that family disruption took place. Defined as the number of members of all religious denominations in a county divided by the county's total population as reported by the Association of Religion Data Archives (ARDA) for the year 1952.

Avg. Parental Age at Manager's Birth	The average age of the fund manager's parents at the time of the manager's birth.
Both Parents working	Indicator variable equal to one for a fund manager if both of her parents worked either as employees for the government or in a private business, on own account, or as employers according to the "class of worker" item in the parents' census record, and zero otherwise.
Father blue-collar Worker	Indicator variable equal to one for a fund manager if her father had a blue-collar job, i.e., he performed manual labor such as manufacturing, mining, or farming, and zero otherwise.
Firstborn	Indicator variable equal to one if a manager is the firstborn child, and zero otherwise.
Number of Siblings	Number of a fund manager's siblings.
Parents' Age difference	Absolute difference between the age of a fund manager's parents.
Parent born outside U.S.	Indicator variable equal to one for a fund manager if at least one of her parents was born outside the U.S., and zero otherwise.
Parent Homeowner	Indicator variable equal to one for a fund manager if at least one of her parents did not live for rent according to the parents' census records.
Parent Self-employed	Indicator variable equal to one for a fund manager if one of her parents worked on their own account or as employer according to the "class of worker" item in the parents' census record, and zero otherwise.
Parent Worked in Finance	Indicator variable equal to one for a fund manager if one of her parents worked in the banking, insurance, investment, or real estate sector according to the parent's census record, obituary, city directory or other state or federal records, and zero otherwise.
Manager Works for Home State Fund	Indicator variable equal to one if a fund is managed by a fund manager whose home state is the state in which the fund firm is located, and zero otherwise. A fund's location is the location of the firm that offers the mutual fund (reported in Morningstar Direct).
Fund and fund-stock characteristics	
Total Risk	Standard deviation of a fund's monthly gross returns during a year.
Idiosyncratic Risk	Standard deviation of residuals from annual estimations of a market model with monthly gross returns and the value-weighted return on all NYSE, AMEX, and NASDAQ stocks.
Market Risk	Fund's beta from annual estimations of a market model with monthly gross returns and the value-weighted return on all NYSE, AMEX, and NASDAQ stocks.

Tracking Error	Standard deviation of the difference between a fund's return and the return of the benchmark index from the fund's prospectus. Quarterly data are obtained from Antti Petajisto's website for the period 1980-2009. See Petajisto (2013) for details.
Fund Age	Number of years since the inception date of a fund.
Fund Size	Natural logarithm of 1 plus the total net assets under management of a fund (in m$) at the end of a year.
Fund Family Size	Natural logarithm of 1 plus the total net assets under management (in m$) of all funds in the same family as the fund in focus at the end of a year.
Avg. Monthly Return	Annual average of monthly gross returns of a fund.
Turnover Ratio	Minimum of a fund's security purchases and sales divided by the average total net assets under management either for the most recently completed fiscal year or the twelve months ending on the CRSP begdt.
Expense Ratio	Ratio of total investment that shareholders pay for as fund fees as of the most recently completed fiscal year.
Alpha	Annualized difference between a fund's monthly gross returns in excess of the risk-free rate and the fitted values from a market model for which the market factor loading is estimated over the period [t-12, t-1].
Sharpe Ratio	Annualized monthly gross return in excess of the risk-free rate divided by the annualized monthly standard deviation of excess returns.
Sell	Indicator variable equal to one for a fund-stock observation if the fund reduced the number of shares of the stock from the previous to the current holdings report date, and zero otherwise.
Terminating Sell	Indicator variable equal to one for a fund-stock observation if the fund reduced the number of shares of the stock to zero from the fund's previous to the current holdings report date, and zero otherwise.
Exogenous CEO Turnover	Indicator variable equal to one for a fund-stock observation if the respective company experienced an exogenous CEO turnover in a year, and zero otherwise. The data are obtained from Andrea Eisfeldt's website for the period 1992-2016. For details see Eisfeldt and Kuhnen (2013).
M&A	Indicator variable equal to one for a fund-stock observation if the respective company announced an M&A transaction between the fund's previous and the current holdings report date, and zero otherwise. Data are obtained from the SDC Platinum Mergers and Acquisitions database for the period 1980-2017.
Cross-border M&A	Indicator variable equal to one for a fund-stock observation if the respective company announced an M&A transaction between the fund's previous and the current holdings report date and if the target company is not located in the U.S., and zero otherwise. Data are obtained from the SDC Platinum Mergers and Acquisitions

	database for the period 1980-2017.
Non-public M&A	Indicator variable equal to one for a fund-stock observation if the respective company announced an M&A transaction between the fund's previous and the current holdings report date and if the M&A target company is not publicly listed, and zero otherwise. Data are obtained from the SDC Platinum Mergers and Acquisitions database for the period 1980-2017.
Portfolio activity measures	
Disposition Effect	Difference between the proportion of realized gains and realized losses for each fund in each quarter. The proportion of realized gains (PGR) is defined as $$PGR_{jT} = \frac{RG_{jT}}{RG_{jT} + UNRG_{jT}}$$ where RG_{jT} is the number of realized capital gains by fund j in quarter T and $UNRG_{jT}$ is the number of unrealized gains. The proportion of realized losses is defined analogously. We use the average purchase price as cost basis. A fund that is prone to the disposition effect will disproportionately realize more gains than losses, and it will thus have a positive and larger *Disposition Effect*. See, for example, Odean (1998) and Frazzini (2006) for details.
Active Share	Share of a fund's portfolio that is different from the fund's prospectus benchmark index. Quarterly data are obtained from Antti Petajisto's website for the period 1980-2009. See Petajisto (2013) for details.

Table A.2
Term definitions

Term	Definition
Fund family	A fund family comprises all funds managed by a single investment company. For example, all of the mutual funds offered by Fidelity are part of the same fund family.
Morningstar Style	Morningstar fund styles are derived from the Morningstar Style Box. The vertical axis of the style box graphs market capitalization of a fund's stock holdings and is divided into three indicators: Large, Medium, and Small. The horizontal axis classifies funds by Value, Growth, and Blend (which represents a combination of both value and growth). Together, the vertical and horizontal axes are used to classify a mutual fund into one of nine styles: (i) Large Value, (ii) Medium Value, (iii) Small Value, (iv) Large Blend, (v) Medium Blend, (vi) Small Blend, (vii) Large Growth, (viii) Medium Growth, and (ix) Small Growth.
CUSIP	The identifier for North American financial securities from the Committee on Uniform Security Identification Procedures of the American Bankers Association.

Internet Appendix A

To identify a fund manager's family in the U.S. census, we use the data collection procedure described in Chuprinin and Sosyura (2018) with minor modifications. The modifications are necessary because we utilize open-access U.S. people-search websites, such as FamilyTreeNow, Intelius, Spokeo, and Whitepages.com, to identify the names and birth years of a fund manager's parents, siblings and other relatives. People-search websites collect publicly available information like birth, court, marriage, and property records to create profiles on individuals that may include their age, name of employer, occupation, and current and past addresses. Whitepages.com, for example, has the largest database of contact information on Americans. As of 2008, it had data on about 90 percent of the U.S. adult population. These websites also propose possible family members based on individuals mentioned in the same public records and provide their age. We search for a manager's profile on these websites using his or her full name, year of birth, and location (city or county) of employer. When we find a potentially matching profile, we require a confirmation of the match according to one of the following criteria: (a) the profile includes as employer a company for which the fund manager has worked; (b) the individual's e-mail addresses indicate the domain of the company the fund manager has worked for; (c) the individual's occupation is “portfolio manager”, “investment manager”, or “investment adviser”; (d) one of the individual’s addresses matches the official business address of the fund manager’s company; (e) one of the individual’s addresses matches the fund manager's personal address from SEC filings, documents of the fund or the advisory management firm; (f) the names of possible family members match the names of the fund manager's spouses or parents retrieved from one of the sources used to gather information on managers’ education, e.g., Marquis Who’s Who.

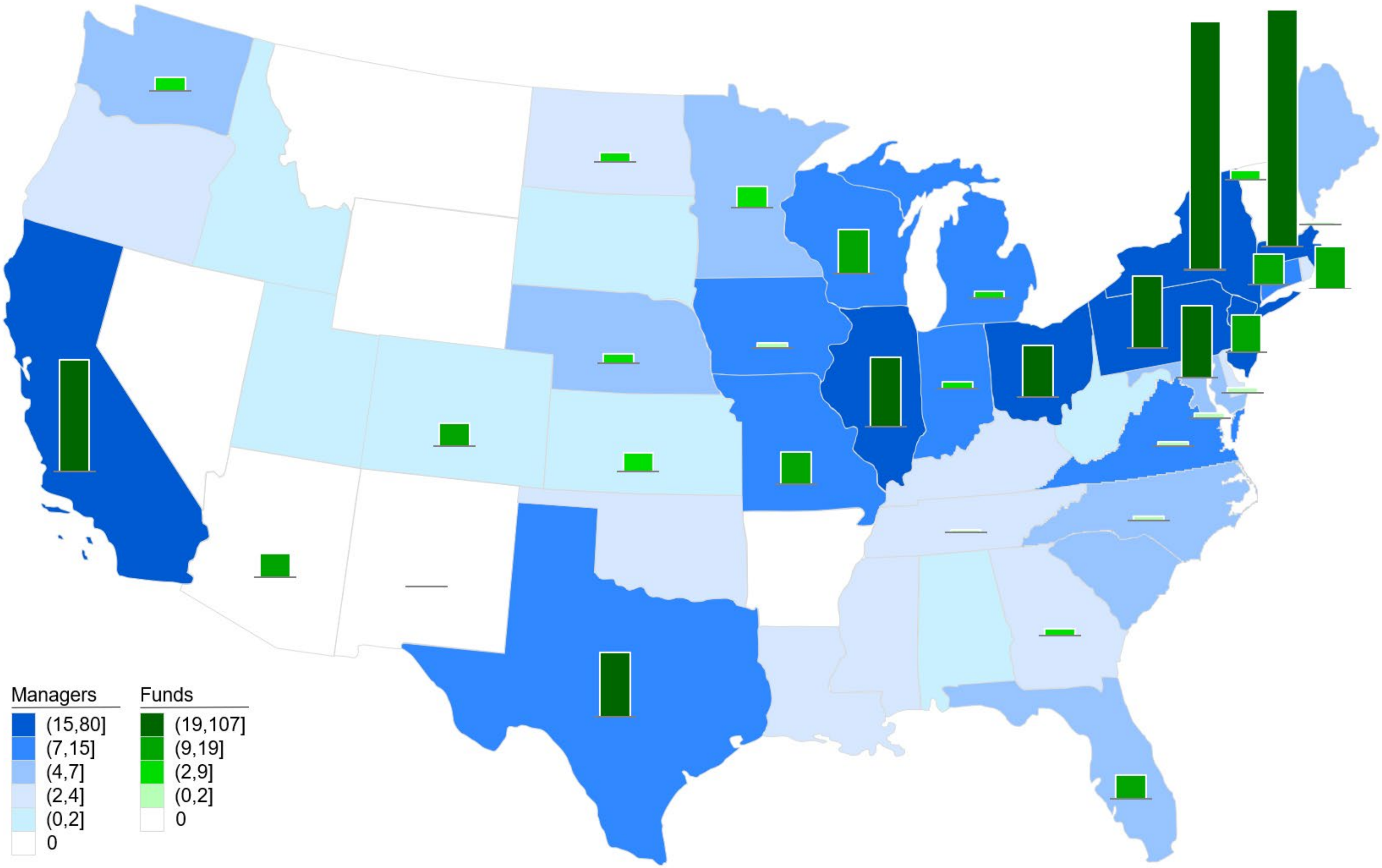
If we verify a profile, we continue our search by sequentially checking three types of events in a fund manager’s life: birth, marriage, and death. First, we attempt to identify a manager's birth record on the genealogy research website Ancestry.com using the manager's full name and year of birth. We require the names of both parents provided in the birth record to match the names of possible family members from the people-search website profile of the fund manager. Furthermore, possible family members from the manager's profile with matching names need to be in an appropriate age so that they could realistically be the manager's parents. If we are unable to find a matching birth record for a manager, we proceed with the second event: a fund manager's marriage(s). Marriage announcements, often published in local newspapers, typically provide the place of residence of bride and groom, their education, current employer and occupation, and their parents' names. We search historical newspapers on Newspaper.com, the largest online newspaper archive, for marriage announcements of individuals using a fund manager's full name. Verification of a match is done using the individual's year of birth, attended universities, employer and occupation. Sometimes marriage records also provide the names of parents of the bride and the groom. Thus, we also search for a manager’s marriage record(s) in the database of state marriage records maintained by Ancestry.com and establish unique matches by obtaining the full names and birth years of the bride and the groom as well as the parent's names. We again verify matches using the names of the individual’s parents and the spouse’s name, which need to match the names of possible family members from the manager's people-search website profile. If we are still unable to identify the manager’s parents, we proceed with the analysis of death records and obituaries. For this purpose, we search for a fund manager’s obituary on Newspaper.com as well as the database of obituaries maintained by the service provider Legacy.com. To verify a potential match, we require that, besides a matching name and birth year, the obituary mentions the fund manager’s occupation and employer. For the remaining fund managers for whom we are unable to identify the names of their parents and siblings, we search for obituaries of all potential family members from the manager's people-search website profile who are in an age so that they could be the manager's parents. Because obituaries typically mention the spouse, children and other family members of the deceased, we identify a fund manager’s parents by locating the obituaries in which the manager is listed as a child. Table IA-A1 classifies parental deaths according to the cause of death.

We use the combination of the names of a fund manager's parents, siblings, and other relatives as well as their birth years to identify the households where fund managers grew up in the 1940 census. For a small subset of managers, we obtain the 1930 census records if the 1940 census record cannot be found or if information is missing in the 1940 census record. Following this data collection procedure, we are able to find the households' census records for 93% of fund managers. As in Chuprinin and Sosyura (2018), unmatched observations mainly result from transcription errors in the indexing of handwritten family names in the digital archives, which prevent us from being able to locate the record.

Table IA-A1
Parental deaths

Cause of death	Count	Share of treated managers (%)
Accident	1	2.3
Died during military service	2	4.7
Long-term disease	8	18.6
Sudden illness	10	23.3
Unreported but sudden	10	23.3
Unreported other	12	27.9

Figure IA-A1
Distribution of fund manager birth states and fund locations



Internet Appendix B

Table IA-B1
Coarsened Exact Matching (CEM)

Dependent variables	*Total Risk*			*Disposition Effect*		
	(1)	(2)	(3)	(4)	(5)	(6)
Family Disruption	**-0.006****	**-0.007****	**-0.008*****	**0.081*****	**0.059****	**0.091*****
	(-2.16)	**(-2.01)**	**(-2.67)**	**(4.01)**	**(2.21)**	**(4.25)**
Exact matching based on:						
Birth Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Birth State	Yes	Yes	Yes	Yes	Yes	Yes
Family Wealth Quintile	Yes	No	No	Yes	No	No
Max. Parental Education	No	Yes	No	No	Yes	No
Both Parents Working	No	No	Yes	No	No	Yes
Controls as in Table 2	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,880	3,774	3,896	13,160	12,854	13,174
Adjusted R-squared	0.759	0.755	0.769	0.200	0.218	0.194

This table reports the estimation results on the CEM-matched sample with three different sets of matching criteria. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Internet Appendix C

To further mitigate concerns of omitted variable bias and to ensure that our results are not caused by inappropriate counterfactuals, we use two different matching procedures. First, we use a coarsened exact matching (CEM) to match managers based on different dimensions of their early family life.[19] We exactly match treated and control observations based on three sets of matching criteria. Each set includes managers' birth cohorts and birth states. The first set additionally includes the wealth of a manager's parents defined as the *Family Wealth* quintile to which his or her family belongs. The second set uses the education of fund managers' parents defined as the maximum education attainment score of the parents (i.e., 3 = college, 2 = high school, 1 = elementary school, and 0 = no education). The last set of matching criteria uses the indicator, *Both Parents Working*, that equals one if both parents had a job according to their census records. We use this variable for matching as it is the only other variable, besides *Family Disruption*, that consistently explains investment behavior in Panel A of Table 5. Matching on these criteria ensures that treated and untreated managers grew up during the same period and in the same U.S. states, experienced similar events and trends, and were subject to comparable (socio)economic, familial, and regional influences. Regression results based on the CEM-matched samples are reported in Internet Appendix B. The coefficient on *Family Disruption* remains significant at the 5% level or better when used to explain *Total Risk* in specifications (1) to (3) and *Disposition Effect* in specifications (4) to (6).

As a second matching approach, we use propensity score matching (PSM) (Rosenbaum and Rubin, 1983) to identify a control group for the treated fund managers in our sample. For each treated fund year (i.e., *Family Disruption* = 1), we select an untreated sample fund year (i.e., *Family Disruption* = 0) with the closest propensity score. The PSM criteria include all fund manager and fund characteristics (used as explanatory variables in the regressions in Tables 2 and 3), as well as year and investment style fixed effects. By matching on investment styles and years, we make sure we compare fund managers working in similar settings that are likely to matter for risk-taking and

[19] CEM allows to group observations in distinct strata based on coarsened values of selected matching variables. Weights are assigned to matched control observations to balance the number of treatment and control observations in each stratum. Observations in strata without treatment and control observations are eliminated to ensure common support, which is why only a limited number of matching criteria can be chosen without reducing the sample size considerably. For details, see Iacus, King, and Porro (2012).

the disposition effect, i.e., the same styles and time. To maintain statistical independence of our tests, we implement a nearest neighbor matching algorithm without replacement. This algorithm uses the distance between covariate patterns to define the "closest" neighbor and removes a matching sample fund year from the matching pool once it was selected. Internet Appendix C presents the intermediate steps (Panels A, B and C), which support covariate balance and results of the PSM approach. Panels D and E show the regression results based on the PSM-matched sample. The regression model we use is identical to that shown in specification (2) of Table 2 and is based on all fund years of all matched funds. In Panel D, specification (1) shows the results when we omit the fund and fund manager characteristics used to match treated and control observations, while specification (2) shows the results from the regression model including all covariates. When used to explain *Total Risk*, the coefficient on *Family Disruption* is significant at the 1% level and similar in terms of economic magnitude to the coefficients found in our baseline regressions in Table 2. Applying the same PSM approach to the dependent variables and *Disposition Effect*, *Idiosyncratic Risk*, *Market Risk*, and *Tracking Error* in Panel E, we find the coefficient on *Family Disruption* to remain statistically significant over all regression specifications. Our results are also similar if we additionally use birth cohort and birth state fixed effects (not tabulated).

To summarize, despite the differences in methodology and matching criteria, both CEM and PSM matching procedures provide corroborating evidence suggesting that treated fund managers indeed take less risk and exhibit a stronger disposition effect.

Table IA-C1
Propensity Score Matching

Panel A: Pre-match propensity score regression and post-match diagnostic regression

Dependent variable	***Family Disruption***	
	(1)	(2)
	Pre-Match	**Post-Match**
Fund Age	0.006***	-0.003
	(3.03)	(-1.34)
Fund Size	0.030	0.020
	(1.61)	(0.62)
Fund Family Size	0.013	0.005
	(1.40)	(0.36)
Avg. Monthly Return	-3.620	1.646
	(-1.17)	(0.36)
Expense Ratio	33.649***	6.924
	(5.85)	(0.94)
Turnover Ratio	0.001	0.045
	(0.03)	(0.96)
Female	-0.918***	-0.202
	(-4.06)	(-0.47)
Manager Age	0.009*	-0.002
	(1.90)	(-0.27)
Manager Tenure	-0.012***	0.017**
	(-2.93)	(2.40)
Ivy League	0.300***	-0.076
	(5.56)	(-0.94)
MBA	-0.053	0.000
	(-0.95)	(0.00)
PhD	0.473***	-0.055
	(5.14)	(-0.42)
Parental Education	-0.305***	-0.025
	(-7.77)	(-0.42)
Family Wealth	0.027***	-0.006
	(2.74)	(-0.69)
Investment Style FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,929	1,194
Pseudo R-squared	0.095	0.020

Panel B: Differences in fund and manager characteristics

Variables	Treated	Control	Difference	t-statistic
Risk before manager assumes office				
Total $Risk_{t-1}$	0.043	0.044	-0.001	0.820
ΔTotal $Risk_{[t-3,t-2]}$	0.076	0.069	0.007	-0.245
ΔTotal $Risk_{[t-2,t-1]}$	0.097	0.113	-0.016	0.579
Covariates used for PSM				
Fund Age	18.519	19.403	-0.884	0.841
Fund Size	4.984	4.894	0.090	-0.825

Fund Family Size	6.367	6.153	0.214	-1.059
Avg. Monthly Return	0.009	0.009	0.000	-0.467
Expense Ratio	0.014	0.014	0.000	-0.927
Turnover Ratio	0.708	0.665	0.043	-0.899
Female	0.007	0.010	-0.003	0.635
Manager Age	56.595	56.000	0.595	-1.114
Manager Tenure	8.627	7.723	0.905	-2.109
Ivy League	0.487	0.484	0.003	-0.116
MBA	0.506	0.489	0.017	-0.578
PhD	0.126	0.127	-0.002	0.087
Parental Education	2.111	2.173	-0.062	1.412
Family Wealth	2.853	2.995	-0.142	0.599

Panel C: Estimated propensity score distributions

Propensity Scores	No. of Obs.	P5	Mean	Median	P95
Treatment	597	0.06116	0.22298	0.20121	0.44715
Control	597	0.06125	0.22648	0.20123	0.46054
Difference		0.00000	0.00996	0.00006	0.03433

Panel D: Estimation with PSM-matched sample

Dependent variable	***Total Risk***	
	(1)	(2)
Family Disruption	**-0.008********	**-0.007********
	(-3.07)	**(-2.81)**
Fund Age		32.768
		(0.00)
Fund Size		0.001
		(1.40)
Fund Family Size		-0.000
		(-0.61)
Avg. Monthly Return		0.068
		(1.46)
Expense Ratio		0.293*
		(1.74)
Turnover Ratio		0.001
		(0.90)
Female		-0.012**
		(-2.05)
Manager Age		-0.000***
		(-3.29)
Manager Tenure		0.000
		(0.10)
Ivy Leagues		0.005**
		(2.09)
MBA		-0.005***
		(-2.59)
PhD		-0.009*
		(-1.94)
Parental Education		-0.001
		(-0.52)
Family Wealth		0.000
		(0.95)
Fund FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,024	3,024
Adjusted R-squared	0.756	0.761

Panel E: Estimation with PSM-matched sample - Other variables

Dependent variables	***Idiosyncratic Risk***	***Market Risk***	***Tracking Error***	***Disposition Effect***
	(1)	(2)	(3)	(4)
Family Disruption	**-0.004****	**-0.134***	**-0.022***	**0.071*****
	(-2.00)	**(-1.93)**	**(-1.94)**	**(2.85)**
All controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	3,024	3,024	7,203	12,657
Adjusted R-squared	0.682	0.507	0.604	0.194

These tables report results from a propensity score matching. Panel A presents estimates from the Probit model used to estimate propensity scores for firms in the treatment and control groups. Specification (1) shows the results from the Probit regression explaining the dependent variable *Family Disruption* prior to matching. We use the propensity scores from this regression to perform a nearest neighbor match. Specification (2) shows the results from the same Probit regression with the matched sample. Supporting covariate balance, none of the independent variables is statistically significant post-match (except for *Manager Tenure*). Panel B reports univariate comparisons between the treatment and control observations and the corresponding t-statistics from difference-in-means tests. The estimates also support covariate balance. Importantly, Panel B additionally reports statistics on fund risk prior to managers assuming office (which we do not use to match groups), i.e., mean total fund risk in the previous year, denoted $\textit{Total Risk}_{t-1}$, and mean growth in total fund risk from year *t*-3 to year *t*-2 as well as from *t*-2 to *t*-1. The differences in average risk and growth rates of risk between treated and control observations are statistically indistinguishable from zero, indicating that the reduction in fund risk we observe takes place when treated managers assume office. Panel C reports the distribution of estimated propensity scores for the treatment and control observations, and the difference in estimated post-match propensity scores. The differences between the propensity scores of treated and control observations are virtually zero (median = 0.00006). Panel D and Panel E report the estimation results based on the PSM-matched samples. All regressions include fund and time fixed effects. Robust t-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Internet Appendix D

Table IA-D1
Does Fund Manager-Fund Matching Explain Less Risk-taking?

Dependent variable	*Family Disruption*			
	OLS		Logit	
	(1)	(2)	(3)	(4)
Total Risk$_{t-1}$	**-0.620**	**-0.357**	**-9.199**	**-5.683**
	(-0.72)	**(-0.35)**	**(-0.61)**	**(-0.40)**
Fund Age	0.001	0.001	0.009	0.020
	(0.67)	(0.87)	(0.50)	(0.97)
Fund Size	-0.029	-0.034	-0.322	-0.508
	(-1.41)	(-1.49)	(-1.37)	(-1.59)
Fund Family Size	-0.003	-0.004	-0.034	-0.058
	(-0.37)	(-0.39)	(-0.29)	(-0.41)
Avg. Monthly Return	-5.216*	-4.662	-83.376**	-66.713
	(-1.75)	(-1.47)	(-2.05)	(-1.56)
Expense Ratio	-4.345*	-5.755**	-66.705	-137.694
	(-1.68)	(-1.99)	(-0.80)	(-1.54)
Turnover Ratio	0.024	0.040	0.342	0.844
	(0.67)	(1.09)	(0.61)	(1.60)
Investment Style FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	224	224	136	136
Adj. / Pseudo R-squared	0.015	-0.010	0.135	0.178

This table reports the results from OLS and Logit regressions of *Family Disruption* on *Total Risk$_{t-1}$* (i.e., total fund risk in the previous year), controls for fund characteristics (for the previous year) and investment style and year fixed effects. The sample is restricted to years in which a manager and a fund match. The sample size is limited because manager-fund matches that occurred prior to 1980 are not part of the sample and because newly set-up funds for which no past data are available have to be excluded. Robust t- and z-statistics (in parentheses) are based on standard errors clustered by manager. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively. Logit regressions contain fewer observations due to the exclusion of explanatory variables in instances in which these variables cause separation (see Zorn, 2005).

Reference

Zorn, C., 2005. A solution to separation in binary response models. Political Analysis 13, 157-170.