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Who works in Finance?

Three essays on the social backgrounds of finance professionals

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Man is by nature a social animal.

Aristotle, Politika, c. 328 B.C.

Executive Summary

Economists widely agree that a country's financial system plays an important role in its economic development and – if well established – can provide considerable benefits to society. Yet, we still know relatively little about those who work in the financial industry. Why do people decide to pursue a career in finance? How do finance professionals differ from other people in terms of their norms and values? And what determines their behavior?

This thesis is aimed at broadening our understanding of *who* are the *social animals* that work in the U.S. financial industry. The three studies that comprise this thesis contribute to the emerging field of social finance by expanding our knowledge of the social factors that influence finance professionals and determine their economic behavior.

The first study begins at the making of finance professionals. It provides evidence that people are substantially more likely to choose a career in finance if their fathers have already worked in the financial industry. This intergenerational correlation between fathers and their children is greater than in most other industries and is related to a considerable income surplus of second-generation finance industry employees.

The second study documents a unique and worrisome deterioration in generalized trust, an important social belief, among finance industry employees over the past decades. This decline in trust is also significantly stronger than the trust decline among the general U.S. population over the same period. It appears to be associated with changes in the economic conditions in the U.S., shifts in the professional environment in the financial industry, and with a decreasing degree of socialization among finance professionals.

The third study reveals a long-lasting association between the disruption of the family of origin during the childhood of mutual fund managers and their investment behavior later in life. Fund managers who experienced the death or divorce of their parents early in life exhibit a stronger disposition effect and take less risk in their delegated portfolios. This study hence promotes our understanding of the long-term impact of traumatic childhood experiences and the origins of investment biases.

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1 Introduction

This thesis consists of three essays that study the social backgrounds of people working in the U.S. financial industry. The essays investigate, firstly, how the decision to pursue a career in finance correlates across generations, secondly, how social beliefs in finance have evolved over the past decades, and thirdly, how formative childhood experiences affect the investment behavior of professional investors. The thesis thus contributes to the growing social finance literature that deals with the question of *who* works in finance.

The role of beliefs and personal experiences for economic behavior has attracted considerable attention among academics in recent years. While traditional economic theory is based on the assumption that people make rational choices, behavioral economics holds that they in fact use dozens of heuristics and are influenced by seemingly irrelevant factors like emotions (e.g., Kahneman and Tversky, 1996). Heuristics are the product of evolutionary processes, genetic or memetic, as well as the result of experiences and learning. They usually work very well but may in some situations lead to severe errors or behavioral biases (Aumann, 2019). A recent *Financial Times* article provides a range of practical examples of how asset management firms have begun to pay attention to these biases that have the potential to negatively impact the performance of their funds, for instance, by hiring psychologists to advise their fund managers (Mooney, 2018).

In academia, there is widespread agreement today that behavioral dimensions can increase the explanatory power of traditional models, which rely on the assumptions of utility maximization and market equilibrium, by enhancing them with more plausible psychological foundations (e.g., Angner and Loewenstein, 2012; Chetty, 2015). At their core, behavioral studies differ from their neoclassical cousins in the fact that they incorporate aspects such as intrinsic motivation to comply, peer effects, information imperfections about deterrence parameters, etc. As an example, substantial laboratory and field research suggests that people do not care solely about their own material payoffs but are willing to cooperate and have a sense of fairness (e.g., Loewenstein, Thompson, and

Bazerman, 1989; Camerer and Thaler 1995). Other studies find that people are inclined to make efforts to pursue social goals, such as saving water and energy, giving to charities, or donating blood, even when the (pecuniary) incentives go in the opposite direction (e.g., Frey, 1997; Camerer and Fehr, 2006).[1]

Most importantly for this thesis is the idea of studying economic agents as people embedded in a dynamic social environment rather than as isolated decision-makers, which has laid the foundation for a new branch of behavioral economics known as *social finance*. Hirshleifer (2015) coined this term to subsume the rapidly growing strand of studies that are concerned with the role of sociological factors for financial behavior and outcomes. In his view, the study of social dynamics can, for example, help to further our understanding of the origins of various investment biases that we observe in financial markets, such as the disposition effect. Studies in this new field draw on social psychology and sociology to examine the interactions within families or circles of friends, the amount of social capital and norms prevailing in a society, and social preferences (see, e.g., Cronqvist, 2018).[2] The three essays in this thesis contribute to this growing and exciting field.

The following sections provide a brief overview of the results of the respective studies, a description of their contributions to the literature, and a discussion of their implications. Possible directions for future research are also pointed out in some places. Chapter 2 investigates the personal characteristics of employees in the U.S. financial industry by analyzing long-term trends in gender diversity, racial composition, age structure, and intelligence in finance. Chapters 3, 4, and 5 constitute the three essays that form the main body of this thesis. Lastly, Chapter 6 concludes with some remarks.

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[1] As Richard Thaler (2016) notes with a wink in his book, according to a traditional economist, hungry shoppers would also not subconsciously be influenced by their stomachs to buy more food.

[2] Studies that examine the flow of financial information through social networks are Cohen, Frazzini and Malloy (2008, 2010), Hvide and Östberg (2015), Pool, Stoffman, and Yonker (2015), Cai, Walkling, and Yang (2016), and Ahern (2017). Papers investigating how social norms and ideologies influence financial behavior include Hilary and Hui (2009), Hong and Kacperczyk (2009), Hong and Kostovetsky (2012), Kumar and Page (2014), and Pan, Siegel, and Wang (2017). Social preferences are studied by Bollen (2007), Cronqvist and Yu (2017), and Luo and Balvers (2017), among others.

1.1 Parents and the decision to work in finance

Parents are the most important factors influencing the development of their offspring. They are responsible for the genetic disposition of their children as well as for the environment in which they grow up. The intergenerational transmission of traits and economic outcomes from parents to children is of long-standing interest in the scientific community (see, e.g., Black and Devereux, 2011). A frequently studied topic in this field is the correlation of wealth, income, or socioeconomic status between parents and their children (e.g., Chetty et al., 2014). A much less discussed topic is the importance of parents for their children's vocational development and especially the inheritance of industries and occupations from parents to children. Yet, as Schulenberg, Vondracek, and Crouter (1984) argue, parents have a far greater influence on the vocational development of their children than school or the circle of friends.

Against this background, the first essay of this thesis, based on Schürmann (2020), examines the intergenerational industry mobility in the U.S. financial industry, i.e., the correlation between parents and their children in their decisions to pursue a career in finance. This study thus deepens our understanding of the structure of the finance industry labor market and specifically the mechanisms that govern the recruitment of employees. Understanding these mechanisms is important for at least two reasons. Firstly, it enables financial firms to establish efficient recruitment processes in order to find the best available talents. Secondly, it helps policy makers to implement effective rules that support social goals such as equal opportunities for entering the industry, an issue that appears frequently on the political agenda. More broadly, investigating the intergenerational inheritance of industries extends the existing literature on the role of parents in their children's career choices and thereby helps explain how inequality is transmitted across generations since wages are higher in some industries than in others.

To analyze the intergenerational industry mobility, I draw on representative survey data from the General Social Survey (GSS) over the 47-year period from 1972 to 2018. I present evidence that children of fathers who worked in the financial industry during their childhood are about eight percentage points more likely to also work in finance themselves. This significant father-child correlation indicates that fathers play an important role in their children's decision to pursue a career in finance. Interestingly, I do not reveal a significant correlation between mothers and their children, even if the child is a daughter.

When comparing the relative industry mobility in finance with other private sector industries, I discover that the magnitude of the father-child correlation in the financial industry is larger than in most others. Specifically, the increase in the likelihood to work in an industry when a person's father already worked in that industry is larger in only three other industries: real estate, professional services, and agriculture. The finding that children often follow in their parents' footsteps in these three industries is consistent with the concept that human capital, corporate networks, and tangible assets in self-employed professions can be more easily transferred from one generation to the next. Accordingly, Laband and Lentz (1992) suggest that the sons of lawyers, who are part of the professional services industry, also frequently become lawyers because the profession is conducive to the cost-effective transfer of relevant skills and knowledge across generations, particularly in the context of family-run law firms.

Furthermore, I document that the significant father-child correlation in the financial industry is driven solely by wealthier families. Generally, this finding is in line with earlier studies suggesting that the socioeconomic status of the family is related to children's career aspirations (Brook et al., 1974). Since wages in financial occupations are comparatively high, children from wealthier families may see these occupations as a way to meet their own expectations. Moreover, wealthier families are likely to invest more in their children's human capital development during their upbringing, while at the same time also having stronger personal networks in the industry (Montgomery, 1991).

In additional tests, I shed light on the question of whether second-generation employees in the financial industry benefit economically from their fathers' prior industry experience. My analysis reveals that they indeed enjoy a substantial income surplus compared to their industry peers. In particular, the estimates indicate that having a father who also worked in finance is associated with a 25 percent higher income.

But why is the intergenerational industry correlation between fathers and their children so particularly high in the financial industry? And what mechanisms drive the substantial income surplus of second-generation finance industry employees? It is naturally difficult to examine these questions empirically, as pointed out, e.g., by Laband and Lentz (1992). Nevertheless, it is still worth looking at the potential explanations that labor market theory provides for the high intergenerational industry correlation in finance.

The first group of explanations is based on the idea that human capital, preferences, and personal attributes are transmitted from parents to their children. Rosenzweig and Wolpin (1985) reveal that the high incidence of intra-family intergenerational successions in farms is due to implicit contracts between generations that maximize the profits from farm-specific knowledge acquired through experience. Similarly, the transfer of finance-specific human capital may induce more children of finance industry employees to choose a career in finance as well. Of course, it is also possible that the affinity to the financial industry among children of fathers who worked in finance reflects similarities among family members in attitudes about or preferences for the industry itself. Moreover, there may be specific personal attributes that are correlated with the probability of pursuing a career in finance and that passed on within families (see, e.g., Ashraf, Bandiera, and Delfino, 2020). Therefore, the above explanations are based on the extensive literature that emphasizes the parental influence, either genetically or through parenting, on the personal development of their offspring.

The second group of explanations is motivated by the theory of job search. Loury (2006) assumes that up to 50 percent of jobs in the United States are found through family, friends, or acquaintances.[3] Companies recruit employees through informal networks either because of incomplete information about the quality and suitability of potential employees or because of detrimental nepotism in the hiring process. In turn, incomplete information exists due to the fact that prospective workers are heterogeneous in their preferences and

[3] Ioannides and Loury (2004) provide a detailed survey documenting this sort of networking.

abilities and that jobs are heterogeneous in terms of the skills required. As this double-sided uncertainty cannot be easily removed without actually matching an employee to a vacant position, employers and employees are inclined to rely on information provided by contacts to reduce the chance that a match will be worse than it initially appeared. For example, Kramarz and Skans (2014) document that young adults in Sweden have a high tendency to find their first job in the same plants that also employ their parents. The authors attribute this phenomenon to the use of social ties in the matching process and find that both sides, the employer and the new worker, benefit from the use of these ties.

In contrast, detrimental nepotism describes the use of parent-provided networks to find employment when other available candidates are better qualified. Hence, this sort of networking represents a mere transfer of rents and is inefficient from a macroeconomic perspective. Evidence for detrimental nepotism is provided by Lentz and Laband (1989) who find that children of doctors are more likely to be admitted into medical school in the U.S. than are comparable non-followers even when their level of human capital is taken into account. In a more general context, Gagliarducci and Manacorda (2020) suggest that private firms in Italy frequently hire or promote relatives of politicians or grant them higher earnings in exchange for or in anticipation of political favors. The financial industry in the U.S. has also experienced nepotism scandals regarding its hiring practices in the past, such as the scandal surrounding J.P. Morgan's "Sons & Daughters Program."[4]

In summary, the comparatively high intergenerational correlation between fathers and their children in the decision to pursue a career in the financial industry could stem from the transmission of human capital, preferences, and personal attributes or from informal parent-provided job networks (or a combination of both). Albeit the GSS does not allow scholars to distinguish between these explanations, I argue in this study that the large income surplus among finance industry employees whose fathers also worked in the industry is difficult to reconcile with detrimental nepotism as the only mechanism at work.

[4] Details about this scandal can be found in recent articles in the popular business press, e.g., Chiu (2019).

This is because the U.S. financial industry is generally known for its high degree of competitiveness. Sufficiently strong competition should arguably discourage firms from recruiting and promoting employees without any regard to productivity.

This study thus provides novel empirical evidence on the important role of the parents in their children's decision to enter the financial industry. In wealthier families, a father who has worked in the financial industry considerably increases the likelihood that his child will later also work in finance. The study also provides a first indication that second-generation finance industry employees, who earn substantially more compared to their peers, likely form better matches with employers. This preliminary finding opens an interesting avenue for future work that unravels the role of informal parental networks and the transmission of human capital (or preferences) from parents to children. A follow-up study could, for example, use the mutual fund industry as a laboratory as the performance, compensation, and family backgrounds of fund managers are well observable.

1.2 The evolution of trust in finance

The second essay, based on an earlier version of Limbach, Rau, and Schürmann (2021), complements the literature on social capital. Specifically, it examines how *generalized trust* has evolved in the U.S. financial industry over the past nearly four decades.

Social capital, defined by Putnam (1993) as networks and norms of civic engagement, is key to the economic prosperity of a society because it allows its members to trust one another. The kind of trust that is inherent in a society is called generalized trust. It is the trust vis-à-vis random members of a society (e.g., Guiso, Sapienza, and Zingales, 2009).

Fukuyama (1995) contends that generalized trust is important from an economic point of view as it enables the establishment of large private corporations, a conjecture supported by Bloom et al. (2009) with empirical evidence. Several studies suggest that generalized trust also matters for financial decision-making at the individual level. For example, people who trust others more are more likely to become entrepreneurs (Guiso, Sapienza, and Zingales, 2006) and to participate in the stock market (Guiso, Sapienza, and Zingales, 2008), and are less likely to default on household debt (Jiang and Lim, 2018). Taken together, since practically every commercial transaction builds, at least to a certain extent, on trust in anonymous others (Arrow, 1972), understanding the formation and evolution of trust has long been a key task in economics. It is thus surprising that, although scholars agree on the relevance of trust for financial intermediation (e.g., Zingales, 2015), little is known about generalized trust in the financial industry so far.

For our study, we use data from the General Social Survey for the period 1978-2016 and document that generalized trust of individuals working in the U.S. financial industry has declined substantially over the past 39 years. Importantly, their trust has not only deteriorated in absolute terms but also relative to the general U.S. population. The trust decline observed in finance is also unparalleled by any other industry. It has been particularly strong in the investment sector and among professionals with higher seniority and influence. Moreover, our results suggest that the erosion of trust is tied to a lack of confidence in institutions deemed especially relevant to the financial industry, such as the executive branch of the government which monitors the financial industry. We examine several potential drivers for the erosion of generalized trust among finance professionals and find a mix of components that have contributed to this trend: A greater sensitivity to economic change compared to the general population, shifts in the composition of the finance industry workforce, and fewer opportunities to engage socially with one another all appear to have driven the loss of trust. Overall, the results of this study paint a relatively dark picture of the current state of the financial industry.

They are worrisome since a lack of trust among finance professionals may have direct implications for the real economy through at least three channels. First, if banks are generally distrustful of their customers, they are likely to be more restrictive in their lending policies and therefore reluctant to finance profitable projects. Empirical evidence suggests that higher informational frictions between borrowers and lenders lead to more difficulties for firms in raising capital and insufficient financing of innovative, high-risk projects (Guiso, 1998). Thus, in the absence of trust, capital costs may increase and firms may consequently underinvest. Second, low levels of generalized trust among finance professionals may lead to them behaving less trustworthy themselves. There is ample evidence to suggest that one's own trustworthiness is highly correlated with the subjective opinion about the trustworthiness of others, a concept known as reciprocity (see, e.g., Glaeser et al., 2000; Butler, Giuliano, and Guiso, 2015). Hence, a lack of trust among finance professionals can lead to a higher propensity to behave in an uncompliant or even unlawful manner, for instance, by committing fraud.[5] Third, greater mistrust across the financial industry and more frequent instances of non-compliant behavior can threaten the reputation and ultimately the stability of the industry itself, especially in more turbulent economic times. As an example, anticipating the lack of trust and trustworthiness among finance professionals can lead to banks becoming the target of bank runs. Because a significant portion of their investments is usually long term, they would be forced to make inefficient fire sales if too many depositors demand redemption simultaneously.

In summary, a trust crisis in the financial industry can have severe negative effects on the real economy and undermine the positive role of finance which is described in an extensive literature going back at least to Schumpeter (1911). Therefore, a natural question arising from our results is what options are available to avert the negative economic consequences of deteriorating generalized trust across the financial industry. What follows is a critical review of the most frequently discussed options that firms and the government have to mitigate trust-related issues in finance.

A seemingly obvious solution for financial firms is to attempt to restore the level of generalized trust and thereby the trustworthiness of their employees. In his seminal book, Putnam (2000) calls for an era of civic inventiveness to rebuild social capital similar to the Progressive Era at the beginning of the twentieth century. Analogously, new formal as well as informal structures in financial firms that lead to higher standards of conduct could ensure the trustworthiness of their employees. As argued by Williamson (1993), many professional occupations, including finance, require their members to fulfill certain

[5] The recent wave of problematic financial practices and scandals have illustrated the enormous economic damage these behaviors of finance professionals can cause. Kantšukov and Medvedskaja (2013) estimate that the practices of rouge traders, for example, often result in damages of more than $1 billion.

obligations, such as obtaining a license, following an ethical code, or meeting fiduciary obligations. If well-established and followed by most professionals, these obligations can increase their reputation and infuse confidence into interactions with them. Yet, despite the existence of some obligations, the financial industry is often criticized for its allegedly low moral standards, and survey evidence suggests that investment banking in particular has an alarming attitude towards moral values (Tenbrunsel and Thomas, 2015).[6]

New measures could, for instance, target the corporate culture and bonus systems of companies so that they do not (unintentionally) create incentives for taking unmanageable risks or engaging in unethical behavior (Diamond and Rajan, 2009; Sheedy, Zhang, and Tam, 2019). Additionally, Putnam (2000) suggests novel workplace practices, such as flexible work hours or incentives to participate in community activities that increase social connectedness and enable the formation of generalized trust. Ultimately, there is no single mechanism that infuses trust but rather a series of measures financial firms themselves can take that help restoring generalized trust across the industry. However, it is important to note that these measures do most likely not have a rapid effect since the level of generalized trust that prevails in a society or group is characterized by considerable inertia. In this regard, Fukuyama (1995, p. 5) states that "[…] durable social institutions cannot be legislated into existence the way a government can create a central bank or an army."

Some economists and policy makers suggest yet another approach: stricter government regulation. Previous studies indicate that when the public is confronted with increasing mistrust or perceived unfairness, it tends to demand more and stricter control by the government (e.g., Glaeser and Schleifer, 2003; Aghion et al., 2010; Pinotti, 2012). Governments provide legal protection for consumers, create and manage regulatory bodies, enforce contracts, and prosecute unlawful behavior. With regard to financial

[6] For example, the official report by the Financial Crisis Inquiry Commission (2011), which was tasked with investigating the causes of the 2008 financial crisis, concludes that before and during the crisis "[…] we witnessed an erosion of standards of responsibility and ethics that exacerbated the financial crisis. This was not universal, but these breaches stretched from the ground level to the corporate suites." (p. xxii).

markets, Carlin, Dorobantu, and Viswanathan (2010) posit in their model that trust and formal regulation can function as substitutes. Consequently, when the level of generalized trust in a society is low, government interventions can help to protect investors and promote economic growth.[7] However, the vast majority of U.S. governments have adopted deregulation strategies in past decades, including the current U.S. administration, which clarified from the beginning that it intends to relax regulations introduced after the 2008 financial crisis. Today, many consider the system of financial regulation in the U.S. to be as complex and fragmented as the industry itself. Responsibilities are divided among several different federal and state authorities and numerous industry-sponsored self-governing associations (Komai and Richardson, 2013). Moreover, strong lobbying activities have repeatedly prevented the implementation of new legislation (e.g., Zingales, 2015). Against this background, it is an open question for researchers, policy makers, and practitioners whether the regulatory system is sufficient to cope with a growing degree of mistrust among finance professionals and its negative consequences.

A third option to address the challenges related to the lack of trust in the financial industry has often been proposed by technology enthusiasts in recent years: blockchains.[8] Originally developed as the technology behind cryptocurrencies like Bitcoin, blockchains allow any two parties to forge an agreement and conduct transactions without the need of intermediaries, i.e., without banks, money transfer services, exchange operators, lawyers, or government bodies (Tapscott and Tapscott, 2017). *The Economist* (2015) describes blockchain as "the trust machine" and the United Nations Development Programme (Wigley and Cary, 2018, p. 6) argues that "the decentralized, transparent, verifiable nature of [blockchain] means we can trust people and organizations precisely because trust is no

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[7] Some studies also provide examples of cases where a high level of trust in a society has been able to fill the void left by an underdeveloped legal system and a lack of enforcement mechanisms, for instance, Greif (1989, 1993), Gomes (2000), Allen (2005), and Allen, Qian, and Qian (2005).
[8] A blockchain is a distributed transactional database secured by cryptography (Beck et al., 2017). Potential blockchain applications in finance are described in Yermack (2017) and Raskin and Yermack (2018).

longer an issue." Yet, the perception that blockchains can completely substitute for trust in economic activities requires closer scrutiny. Nakamoto (2008) describes Bitcoin in his whitepaper as a trustless digital payment system since payments from one party to another, e.g., in e-commerce trading, are secured despite the absence of a third party due to their irreversible and transparent nature. This feature can, for instance, offer a valuable solution to the common double-spending problem (Cong and He, 2019).

Yet, as an electronic payment system, the Bitcoin blockchain only secures the exchange of money but not the transfer of assets or the fulfillment of other types of contractual agreements. Newer blockchains have extended the scope beyond electronic payments to the transfer of digital assets and are also able to represent the transfer of physical assets by means of digital representations of these assets. But since blockchains cannot track events in the physical "off-chain" world, the necessity for human agency and trust still remains.[9] Moreover, most blockchain applications, e.g., smart contracts, simply task technology with securing trust rather than third-party authorities. Put simply, blockchains can prevent some trust-related issues in economic transactions, in particular with regards to the involvement of intermediaries in payment processes, but they will not exempt individuals from the need to trust each other when engaging in economic activities (Altman, 2019). The technology is therefore at best a partial solution to problems related to the lack of trust among finance professionals.

In light of the foregoing, the evidence presented in this study appears fundamental to our understanding of the financial system. An insufficient level of generalized trust across the industry can have serious negative implications for the industry itself and the real economy. While there is no silver bullet solution to the death of trust across the financial industry, there are some measures that can be taken to mitigate trust-related issues. From an academic perspective, our study thus offers several opportunities for future research.

[9] Some scholars also refer to the boundary between the virtual blockchain world and the physical world as the "trust-frontier" (e.g., Glaser, 2017; Hawlitschek et al., 2018).

1.3 The family of origin and investment behavior

In addition to social capital and generalized trust, there is mounting evidence that financial behavior is influenced remarkably by another factor: people's personal life experiences.[10] Long-standing research provides a wealth of empirical evidence that people exhibit various investment biases, such as a lack of diversification (Huberman, 2001), a preference for skewness and lottery-type investments (Kumar, 2009), an extrapolation of recent superior returns (Benartzi, 2001), and the home bias (French and Poterba, 1991). These biases are not always innate but can be acquired in the course of a person's life, for example, through personal experiences.

Using data on Swedish twins, Cronqvist and Siegel (2014) decompose differences in investment behavior into genetic versus environmental components. The authors find that more than half of the behavioral variation across individual investors can be attributed to environmental factors. For investors with professional finance experience, the relevance of environmental factors is even higher. Their study hence suggests that experiences and the environment play a crucial role in shaping investment behavior. Although scholars have attributed investment biases in part to psychological mechanisms (see, for example, the literature cited in Cronqvist and Siegel, 2014), very little research has been devoted to date to uncover their origins. Consequently, Hirshleifer (2015) considers studies in the field of social finance that examine how social factors influence financial behavior to be very promising for advancing our understanding of the origins of investment biases.

The third essay of this thesis, based on Betzer et al. (2021), seeks to partly fill this void in the literature. It investigates whether the childhood rearing environment of mutual fund managers and in particular the disruption of this environment can explain to what extent

[10] A growing literature investigates experience-related heterogeneity in macroeconomic expectations and economic decision making, e.g., for households (Malmendier and Nagel, 2011), mutual fund managers (Greenwood and Nagel, 2009), CEOs (Malmendier and Tate 2005; Malmendier, Tate, and Yan 2011; Bernile, Bhagwat, and Rau, 2017), central bankers (Malmendier, Nagel, and Yan, 2021), and investors participating in initial public offerings (Kaustia and Knüpfer 2008; Chiang, et al., 2011).

these managers are prone to a particular investment bias, the disposition effect. We use unique hand-collected information about the families of origin of fund managers and examine whether experiencing the death of one parent or a parental divorce up to the age of 20 significantly influences their investment behavior in later life. We look at parental death and divorce as both events are common social phenomena in virtually all societies. Psychologists argue that the death of a parent or a parental divorce challenge children's beliefs about themselves and the world (Epstein, 1991; Janoff-Bulman, 1992). As a result, they have been shown to have long-term effects on personality and well-being (e.g., Amato and Keith, 1991; Tennant, 1991; Parsons, 2011; Ellis, Dowrick, and Lloyd-Williams, 2013; Flèche, Lekfuangfu, and Clark, 2019).

The main result of our study is that fund managers who experienced an early-life family disruption exhibit a stronger disposition effect, take lower fund risk, and are more likely to sell their fund holdings following risk-increasing events in their investee firms. In short, we suggest that broken families produce fund managers who are more cautious and more reluctant to realize losses than managers from intact families. But why is this the case?

The disposition effect, which describes the greater propensity of investors to sell assets when they are at a gain than when they are at a loss, was introduced by Shefrin and Statman (1985). It has attracted considerable attention from financial scholars because it has proved challenging to explain it with rational models of trading behavior. Instead, the disposition effect can be derived from behavioral theories, such as Kahneman and Tversky’s (1979) prospect theory in combination with mental accounting (Thaler, 1985). Empirical evidence for disposition-prone behavior is provided across different assets and markets, such as for stocks (Odean, 1998), executive stock options (Heath, Huddart, and Lang, 1999), real estate (Genesove and Mayer, 2001), and online bets (Hartzmark and Solomon. 2012). The disposition effect was also observed across investor types, including futures traders (Locke and Mann, 2005), fund managers (Frazzini, 2006), and individual investors (Grinblatt and Keloharju, 2001), among others. In summary, extensive prior research implies that disposition-prone behavior is near-ubiquitous among non-professional and professional investors with notable asset pricing and welfare implications.

Regarding the psychological mechanisms that drive the disposition effect, the most promising explanations rely on the concept of self-justification, i.e., the tendency of individuals to justify their behavior and deny any negative feedback associated with it. For example, Chang, Solomon, and Westerfield (2016) argue that cognitive dissonance plays an important role. When individuals are presented with new information contradicting their original priors, they tend to use a combination of defense mechanisms and mental tricks to reduce dissonance-related discomfort. These mechanisms are especially effective when the initial cognition relates to a positive self-image (Greenwald and Ronis, 1978). In simple terms, if a stock held by an investor declines in value, he tries to convince himself that he is still a smart investor who bought the asset for a good reason to avoid admitting a bad investment decision and thereby negatively affecting his self-image. This, in turn, results in the observed difference between the willingness to sell an asset at a gain versus a loss. Alternatively, investors in a model by Barberis and Xiong (2009, 2012) derive utility not only from consumption but also from the realization of gains. The authors are able to formally explain the existence of the disposition effect in their setting as investors feel good when they sell stocks at a gain, which leads to the disproportionate realization of gains. Therefore, according to these and other studies, self-justification strategies are key drivers of the disposition effect.

In light of the foregoing, the findings of Holland, Meertens, and van Vugt (2002) are of major importance. They document that a person's self-esteem is a crucial moderator for the application of self-justification strategies. People with a higher level of self-esteem are less likely to engage in self-justification strategies. We can therefore expect that the disposition effect observed in financial markets is, at least to a certain extent, rooted in investors' self-esteem. The reason for exploring the influence of the families of origin on the investment behavior of mutual fund managers is that psychological studies suggest that the family of origin plays a key role in an individual’s personality development, including the formation of self-esteem (Orth, 2018).

After accounting for several alternative explanations, we conclude in our study that the association between early-life family disruption and investment behavior is consistent with persistent symptoms of post-traumatic stress, particularly lower self-esteem and increased anxiety. In particular, we examine whether the observed relationship is caused by a socioeconomic shock to the family due to the loss of a parent or by fund managers taking care of their bereaved parents. Yet, our results suggest that the link between family disruption and investment behavior is unlikely to be determined by these mechanisms because the magnitude of the effect does not depend on the wealth of a manager's family or whether the bereaved parent is still alive. In contrast, the behavioral patterns that we observe for treated mutual fund managers are in line with prior research in psychology which suggests that experiencing a family disruption early in life relates to a greater vulnerability to future loss (Mireault and Bond, 1992), lower self-esteem (Lutzke et al., 1997; Ellis, Dowrick, and Lloyd-Williams, 2013), and higher levels of anxiety (Bifulco et al., 1992; Kendler et al., 1992; Tyrka et al. 2008).

As outlined above, it is well documented that the childhood rearing environment has a significant influence on children’s personality development. Therefore, we additionally explore how various other characteristics of the family environment during childhood (besides family stability) influence the investment behavior of managers, such as the number of siblings and the professions of the parents. Including these characteristics as additional controls in our regressions also addresses potential concerns related to omitted variables. While we find that some of these characteristics are also significantly related to investment behavior, our results suggest that the (in)stability of the family environment in childhood is the only measure that consistently explains the variation in the disposition effect and the risk-taking behavior of fund managers later in life.

Furthermore, to obtain a more sophisticated comprehension of family disruptions in childhood, we exploit observable heterogeneity in the disruption events. In particular, we separately examine parental deaths and divorces as well as unexpected deaths and deaths of non-working mothers. Our results remain significant for each of the four event types. These tests indicate that neither one of the two event types nor a wealth shock nor arguably anticipated deaths from long-term illnesses exclusively explain our results.

The analysis of potential moderators that may cause variations in the treatment intensity between treated fund managers yields further interesting results. In particular, we provide evidence that the association between experiencing an early-life family disruption and fund risk is significantly stronger when the disruption occurred during a manager's formative years, i.e., age 5 to 15, or when the family had less social support. The disposition effect is also stronger in case of less social support. Interestingly, we find that the results reverse for both risk-taking and the disposition effect when a very high level of social support is provided, which implies that family disruptions sometimes even lead to post-traumatic growth (Tedeschi and Calhoun, 2004). Lastly, we investigate whether the existence of a skill gap between fund managers who experienced early-life family disruption and those who did not could explain our findings. We do, however, not observe any indication of a skill gap between the two groups.

To conclude, our study is the first to empirically demonstrate that the stability of the family of origin in childhood has long-term consequences for the investment behavior of professional investors.[11] Our results provide evidence that investment biases, although they are in part a manifestation of innate and evolutionary characteristics of human behavior, are also to a considerable extent determined by the familial environment in which investors grow up. In doing so, this study expands our understanding of the origins of investment biases, as proposed by Hirshleifer (2015), and the economic consequences of a common social phenomenon. More broadly, this study contributes to recent research showing that the management style of economic agents is a result of their life experiences rather than the traits they were born with (e.g., Adams, Keloharju, and Knüpfer, 2018).

[11] It is possible that we underestimate the impact of family disruption during childhood on the investment behavior of individuals later in life because we focus on fund managers who are usually highly educated and trained in dealing with financial risks. Their education and work experience may mitigate the impact of early-life family disruption, while the average retail investor may be more affected by our treatment. Yet, since mutual fund investments constitute a significant portion of the financial assets of the average U.S. household, our results still affect the portfolio characteristics of the typical non-professional investor.

2 Demographic Characteristics and Intelligence in Finance

2.1 Introduction

The structure of the U.S. financial industry has changed drastically during the past decades. Just 30 years ago, sending someone cash electronically using something like a smartphone would have seemed like science fiction. Since then, the financial industry has grown much faster than the economy, pursued aggressive international expansion strategies, and disrupted its traditional processes with new technologies. Moreover, the formation of large conglomerates offering diverse services has substantially transformed the competitive landscape in the financial industry (Black and Strahan, 2002).

Structural changes in an industry are usually also accompanied by shifts in the demand of companies for human capital. Philippon and Reshef (2012), for example, point out that decades of financial deregulation in the U.S. are associated with an increasing complexity of jobs in finance. The people recruited in an industry at any given point in time can thus be seen as the result of a match between human capital demand and supply.[12]

Thus, studying the personal characteristics of employees in the financial industry and how they have evolved over time helps us understand the determinants of their behaviors and promotes our comprehension of structural and organizational dynamics within firms. Gaining an insight into these dynamics is relevant for scholars and policy makers alike since plenty of evidence suggests that a well-functioning financial industry is key to both individual prosperity and economic growth (e.g., Jayaratne and Strahan, 1996; Levine, 2005; Beck, Demirgüç-Kunt, and Levine, 2007; Dupas et al., 2018).

Anecdotal evidence of the latest ambitions of financial firms to change the structure of their workforce is presented in a recent ranking published by the *World Street Journal*.

[12] This match of employees to firms or tasks is naturally imperfect due to various frictions in the labor market, such as the imperfect observability of skill (for details on this topic, see Kremer, 1993).

The financial industry, once considered a stronghold of older, mostly white men, is now ranked at the top of all S&P500 industries in terms of overall workforce diversity, largely due to the implementation of new diversity and inclusion programs (Sardon, 2019).

In this chapter, I describe the development of some important personal characteristics of individuals in the U.S. financial industry over the last more than four decades. I also compare these trends with developments in the rest of the private sector. The analyses aim to document how the financial industry, and especially its human capital, has changed in the U.S. over time. The results thus form the basis for the research questions discussed in the following chapters. Using data from two representative surveys of the U.S. population, the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) and the General Social Survey (GSS), I present novel facts about people who work in the U.S. financial industry in four areas:

(1) *Gender diversity*: The financial industry has historically always employed more women than men. Yet, consistent with prior research, women are less like to work in jobs with above-median wages and above-median working hours (e.g., Bertrand, Goldin, and Katz, 2010). Interestingly, the time pattern of the share of women in finance is inversely U-shaped between 1975 and 2018.

(2) *Racial composition*: The share of non-white employees in finance has almost tripled since 1975. This trend largely mirrors the trend for the rest of the private sector. It is, however, not caused by an increasing proportion of black employees in finance over recent years. This is particularly noteworthy considering that black employees are expected to substantially increase their share of the private sector workforce until 2050 (Toossi, 2002).

(3) *Age structure*: The financial industry workforce has become remarkably older over the past four decades, not only in absolute terms but also relative to other industries. Today, the median age of employees in finance is three years higher than in other private sector industries, although finance in particular is known for its competition for young talents with technological expertise.

(4) *Intelligence*: The cognitive abilities of finance industry employees are at the same level as those of employees in other industries when differences in education and income are taken into account. This finding sheds light on the hypothesis that the relative increase in wages and job complexity in finance may have lured talents away from other industries (Murphy, Shleifer, and Vishny 1991).[13]

These findings demonstrate the wealth of available data on employees in finance and also point to some interesting avenues for further, more detailed research.

Furthermore, they complement prior studies on personal characteristics of workers in the U.S. financial industry. As one example, Philippon and Reshef (2012) reveal a U-shaped pattern for education, wages, and the complexity of tasks performed in finance over the period 1909-2006 which they link to the deregulation trend in the financial industry. Another strand of research examines the trend in the decision of elite university graduates to enter the financial industry. For instance, Oyer (2008) shows that this decision is highly dependent on the stock market conditions upon graduation, while Goldin and Katz (2008) document that the probability of Harvard College graduates deciding to pursue a career in a finance profession has increased strikingly over time. Other studies investigate the personal characteristics of people who are employed in specific finance areas, such as gender diversity (Niessen-Ruenzi and Ruenzi, 2018), education (Chevalier and Ellison, 1999), and family descent (Chuprinin and Sosyura, 2018) in asset management.

The results in this chapter expand this earlier work by exploring for the entire finance industry workforce how gender diversity, racial composition, age structure, and cognitive abilities have evolved. For each of these characteristics, I provide stylized empirical facts, which, to my knowledge, have not yet been documented in this fashion elsewhere.

[13] Throughout this chapter, I use the terms “intelligence” and “cognitive abilities” interchangeably. Although there is no universal definition, some define intelligence as the ability to think, which is an essential part of a person’s cognitive abilities, along with knowledge, i.e., the store of true and relevant knowledge, and the intelligent use of that knowledge. For a more detailed discussion, see Rindermann (2018).

2.2 Trends in employee characteristics in finance

In this section, I describe the evolution of demographic characteristics of employees in the U.S. financial industry as well as their cognitive abilities over the past more than four decades. In line with prior research (e.g., Greenwood and Scharfstein, 2013), the financial industry is defined as a combination of the credit intermediation, securities, and insurance subsectors. I analyze the finance industry workforce relative to the private sector excluding finance by drawing on data from two representative surveys, the ASEC and the GSS. To spare the reader with details of the data here, I offer a comprehensive documentation of my sample selection and all variables in the appendix. The ASEC sample contains over 3 million observations, while the GSS sample contains more than 17,000 observations.

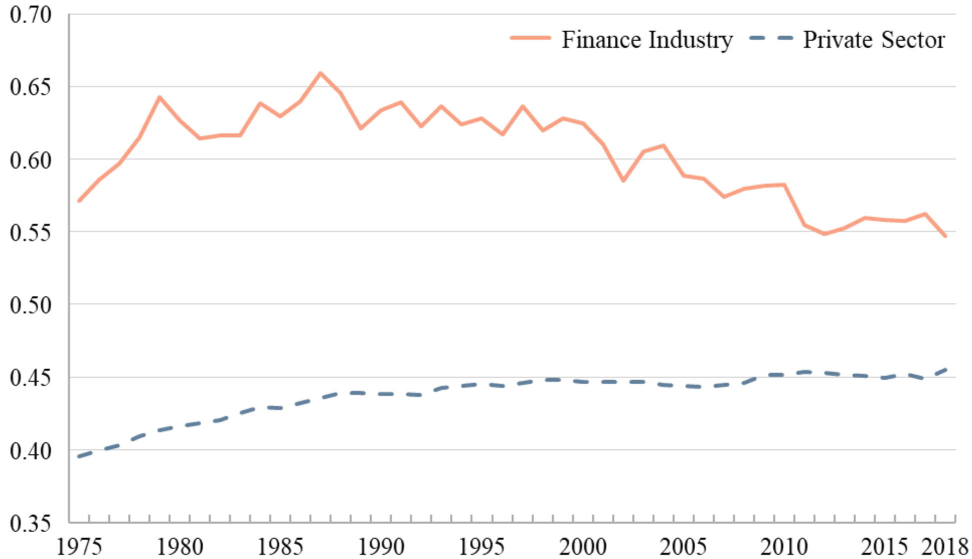
2.2.1 Gender diversity

The question of why there are so few women in management positions in finance has attracted considerable public attention in the past (e.g., Newlands and Ram, 2016; Dunleavey, 2017), and scholars have pointed to various reasons for this phenomenon, e.g., customer-based discrimination (Niessen-Ruenzi and Ruenzi, 2018) or the traditional role of women in family and society (Adams, Barber, and Odean, 2016).

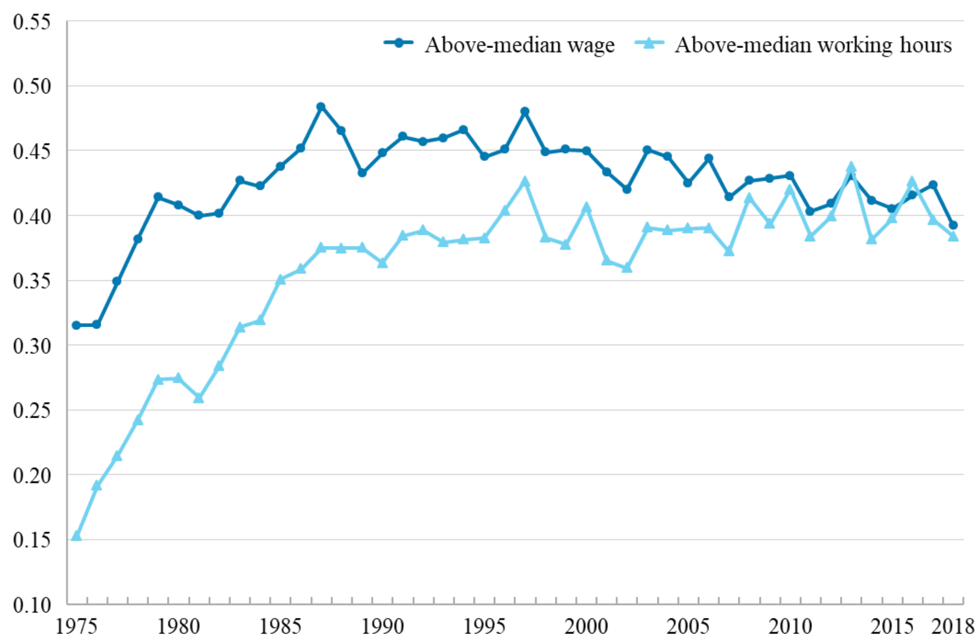
I begin my analysis by examining how the proportion of women who work in finance has trended over time. Figure 2.1 reports the proportion of women in finance and the rest of the private sector from 1975 to 2018. The upper panel shows that the proportion of female employees in finance is generally much higher than in the rest of the private sector. Moreover, there are considerably more women than men employed in finance throughout the sample. The bottom panel reports the proportion of women among finance employees with above-median income and above-median working hours, respectively. The proportion of women among these workers is substantially smaller (on average 43 percent for income and 36 percent for working hours). In most years, the female proportion is even lower than in the rest of the private sector. This finding is consistent with the general notion that women are underrepresented particularly in higher ranks in finance, e.g., only 9.4% of managers of open-end mutual funds are women (Lutton and Davis, 2015).

Figure 2.1: Women in finance

Panel A: Proportion of women in finance and the rest of the private sector



Panel B: Proportion of women in finance jobs with above-median wage and working hours



Notes: This figure shows the proportion of women in the U.S. financial industry and the rest of the private sector excluding finance over the period 1975-2018. Panel A illustrates the development over time of the proportion of women for both groups and Panel B shows the proportion of women in finance with an above-median wage and above-median working hours in a year, respectively.

The pattern that emerges for finance industry employees in the upper panel is inversely U-shaped and suggests three distinct time periods. First, from 1975 to the end of the 1980s, the proportion of women in the industry increased steadily. While the share of female employees in finance was 57 percent in 1975, it reached 65 percent in 1988. This trend, however, reversed in the following years. From the beginning of the 1990s, the proportion of women in the financial industry slowly declined and at the turn of the millennium, the negative trend accelerated. In 2011, the proportion of women had reached 55 percent, a relative decrease of more than 15 percent from its peak in 1988. Finally, in the most recent years, the proportion of women in finance has stagnated at around 56 percent. By contrast, the female proportion in the rest of the private sector rose steadily between 1975 and 1998 and has remained more or less the same since then.

Overall, the data indicate that the U.S. financial industry has always employed more women than men. Nevertheless, the share of female employees in finance was highest in the late 1980s and declined substantially in subsequent years. This finding is particularly interesting in light of the various initiatives that have been implemented by financial firms to attract more female employees. The impact of these initiatives on the industry's gender diversity will therefore still need to be assessed.

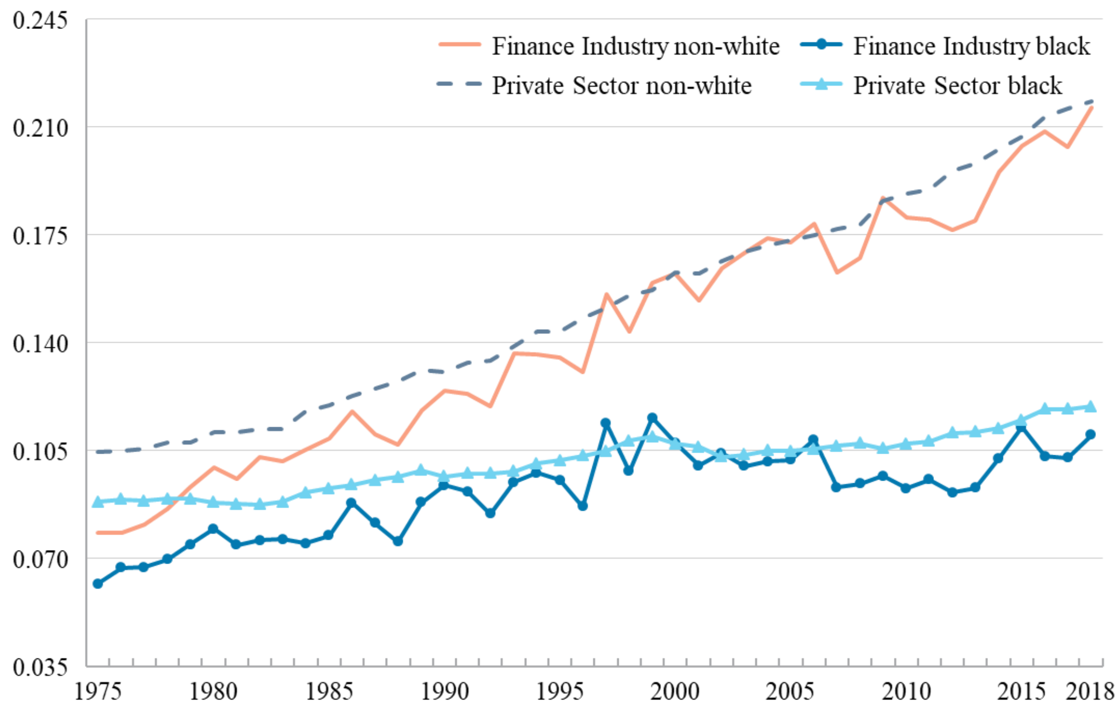
Moreover, women are disproportionally less likely to have jobs with an above-median income and above-median working hours. This is in line with the widely held view that female workers are underrepresented in the upper echelons of financial management and investment services. The result also generally supports the argument that women have lower preferences to work long hours and favor flexible work schedules (e.g., Goldin, 2014). For example, *Women in the workplace*, the largest comprehensive study on the state of women in corporate America, estimates that their proportion in banking and consumer finance is 50 percent at the entry-level and declines in higher management levels. The proportion of women in C-suite jobs is only 27 percent (Thomas et al., 2019).

In summary, the above evidence underlines the importance of research that focuses on women's chances and their willingness to move up the ranks in finance professions (e.g., Adams and Kirchmaier, 2016; Niessen-Ruenzi and Ruenzi, 2018).

2.2.2 Racial composition

Next, I turn to exploring the time trend in racial diversity in the financial industry. Figure 2.2 depicts the share of non-white employees, i.e., the sum of black and other employees, and black employees in finance and the rest of the private sector, respectively. Since the ASEC does not include a consistent and more detailed race classification across all years of my sample, I have to limit my analysis to these categories.

Figure 2.2: Non-white and black employees in finance



Notes: This figure illustrates how the proportion of non-white employees, i.e., blacks and others, and black employees has evolved in the U.S. financial industry and the rest of the private sector excluding finance over the period 1975-2018.

The above figure shows that the workforce in the U.S. has become more racially diverse over the past four decades. The financial industry has largely mirrored this trend, although the proportion of non-white employees has historically been slightly lower than in the rest of the private sector. This gap narrowed slowly and closed around 1997. Both the financial industry and the rest of the private sector have since followed relatively similar trends in overall racial diversity growth. Nevertheless, it is worth taking a closer look at the trend among black employees in recent years. While the share of black employees in the private sector has been slowly but steadily increasing since 2002, as predicted by the Bureau of Labor Statistics (Toossi, 2002), it has fluctuated between 9 and 11 percent in finance since 2000. Thus, black employees have not contributed as much to the growth of racial diversity in the financial sector in recent years as in the first 20 years of the sample.

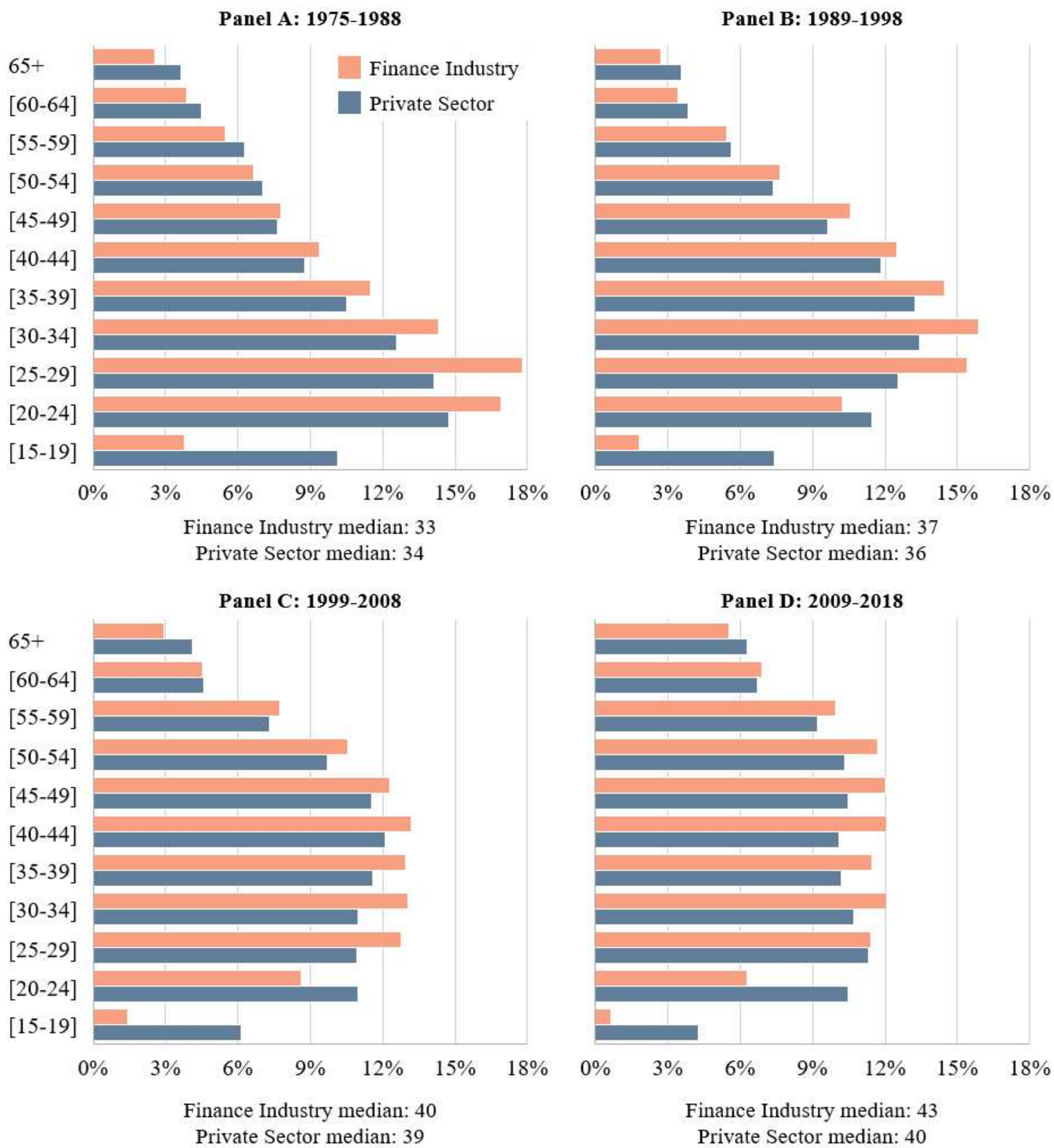
This finding is also interesting in light of a recently heavily criticized statement by Wells Fargo's CEO Charles Scharf. He said that the bank is having difficulties meeting its diversity goals because "there is a very limited pool of Black talent to recruit from" (Ward, 2020). Yet, others argue that biased hiring practices often lead to low shares of black employees. For example, since most white people do not have black friends, it is unlikely that incumbent employees recommend a black person for hiring. Additionally, Bertrand and Mullainathan (2004) find that firms favor résumés with white-passing names. This opens an interesting avenue for further research on the hiring practices in financial firms.

2.2.3 Age structure

The third demographic dimension that I analyze in this chapter is the age structure in the financial industry. The aging of the workforce in the U.S. in general has important direct implications along various dimensions, for example, for labor costs, productivity, and the sustainability of organizations. For financial firms, which are often viewed as pioneers when it comes to adopting new technologies to improve operational effectiveness and customer experience, the aging of the workforce can have even more severe consequences because they face a relatively higher pressure and more competition to attract young talents with the required technological expertise.

To examine the changes in the age structure of the finance industry workforce and to compare them with the rest of the private sector, I split my sample into four subperiods, the first 14 years and the remaining three ten years long, i.e., 1975-1988, 1989-1998, 1999-2008, and 2009-2018. Figure 2.3 shows the age structure in each of these subperiods for employees in the financial industry and the rest of the private sector, respectively. The median age by group in each subperiod is reported at the bottom of each panel.

Figure 2.3: Age structure in finance



Notes: This figure shows the age structure of the finance industry workforce and the private sector workforce excluding finance between 1975 and 2018. The sample is divided into four subperiods: 1975-1988, 1989-1998, 1999-2008, and 2009-2018. The median age per subperiod is reported at the bottom of each panel.

In line with the well-documented aging trend of the working population over the past decades, the four panels illustrate that the proportion of employees in younger cohorts has continuously declined. For example, the proportion of workers aged 25-29 years has decreased from over 14 percent in the first subperiod to 11 percent in the fourth subperiod. Historically, the financial industry has employed more workers from younger and less from older age cohorts compared to the rest of the private sector. Between 1975 and 1988, the proportion of employees under 35 years of age even exceeded 50 percent of the total finance industry workforce.[14] Nevertheless, the median age of employees in finance and the rest of the private sector were historically very similar. Over time, the age structure has become more evenly distributed in finance as in all other sectors, i.e., the proportion of older workers has increased while the proportion of younger workers has decreased. Notably, in the last subperiod, the median age of employees in the financial industry is three years higher than in the rest of the private sector workforce (43 vs. 40).

The data hence suggest that the financial industry has experienced an aging trend that is broadly similar to that of the rest of the U.S. workforce over the past more than four decades. This is largely in line with evidence by Hatfield and Kejriwal (2019) who analyze only the post-1998 period. Yet, in recent years, the median employee in finance has been remarkably older than in other private sector industries. One reason for this age gap could be the increasing complexity of finance jobs as mentioned at the outset of this chapter, which may have led to longer education periods. Indeed, I find that the median employee in finance in the subperiod between 2009 and 2018 holds at least a bachelor's degree, while this was not the case in the first subperiod between 1975 and 1988.

2.2.4 Intelligence

Are employees in the financial industry more intelligent than workers in other industries? The question of superior cognitive abilities of workers in finance has been raised in several

[14] The youngest age cohort in the first subperiod is an exception in this respect, probably because of the minimum education required for many jobs in finance.

theoretical papers (e.g., Acharya, Pagano, and Volpin, 2016; Glode and Lowery, 2016). However, empirical evidence on this issue, particularly for lower occupational ranks in the U.S. financial industry, is scarce mainly due to difficulties in measuring intelligence.

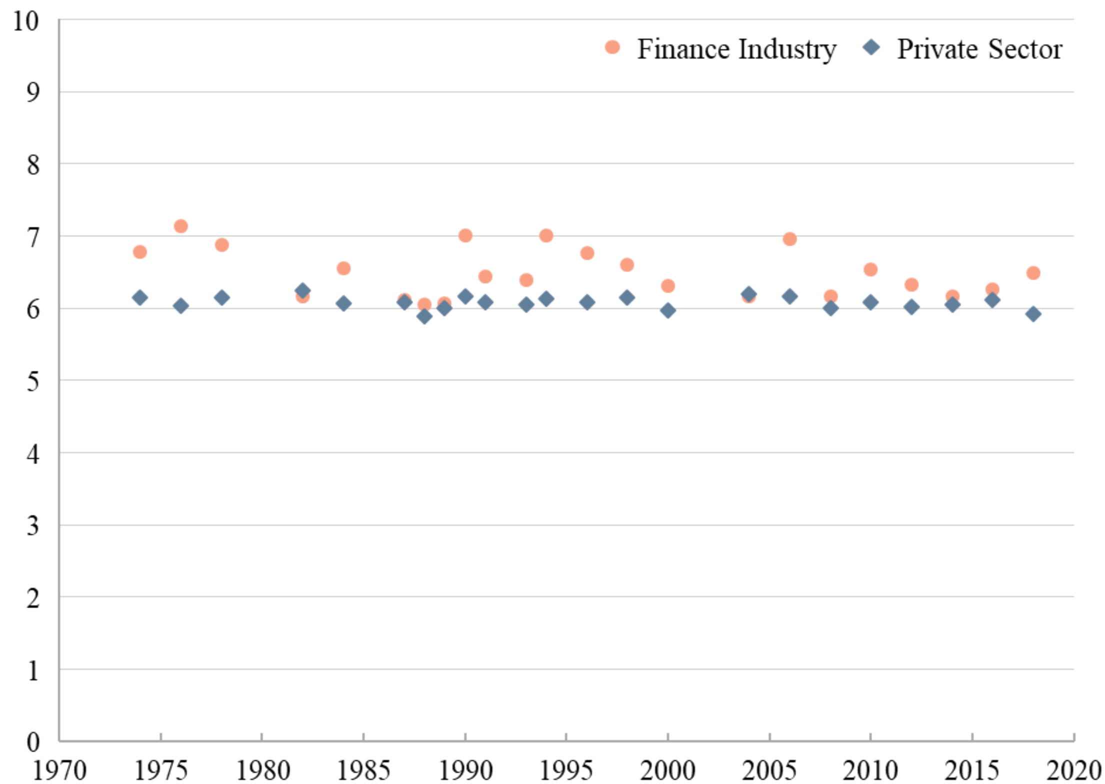
Studies using international data to investigate the cognitive abilities of finance industry employees provide mixed evidence. For example, examining the financial industry in France, Célérier and Vallée (2019) provide evidence for a growing "brain-drain" towards finance over time, i.e., talented people are increasingly likely to join the financial industry since the 1980s. Böhm, Metzger, and Strömberg (2018) suggest that finance industry employees in Sweden are on average more talented than employees in other industries. Yet, they do not observe that their talent level has improved since the 1990s. There are several reasons for these mixed results across studies, namely inherent differences in the structure of the labor markets ass well as financial industries across countries or variations in the methods used to measure cognitive abilities.

To my knowledge, the analysis in this chapter is the first to investigate whether the average employee in the financial industry in the U.S. has superior cognitive abilities compared with employees in other sectors. I measure the intelligence of individuals by the number of correct answers to a ten-word vocabulary test which was taken by half of the respondents of the GSS in each survey over the period 1974-2018, except 1975, 1977, 1980, 1983, 1985, 1986, and 2002, leaving me with 23 cross-sectional waves for analysis. The vocabulary test is a subtest from the WAIS, a commonly used IQ test (Zhu and Weiss, 2005), and has been used in previous studies as a measure of intelligence (e.g., Caplan and Miller, 2010). Wechsler (1958) reports a correlation greater than 0.8 between the overall WAIS score and the WAIS vocabulary subtest.

Figure 2.4 shows the average number of correct answers to the test for employees in the financial industry and workers in the rest of the private sector in each year. It indicates that the number of correct answers from workers in finance is higher in most years, although the difference between the two groups is only small. In fact, the median across all sample years for both groups equals six. Furthermore, no time trend can be observed in Figure 2.4. This appears surprising given the evidence provided by Philippon and Reshef

(2012) that the relative education level of financial industry employees has increased remarkably since the 1980s. As intelligence and education are typically highly correlated, as discussed below, one could have expected a growing intelligence gap over time.

Figure 2.4: Intelligence in finance



Notes: This figure shows the average number of correct answers to a ten-word vocabulary test for people working in the financial industry and the rest of the private sector. The test was taken by half of the GSS respondents over the period 1974-2018 and is a measure of a respondent's intelligence.

To test for superior cognitive abilities of finance industry employees in a more formal fashion, I regress the intelligence measure on an indicator variable for working in finance. The OLS regression results are reported in Table 2.1. All specifications include region and interview year fixed effects. I add controls for respondents' demographic characteristics in column (2), their educational attainment in column (3), and their family income in column (4). All controls are described in detail in the appendix. It is important to point out that education and cognitive abilities, albeit they are typically highly correlated, are inherently different (Ceci, 1991). As Heckman (1995, p. 1111) explains, "[a]bility and education are distinct, and both have economic rewards." It is thus particularly interesting to see how controlling for education affects the link between the finance indicator and intelligence.

Table 2.1: Intelligence in finance

Dependent variable	***Intelligence***					
	Full sample				1974-1994	1996-2018
	(1)	(2)	(3)	(4)	(4)	(5)
In Finance	**0.383*** (5.42)**	**0.357*** (5.27)**	**0.060 (0.88)**	**-0.036 (-0.53)**	**-0.057 (-0.45)**	**-0.012 (-0.15)**
Non-white		-1.030*** (-19.52)	-0.804*** (-15.52)	-0.699*** (-13.29)	-0.837*** (-13.46)	-0.637*** (-9.79)
Female		0.228*** (7.01)	0.190*** (4.61)	0.229*** (5.41)	0.350*** (7.60)	0.148** (2.62)
U.S.-born		0.887*** (9.18)	0.973*** (9.63)	0.891*** (10.22)	0.873*** (4.37)	0.910*** (9.81)
High school			1.241*** (19.60)	1.132*** (18.33)	1.186*** (21.80)	1.009*** (9.15)
Junior college			1.744*** (26.63)	1.544*** (25.37)	1.578*** (15.54)	1.426*** (15.26)
Bachelor's degree			2.541*** (27.82)	2.293*** (24.11)	2.600*** (21.22)	2.015*** (21.05)
Graduate degree			3.266*** (34.67)	2.905*** (29.49)	3.158*** (21.82)	2.667*** (21.79)
Ln (Income)				0.282*** (12.73)	0.320*** (8.42)	0.270*** (10.76)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,416	16,111	16,100	14,941	6,534	8,407
Adj. R-squared	0.024	0.091	0.266	0.277	0.303	0.262

Notes: This table reports coefficients from OLS regressions of *Intelligence* on the indicator *In Finance* capturing whether a respondent works in the financial industry. The variable *Intelligence* is the number of correct answers to a ten-word vocabulary test that was taken by half of the GSS respondents over the period 1974-2018 and corresponds to the variable WORDSUM in the GSS. The four education controls assess the influence of education compared to less than a high school degree. The income control is the natural logarithm of a respondent's equivalized family income. All specifications include region and year fixed effects. All variables are defined in the appendix. Robust t-statistics (in parentheses) are based on standard errors clustered by interview year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Consistent with the observations from Figure 2.4, the results in the first two columns suggest that workers in finance perform slightly better on the vocabulary test. The coefficient on the indicator variable is positive and highly significant in both specifications. Yet, when I additionally account for the educational attainment of respondents in column (3), the finance indicator loses its significance, while all four degree indicators are significant at the 1% level. These indicators measure the influence of the degree that a respondent obtained compared to less than a high school degree. In the regression in column (4), I additionally control for respondents' family income, which is defined as the natural logarithm of the equivalized family income. The coefficient on *Ln(Income)* is also highly significant, while the coefficient on the finance indicator remains insignificant.[15] In unreported tests, I also split the finance indicator variable into two separate variables: one for finance employees with a family income above and one below (or equal to) the median family income in a year. The regression results suggest that neither group has superior cognitive abilities. In the last two columns, I examine whether working in finance and intelligence are correlated differently in earlier compared to later years. Dividing the sample into two subperiods (1974-1994 vs. 1996-2018) does not provide any indication of a higher intelligence of employees in the financial industry in either of the two subperiods.

In summary, the results suggest that the cognitive abilities of employees in the U.S. financial industry are on par with those of employees in other sectors when educational attainment and income are taken into account. Additionally, I do not find support for the hypothesis that cognitive abilities in the financial industry in the U.S. have increased over time relative to other industries. This finding is particularly relevant in light of research that finds a substantial relative increase in wages and job complexity in finance (Philippon and Reshef, 2012) as well as research that argues that these trends could lure talented people away from other industries (Murphy, Shleifer, and Vishny, 1991).

[15] Controlling for income but not for education also reveals no significant correlation between working in finance and intelligence.

3 Who's Your Daddy? Intergenerational Mobility in the Financial Industry*

3.1 Introduction

The persistence between parents and children's outcomes in different domains of life has attracted widespread attention over the past two centuries. Motivated by the interest in the degree to which inequality is transmitted across generations, much of the literature on intergenerational mobility is focused on changes in income, wealth, or social class within a family from one generation to the next (e.g., Solon, 2002; Charles and Hurst, 2003; Chetty et al., 2014).[16] A considerably smaller proportion of papers has moved beyond socioeconomic measures and investigated whether children find work in the same industry or even at the same company as their parents. Nonetheless, the study of intergenerational mobility with regard to people's career choices has proved to be very instructive.

Hellerstein and Morrill (2011), for example, find that the increase in the likelihood of women in the U.S. to enter their fathers' occupation over the twentieth century is due in large part to a growing transmission of occupation-specific human capital from fathers to daughters over time. Kramarz and Skans (2014) provide evidence that young adults in Sweden are more likely to find their first job in the plants in which their parents currently work, which benefits both the new employee and the employer, and Corak and Piraino (2011) document that 40 percent of a cohort of young Canadian men have been employed at some time with an employer for which their father also worked.

These examples illustrate that examining intergenerational mobility across industries, occupations, and even employers can be of major interest for policy purposes. They

* This chapter is based on Schürmann (2020).

[16] For an excellent overview of the literature on intergenerational mobility, see Black and Devereux (2011).

enhance our understanding of the structure of labor markets as well as the barriers embedded in them and, for instance, help to improve the effectiveness of interventions aimed at facilitating access to specific occupations for underrepresented groups, such as women in asset management (Dunleavey, 2017).

With this study, I add to this literature by examining the intergenerational correlation in the decision of individuals to work in the U.S. financial industry using data from the General Social Survey over the 47-year period from 1972 to 2018.

A large body of research shows that a country's financial system plays a crucial role in its economic development (e.g., Levine, 2005). However, as Philippon and Reshef (2012) note, this literature does not explain how the financial industry is organized and, in particular, how it recruits its employees. Although several studies relate people's education and macroeconomic experiences to their decision to start a career in finance (e.g., Goldin and Katz, 2008; Oyer, 2008), little is known about the role of the parental household. This is surprising given the ample evidence that parents have a major influence on their children's career choices (e.g., Watson and McMahon, 2005, and the literature therein).

By focusing on intergenerational industry mobility, my approach provides new insights into the role of parents in their children's decision to enter the financial industry. Among other things, it allows me to show that the likelihood of working in finance is higher than in most other industries if a person's father also worked in the same industry while he or she was growing up. The comparably high correlation between fathers and children in finance has two possible explanations. First, choosing the same industry as their parents may indicate the transmission of industry-specific human capital or other traits from parents to children (Black, Devereux, and Salvanes, 2005). Secondly, it may reflect the importance of informal personal networks for hiring decisions. The latter may also be a sign of nepotism in the recruitment process in the financial industry. In this respect, Bellow (2003) distinguishes between "good" nepotism and "bad" nepotism. While recruitment based on personal ties can be beneficial for both employees and employers, e.g., due to less uncertainty about the quality of a match (Simon and Warner, 1992; Loury 2006), a high rate of people recruited through their parents' networks can also be detrimental. As an example, preferred hiring from a limited talent pool may interfere with the search for the best available talent leading to inefficiencies in financial firms. In addition, a small, elitist group that “feeds” the financial industry relatively more frequently may be more inclined to provide financing and other services preferably to their peers, which, in turn, results in undesirable outcomes for the economy as a whole. Moreover, interventions directed to promote diversity in financial firms will not be as effective if the ultimate access to jobs is determined to a considerable extent by informal networks.

A compelling example of nepotism in hiring decisions in the financial industry in the U.S. is provided by the “Sons & Daughters Program,” which J.P. Morgan introduced to hire children of Chinese officials and executives in order to allegedly win business in China. In 2016, the bank agreed to pay a $264 million fine to settle claims that its hiring practices violated the Foreign Corrupt Practices Act (FCPA).

Finally, by documenting a substantial income surplus for finance industry employees whose fathers were also working in the industry, I provide evidence that is difficult to reconcile with hiring practices purely based on personal ties without considering employee productivity. Instead, I argue that the results are more compatible with better quality matches between workers and employers.

3.2 Parents and children in the financial industry

To investigate whether children of parents who worked in finance are more likely to work in the industry themselves, I use data from the General Social Survey (GSS), a nationally representative survey that is administered by the National Opinion Research Center at the University of Chicago (Smith et al., 2019). In line with prior literature (e.g., Greenwood and Scharfstein, 2013), the financial industry is defined as a combination of the credit intermediation, securities, and insurance subsectors. Information on the industry in which respondents’ parents worked is available in the GSS for fathers in the period 1972-2018 and for mothers in the period 1994-2018. So as not to burden the reader with details of the data here, I provide a comprehensive documentation about my sample construction and all variables used in this study in the appendix.

3.2.1 Intergenerational finance industry mobility

I examine the following linear model for the probability that a person works in the financial industry and one of the parents also worked in finance while the person was growing up:

$$y_{i,t}^{Finance} = \beta_0 + \beta_1 P_{i,t}^{Finance} + \alpha_i + \varepsilon_{i,t} \tag{3.1}$$

where $y_{i,t}^{Finance}$ is an indicator variable taking the value one if individual i interviewed in year t works in the financial industry. $P_{i,t}^{Finance}$ is an indicator capturing whether a parent of that person worked in finance while the respondent was growing up. The parameter β_1 measures the rate of *relative* mobility (Chetty et al., 2020), i.e., the association between the mean probability of children and their parents to both work in finance. The estimate of β_1 hence answers the following question: "*How much more likely is the average respondent to work in finance if a parent also worked in the financial industry while the respondent was growing up?*" In order to account for the time-varying heterogeneity in macroeconomic and social influences to which individuals are exposed, I include birth year fixed effects α_i in all regressions. For example, Oyer (2008) suggests that a person's decision to enter the financial industry is affected by his or her recently experienced stock market performance.

Table 3.1 presents results from regressions of the form described in equation (3.1). The estimates for fathers in columns (1) to (3) are strongly significant and positive implying that individuals are more likely to work in the financial industry if their fathers also worked in the industry. Specifically, the estimated magnitude with only birth year fixed effects in column (1) is 7.4 percentage points. Controlling for demographic characteristics in column (2) has no impact on the significance of this relationship and hardly any effect on its magnitude. Additionally accounting for a person's educational degree and other family background characteristics in column (3), for example, whether a respondent lived with both parents at the age of 16, slightly increases the magnitude of the correlation to 8.1 percentage points.

Table 3.1: Intergenerational industry mobility in finance

Dependent variable	***In Finance***					
	(1)	(2)	(3)	(4)	(5)	(6)
Father in Finance	**0.074*** (5.54)**	**0.075*** (5.30)**	**0.081*** (4.31)**			
Mother in Finance				**0.015 (1.21)**	**0.017 (1.40)**	**0.004 (0.38)**
Non-white		0.001 (0.27)	0.009* (1.83)		0.007 (1.25)	0.017** (2.32)
Female		0.027*** (7.77)	0.027*** (7.55)		0.022*** (5.48)	0.022*** (4.50)
U.S.-born		-0.007 (-1.22)	-0.008 (-1.06)		-0.027*** (-3.17)	-0.025** (-2.39)
High school degree			0.029*** (7.11)			0.024*** (3.84)
Junior college degree			0.027*** (3.39)			0.029** (2.49)
Bachelor's degree			0.063*** (9.96)			0.065*** (8.93)
Graduate degree			0.025*** (3.51)			0.028** (2.44)
Lived with both parents at age 16			0.011** (2.47)			0.008 (1.42)
Number of siblings			-0.001* (-1.98)			-0.002** (-2.10)
Lived in a city at age 16			0.015*** (3.83)			0.013*** (3.07)
Income below average at age 16			-0.007 (-1.59)			-0.005 (-0.94)
Constant	0.000 (0.99)	0.007 (1.22)	-0.038*** (-2.91)	-0.000 (-0.99)	-0.000 (-0.98)	-0.008 (-0.64)
Birth year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,075	25,118	19,829	12,933	12,909	8,823
Adj. R-squared	0.00348	0.00717	0.0169	0.000939	0.00497	0.0144

Notes: This table reports results from regressions of the form described in equation (3.1) and examine the intergenerational mobility in the financial industry. Robust t-statistics (in parentheses) are based on standard errors clustered by birth year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively. All variables are defined in the appendix.

Altogether, the results suggest that a person is about eight percentage points more likely to work in finance if his or her father worked in the industry while the person was growing up. However, columns (4) to (6) indicate that this is not the case for mothers.[17]

Figure 3.1: Intergenerational mobility in relation to fathers across industries

Notes: This figure shows the relative industry mobility of individuals in relation to their fathers across different industries. Each point represents the estimation of β_1 from a regression of the form described in equation (3.1). Regressions include controls for a person's demographic characteristics, educational degree, and family background as well as birth year fixed effects as in column (3) of Table 3.1. Standard errors are clustered by birth year. All parameters are significant at least at the 5% level.

[17] The results presented in Table 3.1 are robust to various alternative specifications, which are reported in the appendix. For example, the coefficient remains virtually unchanged when I add fixed effects for the U.S. regions where respondents lived at age 16 and for the regions where they live today. Replacing birth year with graduation year fixed effects, estimated based on the years of schooling, does also not change the results.

To gauge the magnitude of the relative finance industry mobility with regard to respondents' fathers, I estimate the regression model in column (3) for all private sector industries available in the GSS. Figure 3.1 plots the relative mobility parameter for each industry for which it is significant at the 5% level or higher. Across 16 industries, the probability of a person entering an industry grows significantly if the father has already worked in that industry during the person's childhood. Yet, the increase in likelihood is greater than in the financial industry in only three other industries: real estate, professional services, and agriculture. The comparably high correlation in finance suggests that fathers who gained professional experience in finance have a relatively strong influence on their children's decision to follow them in their footsteps.

3.2.2 The socioeconomic status of the family

Next, I investigate whether the intergenerational finance industry mobility varies with the socioeconomic status of the family of origin during the child's upbringing. This analysis is motivated by early research indicating that a family's socioeconomic status is related to children's occupational aspirations (Brook et al., 1974). Moreover, wealthier families are better able to invest in their children's human capital formation and have (on average) the more *embedded* workers, i.e., those with stronger personal networks in the industry that are useful for the labor market (Montgomery, 1991).

For the purpose of this analysis, I divide the sample into two groups: the people who responded that their family income at age 16 was below and those who responded that their family income was equal to or above the average income. The regression results are reported in Table 3.2. In line with the above arguments, the estimates indicate that the correlation between fathers and their children is solely driven by wealthier families. Hence, the socioeconomic status of a family appears to be a key factor in the intergenerational finance industry mobility. This finding is also remarkable against the background of the literature arguing that personal ties are generally more relevant for people with poor labor market prospects (Galeotti and Merlino, 2014). This general contention may not be true for all sectors and may even be reversed in some.

Table 3.2: Families' socioeconomic status and intergenerational mobility

Dependent variable	***In Finance***	
	Family income at age 16 < Average	Family income at age 16 ≥ Average
	(1)	(2)
Father in Finance	**0.058** (1.40)	**0.084****** **(4.05)**
Constant	0.005 (0.70)	-0.035** (-2.07)
Controls as in column (3) of Table 3.1	Yes	Yes
Birth year FE	Yes	Yes
Observations	5,182	14,647
Adj. R-squared	0.0187	0.0172

Notes: This table investigates the role of families' socioeconomic status during the child's upbringing for the intergenerational finance industry mobility of fathers and their children. Robust t-statistics (in parentheses) are based on standard errors clustered by birth year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

3.2.3 Children's income in finance

A natural follow-up question to the above results is whether children of parents who worked in finance during their upbringing differ in their labor market outcomes when they work in the financial industry themselves. To shed light on this question, I restrict the sample to finance industry employees and regress their family income on the indicator that captures whether a parent of that person worked in finance.

Regression results are reported in Table 3.3. The dependent variable *Ln(Income)* is the natural logarithm of the equivalized family income and defined in detail in the appendix. The models in columns (2) and (4) additionally include a respondent's (squared) age as controls. The estimates indicate that having a father who worked in the financial industry is correlated with a substantially higher income surplus. Specifically, the income of second-generation employees in the financial industry is 25 percent higher if their fathers also worked in finance. Again, I do not find a significant effect for mothers.

Table 3.3: Intergenerational industry mobility in finance

Dependent variable	***Ln(Income)***			
	(1)	(2)	(3)	(4)
Father in Finance	**0.251** **(2.53)**	**0.243***** **(2.66)**		
Mother in Finance			**-0.040** **(-0.30)**	**0.068** **(0.50)**
Age		0.070*** (4.69)		0.104*** (2.90)
Age squared		-0.001*** (-3.26)		-0.001** (-2.21)
Non-white	-0.285*** (-3.65)	-0.286*** (-3.98)	-0.289*** (-2.67)	-0.279** (-2.52)
Female	-0.215*** (-2.95)	-0.215*** (-3.13)	-0.149 (-1.62)	-0.156* (-1.91)
U.S.-born	-0.044 (-0.49)	0.004 (0.04)	-0.076 (-0.56)	-0.070 (-0.47)
High school degree	0.328* (1.75)	0.280 (1.45)	0.488** (2.19)	0.454* (1.99)
Junior college degree	0.569*** (2.92)	0.479** (2.40)	0.720*** (2.73)	0.661** (2.46)
Bachelor's degree	0.675*** (3.09)	0.555** (2.55)	0.995*** (4.15)	0.926*** (3.96)
Graduate degree	1.106*** (5.09)	0.874*** (3.96)	1.323*** (4.69)	1.210*** (4.24)
Lived with both parents at age 16	-0.083 (-0.85)	-0.096 (-1.05)	0.058 (0.54)	0.023 (0.23)
Number of siblings	-0.004 (-0.32)	-0.008 (-0.60)	0.006 (0.28)	-0.000 (-0.02)
Lived in a city at age 16	0.074* (1.79)	0.059 (1.48)	0.042 (0.48)	0.049 (0.54)
Income below average at age 16	0.059 (1.02)	-0.039 (-0.64)	-0.020 (-0.18)	-0.040 (-0.38)
Constant	-0.285*** (-3.65)	-0.286*** (-3.98)	-0.289*** (-2.67)	-0.279** (-2.52)
Birth year FE	Yes	Yes	Yes	Yes
Observations	1,012	1,012	427	427
Adj. R-squared	0.197	0.281	0.226	0.266

Notes: This table studies the income of finance industry employees dependent on whether their fathers or mothers have also worked in finance. The dependent variable in all regressions is *Ln(Income)* which is the natural logarithm of a respondent's equivalized family income. Robust t-statistics (in parentheses) are based on standard errors clustered by birth year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

The substantial income surplus of people whose fathers were also employed in the financial industry is difficult to reconcile with "bad" nepotism as the only mechanism at work, i.e., the hiring of children entirely because of family connections with no regard to productivity (Bellow, 2003). This is because the financial industry is generally known for its high degree of competitiveness and the need for highly educated young talent, especially those with deep technological expertise. These forces arguably prevent financial firms to engage in inefficient hiring activities, at least on a large scale.

In contrast, the income surplus appears to be more in line with the idea that higher-quality matches can be achieved for second-generation finance industry employees, either through informal job networks (Simon and Warner, 1992) or through the transmission of valuable human capital from parents to children (e.g., Rosenzweig and Wolpin, 1985).

3.3 Conclusion

This study corroborates the results of previous research on intergenerational industry mobility and the importance of the parents in people's career choices. I focus on the U.S. financial industry and reveal that the relative industry mobility for fathers and their children, i.e., the increase in the likelihood to work in the same industry, is greater in finance than in most other industries. This comparably high correlation is driven by wealthier families, which, on the one hand, are able to provide more valuable informal networks, and, on the other hand, invest more in the human capital formation of their children. Moreover, I document that second-generation finance industry employees, whose fathers were themselves employed in the industry, enjoy a substantial income surplus compared to their industry peers. I argue that this cannot easily be explained by the hiring of children solely because of family ties without regard to productivity. More likely, the income surplus is due to a superior match quality.

Therefore, my work provides some interesting avenues for further research, especially studies that disentangle the role of informal networks and the transmission of human capital (and preferences) as the two potential drivers of my findings. A follow-up study could, for example, focus on the highly competitive U.S. mutual fund industry. Fund managers perform standardized tasks and compete for the capital of their clients. Their performance as well as their compensation can be observed and compared across mutual fund firms. Superior performance by those managers whose parents also worked in finance would alleviate concerns that recruitment is based on inefficient nepotism. Furthermore, tests using more detailed data, e.g., on the profession, employers, and place of residence of the parents of mutual fund managers, could enable researchers to pin down the exact reasons for potential performance differences.

4 The Death of Trust Across the U.S. Financial Industry[†]

"The fundamental problem isn't lack of capital. It's lack of trust. And without trust, Wall Street might as well fold up its fancy tents."

Robert B. Reich, former U.S. Secretary of Labor

4.1 Introduction

The financial sector plays a crucial role in a country's economic development. More mature financial systems are associated with faster economic growth (Calderón and Liu, 2003), a higher level of entrepreneurial activities (Guiso, Sapienza, and Zingales, 2004), spurred technological innovation (Levine, 1999), and reduced poverty (Beck, Demirgüç-Kunt, and Levine, 2007). The financial industry produces, trades, and settles financial contracts, which, at their core, specify the conditions for exchanging money today for the promise to return more money in the future. Hence, a well-functioning financial system critically depends on the reliability of contractors. This reliability can be either achieved through explicit mechanisms, particularly formal regulation by the government, or by implicit incentives, such as social norms that prevail in a society or class. In fact, in many common economic situations, the behavior of individuals appears to be governed by social norms specifying what is allowed, i.e., socially acceptable, and what is not, i.e., socially unacceptable, rather than by authorities or prices (Richter and Rubinstein, 2020).[18]

Despite the general erosion of trust in American society (e.g., Putnam, 2000), virtually nothing is known about the evolution of trust across finance professionals. In this study,

[†] This chapter is based on an earlier version of Limbach, Rau, and Schürmann (2021).

[18] A recent example of this premise is the vibrant public debate on whether companies, including financial firms, that receive emergency financial aid from governments should pay out dividends or bonuses to their executives. Although this practice is not prohibited, it is socially condemned in many countries.

we show how implicit incentives in the form of *generalized trust*, i.e., trust in anonymous others, have evolved over the past four decades in the financial industry.

We uncover three novel empirical findings. First, we show that generalized trust of professionals working in the financial industry has declined substantially over the last four decades. Notably, the level of trust of finance professionals has not only declined in absolute terms but also relative to the general U.S. population. Simply put, while generalized trust has declined in the U.S. society as a whole, it has declined significantly more across finance professionals. This relative decline in trust is unique to finance. Second, we find that the relative decline in trust is particularly strong in the investment sector and among professionals with higher seniority, i.e., those who set the tone. Third, we find evidence for several channels, particularly changes in economic conditions, the professional environment, and the level of socialization, that are related to and may potentially explain the significant deterioration in trust among finance professionals.

Why does generalized trust in the financial industry matter? According to Arrow (1972, p. 357), “[v]irtually every commercial transaction has within itself an element of trust.” Guiso, Sapienza, and Zingales (2009, p.1101) describe generalized trust as “[t]he trust that people have toward a random member of an identifiable group.” It is therefore crucial for interactions between strangers (Newton, 2007; Nannestad, 2008), which are common in financial markets. Economists argue that generalized trust and other forms of social capital facilitate economic activities because they discourage opportunistic behavior (Guiso, Sapienza, and Zingales, 2011) and increase people's willingness to cooperate (La Porta et al., 1997). Due to the reciprocal nature of trust, it determines their trustworthiness (Berg, Dickhaut, and McCabe, 1995) and trust responsiveness (Bacharach, Guerra, and Zizzo, 2007). In other words, people who trust others more also tend to act more trustworthily since untrustworthy behavior, e.g., cheating, entails psychological and social costs such as guilt and shame. It is also associated with a lack of reciprocation, ostracism, and more direct forms of punishment by others (Knack and Keefer, 1997; Fehr and Gaechter, 2000; Francois and Zabojnik, 2005; Anderlini and Terlizzese, 2017). Therefore, generalized trust discourages norm-deviant and opportunistic behavior. Consequently, in a high-trust environment, individuals need not spend much time in protecting themselves from being exploited in economic transactions (Zack and Knack, 2001). Knack and Keefer (1997) consistently contend that – all else equal – written contracts are also less likely to be needed in these environments and litigation may be less frequent.

In the financial industry, generalized trust is especially important because financial products are complex and conflicts of interest are common. Zingales (2015) notes that the financial industry provides services that most people need but only few understand. The level of information asymmetry between finance professionals and clients is higher than in most other industries. Clients also frequently rely on financial advisers. Providing advice and selling products to clients, however, naturally involves conflicts of interests since advisers may not be willing to tell clients about products of other firms that better suit their needs but instead try to steer them towards one of their own offerings (Bolton, Freixas, and Shapiro, 2007). Ghent, Torous, and Valkanov (2019) show that the complexity of financial products has strikingly grown over time, which increases the information asymmetry between clients and financial intermediaries. Piskorski, Seru, and Witkin (2015) argue that the growing complexity of the industry is also due to the high number of players involved, which makes it even more difficult for outsiders to comprehend. Overall, the relatively high complexity and large informational asymmetries combined with potential conflicts of interest render generalized trust particularly crucial for any kind of financial transaction.

Furthermore, our study is motivated by a political trend observable in the U.S. over the past few decades: The financial industry has experienced almost half a century of deregulation (e.g., Philippon and Reshef, 2012).[19] Both theoretical and empirical studies (e.g., Fukuyama, 1995; Carlin, Dorobantu, and Viswanathan, 2009; Aghion et al., 2010)

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[19] Examples include the relaxations of the Glass-Steagall Act in 1987, 1989, 1997, and 1999 (when the Gramm-Leach-Bliley Act finally repealed the Glass-Steagall Act) the removal of interest rates ceilings in the 1980s, and the repeal of the Bank Holding Company Act in 1999. An exception is the Dodd-Frank Act, which was enacted in 2010. However, several requirements of the Act have already been repealed or are planned to be repealed. The strength of regulation is also likely to be weakened by regulatory capture.

suggest that generalized trust is particularly valuable if formal regulation and governance are less established or efficient because trust, as it discourages opportunistic behavior, can provide a substitute for formal regulation. It is thus likely that a simultaneous decline of generalized trust *and* regulation, as has been the case in the U.S., leads to adverse outcomes for both consumers and society.

Taken together, generalized trust is hence an essential implicit mechanism that guides the behavior of finance professionals. It promotes their willingness to cooperate, reduces the risk of clients being expropriated, and serves as a safeguard against financial fraud. Given their crucial role in today's financial systems, it is therefore fundamental to explore how trust has evolved among finance professionals, not only for clients and financial institutions but also for regulators and policy makers.

In this study, we investigate the time trend in generalized trust of people working in the financial industry relative to the general U.S. population using data from the General Social Survey (GSS). We use survey responses from 25 cross-sectional waves spanning a 39-year period (covering ~1,500 respondents each year from 1978 through 1993 and ~2,800 respondents every other year from 1994 through 2016) to the question: "*Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?*" This measure of generalized trust has been extensively used in the literature and has been shown to be a valid predictor for people's actual level of trust (see, for example, Fehr et al., 2003; Johnson and Mislin, 2012).[20]

We show that the level of generalized trust of professionals working in the financial industry has declined substantially over the last almost four decades. Importantly, not only has the level of generalized trust declined in absolute terms but it has also significantly declined relative to the general U.S. population. Across all industries covered by the GSS,

[20] Sapienza, Toldra-Simats, and Zingales (2013) show that responses to the survey question we use here are motivated by what they refer to as the "belief-based component of trust." In other words, responses strongly correlate with the sender's expectations about the receiver's behavior in the standard trust game (Berg, Dickhaut, and McCabe, 1995).

the relative decline in trust is unparalleled and is thus unique to finance. In particular, this decline in generalized trust is not observed in other industries that depend heavily on trust, such as the healthcare, legal services, or the tech industry. While the decline in trust is prevalent across both different finance subsectors and professionals of different ages, it is particularly strong in the investment sector and for professionals working in higher hierarchy levels who generally strive to “set the tone” of an ethical work culture.

In addition, we examine the degree of confidence that people in the financial industry place in various institutions and groups. We find a steady erosion in confidence across most of these institutions over the past four decades, though in most cases this loss is similar to the loss of confidence experienced by the average American. However, we document a significantly sharper loss of confidence in counterparties that are likely to be particularly relevant to the financial industry, specifically major companies, the executive branch of the federal government, and Congress.

We then ask what has driven the relative trust decline among finance professionals and investigate three non-mutually exclusive explanations – changes in general economic conditions, selection, and socialization. The *economic conditions hypothesis* argues that trends in economic conditions have differential effects on finance professionals and the average citizen. The *selection hypothesis* maintains that the type of people entering the financial industry has changed over time and that this change in the workforce composition affects their level of trust. Finally, the *socialization hypothesis* argues that changes in the style of working in the financial industry over time have led to fewer opportunities for social interactions, which, in turn, made the formation of generalized trust more difficult.

For a factor to constitute an explanation for the relative decline of trust among finance professionals it needs (i) to be correlated with the generalized trust of workers in finance, (ii) to change in the relevant way over our sample period, and (iii) either be correlated significantly more with the generalized trust of workers in the financial industry or the change of the factor over time needs to be significantly larger among workers in finance than among the rest of the population. We test these criteria and document evidence that is consistent with each of the three hypotheses.

Consistent with the first hypothesis, proxies for economic conditions in the U.S. are disproportionally stronger correlated with trust among finance professionals than the average American. In particular, income inequality in the U.S., as measured by the Gini index, is strongly negatively related to trust, while economic growth, as reflected by the change in GDP, is strongly positively related to trust of people working in the financial industry. Since the Gini index also exhibits a significant and positive time trend over our sample, it constitutes a potential explanation for the decline in trust. Our evidence also suggests that, consistent with the previous literature, a more heterogeneous professional environment is related to lower levels of trust. Specifically, we find that a larger fraction of highly educated workers, a more ethnically diverse workforce, and a larger income inequality in the financial industry are correlated with lower levels of trust, while a higher share of women in finance is related to higher levels of generalized trust. Examining shifts in the selection of people into the financial industry over time shows that the share of highly educated finance professionals has grown disproportionally, while the share of female workers has declined disproportionally relative to trends in the general U.S. population. Hence, shifts in the type of people who have entered the financial industry over time provide a second potential explanation for the erosion of trust. Finally, we document that the generation of social capital and consequently the development of generalized trust through social activities has become rarer for finance professionals than for the rest of the population. People in finance work more hours and are less likely to participate in social groups than they used to. In particular, the propensity of workers in finance to be a member of a Putnam-type group, i.e., a group that is unlikely to act as a distributional coalition focused purely on rent-seeking, has declined disproportionally over our sample. These two trends, an absolute and relative increase in working hours and a concomitant decrease in social engagement are again unobserved in any other industry apart from finance.

Our work has important practical implications, in particular for the design of stimulus and bailout programs that governments implement in times of crises. A lack of generalized trust across finance professionals may hamper these programs as actions taken by central banks and governments must be followed by appropriate responses from financial system participants. This is also important, for instance, in the recent crisis as governments are currently implementing various policies to address the negative economic consequences of the pandemic with only few mandatory requirements. As a result, the need for trust as an implicit mechanism increases. One example is the recent Paycheck Protection Program. Designed to provide struggling small businesses with the money they need, which they do not have to pay back if they keep their employees, the program has become mired in controversy over perceptions that banks favor their largest customers, whom they trust most, over customers in need. In addition, the U.S. government may in the future need to pay even more attention to the stability of financial institutions. A publicly perceived instability of an institution coupled with a low level of generalized trust and trustworthiness among finance professionals could cause public bank runs, fire sales, and other adverse consequences that have the potential to exacerbate a crisis.

Our work also contributes to the ongoing public and academic debate on ethics and misbehavior in the financial industry. As an example, Cohn et al. (2014) demonstrate that as soon as bankers' professional identities become engaged in a moral dilemma scenario, they become considerably more dishonest – a finding not replicated across other industries. Zingales (2015, p. 1327) argues that "[…] without proper rules, finance can easily degenerate into a rent-seeking activity." Our evidence suggests that trust, i.e., implicit contracts, has significantly declined, which renders "proper" explicit mechanisms, such as formal regulation, more important.

More generally, we contribute to research on long-term trends in the U.S. financial industry. Prior studies have, for instance, investigated causes for the enormous growth of the financial sector during the second half of the past century (Greenwood and Scharfstein, 2013), the development of the cost of financial intermediation (Philippon, 2015), and trends in wages and education in the U.S. financial industry (e.g., Goldin and Katz, 2008; Philippon and Reshef, 2012). Our study complements this research and is, to the best of our knowledge, the first to explore the long-term trend in an important social factor, i.e., generalized trust, in finance.

4.2 Data and methodology

4.2.1 Data

We examine the trust of people working in the financial industry and the general U.S. population using data from the GSS (Smith et al., 2019). The GSS is a nationally representative survey administered by the National Opinion Research Center at the University of Chicago that is designed to track attitudes, preferences, political views, and social behavior in American society. We use data from 25 cross-sectional waves spanning the 39-year period from 1978 to 2016. The survey contains about 1,500 respondents each year from 1978 through 1993 (except 1979, 1981, and 1992), and continues with around 2,800 respondents every second year from 1994 through 2016. Our study generally relies on a subset of the total sample due to the availability of demographic and other information about respondents and questions that were not asked in every survey wave.

Generalized trust is measured in the GSS by the question: "*Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?*" This question was asked in all but two survey waves (1982 and 1985) and is the most common measure used in the literature to assess individuals' level of generalized trust (e.g., Knack and Keefer, 1997; Guiso, Sapienza, and Zingales, 2004, 2006, 2008; Bloom, Sadun, and Van Reenen, 2012; Lins, Servaes, and Tamayo, 2017). We construct our main dependent variable, *Most people can be trusted*, as an indicator that equals one for a person who responds to the question that "most people can be trusted" and zero for a person who responds that either it "depends" or that you "can't be too careful." We drop from our analyses all individuals who responded that they "don't know" or refused to answer the trust question.

The long duration of the GSS and the use of consistent language for measuring attitudes and preferences make it ideally suited for exploring long-term trends. A few changes to the survey over time, however, require researchers to make some adjustments (see Smith, 1990). Three changes are particularly relevant in our context: (1) an oversample of blacks in the 1982 and 1987 surveys; (2) from 2006 onwards, surveys that could not have been completed by respondents in English were administered in Spanish; (3) until 1988, the order of questions preceding the trust question was not the same in all interviews. This last point is pertinent because Smith (1988) shows that responses to the trust question are sensitive to the immediately preceding battery of questions. In particular, respondents reported a lower level of trust when the question followed questions on crime compared to questions on life and job values. To create a consistent data set, we adjust the data as suggested by prior studies that use the GSS (e.g., Stevenson and Wolfers, 2008a, 2008b, 2009; Ifcher and Zarghamee, 2014). First, we drop black oversamples in the years 1982 and 1987. Second, we exclude all interviews from 2006 onwards that occurred in Spanish and could not have been completed in English. Third, we adapt the methodology described by Stevenson and Wolfers (2008b) to account for the varying question order in 1978, 1983, 1986, and 1988 using the split-ballot experiments of the GSS. Finally, to ensure that our data is representative, we weight all estimates using the GSS weight variable WTSSALL. After these adjustments, the GSS is well suited to studying trends in generalized trust.

We use the 2010 Census industry classification to classify respondents as workers in the financial industry. Following Philippon and Reshef (2012) and Greenwood and Scharfstein (2013), we define the financial industry as the combination of the credit intermediation, securities, and insurance subsectors.[21] This classification yields a proportion of around five percent of respondents who work in the financial industry in a year. We verify this figure using data from the March supplement of the Current Population Survey (CPS) for the same period. The CPS data provide similar yearly proportions, and the average yearly difference between the two data sets is 0.032%.

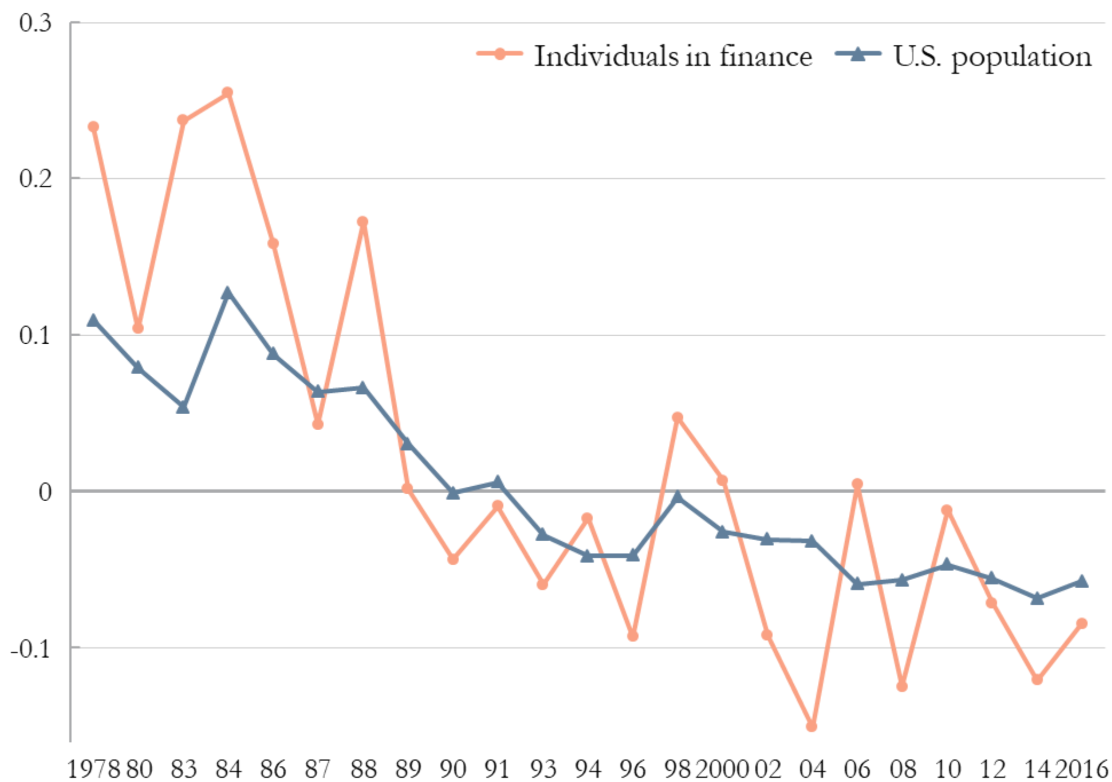
[21] The corresponding industry codes are 6870-6990. The U.S. Census Bureau's Industry Classification System is based on the North American Industry Classification System and is used in several official government data sets in the U.S. The 2010 Census classification system is equivalent to the 2007 NAICS and is the latest available in the GSS.

4.2.2 Graphical representation of the trust trends

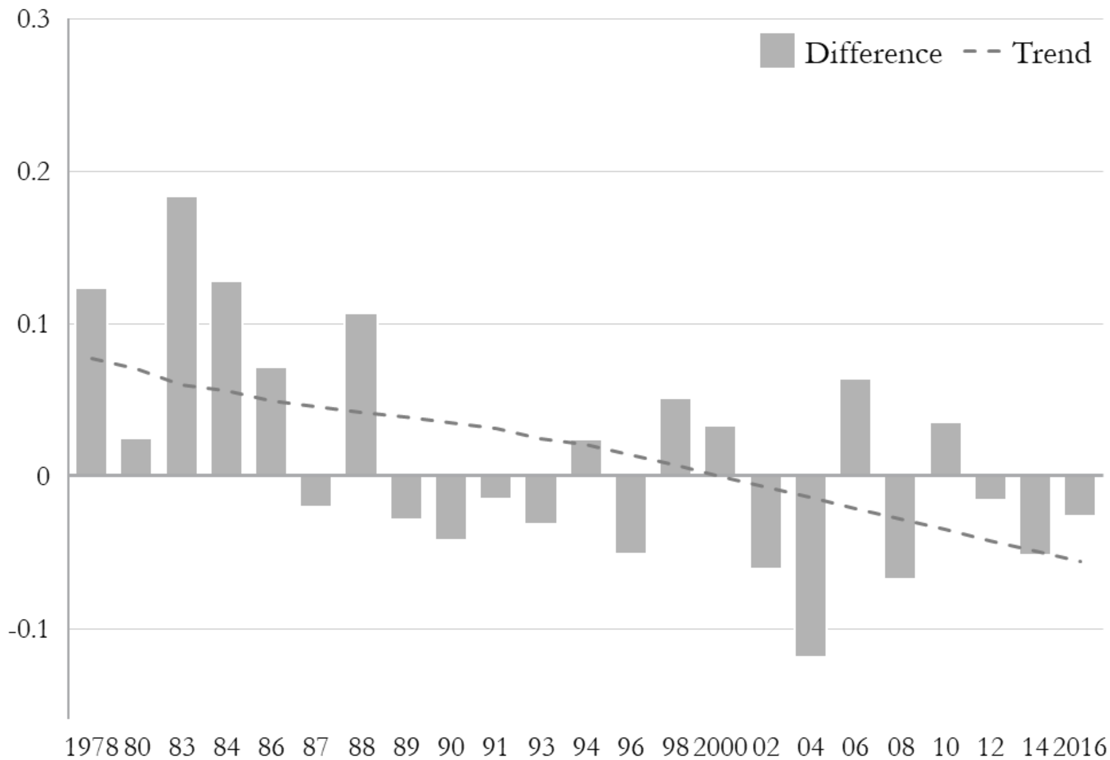
Figure 4.1 shows how generalized trust has trended over time for individuals in finance and the general U.S. population. We adjust the level of trust for the socioeconomic status as well as other subjective characteristics that have been shown to be associated with people's level of trust (e.g., Alesina and La Ferrara, 2002; Guiso, Sapienza, and Zingales, 2008). The figure graphs the residuals of generalized trust after accounting for a wide range of personal characteristics. The top panel plots the residuals from an OLS regression of *Most people can be trusted* on demographic and socioeconomic controls as well as region fixed effects (we describe all controls in more detail below). The bottom panel shows the differences in the residuals as bars and plots its linear time trend as a dashed line.

Figure 4.1: Generalized trust in the United States, 1978-2016

Panel A: Residual trust from OLS estimations



Panel B: Annual differences in residual trust



Notes: This figure illustrates how the residuals of generalized trust have trended over time for people in finance and the general U.S. population after accounting for a wide range of personal characteristics. The top panel plots the residuals from an OLS regression of *Most people can be trusted* on demographic and socioeconomic controls as well as region fixed effects for both groups (all variables are described in the text below). The bottom panel shows the differences in the residuals as bars and plots its linear time trend as a dashed line.

As has been documented by both scholars and the press (e.g., Putnam, 2000; Twenge et al., 2014; Lins, Servaes, and Tamayo, 2017), trust among U.S. Americans has eroded over the past several decades. Importantly for our study, the graphs show that individuals who work in the financial industry were historically more likely to report higher levels of trust. This gap reverses over time as the trust levels of finance professionals declines more than that of the general U.S. population over our sample. Since the beginning of the 1990s, residual trust, i.e., the part of trust that is not explained by demographic, socioeconomic, or regional factors, of individuals in the financial industry is below that of the general population in the majority of survey years.

4.2.3 Empirical methodology

To analyze the time trends in generalized trust for workers in the financial industry and the U.S. population in a more formal fashion, we follow the methodology of Stevenson and Wolfers (2009). Formally, we estimate a regression of the form

$$\begin{aligned} Trust_{i,t} = & \\ & \alpha + \beta_1\ InFinance_i \times \frac{Year_t - 1978}{100} + \beta_2\ NotInFinance_i \times \frac{Year_t - 1978}{100} \\ & + \beta_3\ InFinance_i + \Gamma\ Controls_i + \varepsilon_{i,t} \end{aligned} \tag{4.1}$$

where *i* denotes an individual and *t* denotes the year in which that individual was surveyed by the GSS. The coefficients on the time trend variables report the change in trust per 100 years. Our dependent variables are different measures of generalized trust based on the GSS trust question.

We account for two types of controls in our regressions, exogenous demographic characteristics, and socioeconomic characteristics. Demographic characteristics include decadal age categories, indicators for gender and race (black, white, and other), and an indicator for whether a respondent was born in the U.S. These controls are exogenous in the sense that they are not affected by choices that people make and by individuals' trust itself. Socioeconomic characteristics include controls for education, employment status, income, marital status, a respondent's number of children, his religious denomination, and whether he lives in a rural area. Education is measured using indicators for a respondent's highest degree (less than high school, high school, associates/junior college, bachelor's, or graduate degree). His employment status is captured by indicators for full- and part-time employment, temporary illness/vacation/strike, unemployed, retirement, in school, keeping house, and other in our regressions.

Because the GSS does not provide a consistent measure of income across survey years (Hout, 2004), we manually construct a consistent income measure for our sample as described in Stevenson and Wolfers (2008b). First, we convert a respondent's categorical family income in the previous year to a continuous measure by fitting interval regressions to the data on the assumption that income follows a log-normal disruption. We then translate income to 2005 dollars using the Consumer Price Index provided by the U.S. Bureau of Labor Statistics. Lastly, we use the OECD-modified equivalence scale to make the family income of different household types comparable by taking into account shared consumption benefits (Hagenaars, de Vos, and Zaidi, 1994).[22] We take the quartic of the logarithmic equivalized measure as our income controls to also allow for a non-linear association between income and trust.

We control for marital status using indicators for whether a respondent is married, widowed, divorced, separated, or has never been married and for a respondent's religious denomination with indicators for Protestant, Catholic, Jewish, none, and other denominations. Finally, we construct an indicator for whether a respondent lives in a rural area, which equals one if he lives in a place with less than 2,500 inhabitants. We include region fixed effects in our regressions using information about the U.S. Census Bureau division in which interviews were conducted. All regressions are estimated with standard errors clustered at the interview year level.

4.3 The trust trend of people who work in finance

4.3.1 Baseline results

Table 4.1 embeds our baseline results from regressions estimating equation (4.1). In the first three columns, we report results with *Most people can be trusted* as the dependent variable. Columns (1) and (2) present estimates from OLS regressions with demographic controls and demographic and socioeconomic controls, respectively. Consistent with the observations from Figure 4.1, the coefficient on the *In Finance* dummy is positive and significant in both columns indicating that, historically, individuals who have been

[22] Household needs, e.g., housing space and electricity, do typically not grow proportionally with the number of household members due to economies of scale. The OECD-modified scale assigns a value of 1 to the household head, 0.5 to each additional adult member of the household, and 0.3 to each child. For details see http://www.oecd.org/els/soc/OECD-Note-EquivalenceScales.pdf.

working in the financial industry report higher levels of trust. In addition, the coefficients on the trend variables show that generalized trust has declined significantly during our almost four-decade sample for both individuals in finance and the general population. We compare the decline in trust between the two groups in the fourth row of the table by estimating the difference between the *In Finance* and *Not In Finance* trends. This difference is significant on the 10% level when we control for demographics in column (1) and on the 1% level when we also add socioeconomic controls in column (2). The results hence suggest that generalized trust of individuals working in the financial industry has not only declined in absolute terms but also relative to the U.S. population over our sample.

When evaluating the estimates in column (2), we find that individuals in finance begin the sample around seven percentage points more likely than others to report that most people can be trusted. Relative to the mean likelihood with which a person trusts others, this is a substantial difference of 18 percent. It is hence likely to be economically important. From 1978 to 2016, the propensity of people who work in the financial industry to report that most people can be trusted fell relative to the U.S. population by $(\beta_1 - \beta_2)\Delta t = (-0.864 - (-0.559)) \times (2016 - 1978)/100 \approx 12\%$. This shift amounts to about one-fourth of the cross-sectional standard deviation of the *Most people can be trusted* indicator. Because the trust that prevails in a society is relatively persistent over short periods (e.g., Knack and Keefer, 1997; Mackie, 2001), the cross-sectional standard deviation is typically much larger than the intertemporal variation, and so the same shift is 2.3 times the standard deviation of the annual population proportion that responded that most people can be trusted. By the year 2000, individuals in the financial industry as well as the average person in the U.S. population were roughly equally likely to report that, conditional on their demographic and socioeconomic characteristics, they believed that most other people can be trusted. Respondents working in finance, however, end the sample in 2016 with a five percentage points lower likelihood of responding that most people can be trusted relative to the average U.S. American.

Table 4.1: Generalized trust in finance and the U.S. population, 1978-2016

	Generally speaking, would you say that most people can be trusted or that you can't be too careful with people? [3] Most people can be trusted; [2] Depends; [1] Can't be too careful				
Dependent variables	***Most people can be trusted***			***Can't be too careful***	***Trust***
	OLS	OLS	Probit	OLS	Ordered Probit
	(1)	(2)	(3)	(4)	(5)
In Finance time trend	**-0.575*****	**-0.864*****	**-2.417*****	**0.822*****	**-2.349*****
	(-5.48)	(-7.08)	(-7.09)	(5.68)	(-6.22)
Not in Finance time trend	-0.411***	-0.559***	-1.624***	0.540***	-1.560***
	(-9.20)	(-12.14)	(-12.64)	(12.68)	(-13.36)
In Finance dummy	0.096***	0.074***	0.195***	-0.076***	0.200***
	(4.74)	(3.16)	(2.95)	(-3.22)	(2.96)
Difference in time trends	**-0.164***	**-0.306*****	**-0.793*****	**0.283****	**-0.789****
p-value of difference	**0.0877**	**0.00289**	**0.00617**	**0.0197**	**0.0133**
Ex. demographic controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	No	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	30,959	27,892	27,892	27,892	27,892
Pseudo / Adj. R-squared	0.0671	0.127	0.104	0.132	0.0887

Notes: This table reports coefficients from regressions of the form described in equation (4.1) with different measures of generalized trust. The coefficients on the time trend variables report the change in trust per 100 years. Exogenous demographic controls include indicators for decadal age categories, gender and race (black, white, and other), and an indicator for whether a respondent was born in the U.S. Socioeconomic characteristics include controls for education, employment status, income, marital status, a respondent's number of children, his religious denomination, and whether he lives in a rural area. Income is a quartic in log real family income per equivalent = 1 + 0.5 (other adults) + 0.3 kids. All specifications include region fixed effects using the U.S. region in which an interview was conducted. Robust t and z-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

The remainder of Table 4.1 analyzes whether these results are robust to alternative specifications. In column (3), we run a probit rather than OLS regressions which does not alter our findings. In column (4), we change the dependent variable to *Can't be too careful*, which equals one for a person who responded that "you can't be too careful" when dealing with people and zero if he responded that either it "depends" or that "most people can be trusted." This specification also allows us to analyze whether the decline in generalized trust reflects both changes in the propensity of people to report that most people can be trusted as well as changes in the propensity of people to report that you can't be too careful. We indeed also find a relative incline in the proportion of individuals in finance who are less trusting, although this shift is slightly lower. Finally, in column (5), we estimate an ordered probit with *Trust* as the dependent variable, which is coded as a count variable taking the values 1 ("Can't be too careful"), 2 ("Depends"), and 3 ("Most people can be trusted"). All of these alternative specifications provide estimates that are qualitatively similar to the results in the first two columns (results in column (4) are inversely signed as this specification assess the propensity to trust less). This leads us to conclude that our results provide consistent evidence that generalized trust of people working in the financial industry in the U.S. has significantly declined over the past 39 years, and even more so than in the general population.[23]

To illustrate the economic magnitude of the relative decline in generalized trust of people in the financial industry, we compare it with other determinants of trust in society. One of these determinants is the level of income inequality (e.g., Knack and Keefer, 1997;

[23] Further corroborating evidence for our finding comes from an additional test (not reported in tables), in which we assess how people's beliefs about the benevolence of others has trended over our sample. Respondents' beliefs about the benevolence of others is assessed in the GSS using the question: "*Would you say that most of the time people try to be helpful, or that they are mostly just looking out for themselves?*" Like the question on generalized trust, this question was asked in all survey waves between 1978 and 2016, except for 1982 and 1985. We find that respondents working in the financial industry demonstrate a significantly sharper drop in their perceived benevolence of others than the U.S. population. This result makes sense as individuals who believe that you "can't be too careful" when dealing with people are also most likely to believe that people are "mostly looking out for themselves."

Zak and Knack, 2001; Uslaner, 2002). Analyzing U.S. data, Alesina and La Ferrara (2002) find that an increase in the Gini coefficient by one percent in people's local environment decreases their likelihood of reporting that most people can be trusted by 0.96 percent. The ratio between this estimate and the relative decline in trust for individuals in finance that we find suggests that their relative trust decline over the past 39 years is roughly comparable to a 13 percent increase in the Gini coefficient, for example, from its nation-wide value of 48 percent in 2016 to 61 percent (almost the level of South Africa). An alternative metric is the racial fragmentation in a person's area of living. Prior studies suggest that – at least in the short term – a higher racial diversity in neighborhoods generally leads residents to trust others less (e.g., Putnam, 2007). Drawing again on results from Alesina and La Ferrara (2002), the relative decline in generalized trust of individuals in the financial industry is quantitatively equivalent to moving from the least to the most racially fragmented metropolitan area in the U.S. in the 1990s.

In a further set of unreported robustness checks, we analyze whether the relative decline in trust of people in the financial industry occurred throughout our sample or whether it is caused by a shift in a particular subperiod. We test for this by breaking the sample at various points and estimate equation (4.1) separately in each subperiod. Absent significant shocks, trust is relatively persistent over short periods and shifts occur only slowly. One reason is that the formation of generalized trust in a society is tied to historical developments often dating back hundreds of years. Beliefs and values are transmitted fairly unchanged from one generation to the next one (see, for example, Guiso, Sapienza, and Zingales, 2006; Algan and Cahuc, 2010; Dohmen et al., 2012; Okada, 2020). We do therefore not expect to find a relative trust decline in all subperiods.

We split the sample into three 13-year periods, i.e., 1978-1990, 1991-2003, and 2004-2016, and alternatively into four periods with the first three being ten years and the fourth nine years long, i.e., 1978-1987, 1988-1997, 1998-2007, and 2008-2016. Examining the subperiod-to-subperiod change in trust, we find that the mean difference in residual trust between individuals in finance and the general U.S. population consistently decreases from one subperiod to the next. The sharpest decline occurred during the 1980s and 1990s, followed by the decline in the middle of the 2000s. Turning to within-subperiod shifts in generalized trust, we find that the relative trust decline in the earliest subperiod, i.e., during the 1980s, is most pronounced. Besides this phase, the within-subperiod decline in trust is mostly not significantly different for people in finance compared to the general U.S. population. Hence, the results indicate that the disproportional erosion of trust among workers in finance was a rather gradual process over our sample and not caused by one particular subperiod (or event).

Taken together, the results in this section suggest that people who work in the financial industry have become significantly less trusting over the past decades. Most notably, this decline is quantitatively substantial and significantly larger than the decline in trust in the general U.S. population, which has been frequently discussed by scholars and in the press.

4.3.2 Trust trends in other industries

Is the trend in generalized trust in the financial industry different from the trend in other industries? To answer this question, we investigate the generalized trust trend in two other industries for which scholars have argued that trust is fundamental: the healthcare industry and the legal service industry.[24] Zingales notes that "the healthcare sector is a particularly good comparison for the financial [industry]" because both sectors provide services that most people need but only a few understand. Accordingly, he concludes that "both sectors depend heavily on trust" (Zingales, 2015, p. 1342). Gennaioli, Shleifer, and Vishny (2015) make a similar argument to illustrate the relationship between an investor and his financial adviser. The healthcare sector has also grown steeply relative to the overall economy in a similar manner as the financial industry and both sectors have experienced large amounts of abuse and fraud cases. Consequently, the implementation of new regulation in both sectors is constantly on the agenda of policy makers while companies attempt to influence

[24] Adam Smith has already remarked that a high level of trust is required in these professions. In particular, he argued that "[w]e trust our health to the physician, our fortune and sometimes our life and reputation to the lawyer and attorney" (Smith, 1776, p. 118), which in his view is one reason for their comparatively high salaries.

or prevent government interventions through massive lobbying. Furthermore, trust is frequently cited as an essential element for the provision of legal services and as a prerequisite for effective legal representation (see, e.g., Goldstein, 2005, and the literature therein). Courts often describe the importance of trust in a lawyer-client relationship and stress its reciprocal nature which leads to implicit contracts between a legal advisor and his client. Hence, both industries can be viewed as valid comparisons for the financial industry with regard to the value of trust. Finally, we study the trend in generalized trust in technology firms using the definition of Loughran and Ritter (2004). Many technology firms produce products and offer services that are difficult for the average consumer to understand, even though they form a crucial part of our lives today.

Table 4.2 embeds the results from OLS regressions estimating equation (4.1) for the three industries. Results for the healthcare sector are reported in columns (1) and (2), results for the legal service industry in columns (3) and (4), and results for tech firms in the last two columns. Across all three industries, generalized trust of individuals working in these industries has declined significantly over our sample (albeit only marginally for the tech industry). However, the difference in time trends is not significantly different from the decline in generalized trust experienced by the general U.S. population. In robustness tests (not shown), we also estimate probit regressions and use the alternative measures of generalized trust as in Table 4.1 with qualitatively similar results. Overall, there appears to be no evidence that the decline in generalized trust that we observe for the financial industry is shared by other industries that depend heavily on trust.

In unreported tests, we also investigate the time trend in generalized trust across *all* other industries in the sample. Regardless of the industry, there is no significant relative decline in trust for workers in any of these except finance. This result holds irrespective of whether we include people working in the financial industry in the control group or not. Taken together, our results suggest that the relative decline in generalized trust among workers in finance that we find is unparalleled by any other industry and hence unique to the financial industry. This finding raises the question of why trust has decreased so substantially specifically in the financial industry.

Table 4.2: Generalized trust trends in other industries and tech firms

Dependent variable	***Most people can be trusted***					
	Healthcare		**Legal**		**Tech firms**	
	(1)	(2)	(3)	(4)	(5)	(6)
In Industry time trend	**-0.509******	**-0.613******	**-0.429***	**-0.802****	**-0.032**	**-0.345***
	(-5.19)	**(-5.88)**	**(-1.97)**	**(-2.72)**	**(-0.18)**	**(-1.87)**
Not in Industry time trend	-0.409***	-0.569	-0.421***	-0.572***	-0.431***	-0.580***
	(-9.66)	(-12.47)	(-9.42)	(-11.89)	(-10.11)	(-12.63)
Industry dummy	0.024	-0.005	0.145***	0.062	0.005	0.019
	(1.13)	(-0.21))	(2.83)	(1.09)	(0.14)	(0.53)
Difference in time trends	**-0.0996**	**-0.0442**	**-0.00880**	**-0.229**	**0.399******	**0.234**
p-value of difference	**0.200**	**0.592**	**0.967**	**0.437**	**0.00994**	**0.143**
Ex. demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	No	Yes	No	Yes	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,959	27,892	30,959	27,892	30,959	27,892
Adj. R-squared	0.066	0.127	0.067	0.127	0.067	0.128

Notes: This table reports coefficients from OLS regressions estimating equation (4.1) with *Most people can be trusted* as dependent variable. Columns (1) and (2) report results for the healthcare industry, columns (3) and (4) for the legal service industry, and columns (5) and (6) for all tech firms following the definition in Loughran and Ritter (2004). Columns with odd numbers present estimates with demographic controls, while columns with even number additionally include socioeconomic controls. All specifications include region fixed effects. Robust t-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

4.3.3 Heterogeneity in the trust trend

To explore why trust has declined so much among finance professionals, we divide the generalized trust trend by hierarchy level, seniority, and industry subsectors. It is likely that the decline in trust has not been the same for all workers in finance. It is also plausible to expect differences in the trust trend across subsectors, i.e., banking, insurance, and investment. Not only is the latter often criticized in public for its allegedly low ethical standards, such as the trustworthiness of its employees, but the complexity of products offered by investment firms results in particularly high information asymmetries between customers and financial service providers which renders generalized trust even more important (e.g., Carlin, 2009; Ghent, Torous, and Valkanov, 2019).

We begin our analysis by studying the trend in generalized trust for individuals in higher hierarchy levels of the financial industry, which we refer to as *upper echelons*. To classify respondents as belonging to the upper echelons, we use the latest International Standard Classification of Occupations (ISCO-08) provided in the GSS. The ISCO-08 divides jobs into ten major groups depending on the skill level required to perform the duties of these jobs. We classify a worker in the financial industry as a member of the upper echelons if he belongs to one of the top three major groups, i.e., managers, professionals, or associate professionals. These jobs typically require workers to perform tasks that need an extensive body of knowledge, complex problem-solving, and decision making (International Labour Office, 2012). About 60 percent of individuals in the financial industry and 40 percent of the general population belong to these groups.

To formally test whether trust trended differently for individuals in the upper echelons, we re-estimate our OLS estimation of equation (4.1) accounting for demographic and socioeconomic controls, i.e., paralleling column (2) of Table 4.1, and adjust our sample in different ways. Panel A of Table 4.3 presents the results from these regressions. In the first column, we restrict respondents in the financial industry to only those who belong to the upper echelons of the industry. We thus compare the upper echelons in finance with the general U.S. population. The results show a positive and highly significant coefficient on the *Upper echelons in Finance* dummy suggesting that individuals who work in higher hierarchies in the financial industry are historically about 11 percent more likely to report that most other people can be trusted than the average U.S. American. Particularly important, the coefficients on the time trend variables indicate that this likelihood has decreased substantially during our almost four-decade sample. From 1978 to 2016, the propensity of workers in the upper echelons of the financial industry to report that most people can be trusted fell relative to the U.S. population by 14 percent. Column (2) presents estimates from a regression in which we additionally restrict the respondents who do *not* work in the financial industry, i.e., the general population, to individuals in upper echelons. Although our study's focus is the discrepancy in the generalized trust trend between employees in finance and the average U.S. American, as described in the introduction, it is still interesting to explore whether the relative trust decline is a phenomenon that is generally shared among individuals in higher hierarchies irrespective of their profession.

Table 4.3: Heterogeneity in the trust trend

Panel A: Heterogeneity by hierarchy level

Dependent variable	***Most people can be trusted***	
	(1)	(2)
Upper echelons in Finance time trend	**-0.929*** (-9.73)**	**-0.917*** (-9.88)**
Not in Finance time trend	-0.558*** (-12.26)	
Upper echelons Not in Finance time trend		-0.552*** (-8.11)
Upper echelons in Finance dummy	0.111*** (5.33)	0.081*** (4.11)
Difference in time trends **p-value of difference**	**-0.371***** **1.90e-05**	**-0.365***** **4.72e-05**
Exogenous demographic controls	Yes	Yes
Socioeconomic controls	Yes	Yes
Region FE	Yes	Yes
Observations	27,378	11,973
Adj. R-squared	0.127	0.101

Panel B: Heterogeneity by seniority

Dependent variable	***Most people can be trusted***			
	Juniors in Finance & general population	***Seniors in Finance & general population***	***Juniors in Finance & Juniors not in Finance***	***Seniors in Finance & Seniors not in Finance***
	Age of respondents in finance <= Median in finance	*Age of respondents in finance > Median in finance*	*Age of respondents <= Median in Finance*	*Age of respondents > Median in Finance*
	(1)	(2)	(3)	(4)
In Finance time trend	**-0.858*** (-6.38)**	**-0.866*** (-4.96)**	**-0.831*** (-6.02)**	**-0.808*** (-4.70)**
Not in Finance time trend	-0.555*** (-12.17)	-0.559*** (-12.29)	-0.580*** (-8.57)	-0.486*** (-9.63)
In Finance dummy	0.060* (1.95)	0.091** (2.32)	0.065* (2.07)	0.080* (1.87)
Difference in time trends	**-0.303****	**-0.307****	**-0.251***	**-0.322****
p-value of difference	**0.0264**	**0.0343**	**0.0687**	**0.0441**
Ex. demographic controls	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	27,261	27,209	12,812	15,080
Adj. R-squared	0.126	0.128	0.103	0.126

Notes: This table reports results from OLS regressions exploiting variation in the generalized trust trend by breaking it apart by hierarchy level and age. All specifications report coefficients from OLS regressions of *Most people can be trusted* on time trend variables of trust along with demographic and socioeconomic controls (see equation 4.1). Panel A shows how generalized trust trended in the upper echelons and Panel B investigates how generalized trust trended for individuals of different ages. All specifications include region fixed effects. Robust t-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

However, the results in column (2) do not support this conjecture. The relative trust decline is significant at the 1% level and amounts to nearly 14 percent. Thus, the propensity of people who work in the upper echelons of the financial industry to report that most other people can be trusted declined substantially also relative to people working in the upper echelons in other industries.

Since our demographic controls include decadal age categories, the relative loss of trust by the upper echelons in finance is not simply an age effect. Notwithstanding this control, it is still interesting to examine how generalized trust has trended for people of different age groups. A decline in generalized trust by seniors is perhaps likely to self-correct as these individuals retire and drop out of the industry. Hence, we examine the generalized trust trend using a cohort analysis. Specifically, we include in the sample only those finance professionals with ages either below (and equal to) or above the median age of all persons working in finance in a year. Panel B of Table 4.3 reports the results in columns (1) and (2). They indicate that the relative trust decline holds for both junior and senior cohorts in finance. In columns (3) and (4), we additionally shrink the group of respondents who do not work in finance to those with an age that is either below (and equal to) or above the median age of people working in the financial industry in a year. Again, relative to their cohort peers, the relative decline of trust holds across both senior and junior cohorts.

Table 4.4 examines the trend in trust separately by finance industry subsector, i.e., banking, investment, and insurance.[25] We include all respondents who work in the respective subsector in columns with odd numbers and restrict the sample to only those in the upper echelons of a subsector in columns with even numbers. Our results provide evidence for a decline in generalized trust relative to the U.S. population in all three subsectors. We do, however, observe some differences between subsectors with regard to the size of the decline.

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[25] The corresponding industry codes are 6870 and 6880 (banking), 6970 (investments), and 6990-6999 (insurance).

Table 4.4: Heterogeneity in the trust trend per finance subsector

Dependent variable	***Most people can be trusted***					
	Banking		**Investment**		**Insurance**	
	All	Upper echelons	All	Upper echelons	All	Upper echelons
In Finance time trend	**-0.847******	**-0.627****	**-1.180*****	**-1.280*****	**-0.873*****	**-1.022*****
	(-4.47)	**(-2.45)**	**(-3.84)**	**(-4.42)**	**(-4.84)**	**(-5.72)**
Not in Finance time trend	-0.558***	-0.557***	-0.556***	-0.556***	-0.557***	-0.557***
	(-12.24)	(-12.37)	(-12.22)	(-12.27)	(-12.27)	(-12.30)
In Finance dummy	0.065*	0.074	0.096	0.132*	0.089*	0.129***
	(1.75)	(1.27)	(1.18)	(1.81)	(2.62)	(3.56)
Difference in time trends	**-0.290***	**-0.0703**	**-0.624****	**-0.724*****	**-0.317***	**-0.466****
p-value of difference	**0.0950**	**0.776**	**0.0320**	**0.00843**	**0.0741**	**0.0117**
Exogenous demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,074	26,878	26,756	26,691	27,089	26,891
Adj. R-squared	0.127	0.127	0.127	0.127	0.127	0.127

Notes: This table reports results from OLS regressions exploiting variation in the generalized trust trend by breaking it apart by the financial industry subsectors, i.e., banking, investment, and insurance. Each column shows the coefficients from a regression of *Most people can be trusted* on time trend variables of generalized trust along with demographic and socioeconomic controls (see equation 4.1). We include all respondents who work in the respective subsector in columns with odd numbers and restrict the sample to only those in the upper echelons of the respective finance subsector in columns with even numbers. All specifications include region fixed effects. Robust t-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

The estimates that rely on the full sample in columns with odd numbers show that the largest relative decline occurred in the investment sector, followed by insurance and banking. In line with our findings from Panel A of Table 4.3, estimates in columns with even numbers show that the relative trust decline is generally stronger in higher hierarchy levels. The only exception is the banking sector where we do not observe a significant relative decline in trust for individuals in the upper echelons.

Hence, the results in this section indicate that the decline in generalized trust has not been equally strong for all workers in the financial industry over the past almost four decades. While both juniors and seniors in finance experienced an erosion of trust relative to the general population, we find that the trust decline was particularly strong in the investment sector and for workers in higher hierarchy levels, i.e., those who set the tone.

4.3.4 Confidence in institutions and groups

The fact that generalized trust of people who work in the financial industry has deteriorated not only in absolute terms but also relative to the average American raises the question of whether workers in finance also experienced a disproportionally larger trust erosion in other domains. In this section, we examine responses to several survey questions that assess confidence of individuals in several institutions and groups. These questions are available in all survey waves except in 1985: "*As far as the people running [institution or group] are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?*" We create an indicator that equals one if a respondent reports to have "a great deal" of confidence in a party and zero otherwise. Our analysis covers the following institutions and groups: banks and financial institutions; major companies; the executive branch of the federal government; Congress; the U.S. Supreme Court; the military; the press; and the scientific community.

Table 4.5 reports how confidence in these institutions and groups has trended over time for people in finance and the general U.S. population. Each row shows the estimates of one regression of the form described in equation (4.1) using as the dependent variable the confidence indicator variable for the respective institution or group. All regressions include demographic and socioeconomic controls as well as region fixed effects.

Table 4.5: Confidence in institutions and groups

	Estimated time trends in confidence per party		
	In Finance	Not in Finance	Difference
	(1)	(2)	(3)
Panel A: Financial institutions			
Banks and financial institutions	-0.337* (-2.04)	-0.331*** (-3.87)	**-0.00631** **0.962**
Panel B: Parties especially relevant to the financial industry			
Major companies	-0.596*** (-6.47)	-0.356*** (-6.46)	**-0.240***** **0.00378**
Executive branch of the federal government	-0.293** (-2.35)	-0.101 (-1.49)	**-0.193***** **0.00755**
Congress	-0.277*** (-3.88)	-0.169*** (-3.26)	**-0.108**** **0.0222**
Panel C: Parties not especially relevant to the financial industry			
U.S. Supreme Court	-0.260 (-1.39)	-0.159* (-1.93)	**-0.101** **0.445**
Military	0.963*** (8.05)	0.853*** (13.21)	**0.110** **0.420**
Press	-0.343*** (-6.10)	-0.370*** (-8.46)	**0.0275** **0.633**
Scientific Community	-0.391** (-2.59)	-0.173*** (-4.41)	**-0.217** **0.148**

Notes: This table reports how confidence in various institutions and groups trended over time for people in finance and the general U.S. population. Each row shows the result of one OLS regression of the form described in equation (4.1) and examines the trend vis-à-vis a different party. Panel A reports estimates for banks and financial institutions, Panel B for parties that are especially relevant to the financial industry, and Panel C for various other parties. The first two columns show the coefficients on the trend variables *In Finance* × Time and *Not in Finance* × Time and the third column reports the difference in these estimates and its p-value. All regressions include demographic and socioeconomic controls as well as region fixed effects. Sample sizes vary by data availability. Robust t-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

We first report the relative time trends in confidence in banks and financial institutions in Panel A. The negative and significant coefficient on the time trend variable for the general U.S. population indicates that the confidence that U.S. Americans have vis-à-vis this group has eroded steadily over our sample. The time trend for respondents in finance is also significantly negative. The difference between the two trends is, however, not significant. In other words, both groups have experienced a similar increase in their distrust of financial institutions in recent decades. Yet, when we examine the levels of confidence, which we do not tabulate for brevity, we find strong evidence that they differ substantially for workers in finance and the general U.S. population. Specifically, individuals who work in the financial industry are significantly more likely to report that they have a great deal of confidence in their industry than the average U.S. American.

For the remainder of Table 4.5, we separate parties that are particularly relevant to the financial industry from others. In particular, we deem companies, the executive branch of the federal government, and Congress as especially relevant to the financial industry for different reasons. First, companies make up a large proportion of customers of financial corporations and use various kinds of financial services. Second, the executive branch of the federal government includes the regulatory authorities that are responsible for monitoring financial players, enforcing regulatory standards, and protecting consumers. Third, the U.S. Congress shapes the regulatory environment for financial corporations.

Panel B reports the time trend in confidence vis-à-vis these three parties. While workers in finance begin the sample with a higher level of confidence in each of them, the estimates in Panel B suggest that their confidence in all of them declined significantly over our sample. At the same time, the confidence of the general U.S. population only declined toward major companies and Congress. Most importantly, the last column indicates that the loss in confidence in all three parties has been significantly more pronounced for people in finance compared to the average U.S. American.

Finally, Panel C shows how respondents' confidence vis-á-vis parties that are not particularly relevant to the financial industry trended for workers in the financial industry and other U.S. Americans. The results indicate that the trends in confidence in the U.S. Supreme Court, the military, the press, and the scientific community are not significantly different between the two groups. We also find that the levels of confidence vis-á-vis these parties do not differ.

To summarize, the results in this section allow us to draw some conclusions about how confidence in various parties trended for workers in finance relative to the U.S. population. While their degree of confidence vis-á-vis various institutions and groups eroded over the past 39 years, the loss in confidence is in many cases similar to that experienced by the average U.S. American. Importantly, parties for which we find a sharper loss in confidence are all deemed particularly relevant to the financial industry. It thus seems likely that the relative decline in generalized trust that we observe is linked to a growing skepticism and vigilance towards institutions and groups with whom people working in financial firms regularly interact or on whom they depend.

4.4 Potential reasons for the relative trust decline

What has led to the relative trust decline of people working in finance? In this section, we shed light on this question by examining different types of transitions in people's lives over our sample that may be associated with a steeper trust decline for workers in finance relative to the general U.S. population. In particular, we propose and investigate three potential explanations, which are not mutually exclusive: changes in economic conditions, selection, and socialization.

Before we motivate each hypothesis, it is important to lay out the criteria a factor would need to fulfill in order to constitute an explanation, even a partial one, for the relative decline of trust among finance professionals. First, a proposed factor needs to correlate with generalized trust of workers in finance. Second, it needs to change in the relevant way over our sample period. Third, it needs to be either correlated significantly more with generalized trust of finance professionals or the change in the factor over time needs to be significantly larger in finance than in the rest of the U.S. population to explain the *relative* trust decline. We will test each of these criteria in our analyses.

First, the *economic conditions hypothesis* argues that the development of economic conditions in the U.S. has had a greater impact on the generalized trust of workers in the financial industry than on the rest of the U.S. population. The hypothesis is motivated by research suggesting that social capital wanes when more people struggle economically and the gap between rich and poor widens (e.g., Uslaner; 2002; Picket and Wilkinson, 2010). For example, in light of this literature, one might expect that the rise in income inequality over the past decades has affected workers in finance differently due to the steep increase in wages in this industry, which has accounted for up to a fourth of the overall increase in wage inequality in the U.S. since 1980 (Philippon and Reshef, 2012). Accordingly, we examine the link between various measures of economic conditions in the U.S. and the prevailing level of generalized trust.

Second, the *selection hypothesis* argues that the type of people entering the financial industry has changed over time and that the changing composition of the workforce has in turn influenced the level of generalized trust of workers in the industry. Importantly, since we control for a wide range of individual-level characteristics in our regressions, such as gender, ethnicity, education, and income, the selection hypothesis does not maintain that changes in workers' own characteristics have caused the deterioration of trust. Instead, it argues that a person's generalized trust has eroded, conditional on his characteristics, due to changes in the type of colleagues with whom he works. The hypothesis is motivated by several studies that show lower levels of trust and social capital in more heterogeneous environments (e.g., Alesina and La Ferrara, 2000; Putnam, 2007). Previous research also provides evidence for a shift in the professional environment along several dimensions in the financial industry. For example, the proportion of people with professional graduate degrees in finance increased strikingly over the last decades of the past century (Goldin and Katz, 2008). Philippon and Reshef (2012) reveal a tight link between deregulation and the flow of human capital into and out of the financial industry. Specifically, high-skilled employees began to enter the financial industry in the 1980s and 1990s when more and more regulations were lifted. Moreover, as outlined above, the income in the financial industry has increased dramatically over time leading to a sharp growth in the finance wage premium (Philippon and Reshef, 2012; Célérier and Vallée, 2019).

Third, the *socialization hypothesis* argues that changes in the style of working in the financial industry over time have led to fewer opportunities for social interaction, especially outside work. The hypothesis is motivated by an established literature (see, for example, Putnam, 2000), which suggests that social interactions are particularly conducive for generating social capital and generalized trust. Thus, if workers in the financial industry have had relatively fewer opportunities to engage socially in recent years, for example, due to an ever-increasing workload, their level of generalized trust may have fallen relatively more as a result.

4.4.1 Changing economic conditions

We obtain three annual measures to investigate the association of generalized trust with changing economic conditions over our sample: the Gini coefficient of income inequality, the change in gross domestic product, and the poverty rate. Results of OLS regressions with each of the measures interacted with an *In Finance* and a *Not in Finance* indicator are reported in Table 4.6. Consistent with Twenge et al. (2014), we find a negative relationship between income inequality and generalized trust. The difference between the coefficients for individuals in finance and the U.S. population is significant at the 1% level, indicating that generalized trust of finance professionals declines even more as income inequality rises. Similarly, whilst economic growth promotes trust among both groups, which is consistent with Zak and Knack (2001), among others, finance industry workers seem to be more sensitive to GDP changes than the average U.S. American. As expected, results in the last column indicate that the poverty rate in the U.S. relates negatively to trust. The association with generalized trust is, however, not significantly different for finance professionals compared to the general population. Hence, the results in Table 4.6 suggest that rising income inequality and higher economic growth are correlated with relatively larger shifts in generalized trust of people working in the financial industry.

Yet, when we study the time trends in both measures in unreported tests, we find that only income inequality exhibits a significant linear and positive trend over our sample. Specifically, the Gini coefficient of income inequality increased on average by 0.27 percent per year from its starting point of 36.3 percent in 1978. Therefore, only the sharp rise in income inequality in the U.S., which is to a large part driven by the financial industry itself, represents a potential driver for the relative erosion of generalized trust among finance professionals.

Table 4.6: Changes in economic conditions and the relative trust decline

Dependent variable	***Most people can be trusted***		
	Gini index	GDP change	Poverty rate
	(1)	(2)	(3)
Economic condition measure × In Finance	**-0.031*** (-8.57)**	**0.073*** (12.19)**	**-0.163*** (-13.45)**
Economic condition measure × Not in Finance	-0.020*** (-33.68)	0.051*** (35.72)	-0.156*** (-35.75)
In Finance dummy	0.489*** (3.01)	-0.052** (-2.33)	0.104 (0.61)
Difference in time trends	**-0.0111***	**0.0218***	**-0.00648**
p-value of difference	**0.00358**	**0.000470**	**0.614**
Exogenous demographic controls	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes
Region & Year FE	Yes	Yes	Yes
Observations	27,892	27,892	27,892
Adj. R-squared	0.131	0.131	0.130

Notes: This table reports OLS regression results of analyses that explore whether different changes in economic conditions in the U.S. over our sample constitute potential causes for the relative decline in generalized trust experienced by individuals working in the financial industry. All specifications include demographic and socioeconomic controls as well as region and year fixed effects. Robust t-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

4.4.2 Selection into the financial industry

Next, we explore whether changes in the workforce composition in the financial industry may have driven our observed trust trend. Panel A of Table 4.7 reports coefficients from regressions estimating the relation between trust and four dependent variables for finance professionals and, for comparison, also for the rest of the population. *Highly educated fraction* is the fraction of individuals with greater than high school educations in a year in the financial industry and the rest of the U.S. population, respectively. Similarly, *Non-white fraction* is the fraction of non-white people and *Female fraction* is the fraction of female individuals. *Income dispersion* is measured as the Gini index of equalized family income as described in Section 4.3. Results in the first row of columns (1) and (2) suggest that more highly educated and non-white people working in the financial industry relate negatively to generalized trust of finance industry employees. However, a higher fraction of females correlates with more generalized trust, as indicated in column (3). Finally, column (4) provides evidence that larger income inequalities within finance are associated with less trust of finance professionals.

In Panel B of Table 4.7, we examine the time trends in each of the four dimensions. Although we find linear time trends in each one of them, only two dimensions experienced a significantly different time trend in finance compared to the general U.S. population. First, consistent with the literature (e.g., Philippon and Reshef, 2012), the results in column (1) suggest that finance has become a high-skill industry over the past decades. Second, as shown in column (3), the fraction of females declined in finance, while it slightly increased in the general population. The fraction of non-white people and the income dispersion do not exhibit different time trends.

Table 4.7: Changes in the professional environment and the relative trust decline

Panel A: Relation of trust with the professional environment in finance

Dependent variable	***Most people can be trusted***			
	Highly educated fraction	Non-white fraction	Female fraction	Income dispersion
	(1)	(2)	(3)	(4)
Professional environment in Finance × In Finance	**-0.899*** (-8.11)**	**-1.245*** (-6.40)**	**0.802** (2.21)**	**-1.973*** (-5.26)**
Environment outside Finance × Not in Finance	-0.990*** (-16.99)	-1.274*** (-11.02)	-0.597 (-0.35)	-1.760*** (-8.62)
In Finance dummy	0.087* (1.91)	-0.008 (-0.24)	-0.839 (-0.93)	0.018 (0.14)
Difference	**0.0914**	**0.0287**	**1.400**	**-0.213**
p-value of difference	**0.401**	**0.888**	**0.414**	**0.534**
Ex. demographic controls	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes
Region & Year FE	Yes	Yes	Yes	Yes
Observations	27,892	27,892	27,892	27,892
Adj. R-squared	0.129	0.125	0.113	0.123

Panel B: Time trends in the professional finance environment and the U.S. society

Dependent variables	**Highly educated**	**Non-white**	**Female**	**Income dispersion**
	(1)	(2)	(3)	(4)
In Finance time trend	**0.823*** (6.53)**	**0.534*** (5.88)**	**-0.218** (-2.35)**	**0.259*** (4.63)**
Not in Finance time trend	0.582*** (15.14)	0.398*** (20.02)	0.035** (2.22)	0.231*** (8.86)
In Finance dummy	0.061** (2.45)	-0.044** (-2.57)	0.202*** (10.46)	-0.050*** (-4.83)
Difference in time trends **p-value of difference**	**0.241*** **0.0542**	**0.135** **0.150**	**-0.253**** **0.0115**	**0.0279** **0.606**
Controls / Fixed effects	No	No	No	No
Observations	49,162	49,251	49,251	49,251
Adj. R-squared	0.0219	0.0128	0.00429	0.801

Notes: This table reports results of analyses that investigate whether changes in the composition of the workforce in the financial industry over our sample constitute a potential cause for the relative decline in generalized trust experienced by individuals working in the financial industry. Panel A presents coefficients from OLS regressions that explore the correlation of generalized trust with different indicators of the professional environment in the financial industry as well as the U.S. population. The independent variable of interest in column (1) is *Highly educated fraction*, which is defined as the fraction of individuals with more than high school education in a year in the financial industry and the rest of the U.S. population, respectively. Similarly, *Non-white fraction* in column (2) is the fraction of non-white people and *Female fraction* in column (3) is the fraction of female individuals. In column (4), we use *Income dispersion* as a measure for income inequality, which is measured as the Gini index of equivalized family income. All specifications include demographic and socioeconomic controls as well as region fixed effects. Panel B shows results from OLS regressions that explore the unconditional time trends on individual level of four measures that are defined in accordance with the variables used in Panel A. *Highly educated* is an indicator that equals one for a respondent who has more than high school education, *Female* equals one for a female person, and *Non-white* equals one for a non-white person. *Income dispersion* is the Gini index of equivalized family income. Robust t-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Overall, we conclude that the flow of highly educated human capital into the financial industry and the decline in the share of women over the past almost four decades provide two potential drivers for the absolute as well as relative erosion of generalized trust among finance professionals. The rising income inequality within finance and the growing ethnic heterogeneity are, in contrast, unlikely to serve as explanations for the observed trend.

4.4.3 Socialization of people in finance

Lastly, we analyze shifts in the opportunities people have to generate social capital and generalized trust. Specifically, we investigate whether working hours have increased disproportionally in the financial industry leaving workers with fewer chances to engage in social activities compared to other U.S. Americans. In addition, we explore whether the propensity of workers in finance to participate in social groups has decreased over time. Our interest in people's opportunities to associate with one another is motivated by Putnam's seminal research (Putnam, 1993, 1995, 2000) which points out that social interactions, particularly interactions as a member of a social group, are conducive to generating social capital. He argues that participating in a social group, for example, a bowling club, enhances the transmission of knowledge and facilitates the development of trust in a society. Consistent with this, Alesina and La Ferrara (2000) study group memberships in the U.S. and find that the participation in social activities is significantly less likely in more unequal and more racially fragmented localities in which residents are also known to be less trusting.

Table 4.8 reports findings from regressions estimating equation (4.1) with three dependent variables, *Workings hours*, *Group membership*, and *P-Group membership*. The variable *Working hours* measures the number of hours individuals worked in the past week and is constructed by clustering responses into bins of 20 hours. Following Alesina and La Ferrara (2000), we construct *Group membership* as an indicator that takes the value one for a respondent who belongs to at least one social group and zero otherwise.[26] Because questions on memberships were only asked in 1978 through 1994 (except 1982 and 1985) and in 2004, regressions with *Group membership* as the dependent variable rely on a smaller sample. The population proportion that is part of a social group varies between 72.7 percent in 1983 and 62.1 percent in 2004 and steadily decreases over time.

[26] Social groups include, among others, fraternities and sororities, service groups, veteran groups, political clubs, labor unions, sports clubs, youth groups, school service groups, hobby clubs, nationality groups, farm organizations, literary or art groups, professional societies, and church groups.

Additionally, we explore the trends in social activeness by differentiating between types of groups following Knack and Keefer (1997). In particular, we classify groups as "Putnam-type" groups (denoted P-groups) if they are least likely to act as distributional coalitions focused on rent-seeking, but rather focus on social interactions that allow individuals to build trust and cooperative habits. We define *P-Group membership* as an indicator that equals one for respondents belonging to either a sports or hobby club, a (school) service club, youth groups, literary, art, discussion or study groups, or a church-affiliated group.

Table 4.8: Changes in socialization habits in finance and the relative trust decline

Dependent variables	***Working hours***	***Group membership***	***P-Group membership***
	Ordered probit	OLS	OLS
	(1)	(2)	(3)
In Finance time trend	**0.854*** (3.09)**	**-0.696*** (-4.70)**	**-0.934*** (-5.73)**
Not in Finance time trend	0.318*** (3.55)	-0.514*** (-4.23)	-0.300** (-2.50)
In Finance dummy	-0.195** (-2.45)	-0.050** (-2.69)	0.055* (1.80)
Difference in time trends **p-value of difference**	**0.536*** **0.0564**	**-0.183*** **0.0782**	**-0.634***** **0.00116**
Exogenous demographic controls	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	27,928	13,589	13,589
Adj. R-squared	0.228	0.112	0.0927

Notes: This table reports results of analyses that explore whether changes in the style of working in the financial industry over time have led to fewer opportunities for human interactions. In column (1), the dependent variable, *Working hours*, measures the number of hours individuals worked in the past week in bins of 20 hours. In column (2), *Group membership* is a dummy that indicates whether a respondent belongs to any social group, while in column (3) *P-Group membership* only considers groups least likely to act as distributional coalitions. All specifications include demographic and socioeconomic controls as well as region fixed effects. Robust t-statistics (in parentheses) are based on standard errors clustered by year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

The coefficients on both *Working hours* variables in column (1), which assess the time trend of hours worked, indicate that working hours have increased significantly for both workers in finance and the general U.S. population. The difference between the time trends is significant at the 10% level suggesting that the increase in working hours was slightly larger in the financial industry. Turning to group memberships, columns (2) and (3) suggest that the likelihood to participate in a social group or P-group has generally declined and even more so among people working in the financial industry. The coefficient difference is significant at the 10% and 1% level, respectively. Interestingly, the time trends in P-group memberships, i.e., those groups that are most likely to focus on the association with one another, deviate most strongly from each other. The likelihood of workers in finance to be a member of a P-group declined six percent more over a ten-year period than the likelihood of the average American. Taken together, the results provide evidence that the formation of social capital and consequently the development of generalized trust through social activities has become rarer for workers in finance than the general U.S. population.

In unreported analyses, we additionally test whether workers in any other industries also experienced a significant and positive trend in working hours (in absolute terms as well as relative to the average U.S. American) and simultaneously a negative trend in their likelihood of participating in social groups. Our results do not provide evidence for this pattern in *any* other industry except for the financial industry. The higher number of hours worked by employees in the financial industry paired with their lower propensity to engage socially thus represents a unique pattern for the financial industry and another potential reason for the disproportionate decline in generalized trust.

4.5 Conclusion

We document that generalized trust among finance professionals in the U.S. has declined significantly more sharply than among the general U.S. population and more than in any other industry. This decline holds in different age cohorts and among different levels of seniority and is related to a lack of trust only in institutions that are related to the financial industry. The relative decline of generalized trust appears to be at least partly related to changes in economic conditions, the professional environment in the financial industry, and the level of socialization among finance industry professionals.

Yet, we note that there may be additional factors that have contributed to the absolute and relative decline in generalized trust across the financial industry over the past decades, which we are unable to test for due to a lack of data. For example, organizational forms of financial firms have changed considerably over the past few decades with partnerships being replaced by large publicly traded institutions. In a partnership, the trust of the partners and their reputation as trustworthy businessmen are closely bound to the success of the enterprise. In large publicly traded institutions, in contrast, the level of trust of individual employees, even if they hold management positions, is arguably less closely linked to a company's reputation and performance. Hence, the focus of financial firms on social norms, such as trustworthiness and integrity, may have been blurred in more recent years because these norms do no longer serve as signals of quality.

Similarly, as the complexity of the financial world increases, finance professionals may more often experience a form of imposter syndrome. Clance and Imes (1978) introduce this term to describe a psychological pattern in which individuals experience self-perceived intellectual phoniness despite sufficient external evidence of their own competence. It has been shown that the imposter syndrome is associated with negative feelings such as generalized anxiety, shame, and insecurity, which, in turn, could lead to a situation in which people generally trust others, particularly strangers, less.

All told, our study provides novel empirical findings on the evolution of generalized trust in the U.S. financial industry. It thereby offers several avenues for further research. On the one hand, it is essential for economists to pin down why trust has eroded to severely across the financial industry to broaden our understanding of the motives and drivers of those employed in the financial industry. On the other hand, it is necessary to explore ways to mitigate possible adverse effects resulting from a lack of trust among finance professionals. In this respect, the use of new technologies, such as blockchain, as well as a tighter regulatory corset for the industry to substitute for the loss of trust can provide two starting points for follow-up work.

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

"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."

J. Lawrie, principal and portfolio manager at HLM Venture Partners (Boston, MA)[27]

5.1 Introduction

The emerging field of social finance explores how societal issues affect economic behavior (Hirshleifer, 2015; Cronqvist, 2018).[28] This literature has only recently begun to study financial consequences of broad societal developments, for example, anti-discrimination movements (Lins et al., 2020), climate change (Krueger, Sautner, and Starks, 2019), and terrorism (Dai et al., 2020). We contribute to this growing literature by showing that a common societal issue, *early-life family disruption*, is associated with long-lasting effects on investment behavior.

Specifically, in this study, we examine investment behavior by mutual fund managers. The mutual fund industry is an appropriate setting as it allows us to directly compare observable investment decisions made by professional investors who have been trained to make rational decisions while taking appropriate risks. Moreover, mutual fund managers perform standardized professional tasks and share a comparable socioeconomic status,

‡ This chapter is based on an earlier version of Betzer et al. (2021).

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

[28] Social factors include different aspects of socialization (e.g., Cronqvist and Yu, 2017; Duchin, Simutin, and Sosyura, 2021), social interactions (e.g., Hong, Kubik, and Stein, 2004; Kaustia and Knüpfer, 2012; Huang, Hwang, and Lou, 2020), as well as ideologies and religions (e.g., Kumar, Page, and Spalt, 2011; Hong and Kostovetsky, 2012), among others.

thereby mitigating concerns of investor or task heterogeneity. 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 of household wealth. Yet, while existing evidence indicates that fund managers are subject to behavioral biases such as the disposition effect (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 a stronger disposition effect and take less risk, even after accounting for various socioeconomic and family factors. We also examine moderators of the relationship between family disruption and investment behavior, specifically social support, the age at which a manager experienced family disruption, and family wealth. Overall, our results are consistent with an emotional channel, as suggested by social psychology and medicine.

Understanding how financial decisions relate to early-life family disruption is crucial because family disruption affects children across virtually all societies. According to census data, 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 (Amato, 2000). The proportion of marriages ending in divorce in the U.S. has also historically been high, equaling at least 30 percent since the 1960s (Schoen et al., 1985). Furthermore, one out of every 20 children in the U.S. aged 15 or younger suffers the loss of one or both parents (Owens, 2008). Therefore, given their prevalence and documented impact, it is important to examine whether and how these experiences relate to the investment decisions that can affect the allocation of capital in financial markets.

Our study builds on two strands of literature. First, the social psychology literature, based on seminal work by Freud (1953) and Bronfenbrenner (1979), suggests that a person's early-life family environment plays an essential role in forming his or her personality and preferences. Second, recent finance studies find that "nature" (genetic predisposition) and "nurture" (environmental factors) influence investment behavior, in particular financial risk-taking. Black et al. (2017) suggest that environmental factors 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. Indeed, recent evidence suggests that environmental treatments, such as cultural heritage or the experience of recessions or natural disasters, can have persistent effects even on highly educated CEOs (Malmendier, Tate, and Yan, 2011; Bernile, Bhagwat, and Rau, 2017; Pan, Siegel, and Wang, 2020).

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, i.e., the family created by choice of partner (e.g., Roussanov and Savor, 2014; Cronqvist and Yu, 2017), or the family of origin, i.e., 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 evidence on the lasting role that specific early-life family factors can play for the investment behavior of finance professionals.

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 by pointing out that these experiences may create deep-seated cognitive effects that cannot simply be undone with education or training.

Nonetheless, there is mixed evidence on the directions of these effects in the literature on family disruption. On the one hand, medical studies provide evidence that both parental death and divorce in childhood have a long-lasting effect 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 emotional syndromes of post-traumatic stress in adulthood, particularly vulnerability to future loss (Mireault and Bond, 1992), lower self-esteem (Lutzke et al., 1997), and an increased level of anxiety (Kendler et al., 1992). Anxiety, in turn, increases people's risk aversions (Loewenstein et al., 2011; Kuhnen and Knutson, 2005), while lower self-esteem has been related to the disposition effect. Hirshleifer (2015) argues that self-esteem is a key driver of the disposition effect and Chang, Solomon, and Westerfield (2016) find that the disposition effect reverses when investors can assign blame not to themselves but to others. This literature therefore points to the conclusion that investors who experienced early-life family disruption exhibit a stronger disposition effect and take less risk compared to their untreated peers.

On the other hand, there is also a body of literature that finds evidence of post-traumatic growth (Tedeschi and Calhoun, 2004). Some children can grow personally as they face divorce-related challenges (Gately and Schwebel, 1992) and develop, for instance, higher levels of self-confidence (Mack, 2001). Further, Maier and Lachman (2000) find that the early death of a parent can cause men to have more confidence in their own opinions. As people with high levels of self-confidence believe more in themselves and are not easily swayed by risk, they may be more likely to make riskier choices (Chuang et al., 2013) and may be less subject to the disposition effect.

Ex ante, therefore, it is not clear whether the effects of post-traumatic stress outweigh the effects of post-traumatic growth or vice versa, or if they cancel each other out on average. Furthermore, changes in parenting due to family disruption may add to the emotional experiences of affected children and may also directly affect investment behavior later in life, again with an unclear direction. Hence, in this study, we address the open empirical question of whether investors from disrupted families show different investment behaviors than their untreated cohorts.[29]

Following the procedure described in Chuprinin and Sosyura (2018), we first hand-collect information on fund managers' family backgrounds and their parents' deaths and

[29] Besides the emotional channel, family disruption may also affect people's investment behavior through changes to the socioeconomic status and wealth of the family. We address this channel in several analyses and find consistent support for the emotional channel. We note that observational data on family experiences does not allow to identify all specific channels as thoroughly as experimental data (see the discussions in Malmendier and Nagel, 2011, and Kuhnen and Knutson, 2011). Nevertheless, we contribute to the literature by showing that the stability of the family during childhood relates significantly to investor behavior later in life and providing a direction for future research to explore specific channels in detail.

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 fund 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.

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 may 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 are upheld when we additionally control for a broad set of socioeconomic and family background measures, including age and country of birth of the parents, their homeowner status, and occupation (e.g., whether both parents were working) as well as the fund manager’s number of siblings and whether he or she is a first-born. In contrast to our family disruption measure, none of these measures consistently explain the difference in investment behavior. Our results are robust to the use of both coarsened exact matching and propensity score matching methodologies to further address concerns of omitted variable bias. To the best of our knowledge, this analysis provides the first comprehensive picture of the relationship between investment behavior and family background measures, while controlling for confounding socioeconomic effects. Specifically, we find no indication that the effect of family disruption varies depending on the wealth of the fund manager’s family. This finding speaks to an emotional channel (i.e., persistent stress symptoms) and further mitigates concerns of an unobserved socioeconomic channel, including wealth shocks caused by parental deaths that disrupt the family. We also find no indication that our results are driven by fund managers providing (financial) support for their bereaved parents.

In additional analyses, we investigate whether treated managers trade differently in reaction to events that unexpectedly increase the risk and uncertainty of their investee firms. We find that they are significantly more likely to sell shares of investee firms that exhibit exogenous CEO turnover (using data from Eisfeldt and Kuhnen, 2013) and make takeover announcements. For takeovers, the effect is most pronounced for high-risk deals involving foreign or non-public targets. This analysis allows us to examine how managers react to arguably unforeseeable firm events after the fund-manager matching took place. It also allows us to control for fund manager-stock fixed effects which account for managers' nonrandom selection of stocks and unobserved heterogeneity, i.e., time-invariant manager characteristics and previous experiences.

To provide a more nuanced understanding of early-life family disruptions and 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 further evidence that a wealth shock caused by 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 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 the fund manager's formative years or when the 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. Importantly, the results for both risk-taking and the disposition effect reverse if social support is very high. Hence, there are instances in which early-life family disruption is associated with more risk-taking and a lower disposition effect, consistent with post-traumatic growth promoted by social support. The results imply that the moderators for early-life family disruption are relevant and further speak to a long-lasting emotional channel through which it affects investment behavior. They also mitigate 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 do not indicate 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 link between the socioeconomic status of the family of origin and the 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. Our study contrasts with theirs in that we show evidence that an emotional channel relates early-life family conditions to investment behavior, even after accounting for the family's socioeconomic status. In a concurrent working paper, Liu et al. (2019) exploit the deaths of managers' parents to study whether bereavement has a direct and 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 traumatic early-life events.

Our study contributes to two strands of the literature. First, we contribute to the emerging literature on social finance, particularly to recent research 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. Furthermore, we provide evidence that the reasons to exhibit behavioral biases, in this case the disposition effect, may sometimes lie far back in childhood.[30]

Second, our study contributes to the literature on the role that environmental treatments, particularly "nurture," play in explaining differences in investment behavior (e.g., Barnea, Cronqvist, and Siegel, 2010; Cesarini et al., 2010). In contrast with existing studies, we unravel the family backgrounds of investors 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.

[30] We cannot directly test the role of feelings in contrast to Kuhnen and Knutson (2011). Yet, our study is one of the few papers to indicate that social experiences, which are associated with changes in people's feelings, particularly anxiety and self-esteem, relate to investor behavior in the long term.

5.2 Motivation and theoretical underpinning

Psychological research posits that the early-life family background plays an essential role in forming people's personalities 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 (Monoghan, Robinson, and Dodge, 1979), and that the causes of family disruption are often seen as traumatic turning points in children's lives (Rutter, 1996).

Ample 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 affects people's cortisol levels (e.g., Nicolson, 2004; Bloch et al., 2007). Further, Meinlschmidt and Heim (2007) show an altered central sensitivity to the effects of oxytocin, which is relevant to protect 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 vulnerability to future loss (Mireault and Bond, 1992), lower self-esteem (Lutzke et al., 1997; Ellis, Dowrick, and Lloyd-Williams, 2013), and higher levels of anxiety (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 (Engelmann et al., 2015). Specifically, anxiety has been shown to increase risk aversion (Loewenstein et al., 2011; 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 people's reluctance to realize losses and hence to the disposition effect. While several previous 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 fact that the disposition effect is reversed when investors can shift the blame onto others (Chang, Solomon, and Westerfield, 2016) indicates that people's urge to maintain their 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 because it leads to reduced self-esteem and increased vulnerability to future loss.

Nonetheless, there is also limited evidence for *post-traumatic growth* (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 behavior by fostering risk-taking and by mitigating the disposition effect via enhanced self-confidence.

Taken together, given the evidence for both *post-traumatic stress* and *post-traumatic growth*, the literature does not unambiguously predict whether family disruption leads to an increase, a decrease, or no change in observed behavioral patterns. It is therefore 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 and providing a first understanding of how family disruption relates to investment behavior is important, even beyond just the finance literature.

5.3 Data, methodology, and summary statistics

5.3.1 Data

5.3.1.1 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.[31] 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 US-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 averages across all fund share classes. 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 a fund manager's family background and mutual fund risk, we exclude team-managed fund

[31] We choose Morningstar Direct as the source for fund manager information as it is more accurate than CRSP (Patel and Sarkissian, 2017).

years and years in which a fund is managed by more than one manager. We obtain a sample of 2,139 managers who pass these initial criteria.

Next, we obtain the most complete version of a fund manager's name, including the full middle name and suffixes, drawing on the Financial Industry Regulatory Authority (FINRA) investment adviser registration records. We use the employment history provided in FINRA to validate the accuracy of a match. We then complement our data on 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 the full name and employment history of the manager. 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 year of birth. 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.

5.3.1.2 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. The reason for this restriction is twofold. 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 older fund managers, we ensure that most of the parents are deceased so that we can identify the year of death of the parents. This filter restricts the sample to 615 managers. Investigating managers' backgrounds, we find that 36 managers grew up outside the U.S. and their families were therefore not covered in the U.S. Census. After eliminating these cases, we arrive at 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 the appendix. We are able to find the households' census records for 538 (93 percent) of our 579 fund managers. This share is essentially the same as in Chuprinin and Sosyura (2018). In terms of the number of fund managers, our sample compares well with extant studies on (older) fund managers, for example, Chevalier and Ellison (1999) (492 managers), Chuprinin and Sosyura (2018) (387), Hong and Kostovetsky (2012) (600), and Liu et al. (2019) (471).

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 accessed through 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, year of birth, 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, year of birth, name of spouse and 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 the death years of nearly all parents in our sample mitigates the concern that our data collection is biased, as newspapers and other public sources may be more likely to report the death of parents from wealthier or more well-known families, for example. We do not remove managers from the sample if we are unable to identify the death records of both parents since some parents may still be alive.

To identify parental divorces, we screen death records and obituaries of parents for the following signals: a name of a spouse of a parent 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 death records and obituaries of parents again mitigates the concern that our data collection is biased toward wealthier or more well-known families. If we find any 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 fund manager's parent in the census is "divorced."

We obtain further data from several other 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 parents of fund managers 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.

Overall, our final sample comprises 569 funds 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. Our sample is economically important given that it accounts for 25 percent of all assets of single-managed domestic equity funds in the median sample year, i.e., 1998. This share is significantly higher in earlier years (up to 73 percent) and decreases over the more recent years of the sample, e.g., 15 percent in the 2008 financial crisis. The 569 funds account for 4,839 fund years. Because we are not able to obtain data 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.

5.3.2 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 (5.1):

$$\begin{aligned} Investment\ Behavior_{jt} = & \\ & \alpha + \beta \times Family\ Disruption_{jt} + \Gamma_1 \times Fund\ Controls_{jt-1} \\ & + \Gamma_2 \times Manager\ Controls_{jt-1} + \delta + \varepsilon_{jt} \end{aligned} \tag{5.1}$$

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

Consistent with the theoretical underpinning and predictions of this study, we use the following measures of investment behavior as our main dependent variables. First, 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., *Idiosyncratic Risk*, and its systematic component, i.e., *Market Risk*, by estimating a market model using the monthly gross returns of a fund 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, since the tracking error is an important metric to assess portfolio risk in the mutual fund industry, we retrieve quarterly data on the tracking error of funds from Antti Petajisto's website for the period 1980-2009. *Tracking Error* is defined as the volatility of the difference between a fund's portfolio return and the return of its benchmark index and is a proxy for systematic factor bets (Cremers and Petajisto, 2009).

To assess the extent to which funds exhibit the 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. 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 (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 sets of control variables covering fund and fund manager characteristics. 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*. We define all the above variables in line with the existing literature. 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 education of parents as their average education attainment score, defined as follows: educational 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 fund manager's family during his childhood. 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 is 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 value are expressed in multiples of their state medians.

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. Furthermore, 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, manager birth cohort FE (based on decades), and manager birth state FE. We explain the specific use of different fixed effects as well as two matching approaches, coarsened exact matching and propensity score matching, in Section 5.4.4. 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 (5.1) by two sets of additional variables. The first set of additional variables are indicators related to the occupation of managers' 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 financial 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 working according to their census records.

The second group of variables relates to the lives of fund managers at home during their 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 of the parents of a manager migrated to the U.S., and (x) *Parent Homeowner* equals one if a parent lived in a house that was not rented but owned by the residents according to the census record. 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 three different dependent variables. Specifically, instead of the measures discussed above, we use the following variables on the left-hand side of equation (5.1): *Active Share* (Cremers and Petajisto, 2009) as well as measures of risk-adjusted performance, i.e., *Alpha* (one-factor alpha) and *Sharpe Ratio*. We define these variables in the appendix and discuss the regressions in Section 5.5.

5.3.3 Summary statistics

Table 5.1 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.

Table 5.1: Summary statistics

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

	Total	Family Disruption = 1	Family Disruption = 0	Difference in means
Variable	**Mean**	**Mean**	**Mean**	**t-statistic**
Avg. Parental Age at Manager's Birth	30.459	32.153	30.224	-2.05
Birth Year of Manager	1941	1940	1941	0.85
Both Parents Working	0.190	0.136	0.198	1.27
Family Wealth	2.705	3.096	2.650	-0.98
Father Blue-collar Worker	0.270	0.255	0.272	0.25
Female	0.048	0.034	0.049	0.60
Firstborn	0.546	0.421	0.564	2.03
Ivy League	0.312	0.271	0.318	0.74
MBA	0.545	0.542	0.546	0.05
Number of Siblings	1.782	1.667	1.798	0.61
Parents Age Difference	4.005	5.542	3.805	-2.13
Parental Education	2.373	2.305	2.382	0.81
Parent Born Outside U.S.	0.127	0.145	0.124	-0.42
Parent Homeowner	0.558	0.559	0.558	-0.02
Parents Self-employed	0.143	0.203	0.134	-1.25
Parents Worked in Finance	0.167	0.153	0.169	0.33
PhD	0.068	0.068	0.068	0.01

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

	Total			Family Disruption = 1		Family Disruption = 0		Difference in means
Variable	**N**	**Mean**	**P50**	**N**	**Mean**	**N**	**Mean**	**t-statistic**
Manager characteristics								
Family Disruption	4,839	0.151		732		4,107		
Manager Age	4,839	54.799	55.000	732	56.148	4,107	54.558	-4.18
Manager Tenure	4,839	7.579	5.083	732	8.241	4,107	7.461	-2.44
Fund characteristics								
Total Risk	4,839	0.045	0.041	732	0.043	4,107	0.046	3.13
Idiosyncratic Risk	4,837	0.020	0.016	731	0.020	4,106	0.020	-0.14
Market Risk	4,839	0.979	0.955	732	0.932	4,107	0.987	4.20
Avg. Monthly Return	4,742	0.009	0.011	718	0.009	4,024	0.009	0.04
Expense Ratio	4,742	0.012	0.012	718	0.013	4,024	0.012	-3.75
Fund Age	4,836	15.469	10.167	729	17.105	4,107	15.178	-2.74
Fund Size	4,796	4.680	4.671	726	4.718	4,070	4.673	-0.55
Fund Family Size	4,796	6.172	6.924	726	6.080	4,070	6.188	0.78
Turnover Ratio	4,000	0.744	0.480	609	0.704	3,391	0.751	1.15

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

	Total			Family Disruption = 1		Family Disruption = 0		Difference in means
Variable	**N**	**Mean**	**P50**	**N**	**Mean**	**N**	**Mean**	**t-statistic**
Active Share	9,482	0.849	0.878	1,335	0.846	8,147	0.850	1.10
Disposition Effect	15,256	-0.016	0.000	2,341	0.008	12,915	-0.021	-8.19
Tracking Error	9,479	0.077	0.064	1,332	0.074	8,147	0.077	3.31

Panel D: Parental deaths

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

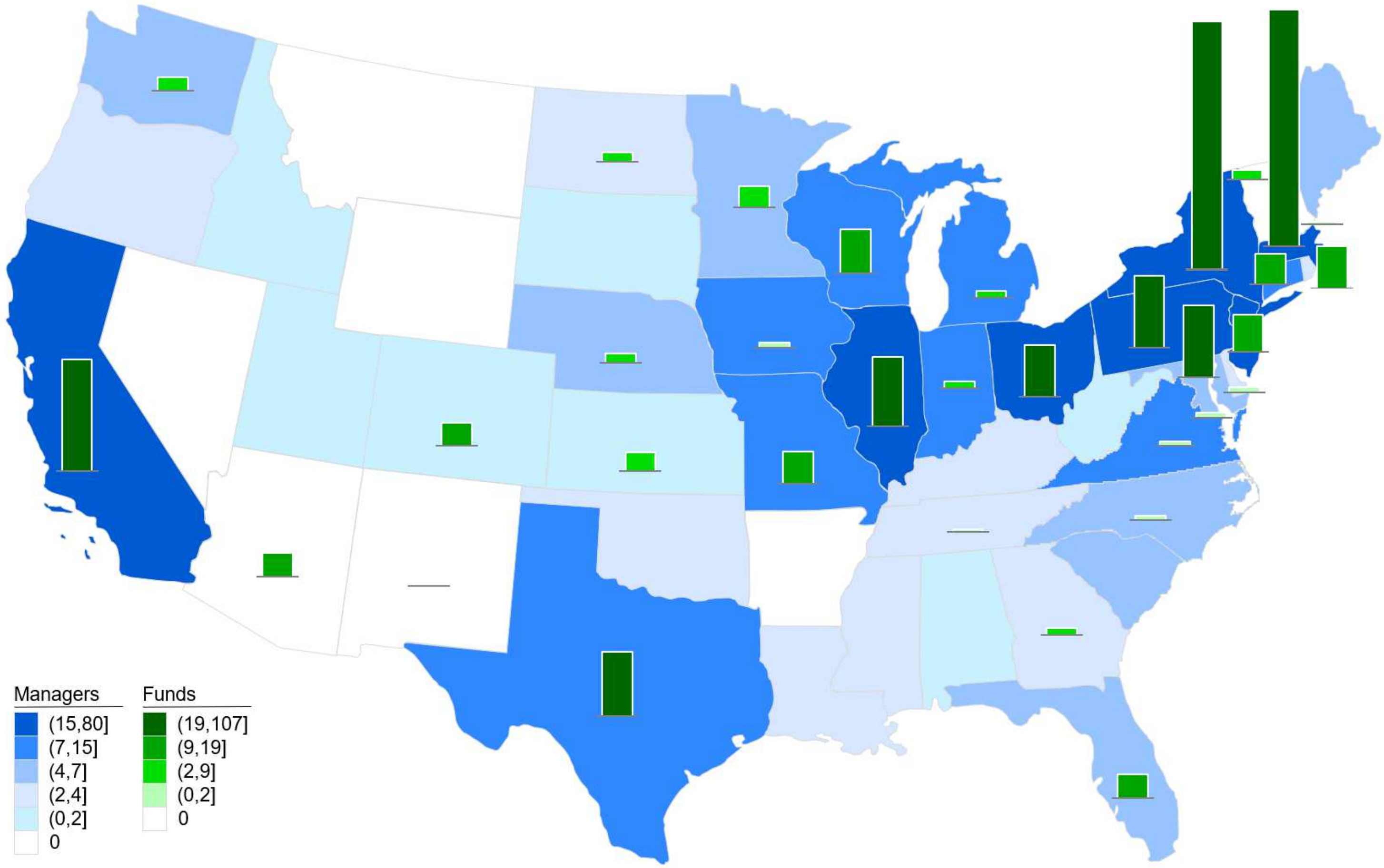
Notes: This table presents summary statistics for the variables used in this study. The sample period is 1980-2017. Summary statistics on manager level for time-invariant manager characteristics are shown in Panel A. Panel B reports summary statistics on fund-year level for family disruption as well 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. Panel D provides an overview of the causes of parental deaths that lead to family disruption for those cases with available information. If both parents died early, the cause of death for the first deceased parent is reported.

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 percent of both groups have an MBA and a PhD, respectively). Moreover, their parents also have similar educational backgrounds, occupations, and wealth. Statistically significant differences only exist for three characteristics: treated managers are less likely to be firstborns, the age difference of their parents is, on average, slightly larger, and their parents are marginally older at the manager's birth.

Panel B reports summary statistics for time-varying manager and fund characteristics at the fund-year level. Treated managers are marginally older and have marginally longer tenures. There are also 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 and the funds' expense ratios. 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 and lower market risk. 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* for the total sample of funds 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 funds managed by treated and untreated managers is significant.

Finally, Panel D of Table 5.1 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 percent of all deaths. Only a few parents died during military service or because they suffered from a long-term disease such as hypertension or skin cancer. Most parents died suddenly, either due to an accident or due to sudden illness, e.g. pneumonia or stroke, or for any other unknown reason reported to have occurred suddenly. 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.

Figure 5.1: Distribution of fund manager birth states and fund locations



Notes: This figure illustrates the geographical dispersion of fund managers' states of birth and the locations of mutual fund firms. The shading of a state illustrates the number of managers who were born in that state, while the height of the bar indicates the number of funds that are located in that state.

To illustrate the wide geographical dispersion of our data points, Figure 5.1 depicts the distribution of fund managers' states of birth and the locations of mutual fund firms across the U.S. Importantly, the figure does not indicate any unusual clustering of birth states or fund locations. As expected, mutual funds are located in states with larger populations and these states are also more likely to be birth states of fund managers, for instance, 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).

5.4 Early-life family disruption, the disposition effect, and risk-taking

In this section, we investigate the relationship of early-life family disruption with the disposition effect and risk-taking of fund managers. Section 5.4.1 presents evidence on the disposition effect, Section 5.4.2 discusses results on risk-taking behavior, and Section 5.4.3 provides evidence on fund managers' trading behavior in reaction to events that increase the risk and uncertainty of their investee firms. In Section 5.4.4, we consider various socioeconomic and family background factors and present evidence from two matching approaches. Sections 5.4.5 and 5.4.6, respectively, present evidence on different events and moderators of family disruption.

5.4.1 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 defined as the difference between the proportion of realized gains and losses for each fund in each quarter (e.g., Odean, 1998).

We regress the variable *Disposition Effect* on the variable *Family Disruption*, along with fund and manager controls and time fixed effects as described in Section 5.3.2. 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 regression estimates are reported in Table 5.2.

Table 5.2: Early-life family disruption and the disposition effect

Dependent variable	*Disposition Effect*			
	(1)	(2)	(3)	(4)
Family Disruption	**0.051*** (3.45)**	**0.071*** (2.78)**	**0.076*** (3.14)**	**0.117*** (5.12)**
Female	-0.001 (-0.04)	0.038* (1.80)	0.034 (1.60)	0.003 (0.10)
Manager Age	0.002 (1.06)	0.001 (0.50)	0.001 (0.73)	0.004* (1.76)
Manager Tenure	-0.000 (-0.21)	-0.000 (-0.00)	-0.000 (-0.05)	-0.001 (-0.66)
Ivy League	-0.003 (-0.35)	-0.022 (-1.14)	-0.022 (-1.19)	0.003 (0.16)
MBA	0.012 (0.99)	-0.009 (-0.50)	-0.008 (-0.48)	-0.010 (-0.57)
PhD	-0.028 (-1.50)	-0.008 (-0.26)	-0.007 (-0.24)	0.021 (0.37)
Parental Education	0.014* (1.85)	0.025* (1.86)	0.025* (1.82)	0.036*** (2.59)
Family Wealth	-0.004* (-1.85)	-0.007** (-2.28)	-0.008** (-2.52)	-0.020*** (-4.38)
Fund Age	0.000 (0.09)	-0.018*** (-3.56)	-0.019*** (-3.66)	-0.021*** (-3.57)
Fund Size	0.000 (0.04)	0.007** (2.47)	0.007** (2.27)	0.005* (1.70)
Fund Family Size	-0.002 (-0.96)	-0.005** (-2.20)	-0.004* (-1.73)	-0.005* (-1.92)
Avg. Monthly Return	-0.213 (-1.22)	-0.199 (-1.15)	-0.178 (-1.01)	-0.205 (-1.17)
Expense Ratio	-0.823 (-1.01)	-1.170 (-1.06)	-1.168 (-1.08)	-0.982 (-0.91)
Turnover Ratio	-0.015** (-2.52)	0.001 (0.26)	-0.001 (-0.28)	-0.001 (-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
Adj. R-squared	0.158	0.195	0.198	0.204

Notes: 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 include fund family FE and fund investment style FE (columns 1 and 3), fund FE (columns 2 to 4), as well as manager birth cohort FE and manager birth state FE (columns 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.

In column (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., because divorce rates have increased over time. Furthermore, fund managers from different states might have been subject to different factors that affect their investment behavior, such as different (macro)economic and social conditions, e.g., state-level policies, crime rates, or natural disasters. In column (2), we use fund FE instead of fund family and style FE to account for unobserved time-invariant heterogeneity across funds, while in column (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 (or fire) treated fund managers as they switch their investment objectives or fund families (typically as the result of fund family mergers). In column (4), we use fund, birth cohort, and birth state FE.

In all four columns, the coefficient on *Family Disruption* is negative and significant at the 1% level. Thus, our estimates indicate that managers who experienced the disruption of their families early in their lives exhibit a significantly stronger disposition effect than their untreated cohorts. In untabulated robustness tests, we also estimate several other regression specifications using varying combinations of fixed effects or no fixed effects at all (except for year FE). We find the coefficient on *Family Disruption* to remain statistically significant with comparable coefficient size.[32] Moreover, our results remain qualitatively similar when we measure the disposition effect via the disposition ratio instead of the disposition spread (see, e.g., Odean, 1998; Cici, 2012).

5.4.2 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 5.3.

Panel A of Table 5.3 presents the results for *Total Risk*, our main risk measure, and parallels the regression specifications shown in Table 5.2. The coefficient on *Family Disruption* is negative and significant at the 5% level in column (1) and at the 1% level in columns (2) to (4). The estimates hence suggest that fund managers who experienced early-life family disruption take significantly less risk than their peers from intact families. Assessing the magnitude of the effect, we find that treated fund managers reduce total fund risk by up to 20 percent relative to the sample mean, which is economically important. 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 unreported robustness tests. Across all untabulated tests, the coefficient on *Family Disruption* remains statistically significant and the size of the regression coefficient remains virtually unchanged.[33]

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[32] 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.

[33] 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.

Table 5.3: 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	0.000	-0.000***	-0.000***	-0.000
	(0.69)	(-3.33)	(-2.93)	(-1.23)
Manager Tenure	-0.000**	0.000	0.000	-0.000
	(-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
Adj. 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
Adj. R-squared	0.696	0.502	0.618

Notes: 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 include fund family FE and fund investment style FE (columns 1 and 3), manager birth cohort FE and manager birth state FE (columns 1 and 4) as well as fund FE (column 2 to 4). Panel B reports results from regressions of *Idiosyncratic Risk* (column 1), *Market Risk* (column 2), and *Tracking Error* (column 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.

In Panel B of Table 5.3, we investigate the influence of family disruption on the components of fund risk, i.e., *Idiosyncratic Risk*, *Market Risk*, and *Tracking Error*. The specifications in Panel B parallel the one presented in column (4) of Panel A, which includes fund, birth cohort, birth state, and year FE. In all specifications in Panel B, the coefficient on *Family Disruption* is negative and significant at the 5% level or better. We therefore conclude that the reduction in total fund risk appears to reflect a reduction in all three risk components. Furthermore, in untabulated tests, we re-estimate our fund risk regression model shown in column (4) of Panel A in Table 5.3 with a fund's semi-deviation and upside beta (Whaley, 2002) as 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.

5.4.3 Reactions to uncertainty-increasing events of investee firms

Next, we 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 takes 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 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). 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 the reactions of fund managers to these two types of events using the regression model in equation (5.2) below:

$$Sell_{jst} = \alpha + \beta_1 \times Family\ Disruption_{jt} \times Event_{jst} + \beta_2 \times Event_{jst} + \Gamma \times Controls_{jt-1} + \delta + \varepsilon_{jst} \tag{5.2}$$

where *j*, *s*, and *t* index funds, stocks, and holding periods, respectively; *δ* stands for fixed effects. 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 column (4) of Table 5.2 as well as fund manager-stock fixed effects and time fixed effects. We cluster standard errors on fund-stock level.

In equation (5.2), *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&As 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&As (variable *Cross-border M&A*) and M&As involving non-public targets (variable *Non-public M&A*).

Table 5.4: Reactions to uncertainty-increasing events at firm-level

Panel A: Reactions to exogenous CEO turnover

Dependent variables	***Sell***	***Terminating Sell***
	(1)	(2)
Family Disruption × Exogenous CEO Turnover	**0.027*** (2.90)**	**0.026*** (3.51)**
Exogenous CEO Turnover	-0.010** (-2.21)	-0.013*** (-3.32)
Manager Age	0.140*** (22.14)	0.108*** (19.38)
Manager Tenure	-0.001*** (-6.42)	-0.000 (-1.25)
Fund Age	0.000*** (6.86)	0.001*** (9.80)
Fund Size	0.003*** (4.41)	-0.002*** (-2.92)
Fund Family Size	-0.002*** (-3.64)	0.004*** (9.35)
Avg. Monthly Return	-2.334*** (-37.91)	-1.480*** (-28.36)
Expense Ratio	-1.955*** (-7.80)	-1.864*** (-8.92)
Turnover Ratio	-0.007*** (-4.98)	-0.004*** (-3.69)
Manager-Stock FE	**Yes**	**Yes**
Time FE	Yes	Yes
Observations	1,233,462	1,233,462
Adj. R-squared	0.029	0.063

Panel B: Reactions to M&A announcements

Dependent variables	***Sell***	***Terminating Sell***	***Sell***	***Terminating Sell***	***Sell***	***Terminating Sell***
	(1)	(2)	(3)	(4)	(5)	(6)
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)**
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	0.139***	0.107***	0.139***	0.107***	0.138***	0.107***
	(22.01)	(19.21)	(22.01)	(19.21)	(22.01)	(19.21)
Manager Tenure	-0.001***	-0.000	-0.001***	-0.000	-0.001***	-0.000
	(-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***
	(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***
	(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***
	(-3.64)	(9.36)	(-3.64)	(9.36)	(-3.64)	(9.36)
Avg. Monthly Return	-2.325***	-1.471***	-2.325***	-1.471***	-2.325***	-1.471***
	(-37.77)	(-28.18)	(-37.77)	(-28.18)	(-37.77)	(-28.18)

Expense Ratio	-1.959***	-1.868***	-1.958***	-1.867***	-1.957***	-1.867***
	(-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***
	(-4.99)	(-3.71)	(-4.99)	(-3.71)	(-4.99)	(-3.71)
Manager-Stock FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Time FE	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
Adj. R-squared	0.029	0.063	0.029	0.063	0.029	0.063

Notes: 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. Panel A presents 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*. Panel B present results for M&As based on regressions of the two stock selling measures on the variables *Family Disruption × M&A* and *M&A* (columns 1 and 2), or on the variables *Family Disruption × Cross-border M&A* and *Cross-border M&A* (columns 3 and 4), or on the variables *Family Disruption × Non-public M&A* and *Non-public M&A* (columns 5 and 6) 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.

The regression results for the trading behavior of fund managers in reaction to the risk-increasing events of investee firms are shown in Table 5.4. Panel A presents the results for exogenous CEO turnover, while Panel B reports the results for M&A announcements. The estimates suggest that treated fund managers are significantly more likely to sell their shareholdings when their investee 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 at the 5% level in the first two columns of both panels. Furthermore, consistent with treated managers taking less risk, the results for takeovers in columns (3) to (6) of Panel B are more pronounced for riskier transactions, particularly those involving non-public targets that fund managers arguably find harder to evaluate. Overall, Table 5.4 provides significant support for the notion that mutual fund managers who experienced family disruption early in their lives exhibit a change in their investment behavior and take less risk in their delegated portfolios.

In an untabulated robustness test, we additionally estimate the regression model shown in equation (5.2) relying on a market-wide measure of risk and uncertainty instead of specific corporate events. In particular, 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" (Bloom, 2009). For the dependent variable *Terminating Sell*, we find that treated fund managers are more likely to sell stocks in reaction to increased market-wide risk and uncertainty as measured by higher VIX values.

Moreover, the appendix reports results of 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. Columns (1) and (2) of Table A5.3 report results from OLS regressions, while columns (3) and (4) report estimates 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.

5.4.4 Additional family background measures and other robustness tests

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

Our detailed data on the families of fund managers allow us to compare how early-life family disruption relates to investment behavior later in life relative to various measures of socioeconomic status and family background. We can hence 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 yields the first comprehensive picture of the long-term association between the early-life family environment and investment behavior, which also enhances our knowledge of how "nurture" affects financial decisions later in life.

We re-estimate our baseline regression model, i.e., column (4) of Table 5.2, and include our variable of interest, *Family Disruption*, together with a broad set of additional controls. To construct these control variables, we hand-collect data from the U.S. Census, obituaries, and city directories. Panel A of Table 5.5 shows the results from regressions with *Total Risk* and *Disposition Effect* as dependent variables. The models include fewer observations than our regressions in Tables 5.2 and 5.3 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 5.3.2 and intend to measure differences in socioeconomic status and wealth as well as parenting style. The first set of variables related to the occupations of managers' parents. Generally, the use of occupation-related variables is motivated by the economics literature, which provides evidence that people's occupation and employment status provide valuable information about their preferences to take risks (Ekelund et al., 2005; Bonin et al. 2007). Here, we use the indicators variables *Father Blue-collar Worker* and *Both Parents Working*. Blue-collar jobs are arguably more dangerous and may thus relate to a person'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). Additionally, we include the indicator variables *Parent Self-employed* and *Parent Worked in Finance* as having self-employed parents or parents who work in the financial industry may influence one's investment style and ability to invest due to different perceptions of risk and a "kitchen table" education.

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. Besides these two, we include three additional 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. 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 than others, which arguably affect their willingness to take financial risks.

Lastly, 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, which may provide them with an informational advantage on or an uninformed bias for local firms (Pool, Stoffman, and Yonker, 2012) that could affect their investment behavior.

Table 5.5: Family disruption, family background, and investment behavior

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

Dependent variables	***Total Risk***	***Disposition Effect***
	(1)	(2)
Family Disruption	**-0.006*** (-3.03)**	**0.155*** (4.37)**
Firstborn	0.008* (1.86)	0.054 (0.69)
Number of Siblings	-0.003*** (-4.02)	0.001 (0.15)
Parent Self-employed	0.002 (0.80)	-0.041 (-1.12)
Parent Worked in Finance	-0.005 (-1.39)	0.083* (1.72)
Father Blue-collar Worker	-0.001 (-0.56)	-0.113** (-2.24)
Both Parents Working	-0.008*** (-3.07)	0.092** (1.97)

Avg. Parental Age at Manager's Birth	0.000 (0.69)	0.000 (0.09)
Parents' Age Difference	0.000 (0.46)	-0.000 (-0.05)
Parent Born Outside U.S:	0.008* (1.72)	0.110* (1.89)
Parent Homeowner	-0.001 (-0.27)	-0.122 (-1.47)
Manager Works for Home State Fund	0.001 (0.21)	0.318*** (3.73)
Controls as in Table 5.2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	2,913	9,813
Adj. R-squared	0.769	0.200

Panel B: Can the socioeconomic status of the family explain our results?

Dependent variables	***Total Risk***	***Disposition Effect***
	(1)	(2)
Family Disruption × Family Wealth	**-0.000** **(-0.40)**	**0.008** **(0.89)**
Family Disruption	-0.008** (-2.14)	0.093** (2.54)
Controls as in Table 5.2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,929	13,290
Adj. R-squared	0.768	0.204

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

Dependent variables	***Total Risk***	***Disposition Effect***
	Only treated fund years after both parents died	
	(1)	(2)
Family Disruption	**-0.000** **(-0.40)**	**0.008** **(0.89)**
Controls as in Table 5.2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,744	12,655
Adj. R-squared	0.770	0.205

Notes: 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., *Total Risk* (column 1) and *Disposition Effect* (column 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 *Total Risk* and *Disposition Effect* 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 5.2 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 *Total Risk* and *Disposition Effect* 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 5.2 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.

Even after adding these eleven controls to our regression model, the coefficient on *Family Disruption* in Panel A of Table 5.5 remains significant at the 1% level for both *Total Risk* and *Disposition Effect*. 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 the emotional channel (i.e., 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. This leads us to the conclusion that the (in)stability of the family environment relates more closely to investment behavior later in life than other specific characteristics of a manager's family background.

Panel B shows reports from re-estimations of our baseline model, i.e., column (4) of Table 5.2, in which we additionally include the interaction *Family Disruption* × *Family Wealth*. If the observed relationship 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 an emotional channel explains this relation, 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, *Total Risk* and *Disposition Effect*. The results thus 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 be associated with 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 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. The coefficient on *Family Disruption* is significant at the 1% level when using *Total Risk* and *Disposition Effect* as dependent variable, indicating that (financial) support for the bereaved parent does not explain our results.

Lastly, to further mitigate concerns of omitted variable bias and to ensure that our results are not caused by inappropriate counterfactuals, we use two matching procedures.

First, we use a coarsened exact matching (CEM) to match managers based on different dimensions of their early family life. CEM is a relatively new matching approach that is described in detail in Iacus, King, and Porro (2012). We consider it here because several studies have demonstrated that it may outperform other matching approaches with respect to covariate balance and effect bias (e.g., King and Nielsen, 2019).[34]

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 for college, 2 for high school, 1 for elementary school, and 0 for no formal education. The last set of matching criteria uses the indicator variable *Both Parents Working*, which equals one if both parents had a job according to their census records. We use this variable for matching because it is the only variable, besides *Family Disruption*, that consistently explains investment behavior in Panel A of Table 5.5. Matching on these criteria ensures that treated and untreated managers grew up during the same time period and in the same U.S. states, experienced similar events and trends, and were subject to comparable (socio)economic, familial, and regional influences. The regression estimates based on the CEM-matched samples are reported in Table 5.6. The coefficient on *Family Disruption* remains significant at the 5% level or better when used to explain *Total Risk* in columns (1) to (3) and *Disposition Effect* in columns (4) to (6).

[34] CEM allows users to group observations in distinct strata based on coarsened values of selected matching variables, e.g., coarse age groups rather than exact birthdays. 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).

Table 5.6: Coarsened exact matching

Dependent variables	*Total Risk*			*Disposition Effect*		
	(1)	(2)	(3)	(4)	(5)	(6)
Family Disruption	**-0.006**** **(-2.16)**	**-0.007**** **(-2.01)**	**-0.008***** **(-2.67)**	**0.081***** **(4.01)**	**0.059**** **(2.21)**	**0.091***** **(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 5.2	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
Adj. R-squared	0.759	0.755	0.769	0.200	0.218	0.194

Notes: 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.

Second, we employ a 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 in our sample (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 that we use as explanatory variables in the regressions in Tables 5.2 and 5.3 as well as year and investment style fixed effects. To maintain statistical independence of our tests, we implement a nearest neighbor matching algorithm without replacement. This algorithm uses the distance between the covariate patterns to define the "closest" neighbor and removes a matching sample fund year from the matching pool once it was selected. For the sake of brevity, we report the PSM results in the appendix. Panels A, B, and C of Table A5.2 present the intermediate steps, which provide evidence for the support of covariate balance, as well as the results of the PSM approach. Panels D and E report the regression estimates based on the matched sample.

The regression model we use is identical to that shown in column (2) of Table 5.2 and is based on all fund years of all matched funds. In Panel D, column (1) shows the results when we omit the fund and fund manager characteristics, which were used to match treated and control observations, while column (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 5.2. Applying the same PSM approach and replacing *Total Risk* by the variables *Disposition Effect*, *Idiosyncratic Risk*, *Market Risk*, and *Tracking Error* in Panel E, we find the coefficient on *Family Disruption* to remain statistically significant in all regressions.

In summary, we can thus conclude that, despite their differences in methodology and matching criteria, both matching procedures provide corroborating evidence that treated fund managers indeed take less risk and exhibit a stronger disposition effect compared to their peers from intact families.

5.4.5 Do different disruption types 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 because it provides a more nuanced understanding of this prevalent societal phenomenon but also because it addresses several endogeneity concerns, which cause threats to identification.

Panel A to Panel E of Table 5.7 each report results from estimations of our baseline regression model, i.e., column (4) of Table 5.2, for the dependent variables *Total Risk* (in column 1) and *Disposition Effect* (in column 2). We regress these 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 analyses in Table 5.2. 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. As before, all cases of family disruption 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 when growing 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.

Table 5.7: Heterogeneity in early-life-family disruption factors

Dependent variables	***Total Risk***	***Disposition Effect***
	(1)	(2)
Panel A: Disruption due to parental death		
Parental Death	**-0.010*** (-3.17)**	**0.092*** (3.67)**
Observations	3,765	12,719
Adj. R-squared	0.770	0.196

Panel B: Disruption due to parental divorce		
Parental Divorce	**-0.010****	**0.193*****
	(-1.98)	**(3.30)**
Observations	3,489	11,785
Adj. R-squared	0.773	0.203
Panel C: Disruption due to unexpected death		
Unexpected Death	**-0.009****	**0.080*****
	(2.59)	**(2.97)**
Observations	3,653	12,334
Adj. R-squared	0.770	0.197
Panel D: Disruption due to maternal deaths (non-working mothers only)		
Maternal Death	**-0.019*****	**0.094****
	(-4.33)	**(2.17)**
Observations	3,516	11,908
Adj. R-squared	0.774	0.199
Panel E: Parental deaths involving bereaved parents with an education level ≥ the deceased's education level and children aged ≥ 6 years		
Parental Death Same Educ.	**-0.008****	**0.074*****
	(-2.30)	**(2.65)**
Observations	3,594	12,112
Adj. R-squared	0.770	0.193
Controls as in Table 5.2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes

Notes: This table investigates how different types of family disruption affect investment behavior. All panels report results from regressions of fund investment measures, i.e., *Total Risk* (column 1) and *Disposition Effect* (column 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 *Parental Death* or *Parental Divorce*, while Panels C, D, and E present results using *Unexpected Death*, *Maternal Death*, and *Parental Death Same Educ.* as variables of interest, respectively. 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.

Panels A and B of Table 5.7 report the results from this test. We consider the two variables *Parental Death* and *Parental Divorce* separately to investigate 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* is negative in column (1) and positive in column (2). It is statistically significant at the 1% level in both columns. Similarly, in Panel B, the coefficient on *Parental Divorce* is negative in column (1) and positive in column (2), and it is 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 solely 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. Panel C of Table 5.7 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 5% level for *Total Risk* and 1% level for *Disposition Effect*.

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 years during which our treatment took place, the father was typically the main income earner in the family. Our results could thus be driven by paternal deaths reflecting shocks to family wealth that might affect children's attitudes toward financial risk.[35]

To test this hypothesis, we examine a specific subgroup of parental deaths: deaths of non-working mothers. Such deaths are unlikely to have significant financial implications and thus allow us to disentangle the wealth and emotional implications of family

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

disruption. Panel D of Table 5.7 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 columns. As an alternative test, shown in Panel E, 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 be weaker if the bereaved parent has at least a similar level of education allowing him or her to compensate for 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, relates to fund managers' investment behavior later in life. 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 for managers' risk-taking and investment behavior because male children lose their male role models

5.4.6 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 an emotional channel of family disruption 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 an individual's later life when experienced during formative years, i.e., between the ages of 5 and 15 (see Bernile, Bhagwat, and Rau, 2017, and the literature therein). Thus, we explore whether fund managers take fewer risks and are more prone to the disposition effect 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, i.e., column (4) of Table 5.2, 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 if family disruption took place during the non-formative years of a manager's early life, i.e., ages 0-4 vs. ages 16-19. Panel A of Table 5.8 presents the results from regressions of *Total Risk* (column 1) and *Disposition Effect* (column 2) on the two above variables.

Column (1) 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 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. Regarding the disposition effect, we find in column (2) that family disruption during formative and non-formative years are related to an equally large increase in the disposition effect.

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 family disruption constitutes an arguably less severe shock, i.e., the treatment intensity is weaker, when the levels of social support and welfare are higher. Support for this idea is provided by the evidence in Ellis, Dowrick, and Lloyd-Williams (2013) who find that social support, for example, provided by friends, religious organizations, and schools, reduces the distress associated with parental death. A large literature regards religious communities as the main source of social support and welfare for individuals in need (see, for example, Cnaan et al., 2002) and as an informal insurance mechanism protecting individuals against certain idiosyncratic risks (Ager and Ciccone, 2017). Furthermore, there is evidence on facilitated coping through spirituality among grieving children (Andrews and Moratta, 2005). However, in the 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.

Table 5.8: Moderators of early-life family disruption

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

Dependent variables	***Total Risk***	***Disposition Effect***
	(1)	(2)
Family Disruption_Formative Years	**-0.025*** (-4.18)**	**0.086* (1.96)**
Family Disruption_Non-formative Years	**-0.005 (-1.60)**	**0.127*** (4.56)**
Difference in Family Disruption coefficients	**-0.0209*** **	**-0.0403**
p-value of difference	**0.00107**	**0.468**
Controls as in Table 5.2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,929	13,290
Adj. R-squared	0.769	0.203

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

Dependent variables	***Total Risk***	***Disposition Effect***
	(1)	(2)
Family Disruption × Religiosity Ratio	**0.048** (2.34)**	**-0.469* (-1.88)**
Family Disruption	-0.036*** (-2.96)	0.373*** (2.60)
Controls as in Table 5.2	Yes	Yes
Fund FE	Yes	Yes
Birth Cohort FE	Yes	Yes
Birth State FE	Yes	Yes
Time FE	Yes	Yes
Observations	3,925	13,276
Adj. R-squared	0.769	0.204

Notes: This table explores factors that potentially moderate the effect of family disruption on investment behavior. Both panels report estimates from regressions of fund investment measures, i.e., *Total Risk* (column 1) and *Disposition Effect* (column 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. 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. 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.

To proxy for social support and welfare, we use the level of religiosity in the home county of a manager's family that prevails around the time that family disruption took place. Specifically, we define the variable *Religiosity Ratio* as the fraction of members of religious denominations in the county that was the home county of a manager's family when family disruption took place. For managers who experienced family disruption, this variable is defined as the number of members of all religious denominations in the home county divided by the county's total population. By definition, this variable is set to zero for managers who did not experience family disruption. Religious membership statistics and county population data are obtained from the Association of Religion Data Archives for 1952 because this year lies in the middle of our family disruption period and religiosity ratios tend to be relatively stable over time.

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 using an additional interaction term, *Family Disruption* × *Religiosity Ratio*. If social support and welfare indeed attenuate our effect, the coefficient on the interaction term would have the opposite sign of the *Family Disruption* coefficient, i.e., positive in regressions with *Total Risk* and negative in regressions with *Disposition Effect* as dependent variable. We regress the same two dependent variables on *Family Disruption*, the interaction term *Family Disruption* × *Religiosity Ratio*, and controls and report the results in Panel B of Table 5.8. Consistent with the notion that more social support and welfare attenuate the relationship between family disruption and fund manager risk-taking, we find the coefficient on the interaction term *Family Disruption* × *Religiosity Ratio* to be positive and significant at the 5% level when used to explain *Total Risk* in column (1). In column (2), the coefficient is negative and significant at the 10% level indicating that social support and welfare also lessen the long-term relationship between family disruption and the disposition effect.

Importantly, our estimates indicate that the above results reverse if social support was very high, that is, if *Religiosity Ratio* is at least equal to 0.75 (the variable has a mean and median of 0.55 and 0.51, respectively). Hence, consistent with post-traumatic growth promoted by considerable social support, there are instances in which early-life family disruption is associated with more risk-taking and a lower disposition effect. This result further supports our proposed emotional channel.

In an additional unreported 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.

5.5 Early-life family disruption and manager skill

As the last step in this study, we explore whether a skill gap exists between fund managers who experienced early-life family disruption and those who come from intact families. Such a skill gap, which may exist, e.g., due to differences in parenting across treated and untreated fund managers, could explain some of the results we present in Section 5.4.

To test for differences in fund manager skills, we analyze three different skill measures. We begin by following Cremers and Petajisto (2009) and Petajisto (2013) and examine whether treated fund managers differ in their active share, i.e., the fraction of their portfolio holdings that deviate from the holdings of the benchmark index. According to Cremers and Petajisto (2009), a fund's active share is a proxy for stock selection, i.e., the ability to pick individual stocks that are expected to outperform their peers. It hence serves as a measure of fund manager skill. For this analysis, we retrieve quarterly data on active share from Antti Petajisto's website for the period 1980-2009. The regressions with *Active Share* are thus based on fewer observations. In addition, we examine whether disruptions of fund managers' families in their early lives are associated with differences in their risk-adjusted fund performance by using 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, i.e., column (4) of Table 5.2. The results of these regressions are shown in Table 5.9. We find the coefficient on *Family Disruption* to be statistically insignificant in all regressions, i.e., for *Active Share* in column (1), as well as for *Alpha* and *Sharpe Ratio* in columns (2) and (3). In untabulated regressions, we find similar results for multi-factor alphas. Thus, our results do not indicate a skill gap between treated and untreated mutual fund managers. We thus conclude that, 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).

Table 5.9: Family disruption and fund manager skill

Dependent variables	***Active Share***	***Alpha***	***Sharpe Ratio***
	(1)	(2)	(3)
Family Disruption	**-0.022** **(-0.59)**	**0.027** **(1.54)**	**0.162** **(1.20)**
Controls as in Table 5.2	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	8,220	3,929	3,929
Adj. R-squared	0.876	0.223	0.753

Notes: This table reports results from regressions of *Active Share* (column 1), *Alpha* (column 2), and *Sharpe Ratio* (column 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.

5.6 Conclusion

This study 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 the 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 shareholdings 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. Social support seems to be an important moderator that can even reverse the documented effects, consistent with instances of post-traumatic growth.

Taken together, the evidence in this study suggests that an individual's early-life family environment is a potential source of variation that may help explain the behavior of professional investors. It thus has potential implications for the allocation of capital in financial markets. Since we focus on mutual fund managers who are highly educated and trained in dealing with financial risks, it is possible that we underestimate the impact of family disruption during childhood on the investment behavior of the average individual later in life. Yet, since mutual fund investments constitute a significant portion of the financial assets of the average U.S. household, our results still affect the portfolio characteristics of the typical non-professional investor in the U.S.

Our evidence further suggests that environmental stability rather than specific observable features of the childhood rearing environment relate to risk-taking and trading behavior later in life. Thus, our study extends the limited literature on the role that "nurture" can play for investor behavior. Thereby, it also expands our understanding of the origins of investment biases, as proposed by Hirshleifer (2015).

6 Concluding remarks

This thesis comprises three studies that shed light on the backgrounds that shape finance professionals and determine their economic behavior. However, research in the field of social finance is still in its infancy and promises to provide many more explanations for various behavioral patterns and anomalies in financial markets in the future. A brief look at the daily events in our economy is sufficient to identify exciting new research questions.

At the time of writing, the world economy is crippled as a result of shutdowns imposed to combat a global epidemic. In the wake of this pandemic, governments have spent an unprecedented 14+ trillion dollars on stimulus measures by June 2020, with the U.S. alone exceeding its responses to the 2008 financial crisis by a factor of 6.5. The crisis has not only upended how businesses operate but also radically transformed our lives and communities. The current economic situation thus offers numerous research opportunities.

As a (prospective) behavioral economist, I am of course particularly interested in the psychological, social, and cultural dimensions of this epidemic that shape our economic behavior in the long run. One example is social distancing, the practice of reducing contact with others to a minimum to physically disrupt the contagion. It could, similar to the social phenomenon analyzed in the third essay of this thesis, have a lasting impact on our professional and also our private lives even when direct economic effects have long been surmounted. Another potential research question addresses the traditionally strong preference of Germans to pay with cash. The current hygiene guidelines could change this preference profoundly in favor of electronic payment methods along with all its advantages and disadvantages, such as more effective prevention of tax evasion but also increased costs for businesses due to service fees.

These examples are only two of many research questions that behavioral finance and in particular social finance scholars can investigate and which are of high relevance for companies and political decision-makers. Overall, I am very curious to see in which directions these research fields will develop in the future.

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Appendices

Appendix to Chapter 2

Sample selection and variables

This appendix contains a detailed documentation of the data sources and sample selection procedure for my analyses of the personal characteristics of employees in the U.S. financial industry in Chapter 2. I obtain data from two representative surveys of the U.S population, the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) and the General Social Survey (GSS).

Annual Social and Economic Supplement

To examine the demographic characteristics, i.e., gender, race, and age, of people working in the U.S. financial industry and the rest of the private sector, I use data from the Annual Social and Economic Supplement of the Current Population Survey, which is also known as the March supplement. The ASEC is a nationally representative survey conducted annually by the United States Census Bureau as part of the CPS. The survey contains detailed questions covering social and economic characteristics, such as employment status, earnings, industry, and demographic characteristics, of all members of a household. Because of the breadth of data available, the ASEC is one of the most popular data sets for analyzing the population in the United States and has been used in several studies in economics (e.g., Beck, Levine, and Lavkov, 2010; Philippon and Reshef, 2012).

For this study, I examine data from the survey years 1976 to 2019, which pertain to the actual years 1975 to 2018 because questions in the survey refer to the preceding calendar year. For example, interviewees are asked in which industry they worked during the previous calendar year. For the sake of simplicity, I call the year to which a survey refers 'year', whereas I refer to a CPS year as 'survey year'. The 1976 ASEC file was the first data set that was released by the U.S. Census Bureau as public use files and the first to include household-level records in the original data. So my sample starts with this data set and covers data from over four decades.

Its long duration and consistent language make the survey well suited for exploring long-term trends. To ensure the representativeness of the data, I weight all estimates using the person-level weight variable ASECWT. As is common in the literature, I exclude a few individuals from the sample for whom the CPS assigns negative or missing sampling weights. I further restrict the sample to persons who are at least 15 years of age and work in the private sector, i.e., I exclude government employees and employees of the U.S. Postal Service. In order to account for the experimental redesign of the sample in 2014, I also limit the data to respondents in the 5/8 file in 2014. Imposing these restrictions results in a total sample of 3,278,943 survey participants. The annual number of observations varies between 52,459 and 98,095 with an average of 74,521.

To classify respondents as workers in the financial industry, I use the 1990 Census Bureau industrial classification. In line with Philippon and Reshef (2012) as well as Greenwood and Scharfstein (2013), among others, the financial industry is defined as a combination of the credit intermediation, securities, and insurance subsectors. The corresponding industry codes are 700 (Banking), 701 (Savings institutions, including credit unions), 702 (Credit agencies), 710 (Security, commodity brokerage, investment companies), and 711 (Insurance). The sample covers between 2,300 and 5,200 finance industry employees per year. On average, 5.5 percent of respondents work in the financial industry in each year. This proportion increases slightly in the late 1970s and remains stable thereafter. The high number of observations allows me to calculate annual estimates that are unlikely to be driven by only a few outliers.

General Social Survey

In order to examine the intelligence of finance industry employees, I obtain data from the General Social Survey (Smith et al., 2019). The GSS is a nationally representative survey administered by the National Opinion Research Center at the University of Chicago that is designed to track attitudes, preferences, and social behavior in American society.

For this analysis, I obtain data from cross-sectional waves spanning the 45-year period from 1974 to 2018. The survey contains about 1,500 respondents each year from 1974 through 1993 (except 1979, 1981, and 1992) and continues with ~2,800 respondents every second year from 1994 through 2018. The analysis relies on a subset of the total sample due to the availability of variables as discussed in more detail below.

The long duration of the GSS and the use of consistent language make it well suited for exploring long-term trends. However, in line with the literature (e.g., Stevenson and Wolfers, 2008b), I make two necessary adjustments to the data to account for changes in the survey over time. First, I drop black oversamples in the years 1982 and 1987, and second, I exclude all interviews from 2006 onwards that occurred in Spanish and could not have been completed in English. Furthermore, I weight all estimates using the GSS weight variable WTSSALL to ensure the representativeness of the sample.

The GSS only includes individuals who are at least 18 years old. So I do not need to impose an age restriction. As in the ASEC sample, I restrict my GSS sample to all respondents working in the private sector. The 2007 Census industry classification is used to classify respondents as workers in the financial industry following the definition in previous studies (see above). The corresponding industry codes are 6870-6990. This classification yields an annual proportion of about five percent of respondents who work in finance in a year, which is very similar to the proportion in the ASEC sample. The indicator variable *In Finance* equals one for a respondent who works in the financial industry and zero otherwise.

To measure people's intelligence, I follow previous studies (e.g., Caplan and Miller, 2010) and use the GSS variable WORDSUM. This simple count variable is defined as the number of correct answers to a ten-word test vocabulary test taken by a randomly selected half of all survey respondents. The vocabulary test is a subtest from the WAIS, a commonly used IQ test (Zhu and Weiss, 2005), and is highly correlated with other measures of general intelligence. For example, Wechsler (1958) reports a correlation greater than 0.8 between the overall WAIS score and the WAIS vocabulary subtest. The test was carried out in the GSS in each survey over the period 1974-2018, except 1975, 1977, 1980, 1983, 1985, 1986, and 2002, leaving me with 23 cross-sectional GSS waves for analysis. The final sample contains 17,916 respondents who meet the sampling restrictions and completed the vocabulary test. The number is reduced due to the inclusion of controls in the regressions.

The regression models in Section 2.2.4 include region and year fixed effects as well as various control variables. Region fixed effects capture differences between the nine U.S. Census Bureau divisions where respondents live, which could affect test scores, while year fixed effects capture differences between interview years, e.g., due to improvements in education over time. The demographic controls are three indicator variables assessing whether a respondent is non-white (black or other), female, and born in the U.S. Education is measured using four indicators for the highest level of education, i.e., high school, associate/junior college, bachelor's degree, or graduate degree. The indicators measure the effect of a respondent's educational degree compared to less than a high school degree. The income control *Ln(Income)* is the natural logarithm of a respondent's equivalized family income. Since the GSS does not provide a consistent measure of income across survey years, I manually construct this control following the description in the supplementary material of Stevenson and Wolfers (2008b). First, I convert a respondent's categorical family income in the previous year to a continuous measure by fitting interval regressions to the data on the assumption that income follows a log-normal disruption. I then translate income to 2005 dollars using the Consumer Price Index provided by the U.S. Bureau of Labor Statistics. Lastly, I use the OECD-modified equivalence scale to make the family income of different household types comparable by taking into account shared consumption benefits (Hagenaars, de Vos, and Zaidi, 1994). The OECD-modified scale assigns a value of 1 to the household head, 0.5 to each additional adult member of the household, and 0.3 to each child.

Appendix to Chapter 3

Sample construction and variables

In this section, I describe the construction of the sample and the most important variables used in the study in Chapter 3. All variables are defined in Table A3.1. Summary statistics are reported in Table A3.2. The study examines the intergenerational industry mobility of individuals working in the U.S. financial industry using data from the General Social Survey (GSS) (Smith et al., 2019). The GSS is a nationally representative survey that is conducted by the National Opinion and Research Center at the University of Chicago. It is among the most influential research studies in the social sciences and is frequently quoted in the press, including the *New York Times* and the *Wall Street Journal*.

The target population of the GSS is adults, i.e. people over 18 years of age, who live in households in the United States. The survey was conducted every year from 1972 to 1994, except in 1979, 1981, and 1992, and has been conducted every other year since 1994. It contains about 1,500 respondents each year from 1972 through 1993 and continues with around 2,800 respondents every second year from 1994 through 2018. The sample in this study includes all 32 cross-sectional waves currently available spanning the 47-year period from 1972 to 2018.

In line with the previous literature on the intergenerational link in career choices (e.g., Corak and Piraino, 2016), I limit the sample to employees in the private sector (full-time and part-time). This means that I exclude respondents who are temporarily not working, are in school, running the household, or are retired. I additionally exclude from the sample all persons working in the public sector, including the U.S. military. Finally, I eliminate all cases where information on a respondent's industry is missing or could not be coded.

Despite the broad consistency of questions across survey waves, a few changes to the GSS over time require researchers to make some adjustments (see Smith, 1990). Two changes are particularly relevant in my context: (1) an oversample of blacks in the 1982 and 1987 survey; (2) from 2006 onwards, surveys that could not have been completed by respondents in English were administered in Spanish. To create a consistent data set, I adjust the data as suggested by prior studies that use the GSS (e.g., Stevenson and Wolfers, 2008a, 2008b, 2009; Ifcher and Zarghamee, 2014). First, I drop black oversamples in the years 1982 and 1987, and second, I exclude all interviews from 2006 onwards that occurred in Spanish and could not have been completed in English (as in previous years). Lastly, to ensure the representativeness of my sample, I weight all estimates using the GSS weight variable WTSSALL.

Financial industry variables. I use the 2007 Census industry classification to classify respondents and their parents as workers in the financial industry. Following the definition in Philippon and Reshef (2012) and Greenwood and Scharfstein (2013), the financial industry is the combination of the following three subsectors: (1) credit intermediation; (2) securities; and (3) insurance. The corresponding industry codes are 6870-6990. This classification yields a yearly proportion of around five percent of respondents who work in the financial industry. I verify this figure using data from the March supplement of the Current Population Survey (CPS) for the same period. The CPS data provide very similar yearly proportions, and the average yearly difference between the two data sets is 0.032%.

To determine the occupation, industry, and occupational prestige of respondents' parents, the GSS uses the following set of questions:

"What kind of did your father (mother) normally do while you were growing up?"

"What did he (she) actually do in that job?"

"What kind of place did he (she) work for?"

"What did they make / do?"

The main variable of interest in this study is the indicator *In Finance* that equals one if a respondent works in the financial industry and zero otherwise. The variables *Father in Finance* and *Mother in Finance* are defined analogously and record whether a respondent's father or mother worked in the financial industry while the respondent was growing up. Information on the industry and occupation of fathers is available for the entire sample period, whereas information for mothers is available for years after 1994. Therefore, regressions that examine the intergenerational correlation in the decision to work in finance with respect to respondents' mothers are based on the period 1994-2018.

Income. Because the GSS does not provide a consistent measure of income across survey years (Hout, 2004), I manually construct an income measure for my sample as described in Stevenson and Wolfers (2008b). First, I convert a respondent's categorical family income in the previous year to a continuous measure by fitting interval regressions to the data on the assumption that income follows a log-normal disruption. I then translate income to 2005 dollars using the Consumer Price Index. Lastly, I use the OECD-modified equivalence scale to make the family income of different household types comparable by taking into account shared consumption benefits (Hagenaars, de Vos, and Zaidi, 1994). The income variable *Ln(Income)* is the logarithmic equivalized income measure.

Occupational prestige. In robustness tests, I also control for parents' occupational prestige using the variables *Father's occupational prestige* and *Mother's occupational prestige*, respectively. A parent's occupational prestige score is based on the 2010 Census occupation classification. It is measured as the mean value of ratings for each occupation category converted to a scale of 0 (bottom) to 100 (top).

U.S. regions. In some analyses, I draw on information about the U.S. regions where respondents lived at age 16 or where they live today, i.e., where the GSS interview was conducted. A region is one of the nine divisions defined by the U.S. Census Bureau, i.e., New England (Maine, Vermont, New Hampshire, Massachusetts, Connecticut, Rhode Island), Middle Atlantic (New York, New Jersey, Pennsylvania), East North Central (Wisconsin, Illinois, Indiana, Michigan, Ohio), West North Central (Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas), South Atlantic (Delaware, Maryland, West Virginia, Virginia, North Carolina, South Carolina, Georgia, Florida, District of Columbia), East South Central (Kentucky, Tennessee, Alabama, Mississippi), West South Central (Arkansas, Oklahoma, Louisiana, Texas), Mountain (Montana, Idaho, Wyoming, Nevada, Utah, Colorado, Arizona, New Mexico), and Pacific (Washington, Oregon, California, Alaska, Hawaii).

Table A3.1: Variable definitions

Variable	Definition
In Finance	Indicator variable equal to one for a respondent who works in the financial industry.
Parental job characteristics and education	
Father in Finance	Indicator variable equal to one if the father of a respondent worked in the financial industry while the respondent was growing up.
Mother in Finance	Indicator variable equal to one if the mother of a respondent worked in the financial industry while the respondent was growing up. Available 1994-2018
Father in same finance subsector	Indicator variable equal to one if the father of a respondent worked in the financial industry and in the same subsector as the respondent (credit intermediation, securities, or insurance).
Father in different finance subsector	Indicator variable equal to one if the father of a respondent worked in the financial industry but in another subsector as the respondent.
Father's occupational prestige	Prestige score of the occupation of a respondent's father; coded from 0 (bottom) to 100 (top).
Mother's occupational prestige	Prestige score of the occupation of a respondent's mother's; coded from 0 (bottom) to 100 (top). Available 1994-2018
Father's highest degree	Variable indicating the highest degree a respondent's father has obtained; coded from 0 (less than high school) to 4 (graduate degree).
Mother's highest degree	Variable indicating the highest degree a respondent's mother has obtained; coded from 0 (less than high school) to 4 (graduate degree).
Demographic characteristics	
Age	Respondent's age in years.
Age squared	Respondent's squared age.
Female	Indicator variable equal to one if a respondent is female.
Non-white	Indicator variable for a respondent's race, which equals one if he or she is not white, i.e., black or other.
U.S.-born	Indicator variable equal to one if a respondent was born in the U.S.

Education	
High school degree	Indicator variable equal to one if the highest degree a respondent has obtained is a high school degree.
Junior college degree	Indicator variable equal to one if the highest degree a respondent has obtained is a junior college degree.
Bachelor's degree	Indicator variable equal to one if the highest degree a respondent has obtained is a Bachelor's degree.
Graduate degree	Indicator variable equal to one if the highest degree a respondent has obtained is a graduate degree.
Family background characteristics	
Lived with both parents at age 16	Indicator variable equal to one if a respondent lived with both parents at age 16.
Number of siblings	Number of a respondent's siblings.
Lived in a city at age 16	Indicator variable equal to one if a respondent at the age of 16 lived in a city with at least 50,000 inhabitants.
Income below average at age 16	Indicator variable equal to one if a respondent answers that his or her family income at the age of 16 was below or far below the average (vs. average, above average, or far above average). Available 1972-2018, except for 1996, 1998, and 2000
Income	
Ln(Income)	Natural logarithm of a respondent's equivalized family income.

Notes: This table provides definitions of all variables used in the study in Chapter 3. Data are obtained from the General Social Survey over the period 1972-2018. It is indicated in the table if a variable is not available for the entire sample period.

Table A3.2: Summary statistics

	In Finance = 1		In Finance = 0		Difference in means
Variable	**N**	**Mean**	**N**	**Mean**	**t-statistic**
In Finance	1,816	1.000	33,028	0.000	
Father in finance	1,496	0.057	26,646	0.022	5.48***
Mother in finance	674	0.055	12,293	0.043	1.19
Father in same finance subsector	1,496	0.036	33,028	0.000	5.97***
Father in different finance subsector	1,496	0.021	33,028	0.000	6.14***
Father's occupational prestige score	1,481	45.350	26,335	44.285	3.15***
Mother's occupational prestige score	674	42.666	12,366	41.742	1.81*
Father's highest degree	1,453	1.260	25,606	1.030	6.58***
Mother's highest degree	1,655	1.124	29,607	0.968	4.85***
Non-white	1,816	0.179	33,028	0.183	-0.37
Female	1,816	0.608	33,028	0.471	10.39***
U.S.-born	1,598	0.896	28,983	0.904	-0.95
Age	1,807	39.576	32,937	40.436	-2.20**
High school degree	1,814	0.518	32,962	0.540	-1.33
Junior college degree	1,814	0.070	32,962	0.068	0.32
Bachelor's degree	1,814	0.299	32,962	0.167	11.44***
Graduate degree	1,814	0.085	32,962	0.086	-0.20
Lived with both parents at age 16	1,777	0.774	32,228	0.727	4.09***
Number of siblings	1,773	3.102	32,176	3.640	-7.28***
Lived in a city at age 16	1,775	0.545	32,200	0.444	7.59***
Income below average at age 16	1,460	0.247	25,926	0.312	-4.38***
Ln(Income)	1,686	10.544	30,609	10.237	15.13***

Notes: This table presents summary statistics for the variables used in this study. The sample period is 1972-2018. Summary statistics are shown for the subsamples of respondents who work and do not work in the financial industry (*In Finance* = 1 vs. 0). The last column reports t-statistics from regressions of the respective variables on the indicator *In Finance* to test for differences in the mean values of each variable between the two groups. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A3.3: Intergenerational finance industry mobility robustness tests

Dependent variable	*In Finance*									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Father in finance	**0.075*** (5.56)**	**0.079*** (4.15)**	**0.078*** (4.24)**	**0.081*** (4.33)**	**0.082*** (4.41)**					
Mother in finance						**0.015 (1.21)**	**0.005 (0.45)**	**0.006 (0.49)**	**0.005 (0.41)**	**0.004 (0.36)**
Non-white		0.010* (1.88)	0.009 (1.59)	0.011** (2.18)	0.010* (1.95)		0.019** (2.51)	0.019** (2.54)	0.019** (2.56)	0.019** (2.59)
Female		0.026*** (7.28)	0.025*** (7.07)	0.027*** (7.54)	0.027*** (7.65)		0.021*** (4.29)	0.020*** (4.07)	0.022*** (4.54)	0.022*** (4.39)
U.S.-born		-0.008 (-0.99)	-0.010 (-1.15)	-0.004 (-0.40)	-0.003 (-0.32)		-0.023** (-2.13)	-0.022** (-2.03)	-0.014 (-0.91)	-0.016 (-0.98)
High school degree		0.029*** (6.25)	0.029*** (6.21)	0.027*** (6.63)	0.028*** (6.07)		0.025*** (3.41)	0.024*** (3.36)	0.024*** (3.55)	0.022*** (3.25)
Junior college degree		0.026*** (3.15)	0.027*** (3.24)	0.024*** (3.09)	0.025*** (3.39)		0.028** (2.24)	0.028** (2.24)	0.029** (2.45)	0.028** (2.41)
Bachelor’s degree		0.061*** (9.40)	0.062*** (9.42)	0.060*** (9.31)	0.061*** (9.57)		0.066*** (8.28)	0.066*** (8.05)	0.063*** (8.38)	0.063*** (8.17)
Graduate degree		0.022*** (2.90)	0.024*** (3.09)	0.022*** (3.01)	0.022*** (2.85)		0.031** (2.36)	0.031** (2.30)	0.024** (2.13)	0.024** (2.05)
Lived with both parents at age 16		0.013*** (2.71)	0.013*** (2.66)	0.011** (2.36)	0.011** (2.40)		0.008 (1.44)	0.008 (1.36)	0.008 (1.38)	0.009 (1.49)
Number of siblings		-0.001* (-1.82)	-0.001* (-1.84)	-0.001* (-1.89)	-0.001* (-1.86)		-0.002** (-2.14)	-0.002** (-2.14)	-0.002** (-2.12)	-0.002* (-1.92)
Lived in a city at age 16		0.014*** (3.33)	0.015*** (3.35)	0.014*** (3.63)	0.014*** (3.59)		0.013*** (3.06)	0.012*** (2.82)	0.013*** (2.94)	0.012*** (2.88)

Income below average at age 16		-0.006	-0.007	-0.007	-0.007*		-0.006	-0.007	-0.006	-0.006
		(-1.27)	(-1.52)	(-1.56)	(-1.71)		(-1.12)	(-1.13)	(-1.02)	(-1.07)
Father's highest degree		0.000	0.002							
		(0.09)	(0.98)							
Father's occupational prestige			-0.000*							
			(-1.93)							
Mother's highest degree							-0.002	-0.003		
							(-0.78)	(-1.03)		
Mother's occupational prestige								0.000		
								(0.55)		
Constant	0.051***	-0.037***	-0.020	-0.030	0.022	0.050***	-0.008	-0.011	0.017	0.010
	(34.40)	(-2.87)	(-1.46)	(-1.46)	(1.19)	(19.96)	(-0.61)	(-0.78)	(0.49)	(0.32)
Birth year FE	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No
Region FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Region at age 16 FE	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Graduation year FE	No	No	No	No	Yes	No	No	No	No	Yes
Observations	28,075	18,882	18,652	19,829	19,814	12,933	8,614	8,566	8,823	8,815
Adj. R-squared	0.00255	0.0159	0.0161	0.0175	0.0185	0.000106	0.0137	0.0135	0.0159	0.0160

Notes: This table reports results from robustness tests of the estimates reported in Table 3.1. Columns (1) and (6) examine the parent-child relation without fixed effects and controls. In columns (2) and (7), I extend the model shown in column (3) of Table 3.1 by including a control for the degree of a parent, and in columns (3) and (8), I additionally include the occupational prestige score of the parent. Columns (4) and (9) include fixed effects for the U.S. regions where respondents lived at age 16 and for the regions where they live today. Finally, in columns (5) and (10), I replace birth year fixed effects with graduation year fixed effects, which are estimated using information on a respondent's year of birth and years of schooling. Robust t-statistics (in parentheses) are based on standard errors clustered by birth year. ***, **, * denote statistical significance at the 1%, 5% and 10% level, respectively.

Appendix to Chapter 5

This appendix provides a detailed description of the data collection methodology used for the study in Chapter 5. Table A5.1 defines all variables used in this study. Table A5.2 presents report results from the propensity score matching, while Table A5.3 investigates the question of whether matching between fund managers and mutual funds can explain our risk-taking results.

Identifying fund managers' ancestry and census records

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 the 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 firm 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 occupation of the individual 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 accessed through Ancestry.com and establish unique matches by obtaining the full names and years of birth 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 fund 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.

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 subgroup of fund managers, we obtain the 1930 census records if the 1940 census record cannot be found or if the information is missing in the 1940 census record. Following this data collection procedure, we are able to find the households' census records for 93 percent of mutual 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 A5.1: 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	Fund manager's age 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 is 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 for the year 1952.
Avg. Parental Age at Manager's Birth	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 as 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 the total investment that shareholders pay 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 is 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 is 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 is 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 is 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 the 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 is obtained from Antti Petajisto's website for the period 1980-2009. See Petajisto (2013) for details.

Notes: This table provides the definitions of all variables used in the study in Chapter 5. 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 backgrounds 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 A5.2: Propensity score matching

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

Dependent variable	***Family Disruption***	
	Pre-Match	**Post-Match**
	(1)	(2)
Fund Age	0.006*** (3.03)	-0.003 (-1.34)
Fund Size	0.030 (1.61)	0.020 (0.62)
Fund Family Size	0.013 (1.40)	0.005 (0.36)
Avg. Monthly Return	-3.620 (-1.17)	1.646 (0.36)
Expense Ratio	33.649*** (5.85)	6.924 (0.94)
Turnover Ratio	0.001 (0.03)	0.045 (0.96)
Female	-0.918*** (-4.06)	-0.202 (-0.47)
Manager Age	0.009* (1.90)	-0.002 (-0.27)
Manager Tenure	-0.012*** (-2.93)	0.017** (2.40)
Ivy League	0.300*** (5.56)	-0.076 (-0.94)
MBA	-0.053 (-0.95)	0.000 (0.00)
PhD	0.473*** (5.14)	-0.055 (-0.42)
Parental Education	-0.305*** (-7.77)	-0.025 (-0.42)
Family Wealth	0.027*** (2.74)	-0.006 (-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*** (-3.07)**	**-0.007*** (-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
Adj. 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** (-2.00)**	**-0.134* (-1.93)**	**-0.022* (-1.94)**	**0.071*** (2.85)**
All controls	Yes	Yes	Yes	Yes
Observations	3,024	3,024	7,203	12,657
Adj. R-squared	0.682	0.507	0.604	0.194

Notes: This table report results from a propensity score matching. Panel A presents parameter estimates from the Probit model used to estimate propensity scores for firms in the treatment and control groups. Column (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. Column (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 $\textit{Total Risk}_{t\text{-}1}$, 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.

Table A5.3: Does fund manager-fund matching explain less risk-taking?

Dependent variables	*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. R-squared	0.015	-0.010	0.135	0.178

Notes: 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 exclusion of explanatory variables in instances in which these variables cause separation.