A Dynamic and Relational Perspective on Vulnerability and Fear of Crime

The Role of Physical, Psychological, and Social Factors as well as
Life Events and Neighborhood Contexts using a
Between-Within Person Approach

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Vulnerability and Fear of Crime
Effects of Physical and Social Factors, Personality Traits, Beliefs, and
Life Events on Affective and Behavioral Responses to Crime
in Urban Neighborhoods

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Abstract

This thesis investigates the usefulness of the concept of vulnerability in explaining the fear of crime. Previous vulnerability approaches in fear of crime research are reworked and expanded, integrating a stronger temporal perspective and differentiating more precisely between persons and their contexts. It is demonstrated that between-person differences and within-person changes of most vulnerability factors (e.g., personality traits, financial strain, and supportive networks) are related to fear of crime. This longitudinal perspective provides more reliable support for the vulnerability approach than previous cross-sectional studies because unobserved heterogeneity is reduced. Victimization leads to increased perceived environmental adversity although not having the hypothesized influence on the locus of control. The impact of (early) life events on fear of crime is investigated in cross-sectional analyses, suggesting that early life events influence fear of crime. The theoretically derived vulnerability mechanisms mediate all investigated vulnerability factors. An examination of neighborhood characteristics and their spatial lags shows that social disadvantage in the (adjacent) neighborhood has a strong contextual influence on fear of crime. Vulnerability links people and environments, indicating an interactive relationship between individual vulnerability factors and external stressors (neighborhood characteristics and victimization). The most substantial interaction is that older people are less affected by neighborhood characteristics than younger people.

German translation of abstract

In dieser Dissertation wird untersucht, inwiefern sich Vulnerabilität zur Erklärung der Furcht vor Kriminalität eignet. Frühere Vulnerabilitätsansätze in der Kriminalitätsfurchtforschung werden aufgegriffen, überarbeitet und um eine dynamischere Perspektive ergänzt. Personen werden deutlicher von deren Kontexten getrennt sowie im Zusammenwirken betrachtet. Die interindividuellen Unterschiede sowie die intraindividuellen Veränderungen der meisten Vulnerabilitätsfaktoren hängen mit Kriminalitätsfurcht zusammen. Aufgrund der Reduktion der nicht beobachteten Heterogenität sind die längsschnittlichen Erkenntnisse gegenüber bisherigen Querschnitts-Studien belastbarer. Viktimisierung verändert die Wahrnehmung der sozialen Umwelt, wirkt sich jedoch nicht wie angenommen auf die Kontrollüberzeugungen aus. In Querschnittsanalysen wird neben dem Einfluss von (frühen) Lebensereignissen auf Kriminalitätsfurcht untersucht, ob die Vulnerabilitätsfaktoren über die theoretischen Mechanismen vermittelt werden. Dabei zeigt sich, dass frühe Lebensereignisse einen deutlichen Einfluss auf die Kriminalitätsfurcht haben und alle Vulnerabilitätsfaktoren über die theoretischen Mechanismen mediiert werden. Die Untersuchung der Kontexteffekte belegt den starken Einfluss sozialer Benachteiligung in der (angrenzenden) Nachbarschaft auf Kriminalitätsfurcht. Da Vulnerabilität Personen mit deren Kontexten verbindet, liegen Interaktion zwischen individuelle Faktoren und externen Stressoren (Nachbarschaftscharakteristika und Viktimisierung) nahe. Anders als der theoretische Ansatz suggeriert, hängt die Kriminalitätsfurcht älterer Menschen weniger von den Charakteristika des Stadtviertels ab als jene von jungen Menschen. Eine Zusammenfassung des theoretischen Ansatzes und der empirischen Ergebnisse findet sich in Kapitel 6. In Kapitel 7 werden die Ergebnisse in den Gesamtzusammenhang eingeordnet, während Vorschläge für weiterführende Analysen unterbreitet und die Limitationen der Forschung diskutiert werden.

Chapter 1

Introduction

Investigations into the fear of crime have captured the attention of criminologists, sociologists, psychologists, and scholars from other disciplines for decades. The longstanding scientific attraction of this topic is attributable to its diverse, complex, and interdisciplinary causes and consequences, as well as its high policy relevance. Fear of crime—although this umbrella term suggests that it is only about the affects (Gabriel and Greve 2003; Farrall, Jackson, and Gray 2009, 50; Vanderveen 2006)—is multidimensional and includes cognitions and behavior besides the obvious affectual component. Thus, decades of extensive research have created numerous insightful theoretical approaches and valuable empirical findings (for an older but excellent review, see Hale 1996).

Despite the wealth of research, integrative theoretical perspectives and empirically validated understandings of the underlying mechanisms are less developed. As Vanderveen (2006, 7) noted in her comprehensive methodological review, "many studies are concerned with what might be called the prevalence of 'fear of crime' in socio-demographic categories." From today's perspective, this assessment is more accurate for individuals but less so for neighborhoods, where substantial progress has been made within the last decade (Brunton-Smith and Sturgis 2011; Drakulich 2013; Oberwittler, Janssen, and Gerstner 2017). In the meantime on the individual level, Jackson (2006; 2009; 2011; 2015; Gouseti and Jackson 2015; Jackson and Gouseti 2015a; Jackson and Gouseti 2015b) integrated psychological theories and developed a more sophisticated understanding of the intra-individual processes generating fear (see Section 2.2).

The long, rich history of fear of crime research, however, has been accompanied by the striking lack of longitudinal studies and, hence, an understanding of what drives changes in fear of crime. Accordingly, almost all current empirical knowledge regarding fear of crime is likely to be affected by time-stable unobserved heterogeneity (see Section 3.3.1). One of the foremost aims of this thesis is to integrate a dynamic perspective of within-person changes into the extended vulnerability model and contrast this with between-person differences. Such a dynamic, longitudinal perspective is especially beneficial for investigating the effects (and pathways) of negative events such as victimization on fear of crime.[1]

Despite some important work (e.g., Boers 1991; Brunton-Smith and Sturgis 2011; Jackson 2008; Taylor 2010), gaps remain in the understanding of the interplay of people with their environment. It is another aim of this thesis to contribute to this area by critically drawing on early criminological vulnerability approaches (Killias 1990; Skogan and Maxfield 1981). The intention is to develop an independent vulnerability perspective that sponsors a more precise distinction between individual vulnerability factors and environmental adversity (see Section 2.5). More than previous approaches, the extended vulnerability approach acknowledges that vulnerability in fear of crime research is an individual perception that is based on objective criteria (such as physical strength and neighborhood crime rates) but also on potentially biased heuristics. Hence, a sense of personal vulnerability might be prone to over- or underestimation depending on personality traits, victimization history, or easily retrievable neighborhood information such as that on social disadvantage.

[1] The advantages of a longitudinal perspective are also emphasized by recent programmatic publications on resilience in psychology, geriatrics, and biology (Kalisch, Müller, and Tüscher 2015; Scheffer et al. 2018).

Many studies in fear of crime research investigated the effects of vulnerability factors (age, gender, and social status) and referred to the theoretical concept of vulnerability to explain individual differences. However, very few studies operationalized vulnerability and investigated whether the suspected pathways mediate the effects of vulnerability factors. This thesis empirically verifies the correctness of this assumption, particularly for physical vulnerability factors.

This thesis also investigates interactions among vulnerability factors and stressors (neighborhood characteristics and victimization). As a relational concept (see Section 2.4), vulnerability is naturally inclined to such interaction analyses and thereby sheds light on person-environment interactions (Magnusson and Stattin 2006). While there indeed is a respectable amount of research on this topic, the majority of quantitative evidence suffers from severe methodological limitations (Brunton-Smith and Sturgis 2011, 339–40). Another shortcoming of previous research is the rarely investigated role of more distal spatial and temporal contexts. This thesis will, therefore, investigate effects of early life events (consequences of the historical context in childhood and youth), as well as those of adjacent neighborhoods.

By examining the impact of early life events, this thesis exploits the historical constellation that many older people today experienced World War II and its aftermath, whereas those born later grew up without such potentially traumatizing circumstances. Historical contexts and their long-term effects are often neglected in the social sciences—a shortcoming that Riley (1973) coined the "life-course fallacy" decades ago—as well as in fear of crime research until recently (Koeber and Oberwittler 2019). This thesis draws upon cumulative inequality theory (Ferraro and Shippee 2009; Ferraro, Schafer, and Wilkinson 2016) to explore the pathways of early life events and fear of crime today.

Although neighborhood effects are by far the most thoroughly investigated contextual influence on fear of crime, a majority of studies did not consider characteristics beyond the immediate residential neighborhood (see, however, Barton et al. 2017; Brunton-Smith and Jackson 2012; Wyant 2008). Most investigations thereby violated the "spatial logic" (Sampson 2012, ch. 10) and treated neighborhoods implicitly as islands or "urban villages" (Morenoff, Sampson, and Raudenbush 2001, 518) that are not affected by the surrounding neighborhoods. This thesis examines how spatially lagged independent variables affect three fear of crime outcomes and discusses the theoretical implications of statistical techniques to model spatial dependency.

1.1 Structure of thesis

The following introductory sections demonstrate the broader relevance of this work by drawing upon political, criminological, epidemiological, and demographical literature. Chapter 2 provides definitions that are necessary to introduce more advanced topics within fear of crime research, as well as early and paradigmatic vulnerability approaches. Section 2.4.3 selectively summarizes recent empirical findings before Section 2.5 outlines the extended vulnerability model. Chapter 3 introduces methods. Chapter 4 discusses the study, research sites, and the operationalization of neighborhood and survey variables. Chapter 5 starts with preparatory visual data analyses that lay the foundation for more complicated regression models. Chapter 6 summarizes the theoretical approach and empirical findings. Chapter 7 discusses the relevance of this thesis for the (non-)scientific community and its methodological limitations. The Appendix provides additional analyses.

1.2 Consequences of fear of crime for societies, neighborhoods, and individual well-being

Many studies in the US and the UK have shown how politicians exploit the fear of crime to gain political power (Garland 2001; Simon 2007). During the 2017 German federal election, security issues gained a prominent place on the political agenda in contrast to past elections. A conservative German politician and then Minister of the Interior called, in his somewhat abstract "guidelines for a strong state in difficult times" (Maizière 2017), for expanding and centralizing key security agencies. A Social Democrat and then Minister of Economics became engaged in the pursuit of this issue and referred explicitly to signal crimes in urban environments. He speculated whether personal security in residential areas had become a "class issue" (Gabriel 2017).

Election posters were even more explicit. As an opposition party, the North Rhine-Westphalian Christian Democratic Union proclaimed: "I do not feel safe here anymore. Why are they not doing anything?" ("Ich fühle mich hier nicht mehr sicher. Warum tun die nichts?"; CDU (2017)). Referring to repeated sexual assaults in German cities around New Year's Eve 2015 (widely attributed to recent immigrants), a poster for the far right-wing "Alternative for Germany" demanded: "More safety for our women and daughters!" ("Mehr Sicherheit für unsere Frauen und Töchter!"). It showed a girl in tears next to a dark crowd of presumably young men (Oeter 2017). Hence, during Germany's 2017 elections, political camps instrumentalized insecurity to rally voters according to their respective political worldviews (personal safety as a "class issue," call for a strong state, and immigrants as a threat).

Demographic changes—notably the "graying of Europe"—suggest political parties' continuing interest in topics surrounding personal security because of a supposed increase in insecurity perceptions and physical vulnerability among an aging population. Besides, this demographic shift has a gender component because women have higher life expectancies. Both age and gender are strong predictors of some dimensions of fear of crime. Thus, it appears reasonable to assume that fear of crime will play a central and possibly increasing role in future campaigns, particularly considering the higher turnout of older voters.[2] The next section discusses flaws in this reasoning.

Concerns with personal security are integral to the "spiral of decay" (Skogan 1990) of urban neighborhoods (Bursik and Grasmick 1993, ch. 4; Wilson and Kelling 1982). According to this perspective, fear of crime is undermining the collective capacity of communities to control crime and solve neighborhood problems. Increasing neighborhood problems induce people to move if they can afford it. At present, German and other European cities are confronted with considerable increases in ethnic diversity. Among the most controversial questions in urban sociology is the potentially adverse effect of increasing ethnic diversity on neighborhood social capital (Putnam 2007; Portes and Vickstrom 2011; Stichnoth and van der Straeten 2013; Meer and Tolsma 2014; Schaeffer 2014). The question as to whether urban residents cope with these changes or respond with heightened feelings of insecurity compels continuous research.

Cross-sectional studies have found perceptions of insecurity to have detrimental effects on health (Chandola 2001; Pearson and Breetzke 2014; Ross 1993; Ziersch et al. 2005) and psychological well-being (Roberts et al. 2012; Whitley and Prince 2005). However, the vulnerability perspective in criminology suggests an opposite causal direction: rather than fear of crime impairing health, people in worse health feel more insecure because of their vulnerability to crime. Proponents of this view argue that fear of crime prompts withdrawal from social activities, avoidance of outdoor activities, and increased mistrust that diminishes physical and mental health. Longitudinal evidence supporting one causal direction or the other is scarce and based on large but selective data: Jackson and Stafford (2009) argued that there is a feedback loop wherein health problems and fear of crime are mutually dependent (see also Stafford, Chandola, and Marmot 2007).

1.3 Toward an older and consequentially more fragile society?

During the coming decades, demographic changes will persist. The graying of populations in Europe will require social reorganization, particularly with respect to pension systems and employment markets. This thesis investigates how vulnerable and older people perceive their safety. To introduce the complex subject of age, this section touches upon the causes and consequences of a graying Europe.

According to Eurostat (2015), the percentage of Europeans over age 65 will increase from 19.5% in 2017 to 26.2% in 2037. Figure 1.1 shows regional differences in this trend: Eastern

[2] In the 2013 German general elections, 34.4% of the electorate was older than 60. Additionally, older age groups have a turnout above average. As an example, 79.8% of all eligible voters aged 60-70 went to the polls compared to 72.4% on average (Bundeswahlleiter 2014)).

Europe, Ireland, Spain, and especially Germany will witness the most substantial increases of people over age 65 during the next two decades, whereas other European regions will be less affected.

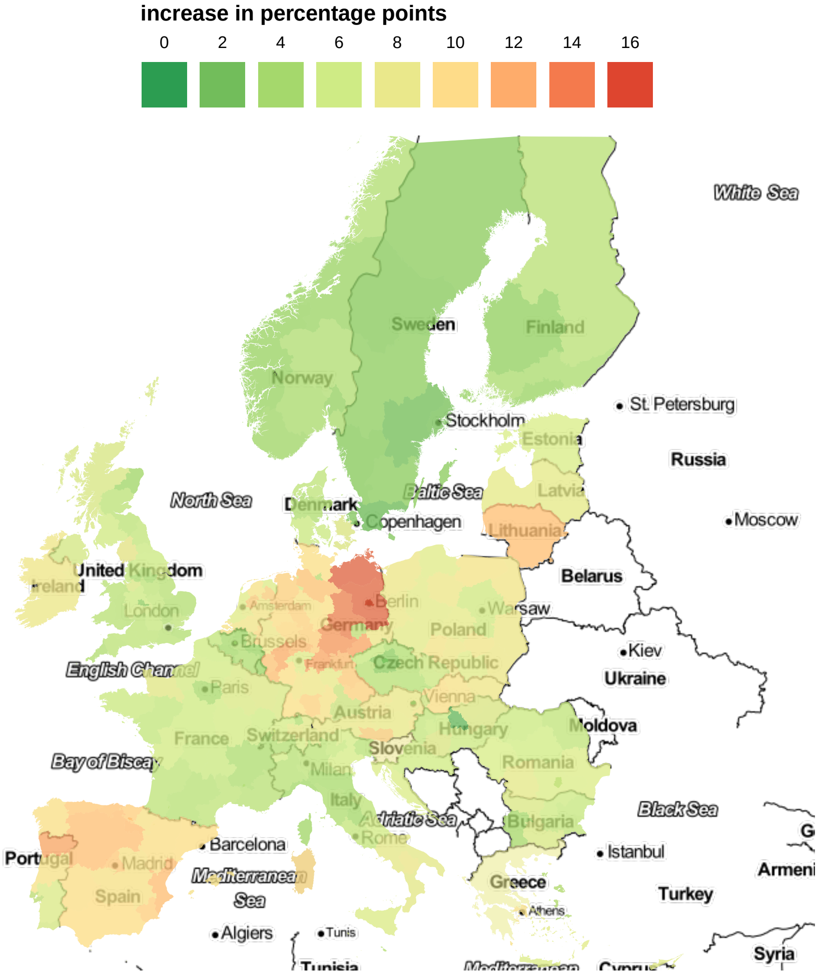

Figure 1.1: Predicted increase of Europeans above 65 (2017–2037)

Demographic evidence shows considerable increases in life expectancy[3] over the previous two centuries. In their influential article Oeppen and Vaupel (2002; see also Christensen et al. 2009) showed that life expectancy had increased by almost three months for every birth year since 1840. This achievement is mainly attributable to medical advances; however, cultural, economic, and social changes[4] during long periods of peace in most of Europe and elsewhere cannot be ignored (Willekens 2014).

Although critics such as Kramer (1980) raised concerns that these additional years are spent in frailty and sickness, more recent research suggests equally strong increases in healthy life expectancy[5] in most countries (Jagger and Robine 2011; Rau, Muszyńska, and Vaupel 2013). The increased prevalence of diseases among older people results primarily from improved health services and medical knowledge (Vaupel 2010; Christensen et al. 2009). Acknowledging this transformation, demographers have suggested that conventional statistical thresholds

[3]By life expectancy, this section refers to period life expectancy at birth. That is the average number of years that a baby born in this year will live if they are exposed to the same death rates as previous cohorts (Wilmoth et al. 2007).

[4]Initial improvements in life expectancy were attributable to drastically declining infant and child mortality until roughly World War II (primarily by reducing the number and consequences of infectious diseases). More recent improvements were based in declines in adult mortality (e.g., from cardiovascular disease). Today, developed economies are extending their efforts to raise life expectancy and wellbeing of the elderly by tackling dementia and depression (Meslé and Vallin 2011; Willekens 2014).

[5]Health life expectancy divides life expectancy into years to live in different health states. It depends, however, on the method of calculation and definitions of health and is, thus, not as clearly defined as life expectancy (Jagger and Robine 2011).

(e.g., percentage of people 65 and older) be supplemented with more flexible and prospective meridians of aging (e.g., the percentage with a life expectancy of 15 years or fewer). This supplement would attenuate the partly alarming forecasts regarding the extent of population aging (Sanderson and Scherbov 2015; Sanderson and Scherbov 2010; Sanderson and Scherbov 2005).

Hence, the unparalleled increase in the number of people aged over 65 years will likely not produce an equally sharp rise in numbers of frail people. In this regard, gerontologists distinguish a "third" (Laslett 1991) from a "fourth age": although the third age is characterized by the positive consequences of postponed senescence, the detrimental effects of old age appear in the fourth age and reveal "extraordinary needs and vulnerabilities" (Baltes and Smith 2003, 124) through loneliness, multi-morbidity, and cognitive decline.

However, convincing evidence suggests that the increase of life expectancy and postponement of senescence are unevenly distributed along socioeconomic lines: poor or less educated people with less prestigious jobs face physical impairment earlier (Baal et al. 2016; Luy et al. 2015; Jasilionis and Shkolnikov 2015; Morciano, Hancock, and Pudney 2015). This research and recent theoretical approaches (Ferraro and Shippee 2009; Ferraro, Shippee, and Schafer 2009; Ferraro, Schafer, and Wilkinson 2016) suggest that good health in later life is increasingly the result of one's course of life and accumulated social (dis-)advantages. Accordingly, chronological age increasingly becomes an insufficient proxy for the physical vulnerability in fear of crime research.

Riley (1973) labeled the cross-sectional interpretation of age group differences without considering someone's historical context as "life-course fallacy" (see also Baltes 1968; Ryder 1965; Schaie 1965 for other early seminal contributions). Unfortunately, the cohort (and period) perspective is almost entirely missing in fear of crime research (see, however, Cutler 1979; Dittmann 2008; Koeber and Oberwittler 2019; Reuband 1989). However, important social changes in crime rates, education, and health occurred during recent decades. Moreover, the rapid contextual shift between World War II and its aftermath offers a rare (and soon disappearing) opportunity to investigate whether traumatic experiences in early life (arguably more widespread during World War II) increased fear of crime decades later. Affirmative findings indicate that previous studies overestimated age effects because they conflated age and cohort effects. *Ceteris paribus*, the impact of age on fear would decline in the coming decades as younger cohorts (grown up in more favorable circumstances) supplant older cohorts.

In sum, research on the consequences of aging on the fear of crime is relevant because the number of people reaching advanced age will increase in the upcoming years. This demographic development will not produce an equal increase in physical frailty for the reasons noted. This thesis investigates the influence of vulnerability, and particularly age, on insecurity perceptions. Age is, however, a complex explanatory variable that touches upon biological, cultural, social, and historical issues. An in-depth investigation of age effects evades simplistic explanations.

Chapter 2

Theory and definitions

This chapter develops the theoretical model and introduces key definitions. It discusses key theoretical developments and operationalizations for fear of crime. Given the long history of fear of crime research, this chapter is necessarily selective and focuses on recent theoretical developments and approaches that explicitly target vulnerability. The next section starts by refining the umbrella term "fear of crime" before discussing the evolution of the immediate causes of affective and behavioral fear of crime. The subsequent sections build the psychological foundation for this thesis. Thereafter, an extensive literature review of vulnerability factors, neighborhood characteristics, and life events is provided before the extended vulnerability approach is developed.

2.1 Components of fear of crime

Until now, "fear of crime" served as an umbrella term. This section goes into detail and requires definitions. Fear of crime can be generally differentiated into social (crime as a social or political issue), altruistic (fear for friends and relatives), and personal fear of crime (DuBow, McCabe, and Kaplan 1979; Ferraro and LaGrange 1987; Warr and Ellison 2000). Within this categorization, personal fear is sub-divided into affective, cognitive, and behavioral components (Fattah and Sacco 1989; Gabriel and Greve 2003; Greve 1998; Hale 1996). The cognitive component is the perceived risk of being threatened by crime and is often operationalized as the perceived likelihood of personal victimization within a foreseeable future (e.g., 12 months). The behavioral component subsumes intentional (avoiding dangerous places or carrying protective devices) and occasionally nonintentional behavior such as gestures motivated by the anticipation of victimization (Gabriel and Greve 2003).

The affective component is the core of fear of crime. It captures the emotional arousal regarding crime and asks how afraid, worried, or safe someone feels. The affective component can be further differentiated regarding the primary object of the survey questions: first, when the crime-specific emotional arousal of fear of crime is of primary interest, concrete offenses should be mentioned explicitly (Ferraro and LaGrange 1987). As shown in Section 4.4.1, worries regarding different types of crime correlate sufficiently to assume a single latent construct called "crime-specific fear."[1]

Second, fear of crime has been frequently assessed by asking explicitly regarding people's perceptions of their security in their residential neighborhoods.[2] Because of their pervasive use, such operationalizations are called "standard items." Standard items typically ask, "How safe do you feel—or would feel—walking alone at night [or during the day] in your neighborhood?", or similarly, "Is there any area right around here—that is, within a mile—where you would be afraid to walk alone at night?" Thus, they should be understood as an assessment of residents' perceived safety in their neighborhoods (Oberwittler 2008, 216). This ecological aspect has received comparatively little attention, but standard items have received

[1] More recent work—which is not taken into account in this definition—suggested stressing the frequency of worry (Gabriel and Greve 2003; Farrall, Jackson, and Gray 2009).

[2] This is not to say that crime specific worry is independent of the residential neighborhood. However, since some people spend only a small amount of time in their neighborhood, it might be less decisive.

Table 2.1: Key definitions

Term	Definition
Fear of crime	Umbrella term defined as personal fear of crime containing an affective, cognitive, and behavioral component.
Affective component of fear	Emotional arousal regarding crime.
Behavioral component of fear	Intentional behavior motivated by anticipated criminal victimization.
Perceived victimization risk	Cognitive component or perceived risk of victimization within a certain period (normally 12 months).
Crime-specific fear*	Affective fear of crime concerning specific crimes.
Avoidance behavior*	Subtype of behavioral fear of crime.
Localized fear*	Neighborhood related affective fear of crime.
Vulnerability	Perception of environmental adversity in relation to individually assessed openness, controllability, and consequences of victimization. Perception is informed by neighborhood characteristics and vulnerability factors (see Figure 2.1)
Neighborhood characteristics	Independently measured neighborhood features (social disadvantage, crime, disorder)
Vulnerability factors	Personality traits and beliefs as well as physical and social factors
Vulnerability dimensions	Anticipated openness, controllability, and consequences of victimization
Perceived environmental adversity	Perceived neighborhood characteristics, perceived risk of victimization, and generalized trust
Stressors	External stimuli that influence the perception of vulnerability dimensions and environmental adversity
Within- and between-person effects	Longitudinal studies allow to distinguish between-person differences from within-person changes. Within-person effects are correlated within-person fluctuations over time (with hypothesized causal directions). In contrast, between-person effects are correlated between-persons differences consisting of 1) time-stable variables and 2) person means of time-varying variables (with hypothesized causal directions)
T^1 and T^2	First and second measurement occasion
Recovery effect	A special kind of within-person effect according to which the outcome returns to the baseline level in T^2 when victimization happened before T^1.

Note: *dependent variables in this thesis.

much criticism. For example, they only implicitly refer to crime: "your neighborhood" or "any area" is spatially imprecise, assessments of feelings ("would you feel") are hypothetical, and standard items blend cognitive and affective components (see Section 4.4.1.2).

The similar age differences of the standard question and the behavioral component led Greve, Leipold, and Kappes (2017, 2) to speculate whether the standard item entails "inherent behavioral bias." Although there is a cognitive element in this operationalization, the author argues that the affective component prevails because both versions explicitly ask how safe the respondent *feels* (see Section 5.1.1 for a short empirical investigation). Thus, despite Ferraro and LaGrange's (1992; 1988; 1987; Ferraro 1995) invaluable contribution to the field, the author does not adopt their categorization of the standard items as being cognitive. Rather, he considers it to be predominantly affective fear and stresses its strong spatial reference, which is particularly relevant to later hypotheses. Therefore, this thesis investigates a summed score of the first standard item (walking alone at night/day) as "localized fear" of crime.

The behavioral component of fear subsumes numerous actions to avoid victimization. They range from avoiding certain places or public transportation (at night) to securing one's residence and even learning self-defense or carrying defensive devices. These actions can be distinguished into "protective" and "avoidance behavior." Furthermore, they are the behavioral costs of crime (Dolan and Peasgood 2007). In contrast to standard items, they are rarely investigated as dependent variables (see, however, Liska, Sanchirico, and Reed 1988; Lüdemann 2006; Ferraro 1995, 102–14). From the perspective of vulnerability, this is surprising for two reasons. First, the two most frequently mentioned variables of physical vulnerability (gender and age) are strong predictors of protective and avoidance behavior (Lüdemann 2006; Ferraro 1995, 102–14; Greve 1998). Second, if vulnerability is understood as a persistent and involuntary personal characteristic (or passive vulnerability; see Section 2.4.1), behavioral responses seem able to minimize the risk of victimization and potential consequences. This thought was developed by Greve (1998; see also Greve, Leipold, and Kappes 2017) and used to dissolve the victimization–fear paradox (see below), arguing that older people neither are considerably more fearful nor do they perceive their risk of victimization as higher than that perceived by younger people. However, older people "behave more cautiously than younger ones, and they are wise and well advised to do so" (Greve 1998, 300). Third, cognitive fear of crime is operationalized by asking respondents regarding its likelihood (e.g., a robbery within a specified period (typically 12 months). The cognitive component is mostly regarded as a predictor of the affective (and behavioral) component of fear of crime; this might be problematic for several reasons (see below).

2.2 Theoretical evolution of the immediate causes of affective and behavioral fear of crime

The affective and behavioral components of fear of crime are not necessarily a response to accurately estimated risks of victimization as early research suggested. This section describes how fear of crime research evolved from the simplistic notion that people possess all information and process it correctly (which generates fear) to complex approaches integrating anticipated consequences (Killias 1990; Skogan and Maxfield 1981; Warr 1987), perception biases (Chadee, Austen, and Ditton 2007; Drakulich 2013; Jackson 2008; Oberwittler, Janssen, and Gerstner 2017), and general uncertainty and discomfort (Ewald 2000; Farrall, Jackson, and Gray 2009, ch. 4; Hirtenlehner and Farrall 2013; Jackson 2004). This thesis supports this development by touching upon bounded rationality (as opposed to strong rationality thoroughly discussed, e.g., by Rubinstein (1998)] as well as heuristics and biases (Kahneman and Frederick 2002; Tversky and Kahneman 1973; Tversky and Kahneman 1974), and integrating them into a theoretical model of vulnerability.

The so-called "victimization–fear paradox" is a less glorious chapter in fear of crime research. The paradox is that older people and women report above-average fear even though their risk of victimization is below-average (according to official crime statistics and victim surveys). Labeling this a paradox reveals an oversimplified view of human nature, wherein only (accurately estimated) risk of victimization generates fear. The victimization–fear paradox can be seen as a simple application of strong rationality and is under-complex for at least three reasons: it 1) assumes that the risk of victimization is accurately estimated, 2) neglects the role of anticipated consequences, and 3) implies a direct and one-directional causal link pointing from risk to fear.

More sophisticated approaches in fear of crime research included anticipated consequences but adhered to the idea of strong rationality. Accordingly, these approaches comprehend the surveyed risk of victimization as a reliable estimate of its actual risk and assume a unidirectional link between risk and fear. Warr's (1987) sensitivity-to-risk model argues that risk interacts with seriousness when generating fear (see Section 2.3.1). His empirical analyses, however, found small amounts of fear to be present without any perceived likelihood of victimization. Acknowledging that this might be "irrational," Warr (1987, 37) favored a methodological explanation: as the likelihood of victimization is commonly assessed within the approaching year, a prolongation to 3 or even 5 years would explain this finding. Similarly, and as discussed in detail below, Killias' (1990) vulnerability approach underlines the importance of anticipated consequences and "exposure to risk."

The author argues that implicitly assuming strong rationality is inappropriate in fear of crime research. Detailed and comprehensive information regarding crime is abstract and seldom available for laypersons. Furthermore, emotions are fueled with factors outside rationality. When compared with strong rationality, bounded rationality does not assume that individuals have all information, unlimited cognitive capacity, and the willingness to process it. Numerous studies on biases and heuristics (e.g., Damasio 1994; Gigerenzer 2000; Kahneman 2003; Slovic et al. 2002; Slovic et al. 2004) investigated what information (lay) people retrieve and how they process it to reach judgments and decisions. However, sometimes, these heuristics are error-prone. Bounded rationality is also beneficial for a longitudinal understanding of fear of crime because imperfect information (processing) permits change, e.g., when people adjust their threat assessments after victimization or media reports.

A full review of the vast literature on heuristics and biases is beyond the scope of this thesis. However, important aspects are discussed below. Among the most prominent heuristics are those based on availability and representativeness (Tversky and Kahneman 1974; Tversky and Kahneman 1973). The availability heuristic claims that laypersons estimate the likelihood of an event on basis of the retrievability of information. Hence, the occurrence of dramatic but rare events is overestimated, whereas less spectacular but more frequent events might be underestimated. The representativeness heuristic states that people assign a specific class (e.g., a dangerous area) to objects with particular features (e.g., low socioeconomic status of a neighborhood). This assignment might happen irrespective of prior probabilities. When applied to fear of crime, the level of crime in an area or the probability of someone being a criminal is assessed (implicitly) on readily available proxy variables for criminality, such as ethnicity and poverty. This notion is supported by Quillian and Pager (2001; 2010), who found that Whites' perceptions regarding inaccurately high percentages of Blacks led to higher assessments of the risk of victimization when compared with actually experienced victimization, a phenomenon they named "stereotype amplification" (see also Drakulich 2013; Sampson and Raudenbush 2004; Sampson 2009; Oberwittler, Janssen, and Gerstner 2017; Wickes et al. 2013). Both heuristics suggest, unfortunately, that actual reductions in crime have little influence on the perceived risk of victimization. Instead, tackling the often-implicit biases linking crime to ethnicity and poverty appears to be the more effective strategy to reduce the fear of crime from this perspective.

A majority of studies in this field investigate judgments and decisions—not affective responses. However, sophisticated approaches examine the interplay among affective responses, cognitive evaluations, and decisions. In their comprehensive literature review, Loewenstein et al. (2001) sharply distinguished their risk-as-feelings perspective from previous "consequentialist" perspectives that assumed that anticipated outcomes and subjective probabilities are mediated entirely through cognitive evaluations. They stressed the bidirectional effects of cognitive and feelings and backed their suggestion with numerous (neuro-)psychological studies (Loewenstein et al. 2001, 271; see also Kasperson et al. 2003; Kasperson et al. 1988; Lerner and Keltner 2000; Slovic et al. 2004; Slovic et al. 2002).

Applying the notion of bidirectional effects between cognitive evaluations and emotional reactions to fear of crime suggests that people who perceive a high risk of victimization are more afraid (as widely assumed) and the fearful perceive more risk. This simultaneous causality constitutes a considerable threat to regression models in fear of crime research: if correct, cross-sectional studies cannot estimate an unbiased relationship between risk and fear because of endogeneity. In the same vein, perceived risk likely increases avoidance behavior (as widely assumed). However, frequent and effortful avoidance behavior might reduce perceived risk (see Ferraro 1995, 102; Greve 1998), which leads to a downward bias in estimations. With regard to the causal relationship between crime-specific fear and avoidance behavior, Liska, Sanchirico, and Reed (1988) argued for a "positive escalating loop." Ferraro (1995, 102–3) found no such simultaneous causality and assumed fear to be the consequence of avoidance behavior and perceived risk. Both studies were, however, cross-sectional, which restricts their validity. Answering this question is, unfortunately, beyond the scope of this empirical investigation. However, Section 8.1 in the Appendix estimates an exploratory cross-lagged panel model that supports doubt regarding unidirectional causality. This problem is circumvented by not investigating perceived risk, avoidance behavior, and affective fear in the same regression model, with one exception: the author controls both for previous levels of the dependent variable and perceived risk.

Integrating such sophisticated psychological approaches is helpful in understanding how risk is evaluated and processed into emotions and behavior. Surprisingly, this prospect largely escaped the attention of fear of crime researchers until recently. Chadee, Austen, and Ditton (2007) stressed and discussed the discrepancy between actual and perceived risk of victimization and provided a correlation analysis. In theoretically more demanding publications, Jackson (2006; 2008) sketched an integrative framework with a sophisticated notion of how people perceive risk and how doing so generates fear. Just as Chadee, Austen, and Ditton (2007), he abandoned the simplistic idea that solely accurate risk assessments cause fear; however, he touched upon broader issues such as media, moral outrage, economic actors, and values. Both approaches drew upon the literature of heuristics and biases, as well as the risk-as-feelings hypothesis, but discussed neither simultaneous causality between risk and fear nor the potential consequences for regression modeling.

Perception biases also invite questions regarding a substantial quantum of previous criminological research in neighborhood differences in fear of crime. Earlier theories (Hunter 1978; Lewis and Salem 1986; Wilson and Kelling 1982; Skogan 1990) argued that incivilities (introduced in Section 2.4.5) are a decisive predictor of fear. In their seminal contribution, Sampson and Raudenbush (2004) showed that perceived neighborhood incivilities are much more strongly influenced by neighborhood poverty and ethnic composition than by independently and systematically assessed neighborhood incivilities (see also Drakulich 2013; Jackson et al. 2017; Sampson 2009; Oberwittler, Janssen, and Gerstner 2017; Wickes et al. 2013). Hipp (2013) could not confirm this finding regarding perceived crime. In addition, Covington and Taylor (1991) and others (Taylor 2001, 228; Oberwittler 2008, 218; Brunton-Smith and Sturgis 2011; Häfele 2013) argued that contrary to the commonly hypothesized causal direction, people might perceive more incivilities because they are more fearful. Again, the potential for simultaneous causality casts shadows of doubt upon previous findings that (implicitly) assumed a unidirectional causal link between perceived incivilities and fear.

The sociological approach considers fear of crime to be an expression of broader feelings of uncertainty originating from social changes (Ewald 2000; Farrall, Jackson, and Gray 2009, ch. 4; Hirtenlehner and Farrall 2013; Hirtenlehner 2006; Jackson 2004). To underpin this hypothesis, some scholars (Hirtenlehner 2006; Hirtenlehner and Farrall 2013; Hollway and Jefferson 1997; Sparks, Girling, and Loader 2001) draw upon grand, abstract sociological theories of "late," "liquid," or "new" modernity from Beck (1992), Giddens (1991), or Bauman (2000; 2006; 2001). The latter argued that contemporary societies are characterized by uncertainty and the general lack of control. At the same time, this uncertainty is the main source of diffused contemporary fear. Since people seek to concretize their diffuse fear, crime and foreigners become suitable targets for multi-sourced diffuse fears. In a more recent quantitative study, Hirtenlehner and Farrall (2013) distinguished the generalized insecurity model from the expanded community concern model. The former model tested whether economic and social fears correlate with a latent "generalized sense of insecurity" in what is similar to Bauman's hypothesis. The latter model (advocated, e.g., by Jackson 2004) assumes that these fears are mediated by concerns regarding incivilities. They found satisfactory empirical support for both models. However, they favored the generalized insecurity model mainly because fewer parameters were needed and because the mediation of economic and social fears via incivilities on fear was rather weak.

In short, fear of crime research indulged a comparatively long era of under-complex notions regarding the primary drivers of affective and behavioral fear. Recently, the literature of psychological heuristics and biases, the criminological literature concerning “seeing disorder”, and the sociological literature on the diffusion of uncertainty in the “late,” “liquid,” or “new modernity” were integrated into fear of crime research to rectify this shortcoming. All three streams suggest that perceived risks are not the only (or most important) force driving fear but that other factors projected onto crime generate fear as well.

2.3 Psychological foundations

A solid psychological fundament is necessary for an informative, in-depth explanation of what causes the fear of crime. The lack of that basis has led to comparatively simple descriptions of the subgroup differences of fear of crime. Warr (1984) reached that conclusion decades ago and developed his sensitivity-to-risk model (see Section 2.3.1). Section 2.3.2 discusses the construal theory of psychological distance because it helps to understand what information regarding crime people perceive as concrete or abstract and what role (temporal, spatial, social, or hypothetical) distance and proximity play. Shattered assumptions theory provides further insights into how the experience of victimization is psychologically processed and suggests that self-assessments and perceived environmental adversity might change because of traumatic victimization (see Section 2.3.3).

2.3.1 Perception of and sensitivity to victimization risk

An early contribution to a more elaborate understanding of the psychological processes was made by Warr (1987; 1985; 1984) in a series of publications. In an early paper, he (1984) tested a multiplicative relationship between perceived risk and the seriousness of consequences (the “multiplicative model of fear”), arguing that without perceived risk even the most serious consequences might be irrelevant. That argument was empirically confirmed. In later papers, he developed this thought into the “sensitivity to risk” model, arguing that affective fear of crime is the outcome of a linear function that transforms the perceived risk of victimization into fear, depending on subgroups (e.g., age groups) and offenses. In this model, thresholds are levels above which perceived risk causes noticeable fear, the intercept is the level of fear without perceived risk, and the slope is the increase in fear when risk rises by a stipulated amount.

He tested whether the perceived seriousness of offenses generates fear differently among older adults and women (Warr 1984; Warr and Stafford 1983) and found various significant interactions between age and gender on one side and perceived risk on the other. For example, an older age group (51–65) was significantly more afraid of fraud upon considering the same perceived risk. The oldest group (66+) reacted *more* fearfully to the same level of perceived risk of being approached by beggars but *less* fearfully to the risk of rape. Warr’s early approach was very influential for later advancements in this field.

Boers (1991, see pp. 349-360 for an English summary; 2003, 1142–5) based his interactive model on Lazarus’ appraisal theory. Just as with Warr’s approach, Lazarus’ appraisal theory evaluates people’s different reactions to identical threats. According to this theory, people interpret a stressor and assess its potential threat (primary appraisal). If it is so assessed, people evaluate their coping capacities (secondary appraisal). Applying this model to fear of crime, Boers (1991) argued that perceiving the risk of victimization is the primary appraisal. Second, Boers borrowed another psychological approach (Becker 1980) stressing the situational character of different kinds of fear. Boers argued that whether situations induce fear of crime depends on individuals’ perception of the situation.

In contrast to Warr, Boers (1991, 194–98) argued that experiences inform this perception in addition to differential sensitivities to risk (although experiences can result in differential sensitivity). With that argument, Boers opened the theoretical door for a comprehensive understanding of what determines an individual’s perceived risk of victimization beyond the statistical likelihood of being a victim. He states that an individual’s assessment of risk might differ from what society has agreed upon because personal experiences are considered. Therefore, labeling behavior or emotions as irrational and dysfunctional is inappropriate.

Ferraro (1995, 18) suggested a risk interpretation model that drew upon symbolic interactionism, the literature on incivility, and the criminal opportunity framework. Strongly underlining the distinction between emotions (fear) and cognitions (likelihood), he argued that perceived risk (influenced by contextual and individual characteristics) predicts affective and behavioral fear of crime. Crucially, Ferraro (1995) hypothesized that both perceived risk and neighborhood conditions are partly mediated by behavioral fear of crime predicting affective fear of crime.

Jackson (2009; 2011) suggested a psychology of risk approach to analyze the fear of crime by melding Warr's sensitivity model with Killias' vulnerability approach (see Section 2.4.2). Jackson (2011) hypothesized that if people judge crime as being particularly uncontrollable and consequential, lower degrees of perceived risk generate comparatively high levels of fear of crime. Moreover, perceptions of slight consequences and high degrees of control reduce the perceived risk of becoming a victim. Upon asking respondents how often they had been worried about becoming a victim of several crimes, how likely it was that those crimes would happen within the next 12 months, how much these crimes would affect them, and whether they could control possible victimization, he found all main hypotheses confirmed. Jackson and Gouseti (2015b; see also Jackson 2015) extended this model by adding cognitive closure and victimization. Their cross-sectional dataset from Italy, Bulgaria, and Lithuania contained a positive interaction between the psychological concept of cognitive closure and perceived risk, as well as a mediation of cognitive closure via perceived consequences. Jackson and Gouseti (2015b) further found that victimization was partly mediated by perceived risk, controllability, and consequences of crime.

In all the models mentioned above, the perceived risk of victimization is pivotal in causing affective (and for Ferraro (1995) behavioral) fear of crime. These approaches went far beyond previous investigations of the "prevalence of 'fear of crime' in socio-demographic categories" (Vanderveen 2006, 7) and developed an in-depth understanding of how several individual and environmental factors together generate fear. However, research on heuristics and biases (Chadee, Austen, and Ditton 2007; Quillian and Pager 2001; Quillian and Pager 2010; Sampson and Raudenbush 2004; Sampson 2009; Tversky and Kahneman 1973; Tversky and Kahneman 1974), cognitions and emotions (Lerner and Keltner 2000; Loewenstein et al. 2001), and interrelationships of the components of fear of crime, particularly for older people (Greve, Leipold, and Kappes 2017), cast considerable doubt on the "consequentialist" notion of a unidirectional influence of perceived risk on affective fear of crime (see Section 2.2). Because of the absence of longitudinal evidence for relationships among all three components, this remains an intriguing open question for future fear of crime research.

2.3.2 Distance and relevance

Recently, the construal-level theory of psychological distance (Trope and Liberman 2010) was applied to fear of crime by Gouseti and Jackson (2015; see also Gouseti 2016; Jackson and Gouseti 2015a). This theory investigates how people react to distal events or objects. Two connected mechanisms are involved: psychological distance and mental construal. The former involves judgments of how far (or close) an object or event is from the observer. Trope and Liberman (2010; see also 2003; Liberman and Trope 2008) suggest four dimensions to psychological distance: temporal (when?), spatial (where?), social (whom?), and hypothetical (whether?). They also suggest that construal-level and psychological distance are related. The farther an object or event is, the greater (abstract, superordinate, and decontextualized) someone thinks about it. Something that is proximate is processed at a lower construal level (concrete, subordinate, and context-bound).

Applying this concept to fear of crime, Gouseti and Jackson (2015) argued that people who perceive crime as distant think about crime at a higher construal (more abstract) level. Offenses perceived as closer exert stronger effects because people tend to think about those offenses at a lower construal level and consequentially as more concrete. People tend to "project [the risk of crime] into one's own environment" (Gouseti and Jackson 2015, 34) and attribute specific groups of people to it. Accordingly, horrible offenses happening far away (e.g., perceived only via the media) might have weaker consequences as people process them at a higher construal level.

For the extended vulnerability model introduced in Section 2.5, Gouseti and Jackson's (2015) application of construal-level theory was useful because it underlines the importance of contexts and stresses the gradually mitigating role of distance. This notion is reflected in the assumptions that 1) residential neighborhoods have stronger effects than adjacent areas,

2) recent victimization has stronger effects than older, and 3) life events happening to an individual are more important than those occurring in their social environment.

2.3.3 Shattered assumptions, victimization, and vulnerability

Numerous psychological theories explain how people cope with potentially traumatic life events such as victimization to explain their detrimental consequences (see, e.g., Richter 1997, 12–17 for a discussion; Peterson and Seligman 1983). Other psychological theories investigate how victimization and other traumata might influence fundamental beliefs about the self, others, and the world (Janoff-Bulman 1992; Norris and Kaniasty 1991; McCann, Sakheim, and Abrahamson 1988).

Among the prominent approaches is Janoff-Bulman's shattered assumptions theory (1992; 1989; Janoff-Bulman and Frieze 1983). She (1989, 116) argued that traumatic experiences can shatter our often-implicit assumptions about the world and ourselves and correct the common "illusion of invulnerability, a basic belief that 'it can't happen to me.' " Although victimization is not necessarily traumatic, her theoretical model provides insights into how people process unpleasant events psychologically. She argued that adverse life events alter our view of the benevolence and meaningfulness of the world and our own worthiness. Benevolence involves the general assumptions that the world is a friendly place and that harmful events are relatively rare. That the world is meaningful refers to the distribution of outcomes on the basis of justice, controllability, and chance. Finally, she argues that the sense of self-worthiness suffers following traumatic events.

Previous studies support the contention that the subjective risk of victimization increases and that psychological well-being suffers following victimization (Murphy et al. 1988; Ruback and Thompson 2001, ch. 4; Norris and Kaniasty 1994; Norris and Kaniasty 1991; Winkel et al. 2003; Winkel 1998). Analyzing panel data from Switzerland, Bauer (2015) found that general trust is affected by victimization (until he applied genetic matching).

In contrast, a growing body of research draws on the comparatively new branch of positive psychology that investigates attenuating personal characteristics and positive consequences (e.g., personal growth) of victimization (Ai and Park 2005; Joseph and Linley 2005; Tedeschi and Calhoun 2004; Verdun-Jones and Rossiter 2010, 630). The idea of partly positive effects is also a component of Winkel's (1998) fear-victimization model that suggests victimization triggers two contrary processes: Under the vulnerability approach introduced below, past victimization increases subjective risk. However, it also lowers the perceived negative impact of future victimization. As both aspects relate positively to fear of crime and negatively to victimization, they likely cancel each other out. Further, Richter (1997, 16) argued that successfully coping with previous victimization might increase the ability to cope with future victimization, whereas the opposite might produce the opposite outcome. This more positive perspective on resiliency, recovery, and personal growth differs conceptually from the concept of vulnerability and lies beyond the scope of this thesis.

2.4 The vulnerability approach

The concept of vulnerability transcends scientific disciplines and applies to different but always potentially harmful situations. The Oxford Dictionary (2018) defines vulnerability as the "quality or state of being exposed to the possibility of being attacked or harmed, either physically or emotionally." Accordingly, vulnerability is susceptibility to detrimental environmental influences (victimization). It is (as resilience) a "relational concept" (Ionescu et al. 2009; Leipold and Greve 2009) because the vulnerable are (temporarily) exposed to a potential external threat. Without a vulnerable individual or a potential threat, vulnerability is irrelevant. Vulnerability concerns detrimental events in the future. This anticipation of events separates vulnerability from the general understanding of resilience[3] (i.e., the ability to maintain or quickly recover to the initial level of functioning when facing detrimental events (Kalisch et al. 2017; Scheffer et al. 2018)). A somewhat implicit, but less important, insight from this definition is that the vulnerable entity is well known, whereas sources of potential

[3]Although this distinction fits the vast majority of conceptions of resilience, Greve, Leipold, and Kappes (2017, 3) suggest a notion of "proactive resilience." However, they acknowledge "Almost always, its effects have been investigated in response to a concrete threat, problem or crisis, whereas possible proactive components of regulatory or coping processes are less often focused on."

threats can be either known or unknown. Applying this concept to fear of crime—more precisely, to fear of stranger crime—vulnerability has two elements: the personal and the environmental. They are linked by a future event: potential victimization.

Beyond these fundamental aspects, vulnerability evolved surprisingly similarly in many scientific disciplines and generated varying conceptual insights (Alwang, Siegel, and Jørgensen 2001; Bankoff, Frerks, and Hilhorst 2004; Ionescu et al. 2009). These concepts revolve around questions of exposure (i.e. risk), sensitivity (i.e. the effect of a given input), and adaptation (i.e. the ability to cope with potential consequences). These similarities gave rise to thematic differences through differences in research objects and disciplinary perspectives.

The remainder of this chapter develops the extended model of vulnerability. Therefore, the author discusses the origins of vulnerability in criminology initially. Recent studies mainly draw on two older studies (Skogan and Maxfield 1981; Killias 1990) that share a common idea: some groups of people are physically (older people, women) or socially (poor, minorities, people without social support) more vulnerable to crime and therefore more fearful. This similarity allows discussing them critically in Section 2.4.2. Section 2.4.3 reviews psychological, physical, and social vulnerability alongside life events and neighborhood contexts. Section 2.5 introduces the extended vulnerability approach.

2.4.1 The roots of the vulnerability approach in criminology

The openness for victimization (one dimension of vulnerability) has been of particular interest in criminology for decades and has its origins in the seminal work of von Hentig's (1948, 33–35) classification of victims. He discussed the increased risk of victimization of young or older people as well as women, mentally impaired, temporally intoxicated, immigrants, minorities, or "dull normals" and demonstrated how social and physical factors generate openness to attack and even discussed interactions between both factors. Regarding older people, von Hentig (1948, 410) assumed that their occasional wealth interacted with their physical weakness: "In the combination of wealth and weakness lies the danger" that makes them "ideal victims of predatory attacks."

Penick, Owens, and others (1976, 93–101) distinguished between status, role, and ecological vulnerability. Status vulnerability implies increased offense-specific vulnerability because of gender, occupation, or wealth. They understood race and age as mediated by employment status (since the unemployed have higher street exposure) and economic situation (because wealthier people are more threatened by theft). Role vulnerability denotes specific power relations between two people, e.g., husband–wife, parent–child, or landlord–tenant. Ecological vulnerability refers to characteristics of the environment that someone lives in, including levels of poverty, crime rates, land use, age structure, racial composition, racial and population density, and adjacent high- and low-income census tracts. The concept of ecological vulnerability was revived by criminologists decades later (see, e.g., Covington and Taylor 1991).

Gubrium (1972) and Dussich and Eichman (1976) stressed the interactive character of victimization between the offender and the (vulnerable) victim. Gubrium assumed that the likelihood of victimization varies with personal visibility. This visibility, in turn, depends on the age structure of the environment. Dussich and Eichman (1976) pointed out that in age-heterogeneous environments, older adults with poor health are more visible. Likewise, older adults with good health are more visible in age-homogenous environments. However, Dussich and Eichman (1976) questioned whether that visibility alone would automatically lead to increased risk of victimization.

Dussich and Eichman's (1976) distinction between active and passive vulnerability is useful and under-acknowledged. Active vulnerability refers to the behavior of a potential victim by which they increase the likelihood of victimization. In contrast, passive vulnerability refers to persistent and involuntary characteristics (e.g., age, gender, race, and stature). Passively vulnerable people appear as easy targets. While fragile older adults embody a pronounced passive vulnerability, their lifestyle might lead to low levels of active vulnerability regarding street crime. This behavior contributes to low victimization rates of elderly people but makes them highly vulnerable when they "leave their isolation" (Dussich and Eichman 1976, 95).

A short digression illustrates the usefulness of the distinction between passive and active vulnerability. Today, pickpocketing and hug scams at the expense of intoxicated people (e.g., those drunken and fallen asleep at train stations) gained increasing relevance in German cities. Both offenses take advantage of active vulnerability where prior intoxication undermines defensive capabilities. This form of vulnerability can be described as "window of vulnerability," a widely used metaphor in the computer sciences (Arbaugh, Fithen, and McHugh 2000).

2.4.2 Paradigmatic concepts of vulnerability in criminology

Studies regarding vulnerability originate mainly with two publications (Skogan and Maxfield 1981; Killias 1990). Although not immediately apparent, both approaches share crucial theoretical aspects. The underlying idea is that some people (older people, women, minorities, and the poor) are (passively) more vulnerable to crime and therefore more fearful. Skogan and Maxfield (1981, 69) defined physical vulnerability as "openness to attack, powerlessness to resist attack, and exposure to traumatic physical (and probably emotional) consequence if attacked." In addition, they (1981, 73–74) defined the socially vulnerable (especially Blacks and the poor) as people "frequently exposed to the threat of victimization because of who they are." The socially vulnerable "are more likely to be bound to less desirable inner zones of the community, where crime rates are always high regardless of who happens to be inhabiting them."[4] They indicate another aspect of social vulnerability—one that is unrelated to the neighborhood—arguing that "the social and economic consequences of victimization weigh more heavily" upon socially vulnerable groups.

Killias (1990) generally agreed with Skogan and Maxfield (1981) regarding physical factors making people vulnerable to crime. In Killias' approach, however, social vulnerability more strongly refers to lonely victims with limited social support and people with a "dubious reputation." He added (individual) social capital to Skogan and Maxfield's approach. Most of Skogan and Maxfield's social vulnerability is expressed in Killias' "situational factors," wherein "residence in a high crime area" exposes vulnerable people to risk. Killias expanded Skogan and Maxfield's approach by considering nonresidential "deserted areas" and daylight hours. Killias contributed a cross-tabulation, which allows a more structured theoretical consideration of the topic.

A substantial advancement in both approaches is their implicit perspective on the anticipation of victimization. Both distinguish a time before (openness), during (powerlessness to resist), and after (consequences) victimization. Anticipation is most apparent in Skogan and Maxfield's (1981, 69) definition of physical vulnerability, which follows the sequence outlined above but is less visible in Killias' approach.[5]

Reformulations of this vulnerability approach should address four problems (discussed more detailed in the remainder of this Section). Neither approach sufficiently distinguishes between vulnerable individuals and their environments nor does it acknowledge that individual vulnerability and environmental adversity are subjectively perceived and are, therefore, likely under- or overestimated. Moreover, they are static (not temporally dynamic) because they focus on vulnerability with respect to anticipated victimization and implicitly assume full and correctly processed information. Finally, they do not differentiate among affective, cognitive, and behavioral fear of crime.

Skogan and Maxfield's social vulnerability, as well as Killias' situational factor, explicitly referred to environmental aspects. Killias' situational factor additionally considered daytime. With regard to this, the author stresses that the concept of vulnerability has—across scientific disciplines—two distinct components of analysis: individuals with differing degrees of vulnerability and environments with varying degrees of adversity. Both elements interact to generate individual- and context-specific levels of (perceived) peril. However, Skogan and Maxfield (1981, 74) explicitly stated that high-crime areas generate fear "regardless of who happens to be inhabiting them," and Killias hardly mentions individuals when discussing situational factors of vulnerability. The author argues that it is more appropriate to speak of context effects in this regard because they involve neighborhood factors and disregard

[4] In this sentence, they refer to Shaw and McKay (1942). Today, however, "inner zones" can be replaced with crime-ridden neighborhoods in general since it is widely acknowledged that crime is not necessarily restricted to the city center but problematic neighborhoods across the city.

[5] Unfortunately, factors and dimensions were conceptualized somewhat carelessly by Killias. Although he termed exposure, consequences, and loss of control as *dimensions*, e.g., in the abstract and his cross table, he labeled them *factors* elsewhere (1990, 98) which led to some confusion (Pantazis 2000, 415). The author will stick to the terminology of exposure, consequences, and loss of control as dimensions and physical, social, and situational factors.

individual differences. Hale's (1996, 95) seminal review underpins this critique because he also criticized Killias for "stretching the concept so far as to be in danger of losing its focus and explanatory power" without going into more detail. However, when Hale (1996, 96) reprinted Killias' table, he left situational factors aside without explanation.

Second, this vulnerability model paid little attention to the fact that vulnerability is an individual and relational perception of individual capabilities and environmental adversity. Both might be based on measurable characteristics such as crime rates and physical strength. However, they also result from effective but occasionally error-prone heuristics grounded in incomplete information and limited willingness or recourse to process them (Gigerenzer 2000; Jackson 2011; Tversky and Kahneman 1974; Tversky and Kahneman 1973). This possibility calls for a stronger consideration of personality traits (such as the locus of control) because they express how forcefully people perceive their abilities regarding (un)desirable events. The relationship between fear and perceived environmental adversity is even more complicated because criminological and sociological research shows that aspects other than crime are projected onto perceived environmental adversity. Further, psychological research argues for simultaneous causality between perceived risk and fear (see Section 2.2).

Third, both approaches share a static conceptualization of vulnerability to crime. Implicitly, both argue that people assess vulnerability via their (accurate) anticipation of openness to attack, loss of control, and seriousness of consequences (see Figure 2.1). The author argued above that this anticipation might be biased in both directions. In what is understood as a continuum, someone can neglect environmental adversity entirely (the most extreme form of underestimation) or be extremely cautious regarding every hint of crime (overestimation). Similarly, people can perceive their response and coping capabilities as being nonexistent or unreasonably high. The author draws upon shattered assumptions theory (Janoff-Bulman and Frieze 1983; Janoff-Bulman 1989; Janoff-Bulman 1992) to investigate whether both perceptions are updated following victimization.

Fourth, neither of the vulnerability approaches discussed above distinguishes among components of the fear of crime. Noting the difference between Skogan and Maxfield's notion of "openness to attack" and Killias' "exposure to risk" illustrates this criticism. "Openness to attack" appears to be preferable because it is better suited to express the common understanding of vulnerability to crime as passive (see Dussich and Eichman (1976) discussed in Section 2.4.1). Passively vulnerable people (particularly older people) likely avoid (active) exposure to danger (in addition to their age-related lifestyle changes). Hence, passive vulnerability likely increases avoidance behavior more strongly than affective fear of crime (see also Section 2.2 and 2.4.3.2.3).

2.4.3 Vulnerability factors

After introducing the basic concept of vulnerability in Section 2.4 and the paradigmatic vulnerability approaches of criminology in Section 2.4.2, the author reviews more recent and predominantly empirical literature in this section. Section 2.4.3, which is more detailed, extensively discusses advancements in fear of crime research regarding physical and social factors, personality traits, generalized trust, life events, and neighborhood characteristics. This section selectively reviews the vast literature and discusses cornerstones and recent developments in each field in order to build the foundation for the extended vulnerability model.

2.4.3.1 Personality traits and generalized trust

Numerous studies investigated links between the fear of crime and personality traits (Adams and Serpe 2000; Guedes, Domingos, and Cardoso 2018; Hirtenlehner 2008; Houts and Kassab 1997; Wurff and Stringer 1988; Marshall 1991). For instance, Wurff, Van Staalduinen, and Stringer (1989, 144) proposed the power factor, which measures "the degree of self-assurance and feeling of control" in case of threat or assault. They found that these measurements explained fear better than sociodemographic variables such as age and gender (see also Farrall et al. 2000; Hale 1996, 120–21). Houts and Kassab (1997) tested Rotter's social learning theory, one element of which is the popular locus of control construct. They adapted Rotter's concept and developed three items measuring the external and internal locus of control for victimization. Interestingly, one of their measures of external control (powerful others) interacted with trust in neighbors for white respondents: respondents who agreed that others were powerful were less fearful when they lived in areas with trustworthy neighbors.

Regarding ambiguity, Jackson (2015) integrated the need for cognitive closure (Kruglanski and Webster 1996) into the risk sensitivity model mentioned above. Notably, cognitive closure resembles conceptualizations of ambiguity tolerance (Furnham and Marks 2013; McLain, Kefallonitis, and Armani 2015) that are investigated hereafter. Jackson (2015) found weak bivariate correlations between the need for cognitive closure and worry regarding crime. Furthermore, people with strong needs for cognitive closure (which is similar to low ambiguity tolerance) perceived more consequences of victimization.

Surprisingly, generalized trust has only recently been investigated with regard to fear of crime. Hummelsheim, Oberwittler, and Pritsch (2014) elaborated upon the inverse relation between generalized trust and fear of crime. They hypothesized that the fear of crime and generalized trust are closely related and investigated their hypothesis empirically by comparing individual and contextual predictors on both outcomes in 21 European countries. They uncovered similarities regarding education, employment, victimization, and similar influences of country predictors. However, they also found differences regarding age and gender: women had more fear but were equally trusting and older people were more fearful but more trusting.

2.4.3.2 Physical factors

Gender and age are the most frequently assessed demographic variables regarding physical vulnerability, albeit with remarkable differences in theoretical reasoning. Health has gained increasing attention from fear of crime researchers although the causal relationship may be ambiguous (Jackson and Stafford 2009).

2.4.3.2.1 Gender

In most studies, gender is among the strongest predictors of fear of crime (for a review see Hale 1996, 96–100; Cobbina, Miller, and Brunson 2008, 675–77), and some argue that it is the most influential predictor (Rader, Cossman, and Porter 2012; Rader and Haynes 2011). The literature offers various explanations for this finding. Drawing upon the victimization–fear paradox (see Section 2.2), criminologists argue that official statistics and victimization surveys underestimate the actual victimization of women (see Hale 1996, 97–98 for a summary). Others hypothesize that women generalize across different types of victimization. Considerable research investigates whether women connect various forms of victimization (e.g., burglary) implicitly with the risk of (contemporaneous) sexual victimization (for an overview see Ferraro 1996; Truman 2010; Warr 1985, 247–48; and critically Hirtenlehner and Farrall 2014). Gender-specific socialization may convince women that they are less capable of controlling victimization (Rader and Haynes 2011). Similarly, (perceived) vulnerability is among the successful explanations for women's greater fear of crime (Jackson 2009; Smith, Torstensson, and Johansson 2001, 177; Smith and Torstensson 1997, 628–29). Jackson (2009) showed that the effect of gender was entirely mediated by controllability or consequences with a comparatively small sample ($n = 479$).

Another stream of research examines gender differences of individual predictors explaining fear of crime. Franklin and Franklin (2009) found gender differences regarding income, skin color, and age but not education, perceived disorder, or social integration (with higher coefficients of income and age but smaller effects of skin color for women). With regard to age, however, this and other studies (Box, Hale, and Andrews 1988; Schafer, Huebner, and Bynum 2006; Smith and Torstensson 1997) share a non-negligible limitation: they did not report curvilinear age effects. Investigating gender-differentiated age–fear curves is essential because research suggests that young women are particularly fearful when compared with young men, whereas gender differences narrow over the life course. Testing a curvilinear relationship between age and fear, Brunton-Smith and Sturgis (2011) found a significantly stronger negative main effect for women.

Studies on differential neighborhood effects depending on gender report ambiguous findings. Schafer, Huebner, and Bynum (2006) found that perceived disorder was a stronger predictor of crime-specific fear for men than it was for women. However, most research suggests that neighborhood characteristics are more important for women. In her qualitative study, Cobbina, Miller, and Brunson (2008) found that potentially aggressive, unemployed men and gang members frequently confront women. Such devaluations and mistreatments might be less socially despised in more problematic areas (Miller 2008). Snedker (2015) found significant interactions of gender with perceived disorder and crime, suggesting that women associate perceptions of neighborhood problems more strongly with fear. In their reanalysis of Stockholm (county) data using multilevel analysis, Smith, Torstensson, and Johansson (2001) generally (but inconsistently) found that neighborhood characteristics mattered more for women than they did for men. Neighborhood cohesion and police-recorded numbers of neighborhood assaults were stronger predictors for women than they were for men. Despite their ambivalent findings, they concluded that women are more affected by neighborhood characteristics, whereas individual "empowerment" (age, migration status, and education) influences men more strongly than women. The most convincing quantitative evidence for stronger neighborhood effects among women originated with Brunton-Smith and Sturgis (2011), who found that independently assessed disorder was a stronger predictor for women.

With regard to gender differences of victimization effects, Braakmann (2012) found that women (but not men) altered their method of transportation after being victimized, whereas men more often carried weapons. Since this study is one of just a few longitudinal investigations of victimization effects on (behavioral) fear of crime, Section 2.4.4.1 discusses it more thoroughly. Section 2.5.1 discusses the theoretical reasons for gender differences in victimization effects on fear.

2.4.3.2.2 Physical health and shape

Impaired physical health is the often unmeasured and implicit mechanism that links age to the fear of crime. Many studies either lack adequate health measures, are based on small and selective samples, or use unsophisticated analytical methods (Braungart, Braungart, and Hoyer 1980; Galey and Pugh 1995; McKee and Milner 2000; Ollenburger 1981; Stiles, Halim, and Kaplan 2003). Cossman and Rader (2011; see also Cossman, Porter, and Rader 2016) compared self-rated health with poor physical or mental health and activity limitations. Controlling for dichotomized age, they found that self-rated health was strongly related to localized fear. They argued that perceived self-rated health more strongly predicts fear because it captures elements of perceived vulnerability.

Epidemiological studies (Browning, Cagney, and Iveniuk 2012; Chandola 2001; Ross and Mirowsky 2001; Stafford, Chandola, and Marmot 2007; Pearson and Breetzke 2014; Ziersch et al. 2005) regarded fear of crime as the independent variable and health as the dependent variable. According to these studies, the fear of crime leads to withdrawal from social activities, avoidance of outdoor activities, and increased mistrust, all of which impair physical and mental health. Either way, their empirical findings support a strong correlation between health and fear. The rare longitudinal evidence indicates a feedback loop (Jackson and Stafford 2009).

2.4.3.2.3 Age

Age differences in fear of crime have attracted generations of researchers (e.g., Clemente and Kleiman 1976; Clemente and Kleiman 1977; Ferraro and LaGrange 1992; Goldsmith and Goldsmith 1976; Greve 1998; Greve, Leipold, and Kappes 2017; Herbst 2011; Kappes 2012; Skogan 1978; Sundeen and Mathieu 1976; Yin 1982) ever since fear was first quantitatively investigated in a victimization survey (Biderman 1967). Early studies (e.g., Goldsmith and Tomas 1974) suggested (fear of) crime exerts a strong detrimental influence on older people as expressed in the memorable *Time Magazine* (1976) headline "The Elderly: Prisoners of Fear."

In academic research, however, the general tone was soon muted. For example, Clemente and Kleinman (1977) found that age was a weaker predictor of fear than gender or community size. A full review of numerous studies is beyond the scope this work (for older reviews see Yin 1980; Yin 1985; Kury, Obergfell–Fuchs, and Ferdinand 2001, 77–82; Hale 1996, 100–103; Fattah and Sacco 1989, ch. 10). Overall, age might exert a small positive effect on fear. However, such generalized, sweeping statements are difficult because of strong dependence on the operationalization of the dependent variable (see paragraph below), different modeling strategies (e.g., curvilinear relationships, gender interactions, or (not) controlling for victimization (see Section 3.2.1), and regional differences: studies in England and Wales repeatedly found negative age effects (Brunton-Smith and Sturgis 2011; Farrall, Jackson, and Gray 2009; Jackson 2009). Nonetheless, the catchphrase that older people are "prisoners of fear" survived and was echoed over the decades (see, e.g., Ferraro 1995; Greve, Leipold, and Kappes 2017).

Importantly, the influence of age strongly depends on the (affective, cognitive, or behavioral) component of fear of crime. Ferraro and LaGrange (1992; see also 1987; 1988; Ferraro 1995) provided a comprehensive study (n = 1,010) that investigated age effects on different measures of fear of crime. They compared crime-specific measurements of the affective component asking people to "rate" their fear of, e.g., "being robbed or mugged on the street" and 10 other criminal offenses with different variants of localized fear. For all but one measure, they found no effect of age—including the normally strong effect of age on localized fear—which cast doubts on previous findings (but also the representativeness of their study). On the basis of a considerably larger survey (n = 15,771) in Germany, Greve (1998, 277) underscored that fear of crime is no "monolithic concept." Some components and measurements of fear (avoidance behavior and localized fear) were strongly related to age, whereas others (crime-specific fear and perceived risk) were not.

How older people perceive their safety with regard to environmental characteristics was long debated in different disciplines. In criminology, Yin's (1985, 36–40) person–environment theory of fear of crime stressed the mutual dependency of vulnerability and "neighborhood peril" but assumed a linear relationship between both (see also Section 2.5.1). However, two older and methodologically less advanced studies indicated that neighborhood characteristics were less important for the fear of crime among older people (Maxfield 1984; McGarrell, Giacomazzi, and Thurman 1997). Both studies argued that older people are not less affected but that younger people are more affected by neighborhood conditions.

In respect of this, environmental gerontology suggests two potentially opposing circumstances. On the one hand, older residents might have become strongly attached to their neighborhoods because many had lived in the same neighborhood for decades (Wahl and Oswald 2016). This could generate a deliberative ignorance of fear-provoking neighborhood characteristics. On the other hand, the "environmental docility" hypothesis (Lawton and Simon 1968), states that the environment gains importance if people's competencies (e.g., health, socioeconomic status, and cognition) decline. Therefore, older people are more reliant on their neighborhoods and spend more time there (Saup and Reichert 1999). Empirically, Ward, Sherman, and La Gory (1988; pp. 56-57; see also Ward, LaGory, and Sherman 1986) found that the percentage of Blacks and tract income were stronger predictors of less competent people's feelings of safety (taking age, widowhood, and functional health limitations as proxies for competency). Ward, Sherman, and La Gory (1988) investigated interaction effects among neighborhood conditions, physical limitations, and household composition on neighborhood satisfaction and feelings of safety. They found that living alone and having physical limitations were related to both, neighborhood satisfaction as well as feelings of safety. However, living in a deprived neighborhood, having physical limitations, and living alone resulted only in lower feelings of safety. Independent of age, Brunton-Smith and Sturgis (2011) found that people with limiting illnesses were more affected by the independently assessed disorder.

Although Agnew (1985) suggested that victimization has stronger effects on older people, the author is unaware of a recent quantitative study that examined this interaction effect (see Section 2.5.1).

2.4.3.3 Social factors

Social vulnerability factors were less clearly conceptualized than physical vulnerability factors and summarized dissimilar categories of individual social disadvantage and social capital.

2.4.3.3.1 Financial strain and education

A conventional explanation for the reason behind poor people being more vulnerable is that they live in neighborhoods with greater incivility and crime (e.g., Covington and Taylor 1991; Hale 1996; Pantazis 2000; Skogan and Maxfield 1981). Strictly differentiating between individual and contextual units of explanations, this argument holds little weight: the actual cause of fear is the neighborhood, not the financial situation. This differentiation casts doubt on the explanatory power of social vulnerability in (classical) studies as being unable to control adequately for (independently assessed) neighborhood characteristics (e.g., Clemente and Kleiman 1977; Liska, Sanchirico, and Reed 1988; Biderman 1967). This argument gains relevance with a look at Oberwittler's (2008) study in Cologne, Freiburg, and rural areas. He found that the significant effect of being a welfare recipient disappeared when he controlled for the percentage of welfare recipients under age 18 in the neighborhood.

Pantazis (2000, 416) summarized other theoretical arguments that relate individual poverty to vulnerability to crime. According to her, poor people might be unable to secure their home adequately, have greater problems compensating for material losses (e.g., robbery), and are exposed to more threatening situations because they cannot afford private transportation. She sounded a note of caution about social networks: although poorer people have fewer friends, their relationships might be closer. Boers (1991, 218) argued that higher education leads to more differentiated threat assessment and reduced symbolic salience of crime and insecurity.

2.4.3.3.2 Personal social capital

Social capital in its various forms has attracted scholarly attention over the past three decades. It refers to various loosely connected concepts from different social science traditions (Bourdieu 1984; Coleman 1994; Putnam 1995; Putnam 2001). This section focuses on individual social capital (e.g., emotional support) rather than supra-individual social capital (e.g., collective efficacy[6] in a neighborhood). Fear of crime literature conceptualizes social capital in numerous ways and often carelessly as a personal or environmental unit of analysis (Taylor 2002). The extended vulnerability approach differentiates between both levels of social capital.[7]

From the vulnerability perspective, high personal social capital reduces fear of crime because people can rely on a supportive network that ameliorates the consequences of victimization. However, Sacco (1993) found no overall evidence for that hypothesis. No consistent pattern emerged in a subsequent subgroup analysis. Although family support exhibited a small negative effect on perceived neighborhood safety among women, it also correlated positively with the same dependent variable for people below age 60. In contrast, Ross and Jang (2000) found that informal exchanges with neighbors attenuate the effect of perceived disorder on fear and mistrust. Ferguson and Mindel (2007) hypothesized that social support networks are negatively related to fear of crime. However, they found that social support was not directly related to how often respondents thought about crime but was related positively to behavioral fear. A closer look at their operationalization makes that finding unsurprising.[8] Oberwittler (2008) found that neighborhood social contacts were significant only after he controlled for the individually perceived disorder.

Some studies investigate the effects of social capital among older people. De Donder et al. (2005) tested a series of bivariate correlations with fear and several relevant predictors. They found that loneliness increased fear, whereas social and cultural participation reduced the fear of crime in their sample of 4,747 people above age 60 in West Flanders. In a subsequent study with a considerably larger sample of 24,962 people above age 60, De Donder et al. (2012) confirmed these findings via multivariate regression, albeit without controlling for health, although some forms of social capital might depend on health. Oh and Kim (2009) investigated the relationship between neighborhood attachment and fear of crime with a focus on age. They argued that social networks change as people age: the quantity of social contexts declines. However, the intensity of the remaining social contacts increases (Carstensen 1995), and the number of social contacts in the neighborhood might increase slightly (Campbell and Lee 1992). Oh and Kim (2009) found that the number of friends was unrelated to fear of crime; however, the frequency of neighborhood contacts was related to it marginally and negatively. No measure of social capital (also tested for cohesion and control) interacted with (dichotomized) age. However, fear positively interacted with age when explaining the frequency of neighborhood contacts and social cohesion.

[6] Sampson (2012 ch. 7) defined collective efficacy as the combination of social cohesion and shared expectations for social control.

[7] Strictly speaking, social networks, e.g., with friends, neighbors, or club members are also contexts, however, on a much smaller scale and with way higher personal controllability to choose between alternatives. Therefore, they are regarded as an individual factor here.

[8] They measured social support networks as mutual home watch between neighbors which is very close to the behavioral component of fear of crime.

2.4.4 Life events

Fear of crime research has paid considerable attention to victimization but neglected other life events. Recent life events can be stressors that influence perceptions of environmental adversity. The causal pathways of potentially traumatizing experiences in (early) childhood and adolescence differ substantially from those of recent life events. They are hypothesized to have a long-lasting impact and possibly generate developmental disadvantages that manifest their effects throughout life.

2.4.4.1 Victimization and other recent life events

Strong empirical evidence supports the effect of victimization on fear from early panel data (Skogan 1987). However, other studies (Hindelang, Gottfredson, and Garofalo 1978, ch. 8; Arnold 1991; Skogan and Maxfield 1981, ch. 4; Gibson et al. 2002; Kury and Ferdinand 1998; Denkers and Winkel 1998) found weak and sometimes negative (Box, Hale, and Andrews 1988) effects of victimization on fear that cast doubt on its relevance in explaining victimization. Possible reasons for inconsistent findings unveil the difficulties in estimating the effects of life events with cross-sectional data. These problems have long been known (Hindelang, Gottfredson, and Garofalo 1978, 190; Skogan and Maxfield 1981, 65; DuBow, McCabe, and Kaplan 1979, 10; Skogan 1987) but only recently addressed with sophisticated methods and adequate panel data (Averdijk 2011; Bauer 2015; Braakmann 2012).

Previous studies argue that reaction to the experience of crime is shaped by its severity and repetitiveness, respondents' personal characteristics, and the social environment (Agnew 1985; Kaniasty and Norris 1992; Kilpatrick and Acierno 2003; Kury and Ferdinand 1998; Verdun-Jones and Rossiter 2010). These individual considerations can have widely divergent physical, mental, and economic consequences. Although considerable research has identified and evaluated the offenses that are particularly severe at the social level (see Ramchand et al. 2009 for a review), in-depth victimization studies should differentiate among noncontact crime (e.g., theft), (attempted) burglary, and personal crimes (Kury and Ferdinand 1998, 107) so as to consider the variance in severity.

Today, there is little doubt that victimization increases fear of crime. However, most previous studies did not distinguish within-person effects from between-person differences because doing so was impossible, given researchers' cross-sectional data or choice of model. Analyzing cross-sectional data from Italy, Bulgaria, and Lithuania, Jackson and Gouseti (2015b) showed direct and mediated effects of victimization on worry regarding violent victimization by a stranger. They found that the effect was partially mediated by perceived controllability, likelihood of occurrence, and consequences of violent victimization. With data from Athens (n = 431), Tseloni and Zarafonitou (2008) predicted three fear of crime measures simultaneously and found that being a victim or knowing a victim within the past 12 months predicted feelings of being unsafe about walking alone after dark as well as the perceived risk of victimization. For other, recent cross-sectional studies, see Brunton-Smith and Sturgis (2011), Hanslmaier (2013), and Hanslmaier, Kemme, and Baier (2016).

Analyzing two waves of a Mexican panel study with 12,192 respondents, Braakmann (2012) found several within-person changes in behavioral fear of crime (applying fixed-effects modeling). Female victims of crime altered their mode and route of transportation. Male victims, on the other hand, more often carried weapons. Counterintuitively, he also found that victims carried valuables and men went out more often, a finding that he explained with reversed causality. Russo, Roccato, and Vieno (2013; see also Russo and Roccato 2010) analyzed four waves of a nationally representative panel survey in Italy with multilevel models. Their findings support the contention that victimization is related to within-person changes in fear of crime. Unfortunately, they did not distinguish between-person differences from within-person changes (Hoffman 2015, ch. 8; Bell and Jones 2015). Other longitudinal studies investigated within-person changes that are attributable to victimization but investigated dependent variables other than fear of crime (Ambrey, Fleming, and Manning 2014; Bauer 2015; Frijters, Johnston, and Shields 2011).

Few studies examine how life events other than victimization influence fear of crime. In a qualitative study of older people in England, Pain (1997) found that life events such as a partner's severe illness occasionally increase (behavioral) fear.

2.4.4.2 Experiences in (early) childhood and adolescence

Despite the frequent analysis of age in fear of crime studies, there is almost no knowledge regarding generational effects. Importantly, (non-kinship) generations differ from cohorts because particular social or historical circumstances are regarded as exclusive to adjacent cohorts (for a definition of generational effects in contrast to cohort effects, see Alwin and McCammon 2003). In comparison with age effects (which are attributable to physical, psychological, or attitudinal changes with age), generational effects reflect changing social conditions around birth and during childhood and adolescence. Scholars from various disciplines have underscored the importance of this more complex view for decades (Baltes 1968; Glenn 2005; Mason et al. 1973; Mason and Fienberg 1985; Ryder 1965; Schaie 1965; Riley 1973; SMR 2008).

A widely known application of a generational perspective is Putnam's (2001, ch. 14) study on social capital. He distinguished the "civic" generation born between 1925 and 1930, who witnessed the Great Depression and World War II, from "post-civic" generations ("Boomers" and "X'ers") born after 1945 and raised with television, who never developed a comparable sense of civic engagement despite their higher educations.

Koeber and Oberwittler (2019) recently investigated generational effects on localized fear in a hierarchical age-period-cohort model of eight waves of the German subset of the European Social Survey. While they found that the War Generation (i.e., people born between 1929 and 1947) had marginally increased fear of crime (controlling for age, period, and a continuous cohort trend), they were unable to test the effects of detrimental experiences directly because these events were not surveyed. Accordingly, they concluded that "if such effects exist, we are likely to underestimate them in the absence of direct measurements."

2.4.5 The residential neighborhood

Residential neighborhoods are spatial environments wherein residents encounter various social forces. It is a geographic area where daily life transpires and people face potential threats. For reasons of feasibility, neighborhoods are considered to be a primary source of perceived environmental adversity.[9]

Scholars, mainly criminologists, have spent considerable effort on explaining the reasons behind certain places being more fear-generating than others. Today, criminologists can lean on comprehensive theory and advanced methods to explain the spatial concentration of fear of crime in some neighborhoods (Brunton-Smith and Sturgis 2011; Brunton-Smith and Jackson 2012; Brunton-Smith, Jackson, and Sutherland 2014; Drakulich 2013; Drakulich 2015; Häfele 2013; Robinson et al. 2003; Taylor 2001; Oberwittler, Janssen, and Gerstner 2017; Oberwittler 2008; Wyant 2008).

The incivilities (or disorder) hypothesis is among the most frequent explanations for neighborhood differences in fear of crime. The term "incivility" denotes a violation of broadly shared norms of behavior in public (Skogan 2015) and is typically divided into physical (graffiti, signs of vandalism, and drug use) and social incivilities (adolescents hanging around, drunks, and brawls). According to American scholars (Hunter 1978; Lewis and Salem 1986; Skogan 1990; Wilson and Kelling 1982), incivilities trigger fear of crime because people perceive them as "cues of crime" that increase the perceived risk of victimization and indicate little social control in the area.

However, individually perceived and independently measured levels of disorder differ systematically (Drakulich 2013; Jackson et al. 2017; Hipp 2010b; Franzini et al. 2008; Oberwittler, Janssen, and Gerstner 2017; Perkins, Meeks, and Taylor 1992; Sampson and Raudenbush 2004; Sampson 2009). Studies repeatedly find that poverty, ethnic composition, fear of crime, and victimization affect perceived disorder more than they affect independently assessed disorder. This simultaneous causality between fear and perceived disorder casts doubt on studies that relate perceived disorder to the fear of crime. In addition, such studies might underestimate the actual effect of poverty and ethnic composition attributable to the inflated

[9] This assumption is maintained even though some people spend little time in their residential neighborhoods and more time at work, the city center, or elsewhere. Other theoretical concepts are needed to capture such floating contexts (see, e.g., Goffman's (1971, ch. 6)) that pose challenges to empirical research. For a successful implementation regarding crime causation, see Wikström et al. (2012). A promising project in this regard is conducted by the Griffith University (Chataway et al. 2017).

correlation between perceived disorder and social disadvantage at the neighborhood level. Accordingly, studies found smaller or nonexistent effects of independently assessed disorder on fear of crime (Covington and Taylor 1991; Häfele 2013; Perkins and Taylor 1996). As a further complication, Oberwittler, Janssen, and Gerstner (2017) found that independently assessed disorder explained 65% of neighborhood variance in Essen (a declining "rust belt" city) but not in Cologne (a city with a large "creative class").

Contrary to common sense, the effect of police-recorded neighborhood crime rate on fear is low or nonexistent. Although some studies link some types of crime to fear of crime (Brunton-Smith and Sturgis 2011; Drakulich 2015; Hipp 2010a; Hipp 2013; Oberwittler, Janssen, and Gerstner 2017; Wilcox Rountree and Land 1996; Taylor 2001), other investigators find no such link (Ferraro 1995; Häfele 2013; Lewis and Maxfield 1980; Liska, Lawrence, and Sanchirico 1982; Taylor and Shumaker 1990; Wyant 2008).

Among the most robust findings is that neighborhood social disadvantage (e.g., poverty and ethnic composition) explains the lion's share of neighborhood differences of fear of crime (Covington and Taylor 1991; Markowitz et al. 2001; Oberwittler, Janssen, and Gerstner 2017). On the basis of British Crime Survey data from 102,133 respondents in 5,196 neighborhoods, Brunton-Smith and Sturgis (2011) found that sociodemographic variables explained 30% of neighborhood variance in worries regarding victimization. Adding recorded crime rates and systematic observations of disorder increased the explained variance only meagerly, by 3%. Taylor, Shumaker, and Gottfredson (1985) attributed 52% of neighborhood differences in fear to percentages of renters, Blacks, and low-income residents. More recently, Drakulich (2013) explained 46% of neighborhood variance in localized fear (which he called "perceived crime") with independently assessed incivilities. Adding neighborhood crime, poverty, and ethnic composition to the model, however, explained 94% of the total neighborhood variance and rendered incivilities nonsignificant. These findings suggest problems with multicollinearity and highlight the importance of careful and simultaneous consideration of different neighborhood characteristics (particularly social disadvantage, crime, and disorder). In a German study by Oberwittler (2008), the percentage of welfare-dependent children accounted for 86% of neighborhood variations in localized fear, whereas crime rates explained none. In another study in Hamburg, Häfele (2013, 195) found a highly significant effect for social disadvantage (percentage of foreigners, council flats, unemployed, and social welfare recipients) and a weak effect for independently assessed social incivility on localized fear. However, Häfele (2013) found no effect for physical incivility and a negative effect of neighborhood crime on localized fear. In this study, social disadvantage accounted for 47% of neighborhood differences and crime explained an additional 9%.

2.4.5.1 The spatial spread of neighborhood problems

Criminology and other spatially oriented social sciences discussed the optimal size of spatial units to measure and explain social phenomena for decades. This is known as the modifiable area unit problem. (Openshaw and Taylor 1979). There is growing consensus that small and homogeneous spatial units are preferable references for predicting crime (Gerell 2017; Oberwittler and Wikström 2009; Reynolds 1998). However, an exclusive focus on small-scale neighborhoods presents the risk of violating "spatial logic" (Sampson 2012, ch. 10), i.e., missing essential information regarding urban spaces beyond the immediate residential area.

When modeling spatial dependency (Anselin et al. 1996), three statistical methods with critical theoretical differences can be distinguished.[10] Spatial error models emphasize the assessment and consideration of spatial autocorrelation. Spatially lagged outcomes and spatially lagged predictor models share stronger causal claims. Unlike the spatial error model, spatially lagged outcome and predictor models require hypothesizing whether and which variables of adjacent neighborhoods influence outcomes. Spatial error models and spatially lagged outcome models investigate whether error terms of the dependent variable correlate. Global statistics (e.g., Moran's (1950) I) or local indicators of spatial associations, such as local Moran's I or G_i^* (Anselin 1995; Getis and Ord 1992), indicate whether (or where) spatial autocorrelation is detectable and might be considered. In contrast, spatially lagged

[10]While some textbooks (e.g., Elhorst 2014) prefer introducing spatial error and spatially lagged models Taylor (2015, 111) argues that important theoretical discriminations within the spatially lagged models receive insufficient consideration. Following Taylor, spatially lagged outcome and predictor models are introduced separately even though a classification like this fails to capture so-called Spatial Durbin Model (Anselin 1988, 196) which entail both a spatially lagged outcome and predictor.

outcome or predictor models postulate hypotheses regarding the diffusion or exposure of already considered variables. Such models are theoretically "more ambitious" (Sampson 2012, 246) in contrast to the somewhat exploratory use of spatial auto-regression parameters within the spatial error framework. Further, the objective of spatially lagged outcomes and spatial error models is to explain the spatial autocorrelation of the dependent variable. According to Taylor (2015, 116), this is not required by spatially lagged predictor models.

With the assumption of constant activity and perception radius of inhabitants, it can be said that the smaller the spatial unit the higher the risk of losing explanatory potential from adjacent areas. Psychological distance (see Section 2.3.2) and research on perceived disorder and crime underscore the theoretical and empirical importance of investigating neighborhood effects on different spatial scales (Conley, Stein, and Davis 2014; Hipp 2007; Groff and Lockwood 2014). The underlying mechanism of spatially lagged predictor models is, e.g., that high crime rates in surrounding neighborhoods increase fear of crime. This causal claim is, for studies investigating fear of crime, more intuitive than the spatially lagged outcome model that tests whether fear of crime in one neighborhood spills over to adjacent neighborhoods. The theoretical explanation why a personal emotion such as affective fear of crime should be contagious or diffuse between neighborhoods is hardly justifiable. In contrast, exposure to social problems in adjacent neighborhoods that is attributable to daily mobility is a more reasonable causal mechanism.

Fear of crime research generally ignores spatial dependency despite its focus on neighborhoods. Wyant (2008) hypothesized that people (offenders and potential victims) are likely to cross neighborhood boundaries or hear about crime in nearby neighborhoods. Confirming this hypothesis, he found a significant spatial autocorrelation (Moran's I: .148) in his measurement of localized fear. Although his underlying causal mechanism suggests exposure to the adjacent neighborhood and not contagious fear, he calculated in the second step a spatially lagged outcome model that had no additional effect on his dependent variable after controlling for neighborhood characteristics (e.g., incivilities, racial heterogeneity, and officially recorded violent crime). Information regarding spatially lagged predictors is not supplied. Brunton-Smith and Jackson (2012) investigated the influence of adjacent neighborhoods with a large sample of urban and inner-city areas in England (n = 76,494, N = 4,787). They found that interviewer-assessed disorder and crime in residential and surrounding neighborhoods predicted fear, whereas including the spatial lags reduced the strength of corresponding variables in the immediate area by approximately 30%. Barton et al. (2017) analyzed spatially lagged crime and found that crime in adjacent neighborhoods had a significant effect on localized fear only when controlling for no other neighborhood variables.

2.5 An extended vulnerability model

Section 2.4 introduced vulnerability as a relational concept. Drawing upon the general definition, it was indicated that vulnerability in fear of crime research is an interaction between perceived environmental adversity and anticipated individual openness, controllability, and consequences regarding victimization. Hence, two analytical components and an anticipated link generate fear of crime. At the center is someone who anticipates three dimensions of vulnerability (openness, controllability, and consequences) and is or perceives him- or herself as more or less vulnerable[11] because of vulnerability factors (see Figure 2.1). This person inhabits a social environment that is (interpreted as) more or less adverse. That interpretation is based on neighborhood characteristics (social disadvantage, crime, and incivilities), life events (particularly victimization), and individual beliefs (e.g., generalized trust). This evaluation does not need to generate increased worry or the perceived risk of victimization. Perceived vulnerability, in combination with perceived environmental adversity, might also result in precautions that can reduce the perceived likelihood of victimization and unease regarding crime.

As a relational concept (see Section 2.4), vulnerability is irrelevant in the absence of individual factors or environmental adversity. However, in real-life considerations of crime, environmental adversity and resistance to victimization are never completely absent. Hence, it is more regarding degrees of one (environmental adversity or vulnerability factors) in comparison with the other (see Section 2.5.1).

[11] Regarding property crime, this anticipation also includes possessions.

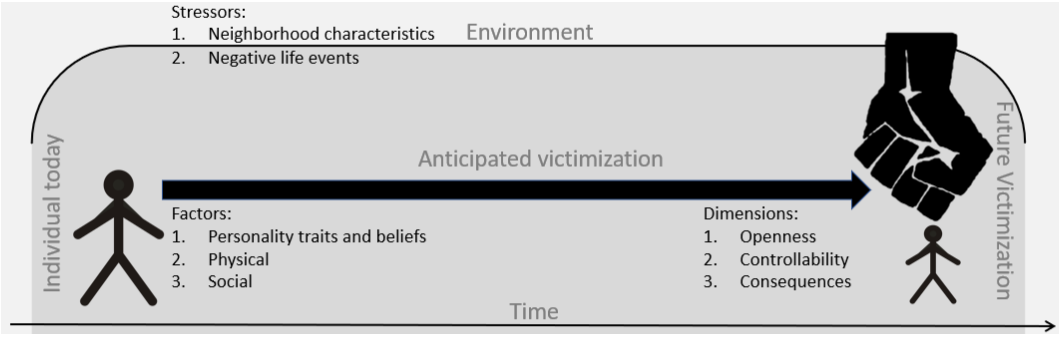

Figure 2.1: The anticipation process of vulnerability to crime embedded in a social environment

Unlike vulnerability in other disciplines,[12] laypersons rarely assess environmental adversity and individual factors on the basis of reliable data or analyses. Instead, their evaluations are based on retrievable data and representativeness heuristics (see Section 2.2). Hence, perceived vulnerability to crime might approximate an actual assessment of personal and environmental characteristics but is likely to be under- or overestimated. Accordingly, an individual can either ignore the environmental adversity (the most extreme form of underestimation) or roughly assess it on the basis of retrievable information (based, e.g., on media reports or personal victimization history in a neighborhood) as well as specific features of the environment (e.g., ethnic composition or incivilities). Similarly, the individual capabilities to respond to a victimization approach are assessed not only on objective criteria (such as physical strength) but also on less tangible factors such as personality traits, beliefs, or attitudes (e.g., locus of control, generalized trust, and xenophobia).[13]

Figure 2.2 displays the causal structure of the extended vulnerability approach. The vertical direction distinguishes between the individual and the environment. Unidirectional arrows indicate causal effects, and double-sided arrows indicate interactions. Darkened arrows indicate tested hypotheses. Outlined arrows indicate potential but untested effects. Overall, Figure 2.2 shows that individual factors, life events, and neighborhood characteristics influence perceptions regarding the environment, the risk of victimization, and perceptions of vulnerability based on considerations of openness, control, and consequences. These perceptions are the proximal causes of crime-specific and localized fear, as well as avoidance behaviors. These outcomes might influence perceptions of risk, but that question is not investigated. Most analyses circumvent problems of simultaneous causality by not modeling the perceived risk of victimization or the perceived neighborhood characteristics as predictors. Perceptions of risk and fear of crime are positioned between levels, indicating that some variance is attributable to the neighborhood even though individual predictors determine the larger part.

To an extent, this approach resembles Warr's "sensitivity to risk" model (see Section 2.3.1). However, there is an important analytical difference: instead of focusing on the (accurately perceived) risk of victimization, the extended vulnerability approach stresses that personal vulnerability is a relational perception where environmental adversity interacts with vulnerability dimensions (openness, controllability, and consequences). Drawing upon Loewenstein et al. (2001) and Greve, Leipold, and Kappes (2017), Section 2.2 argues that perceived risk is not only a function of individual and environmental factors but also results from precautionary actions and emotional arousal. This concept of vulnerability is compatible with the generalization approach that diffused anxieties are projected onto crime. Through the lens of vulnerability, this results in a heightened perception of environmental adversity.

[12] An example of such an expert vulnerability assessment is the study of O'Brien et al. (2004). They mapped vulnerability to climate change of Indian regions. O'Brien et al. (2004) operationalized adaptivity and sensitivity with a range of regional information and summed both scores to provide a single vulnerability index of a particular region to climate change. An overview and comparison of other vulnerability approaches is provided by Alwang, Siegel, and Jørgensen (2001).

[13] The so-called appraisal style in the positive appraisal style theory of resilience (Kalisch, Müller, and Tüscher 2015) expresses the same idea regarding psychological dysfunctions but is more comprehensive and versatile. The notion of under- or overestimation of risks and coping capabilities within the extended vulnerability approach was, however, developed independently from it.

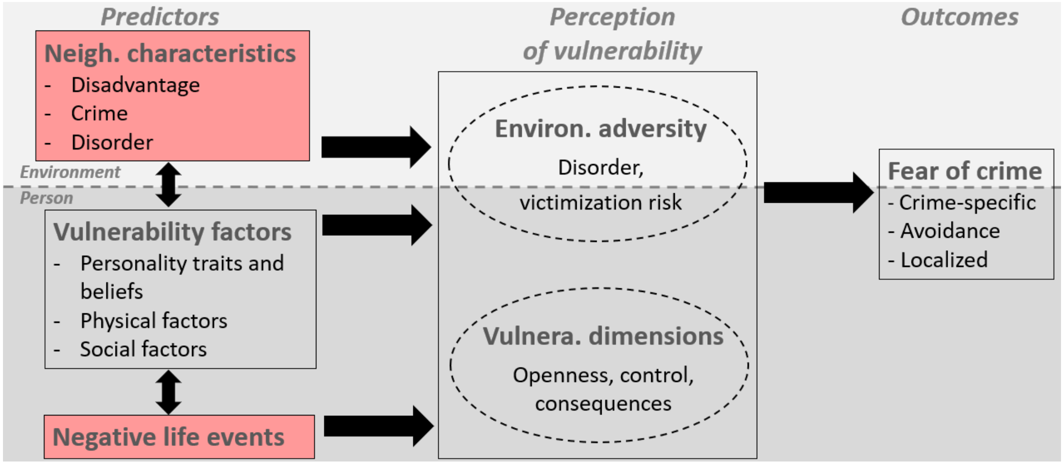

Figure 2.2: Overview of hypothesized causal relationship

2.5.1 Interactions between physical vulnerability factors and stressors

As a relational concept, vulnerability is inclined toward interaction analyses between (physical) vulnerability factors and adverse external stimuli such as neighborhood characteristics and detrimental life events. Despite this plausible relationship, hardly any theoretical approach investigates such interactions except Yin's (1985, ch. 3) person-environment theory and Agnew's (1985) neutralization techniques. However, Yin's theory suggests an additive relationship that is equal to no interaction. More precisely, this approach argues that low levels of fear exist only in the absence of environmental peril and individual vulnerability. Medium fear occurs if environmental peril is high (low) and vulnerability is low (high). Intense fear requires high individual vulnerability and environmental peril.

Regarding vulnerability factors and victimization, Agnew (1985) identified five neutralization techniques and summarized them with rough but memorable statements.[14] Accordingly, some victims apply coping techniques that are less successful than others (e.g., convincing themselves that their victimization was not harmful). He underpinned this hypothesis with qualitative findings and suggested that their usage depends on the characteristics of the victim (and the victimization itself). Agnew (1985, 233–34) argued that older people and women might have greater problems in applying these techniques successfully because their higher likelihood of physical damage makes it harder for them to deny injury. Further, he hypothesized that women and older people who were once victimized have problems denying their vulnerability. Both neutralization techniques suggest positive interactions between physical vulnerability and victimization.[15]

Overall, theoretical reasoning until now has indicated that vulnerable people are more (or at least not less) affected by the same amount of adverse external stimuli. Stressors can trigger equal, higher, or lower effects on people, depending on their vulnerability. If there is no significant interaction, the vulnerability model holds true because vulnerable people are consistently more fearful irrespective of stressors (see Figure 2.3 a). The conceptually more relevant question is whether vulnerable people are more or less fearful depending on the adversity of external stimuli. Such interactions reveal that physically vulnerable people have differing susceptibility to stressors.

More detailed, positive interactions (see Figure 2.3 b) between individual vulnerability factors and external stimuli imply stronger reactions. This is the theoretically more plausible reaction that considers higher stressor adversity in combination with heightened individual openness, reduced controllability, and more detrimental consequences of victimization (see Section

[14] Denial of injury ("I wasn't hurt badly"), denial of vulnerability ("I probably won't be hurt again"), denial of responsibility ("The victimization was not my fault"), belief in a just world ("The criminal has been (will be) punished properly"), and appeal to higher loyalties ("I did it for a good cause").

[15] Jackson and Gouseti (2015b) investigated interactions between the need for cognitive closure and victimization but found no differential effects. They provided some interesting theoretical arguments which are, however, not relevant for this section since they are not applicable to physical vulnerability factors.

2.4). A negative interaction, however, would falsify the conventional notion of vulnerability because (in the absence of floor or ceiling effects) the presumably vulnerable group reacts less to stressor adversity (see Figure 2.3 c).

Empirical findings for such interactions are ambiguous. Subgroup-specific interactions are discussed more thoroughly in the literature review (see Section 2.4.3) and are summarized here. Early investigations hypothesized positive interactions between vulnerability and neighborhood problems but found no empirical support (Skogan and Maxfield 1981, 117–21). Subsequent studies (Maxfield 1984; McGarrell, Giacomazzi, and Thurman 1997) found that age significantly predicted fear only in low- and medium-disadvantaged neighborhoods. That suggests a counterintuitive negative interaction between age and social disadvantage (see Figure 2.3 c). This finding was interpreted as indicating the "limits of vulnerability" because "everyone is more afraid" (Maxfield 1984, 246) in crime-ridden neighborhoods. Although Maxfield (1984) found no such differences in the case of women, recent studies found stronger effects of (perceived) disorder among women than they did among men (Brunton-Smith and Sturgis 2011; Smith, Torstensson, and Johansson 2001; Snedker 2015). Little quantitative evidence supports that physical vulnerability interacts with victimization. However, Braakmann (2012) found that women, but not men, altered their mode of transportation after being victimized, whereas men more often carried weapons.

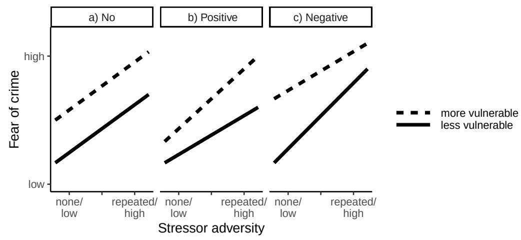

Figure 2.3: Interactions between individual vulnerability factors and environmental adversity

Theoretical explanations and empirical findings underpin these differential effects. Many studies found that women perceive more disorder than men after controlling for independently assessed disorder, and that likely induces more fear (Drakulich 2013; Hipp 2010b; Sampson and Raudenbush 2004; see, however, Jackson et al. 2017; Quillian and Pager 2001). Cobbina, Miller, and Brunson (2008) found that potentially aggressive unemployed men and gang members confront women more often than men. Other qualitative studies from the US argued that devaluations and mistreatment of women might be less despised in socially disadvantaged areas (Miller 2008; Bourgois 1996). With regard to the differential effects of neighborhood characteristics, depending on age and health, the environmental docility hypothesis (Lawton and Simon 1968) suggests that the immediate environment becomes more decisive with decreasing competences in old age. Acknowledging this argument, Wahl and Oswald (2016) added that older residents might have stronger attachment to their neighborhoods (and other, nearby environments) than younger people because many have lived in the same neighborhood for decades. Therefore, older people might ignore fear-provoking neighborhood characteristics.

2.5.2 A dynamic perspective on vulnerability and fear of crime

Notwithstanding the abundance of research, the author is not aware of theoretical or empirical studies that examine how changes in vulnerability affect fear of crime. In Skogan and Maxfield's (1981) vulnerability approach, time is implicitly relevant to a temporal ordering of dimensions (exposure, control, and consequences). There must have been 1) exposure to criminogenic settings for victimization to occur. Only if 2) victimization occurs someone might lose control of the situation (e.g., being unable to respond), and 3) consequences can be felt only after victimization (see Section 2.4). The cross-sectional nature of most studies and the implicit assumption of strong rationality (see Section 2.2) might explain this restriction. Thus, there was no need for more complex temporal approaches. However, a stronger focus on perceptions and explicit consideration of bounded rationality shift attention to changes in perceptions and eventually to fear of crime. The key idea is that perceptions of vulnerability might change when certain events occur (e.g., victimization, signal crimes, or political events such as the fall of the Berlin Wall). While the objective fight-or-flight capabilities and the environmental risk of victimization might remain (largely) unchanged, the perceived environmental adversity and the anticipated individual openness, controllability, and consequences regarding victimization can change abruptly.

The benefits of a dynamic perspective are twofold: it allows testing whether hypothesized influences are longitudinally valid. This investigation would provide more solid evidence for or against the vulnerability approach because it reduces unobserved heterogeneity by distinguishing between-person differences from within-person changes (see Figure 2.4). This also enables the integration of the consequences of life events on perceived vulnerability—more precisely, on both time-varying individual factors and perceived environmental adversity.

The differentiation of between-person differences and within-person changes is outlined in Figure 2.4, with fear of crime on the y-axis and time on the x-axis. Instead of investigating only between-person differences, as cross-sectional research necessarily does, longitudinal multilevel analyses allows for the disaggregation of within-person changes from between-person differences and modeling them simultaneously (for a technical discussion, see Section 3.3.1). Within-person estimates provide less biased estimates of predictors' causal effects. Gender and age are regarded as time-stable[16] variables. Therefore, the longitudinal analysis is restricted to personality traits (internal and external locus of control and ambiguity intolerance), generalized trust, and physical (self-rated health) and social (poverty, neighborhood contacts, and civic engagement) factors of vulnerability.

The author expects little overall change that is attributable to the presumably high stability of personality traits. However, several recent studies contest that conventional notion. Cobb-Clark and Schurer (2013) investigated the influence of time and life events on the locus of control and found modest changes (predominantly for older and younger people) over the life course. Most analyzed life events had no significant effect on the locus of control. Notably, the birth of a child and worsening financial situations increased external locus of control, whereas changing jobs and financial improvements increased internal locus of control (see also Borghans et al. 2008; Cobb-Clark and Schurer 2012; Roberts, Walton, and Viechtbauer 2006).

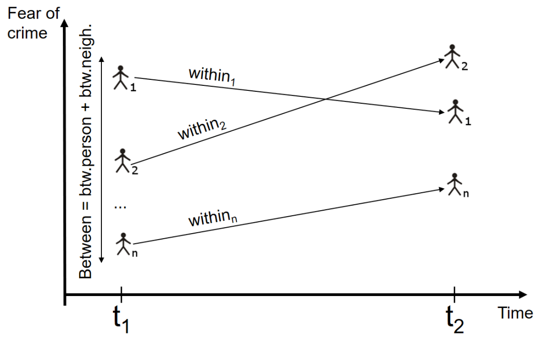

Figure 2.4: Intuition of between-person differences and within-person changes

2.5.3 Vulnerability factors

2.5.3.1 Personality traits and beliefs

Personality traits such as the locus of control (Rotter 1966) and ambiguity tolerance (Budner 1962) provide useful psychometric information regarding people's self-assessments of their ability to evade or attenuate victimization and cope with its consequences. This thesis hypothesizes people who believe that the outcome of events is mainly controlled by others as more fearful (and people who perceive the outcome of events mostly in the realm of their actions as less fearful). Further, since victimization is seldom foreseeable, it might be particularly fear-generating for ambiguity intolerant people (Jackson 2015). According to these hypotheses, the locus of control and the intolerance of ambiguity are further mediated by perceived controllability and consequences.

$\text{H1}_{\text{pers\&bel}}$: *External locus of control increases fear.*

$\text{H2}_{\text{pers\&bel}}$: *Internal locus of control lowers fear.*

$\text{H3}_{\text{pers\&bel}}$: *Ambiguity tolerance lowers fear.*

$\text{H4}_{\text{pers\&bel}}$: *The effect of locus of control on fear is mediated by vulnerability.*

$\text{H5}_{\text{pers\&bel}}$: *The effect of ambiguity tolerance on fear is mediated by vulnerability.*

Generalized trust is interpreted as a neighborhood-independent assessment of environmental adversity and hence as part of the proposed vulnerability model. Unlike personality traits,

[16]Gender is not necessarily time-stable. However, the likelihood of changes within the survey period is very low. Age, on the other hand, changes constantly for everyone (on earth). Hence, it is also regarded as time stable in this analysis.

generalized trust does not capture the manner that people evaluate their abilities to deal with victimization (approaches). It provides information regarding how adversely the social environment is perceived (see Section 2.5). In other words, generalized trust is the "intention to accept vulnerability based on positive expectations or beliefs regarding the intentions or behavior of another person or other people in general" (Lange 2015, 71).

$H6_{pers\&bel}$: *Generalized trust lowers fear.*

2.5.3.2 Physical factors

Physical factors of vulnerability are defined as the physical capability to fight back or flee to avoid victimization, the anticipation of more severe consequences, and openness to criminal offenders. Numerous studies investigate gender and age group differences in fear and provide theoretical and methodological explanations for their empirical results. They repeatedly describe gender as the most influential predictor of fear (see Section 2.4.3.2.1).

$H1_{physical}$: *Women are more fearful than men.*

The vulnerability approach was particularly successful in explaining gender differences in fear because it completely mediated the gender effect (Jackson 2009). That finding is retested in this study.

$H2_{physical}$: *The effect of gender on fear is mediated by vulnerability.*

Numerous studies suggest that neighborhood characteristics are more important for women's fear of crime because women might perceive more disorder and are more often confronted by potentially aggressive unemployed men and gang members. Furthermore, the devaluation and mistreatment of women might be less socially despised in more problematic areas (Cobbina, Miller, and Brunson 2008).

$H3_{physical}$: *Neighborhood characteristics are more important for women.*

Decades of fear of crime research studied age-group differences in fear of crime and so does this thesis.

$H4_{physical}$: *Age increases fear of crime.*

The author pays close attention to the particularities of age as a complex predictor of fear of crime. Section 2.4.3.2.1 and 3.2.1 argued that it is crucial to test nonlinear coefficients of age, age-gender interactions, and potentially confounding third variables (particularly victimization).

Insightful studies show that age coefficients strongly depend on the component of fear of crime: behavioral fear of crime is most strongly affected by age. Greve (1998; Greve, Leipold, and Kappes 2017) argued convincingly that older people respond to their increased vulnerability with behavioral adaptations rather than emotional arousal. This hypothesis is retested and expanded to include gender as another frequently investigated predictor.

$H5_{physical}$: *Age and gender has a stronger effect on avoidance behavior rather than on crime-specific fear.*

In contrast to the causal direction assumed in epidemiological studies and drawing upon the vulnerability approach, the author argues that health exerts a more immediate effect on fear when compared with the opposite causal direction. However, results are interpreted with caution, considering the potential for simultaneous causality.

$H6_{physical}$: *Bad health increases fear of crime.*

Health is a more direct measure than age of physical condition. Assuming that the effects of age on fear could be restricted to worsening physical condition, health is likely to be the better predictor of fear because it targets underlying physical mechanisms directly. In a series of mediation analyses, Herbst (2011) found partly strong mediation effects of age on avoidance behavior via objective and subjective health measures.

$H7_{physical}$: *The effect of self-rated health on fear is mediated by age and is the stronger predictor.*

This thesis also investigates whether self-rated health is mediated by beliefs in the controllability of victimization and the anticipated consequences.

$H8_{physical}$: *The effect of health on fear is mediated by vulnerability.*

Drawing on Agnew's (1985) neutralization techniques, the author hypothesizes the consequences of victimization to be stronger for older people, women, and people in poor health.

$H9_{physical}$: *Victimization increases fear more strongly for older people.*

$H10_{physical}$: *Victimization increases fear more strongly for women.*

$H11_{physical}$: *Victimization increases fear more strongly for people with bad health.*

Whether and how health and age interact with environmental adversity is empirically and theoretically ambiguous. Some theoretical approaches argue that neighborhood conditions become more decisive when (older people's) competences decline with diminishing health and a narrowed living environment (Lawton and Simon 1968). More recent approaches argue, however, that older people might develop strong attachment to their neighborhoods after living there for decades (Wahl and Oswald 2016), which could generate deliberate ignorance of fear-provoking neighborhood characteristics. Empirically affirmative results were found for both hypotheses: although people with physical limitations were more affected by neighborhood conditions (Brunton-Smith and Sturgis 2011), older people were less affected by neighborhood problems (Maxfield 1984; McGarrell, Giacomazzi, and Thurman 1997).

$H12_{physical}$: *Age effects depend on neighborhood characteristics.*

$H13_{physical}$: *Health effects depend on neighborhood characteristics.*

2.5.3.3 Social factors

The social factors of vulnerability are often mixed with neighborhood characteristics. As discussed in Section 2.4.3.3.1, financial strain might increase the fear of securing one's home inadequately, recouping material losses from victimization, and affording private transportation (Pantazis 2000, 416). When assessing this hypothesis, it is essential to control for neighborhood social disadvantage to separate individual from contextual effects.

$H1_{social}$: *Financial strain increases fear.*

Once the influence of financial strain on fear is established, the hypothesized mechanisms can be investigated.

$H2_{social}$: *The effect of financial strain on fear is mediated by vulnerability.*

Further, less education might generate less differentiated threat assessments and increased symbolic salience of crime and insecurity (Boers 1991, 218).

$H3_{social}$: *Education lowers fear.*

The vulnerability approach suggests that people with small social networks or less supportive ties have more fear of crime because the consequences might be thought of as being more detrimental without social support.

$H4_{social}$: *Social support lowers fear.*

If this relationship can be established, a subsequent step is to investigate whether this effect is mediated by vulnerability.

$H5_{social}$: *The effect of social support on fear is mediated by vulnerability.*

Similarly, frequent or supportive contact fosters attachment to a residential neighborhood (which reduces perceived environmental adversity in this context) and promises support to prevent victimization or to cope with its consequences.

$H6_{social}$: *Neighboring lowers fear.*

Active citizenship and participation in public life might undermine diffuse anxieties that would be projected on environmental adversity. This hypothesis is not tested here because adequate operationalization was unavailable.

2.5.4 Life events

2.5.4.1 Recent life events

How do experiences change the way people feel, think, and behave concerning crime? The most apparent and heavily investigated life event is victimization, which, according to the vulnerability approach, unfolds its influence through changes in people's perception of environmental adversity and self-evaluation.[17]

$\text{H1}_{\text{events}}$: *Victimization increases fear.*

According to Janoff-Bulman's (1992; 1989; Janoff-Bulman and Frieze 1983) shattered assumptions theory (discussed in Section 2.3.3), potentially traumatic life events such as victimization shatter assumptions regarding the benevolence of the world. Meaningfulness refers to the distribution of outcomes on the basis of justice, controllability, and chance. Therefore, the author examines whether the effects of within-person victimization on fear are mediated by the perceived likelihood of victimization and generalized trust (as environmental components or benevolence), as well as the locus of control.

$\text{H2}_{\text{events}}$: *The effect of victimization on fear is mediated by locus of control.*

$\text{H3}_{\text{events}}$: *The effect of victimization on fear is mediated by perceived victimization risk.*

$\text{H4}_{\text{events}}$: *The effect of victimization on fear is mediated by generalized trust.*

In the absence of empirical studies on recent life events other than victimization, this thesis draws upon the generalized insecurity approach (Hirtenlehner and Farrall 2013) to hypothesize that the unease that accompanies detrimental life events other than victimization is projected onto environmental adversity and increases fear of crime.

$\text{H5}_{\text{events}}$: *Other negative life events increase fear.*

2.5.4.2 Early life events

Section 2.4.4.2 introduced the generational perspective and discussed the limited empirical findings regarding fear of crime. Importantly, (non-kinship) generations differ from other cohorts because particular social or historical circumstances are exclusive to some adjacent cohorts (for a definition of generational effects (in contrast to cohort effects), see Alwin and McCammon 2003). Thus, and in comparison with cohort analysis that draws on longitudinal research to disentangle age, period, and cohort effects, this thesis seeks relationships between detrimental early life events and fear of crime decades later. Bridging such a long period requires strong assumptions and theoretical claims.

The research question pertains to whether social circumstances in Germany during and shortly after World War II created traumatic experiences during childhood and adolescence that have lasting effects on fear of crime today. Theoretically, this generational perspective is an enlargement of the temporal focus that resembles the analysis of adjacent neighborhoods to some degree: instead of investigating the effects of distal spatial units, traumatic early life experiences (peculiar to this historical context) might still have consequences.

The underlying notion of this analysis is that a considerable percentage of older people experienced traumatic life events in their childhood and adolescence that are attributable to World War II, the subsequent "Hungerwinter," and its immediate consequences. Research on health and mortality supports that early life events have significant and long-lasting effects (Barker 2004; Berg et al. 2010; Berg, Doblhammer, and Christensen 2009; Haas 2008; Hayward and Gorman 2004; Jürges 2013; Kesternich et al. 2014; Ben-Shlomo and Kuh 2002; Lundberg 1993; Scholte et al. 2017; Xie and Lagergren 2016). Such positive effects of war-related experiences on fear would indicate, *ceteris paribus*, lower increases in fear with age in future surveys because later cohorts will replace the generation that experienced World War II.

$\text{H6}_{\text{events}}$: *Early life events increase fear.*

[17] This notion is restricted in that sense that it neglects potential positive influences of life events which. This perspective is necessarily circumvented because it entails a notion of resilience or personal growth which is different from vulnerability and, hence, not the focus of this thesis.

Do detrimental life events affect health, personality, or economic position such that it makes respondents more fearful? Bridging the decades between causes and consequences requires solid theoretical reasoning. Cumulative inequality theory (Ferraro, Shippee, and Schafer 2009; Ferraro and Shippee 2009) states that adverse (or advantageous) conditions and experiences earlier in life are likely to accumulate (Ferraro and Morton 2016) to considerable inequalities later in life (e.g., health and social status). Such mediations arguably strengthen the theoretical claim that early life experiences increase fear decades later.

More concretely, cumulative inequality theory suggests that adverse childhood experience such as hunger, expulsion, and persecution generate early disadvantages in health and social status that result in worse health and lower social status in old age. It will be examined whether the effects of detrimental war-related experiences are mediated by poverty, worse self-rated health, and psychological traits (locus of control and ambiguity tolerance), and perceptions of vulnerability (loss of control and seriousness of consequences).

$\text{H7}_{\text{events}}$: *The effect of early live events on fear is mediated by financial strain.*

$\text{H8}_{\text{events}}$: *The effect of early live events on fear is mediated by health.*

$\text{H9}_{\text{events}}$: *The effect of early live events on fear is mediated by of control.*

$\text{H10}_{\text{events}}$: *The effect of early live events on fear is mediated by ambiguity tolerance.*

$\text{H11}_{\text{events}}$: *The effect of early live events on fear is mediated by vulnerability.*

2.5.5 Neighborhood characteristics

In this vulnerability approach, neighborhoods exert an independent influence on their residents. Empirical studies showed that social disadvantage is the most influential predictor of fear of crime at the neighborhood level. This finding supports the notion of a representativeness heuristic according to which people infer environmental adversity from easily comprehensible information about ethnic composition and poverty instead of investigating more complex and volatile occurrences of crime and social incivility.

$\text{H1}_{\text{neighb}}$: *Social disadvantage increases fear.*

$\text{H2}_{\text{neighb}}$: *High crime rates increase fear.*

The smaller effects of independently assessed (physical) incivilities in more recent studies are puzzling and weigh against prominent criminological theories.

$\text{H3}_{\text{neighb}}$: *Incivilities increase fear.*

Drawing upon the construal-level theory of psychological distance (see Section 2.3.2), particularly in combination with spatially small neighborhoods (discussed in Section 2.4.5.1), the author hypothesizes that the fear-provoking effects of neighborhood problems such as social disadvantage and crime spread beyond neighborhood borders.

$\text{H4}_{\text{neighb}}$: *Social disadvantage in adjacent neighborhoods increases fear.*

$\text{H5}_{\text{neighb}}$: *Crime in adjacent neighborhoods increase fear.*

To investigate the spatial spillover hypotheses, global fit measures assess whether spatial lags add explanatory power to the model or merely redistribute the effects of residential neighborhoods that are attributable to collinearity.

Chapter 3

Methods

Quantitative social sciences use sophisticated statistical methods. Section 3.1 introduces techniques to reduce the number of explanatory variables and extract latent variables. All substantial findings, however, are based on regression analysis. Therefore, Section 3.2 is devoted to fundamental aspects of modern regression analysis (hierarchical regression, interactions, and mediation). Furthermore, Section 3.3 introduces multilevel analysis, since its benefits for longitudinal and contextual analysis are increasingly appreciated in the social sciences (Bell and Jones 2015; Heisig, Schaeffer, and Giesecke 2017; Taylor 2010).

Good data visualizations[1] provide a useful supplement to inferential statistics. In comparison to tables or text, visualizations allow compressing considerable amounts of data, knowledge, and results into a small space where they can be perceived almost effortlessly (Ware 2012). By reducing these perceptional burdens, informative data visualization can uncover information and patterns that are hardly processable otherwise. Thus, graphs are used in this thesis for sample description, bi- and multivariate relationship, as well as to present mediation and interaction analyses.

Comprehensive data analysis and presentation is impossible without proper software. All analyses were conducted in `R` (2019). The majority of data preparations was done with `dplyr` (Wickham et al. 2019) and `tidyr` (Wickham and Henry 2019). Rosseel's (2012) `lavaan` and the comprehensive add-on package `semTools` (Jorgensen et al. 2016) are used for confirmatory factor analyses. `mice` is used for multiple imputations (Buuren 2012). Multilevel regression analysis is done with the `lme4` package (Bates et al. 2015). Predicted values of regression models were computed using the `effects` package (Fox and Hong 2009; Fox 2003). Data visualization is done with `ggplot2` (Wickham 2016). Shapefiles for maps were imported and processed into `R` using `sp` (Pebesma and Bivand 2018) and `rgdal` (Bivand, Keitt, and Rowlingson 2019), maps were extracted from `stamen` via `ggmap` (Kahle and Wickham 2016), and spatial dependency was taken into account using the `spdep` package (Bivand 2019; Bivand, Pebesma, and Gomez-Rubio 2008). Finally, this thesis is written following the reproducible research paradigm (Gandrud 2015) which is less widespread in the social sciences than in other disciplines (Hofner, Schmid, and Edler 2016; Peng 2011; Stodden, Guo, and Ma 2013). This would be impossible without appropriate software, most importantly `stargazer` (Hlavac 2018), `rmarkdown` (Allaire et al. 2019), and Xie's (2019; 2017) beneficial packages `knitr` and `bookdown`.

3.1 Dimensionality reduction and latent variable extraction

Dimensionality reduction techniques differ considerably in the social sciences and can be located along the continuums of technical complexity and underlying theory. Sum scores are technically simple, however, they involve strong theoretical assumptions (e.g., tau-equivalency,

[1] To provide good data visualizations, the author follows Tufte's principles of graphical excellence. According to Tufte (2001, 51), good data visualizations are a matter of substance, statistics, and design. It is usually multivariate and aims to tell the truth about data. Thus, it allows communicating complex ideas with "clarity, precision, and efficiency."

see below). Principal components analysis requires no theoretical assumptions about the investigated variables but is technically more demanding. Lastly, factor analysis needs stronger theoretical background than principal component analysis and allows technically far more sophisticated solutions than sum scores.

With regard to survey items, two categories of dimensionality reduction methods are widely applied: The comparatively simple solution to sum all equally poled items up to so-called sum scores or the wider field of factor analysis. The simplicity of sum scores makes them comparable across studies and waves (because they implicitly assume equal loadings of all items tau-equivalency). Latent variables from factor analyses, on the other hand, allow to reduce the influence of less useful items and provide diagnostic tools and optimization possibilities.

Within factor analysis, two different techniques exist. Exploratory factor analysis is most appropriate if underlying dimensions of highly correlated survey items are of interest, but a theory is missing. It starts with no prior assumptions about how the observed variables are related to a factor. Thus, it is a fast technique to discover latent factors for related survey items. However, the possibilities to control the structure of those factors, as well as an assessment of their fit, are limited. This procedure is occasionally used to assess the covariance structure in advance. However, Section 4.4 reports no such results in favor of the more informative confirmatory factor analysis. Sum scores are only used if the logic behind the concept (e.g., life events) requires summation.

More detailed, confirmatory factor analysis, compared to exploratory factor analysis, is the more powerful tool to investigate and enhance the extracted latent variables. It requires explicit assumptions about how the items are related which enables the researcher to distinguish between the true score and the measurement error. As Brown (2015, 41) argued, investigating correlated measurement errors is a decisive advantage of confirmatory compared to exploratory factor analysis because it allows examining, e.g., the consequences of differently poled items. Further, it provides useful information to improve the latent variable in the current data set and suggests potential future advancements of the operationalization. Finally, confirmatory factor analysis allows testing for measurement equivalences between groups (Brown 2015, ch. 7) and measurement occasions (Brown 2015, 221–34; Little 2013, ch. 5). Since this is a necessary but often merely assumed precondition for meaningful subsequent regression analyses, Section 8.2 reports measurement equivalence across waves.

Classical factor analysis relies on Pearson's product moment correlation and maximum likelihood estimation that assumes continuous and normally distributed items. This assumption is violated in most surveys since, e.g., Likert items with a limited number of answering categories are applied. As early simulation studies showed, this violation is particularly harmful to items with less than five items (and low correlations (Bollen and Barb 1981)). In such cases, polychoric correlation coefficients and weighted least squares estimation lead to better results (Holgado-Tello et al. 2010; Jöreskog 1990). This was confirmed more recently in a comprehensive study by Rhemtulla, Brosseau-Liard, and Savalei (2012) who compared robust continuous with robust categorical estimation methods and reached basically the same conclusion: Confirmatory factor analysis based on Pearson's r and maximum likelihood produces downward biased factor loadings and standard errors if applied to items with less than five answering categories, even when correcting for non-normality. In their study, categorical least squares estimation based on polychoric (or tetrachoric) correlation matrices outperformed the more classical approaches. Since the majority of items in the SENSIKO study (see Section 4.1) has four answering categories, diagonally weighted least squares estimation based on polychoric correlations is used.[2]

3.2 Fundamentals of regression analysis

Regression analysis is by far the most frequently used method in the quantitative social sciences. The author recapitulates only the essential aspects which are necessary for subsequent analyses and skips many basics (therefore, see Cohen et al. 2003; Fox 2015; Gelman and Hill 2006). This section discusses the fundamentals of regression analysis or, more specifically, hierarchical regression analysis as well as mediation analysis and interaction effects. These

[2] Li (2016) provides the mathematical details.

techniques allow investigating the wealth of information about the interrelationships between variables of interest that are not extractable from single equations.

3.2.1 Hierarchical regression analysis

Hierarchical regression analysis is the practice of building regression models with the same dependent variable but different (sets of) predictors. The term hierarchical regression was coined by Cohen et al. (2003) and should not be confused with hierarchical models (which are also known as multilevel, mixed, or random effects models). While it is one of the most often applied practices in social sciences, surprisingly little literature on the principles of this technique was found.

Figuring out an appropriate modeling strategy is a complex endeavor where no single concept fits all research questions. Cohen et al. (2003) stressed the importance of including those variables which possibly confound the relationship between key independent variables and the dependent variable. The relationship between age and fear of crime might be attenuated when not considering victimization: assuming that 1) victimization increases fear and 2) victimization decreases with age an unbiased age estimate requires controlling for victimization.

Causal priority of the independent variables structures the model order. Independent variables, which are regarded as causes for other independent variables (e.g., old age as the cause of worse health), should be entered first to examine the true effect of the independent variable. Otherwise, the influence of the initial cause is likely to be underestimated. Further, for some independent variables, other variables exist measuring similar concepts. The decision for or against a specific variable is based on theoretical reasons.

3.2.2 Mediation

Mediation analysis allows the researcher to investigate the pathways of theoretically important independent variables on the dependent variable. For example, vulnerability theory suggests that, e.g., gender, health, and social capital influence fear of crime because they influence perceived control and increase anticipated consequences of victimization. Hence, this approach suggests a testable mediation mechanism. Investigations of the underlying mechanisms often emerge after a consensus about the importance and strength of the causal effects is reached and require corresponding causal assumptions (or reasoning).

With its origins in the 1950s, mediation analysis became increasingly popular in the late 1980s after Baron and Kenny (1986) published their seminal paper. Today, their causal steps approach is increasingly abandoned in favor of a similar but less rigorous approach discussed hereafter (Hayes 2013, 166–70). Figure 3.1 shows a typical mediation model.

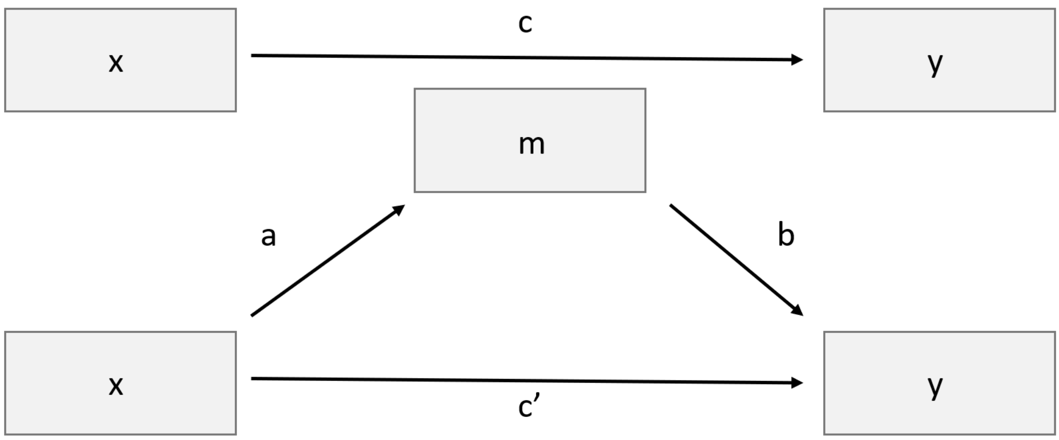

Figure 3.1: Conceptual diagram and fundamental terminology in mediation analysis

If all paths are considerably strong, the independent variable x influences the dependent variable y directly (c') as well as indirectly via the mediator (a and b). This mediation model can be algebraically formalized as:

$$y_i = \beta_{0y} + \beta_{c'} \times x_i + \beta_b \times m_i + \epsilon_{iy} \quad \text{and}$$

$$m_i = \beta_{0m} + \beta_a \times x_i + \epsilon_{im}$$

where y_i is the dependent and m_i is the mediator variable of person $i \in \{1, \ldots, n\}$ with β_{0y} and β_{0m} as their corresponding intercepts and ϵ_{iy} and ϵ_{im} as the error terms. Importantly, $\beta_{c'}$, β_a, and β_b are the corresponding regression coefficients where the common notation of a, b, and c' is indicated in the indices. For a matter of coherence to later sections, they are replaced with βs here. Whilst β_a is the effect of the independent variable x_i on the mediator m_i, β_b is the effect of m_j on y_i controlling for x_i. Accordingly, $\beta_{c'}$ is the effect of x_i on y_i controlling for m_j. $\beta_{c'}$ is also known as the direct effect which needs to be distinguished from the total effect $\beta_c = \beta_{c'} + \beta_a \times \beta_b$.

Importantly, the product of the regression coefficients $\beta_a \times \beta_b$ is known as indirect effect. It is of great importance for the mediation analysis and can be interpreted as the change of y_i when x_i increased by one due to the effect of x_i on m_i. Hence, an indirect effect provides information about the strength and significance of the hypothesized mediation path. While its computation is straightforward, there are various comprehensively compared methods to define the inferential significance (Biesanz, Falk, and Savalei 2010). The author follows Tofighi and MacKinnon's (2011) recommendations and uses the distribution of the product method.

When several mediators are involved, the author applies the parallel multiple mediator model (Hayes 2013, 125–43). However, the author deviates from this convention when the number of mediators or independent variables is high for reasons of statistical power (especially regarding smaller subsamples) and collinearity of the independent or mediator variables. Furthermore, all results presented below are based on multilevel regression analysis. The introduced approach can be applied to 1-1-1 mediation analyses since no random slopes are involved (Krull and MacKinnon 2001).

3.2.3 Interaction

A large body of literature discusses procedures to investigate multiplicative interaction effects (Aiken, West, and Reno 1991; Berry, Golder, and Milton 2012; Brambor, Clark, and Golder 2006). The simplest possible interaction can be introduced with the regression equation

$$y_i = \beta_0 + \beta_1 \times x_{i1} + \beta_2 \times x_{i2} + \beta_3 \times x_{i1} \times x_{i2} + \epsilon_{iy}, \tag{3.1}$$

where β_3 is the coefficient of the interaction term. Brambor, Clark, and Golder (2006) remembered analysts, e.g., to leave all lower order coefficients (β_1, β_2) in the model (even if they appear to be not significant at the first (or second) glance) and to provide substantively meaningful marginal effects plots (where the effect of one independent variable is shown depending on the value of the other). This is because raw estimates of lower order coefficients are conditional on each other. More precisely, they represent the effect of the interacting variable on the outcome only if the other interacting variable is zero.

In some interaction analyses, age and victimization are occasionally modeled as a second-order polynomial. In this case, Aiken, West, and Reno (1991 ch. 5) and others suggested to test the interactions between all (higher and lower order) terms with the other interacting variable. However, Aiken, West, and Reno (1991 ch. 6) also suggested a sequential testing strategy where highest order interactions are removed if their contribution to the model is not significant. Overall model improvement is assessed by comparing the AICs (introduced in Section 3.3.3.2) of the model with(out) the second order polynomial interaction as well as the significance of the coefficient. If both tests suggest an insignificant contribution of the higher order interaction, it is removed for later predictions. Crucially, this was the case in all models presented hereafter. Therefore, this section only discusses the interaction between x and a linear age term but not with its second order polynomial. Hence, x_{i1} in equation (3.1) is replaced with age_i and age_i^2:

$$y_i = \beta_{0y} + \beta_1 \times age_i + \beta_2 \times age_i^2 + \beta_3 \times x_i + \beta_4 \times age_i \times x_i + \epsilon_{iy}. \tag{3.2}$$

To visualize the marginal effect of x depending on age, equation (3.2) is derived to x:

$$\frac{\partial y}{\partial x} = \beta_3 + \beta_4 \times age.$$

Since multiplicative interaction effects are symmetric, a complementary perspective is likely to enhance the analysis: If the effect of x on y depends on age the effect of age is conditional on x as well. Berry, Golder, and Milton (2012) argued, researchers should investigate both conditional effects to get a better understanding of the interactive process. However, when higher-order polynomials are involved, the derivative of equation (3.2) to age is more complicated:

$$\frac{\partial y}{\partial age} = \beta_1 + 2 \times \beta_2 \times age + \beta_4 \times x.$$

Hence, the marginal effect of age depends on age and x. There are at least four methods to visualize this three-dimensional marginal effect: 1) fix centered age at its mean, then the derivative depends only on $\beta_1 + \beta_4 \times x$ and can be visualized as a line plot. However, all information about the curvilinearity of the main effect is lost. This information can be preserved by introducing a third dimension and plotting the fine-grained marginal effects either as 2) heat maps or as 3) surface plots. Despite their high level of information about the interrelation of both independent variables, it is hardly possible to provide confidence bands which are crucial for the interpretation of marginal effects plots. Hence, another option, which is applied hereafter, is to 4) calculate the marginal effects only for selected values of age, e.g., 30, 55, and 80 years of age and visualize them as additional categories with familiar line plots. The author is not aware of any software where this is implemented. Therefore, Section 8.3 provides an R function written by the author. For simpler formulas, e.g., on interactions between linear predictors and their respective variance estimates (necessary for the confidence bands of the marginal effects), the author refers to Aiken, West, and Reno (1991, 64).

3.3 Multilevel regression analysis

Social sciences have a natural interest in the influence of various contexts like families, schools, neighborhoods, or countries. For reasons of clarity, this section introduces a simplified multilevel regression model. Unfortunately, relevant textbooks in social sciences (and elsewhere) came up with different notations for describing the same method (Raudenbush and Bryk 2002; Hox 2010; Snijders and Bosker 2011; Gelman and Hill 2006; Goldstein 2011). The author follows the notation suggested by Scott, Shrout, and Weinberg (2013) which tries to standardize the different notations. The simplified multilevel regression model includes two levels, one fixed predictor on the individual level, one predictor on the contextual level, and a random intercept which is extended in later sections. On the between-person level, such a model is expressed like this:

$$y_{ij} = \beta_{0j} + \beta_{1j} \times x_{ij} + \epsilon_{ij}, \tag{3.3}$$

where y_{ij} is the dependent variable of individual $i \in \{1, \ldots, n\}$ in the contextual unit $j \in \{1, \ldots, N\}$ with capital N as the number of contextual units. x_{ij} is the fixed independent variable on the between-person level and regression parameters on the between-person level are expressed as βs. Similar as in the previous section, β_{1j} is the slope of the variable x_{ij} and ϵ_{ij} is the residual error of individual i in group j. Random slopes are *not* introduced here for two reasons: First, on the within-person level, random slopes are statistically impossible due to the number of observations (see Section 3.3.1) and, second, the author prefers to model cross-level interactions of the between-person and neighborhood level without a random slope. Snijders and Bosker (2011, 82 and 105) discuss this as an alternative approach instead of allowing the coefficient to vary and explain its variance in a subsequent step by including interactions. The group dependent intercept β_{0j} is determined as

$$\beta_{0j} = \gamma_{00} + \gamma_{01} \times w_j + u_{0j}, \tag{3.4}$$

where the γs represent the regression coefficients on the neighborhood level. γ_{00} is the grand mean or average intercept which the neighborhood intercepts are distributed around, depending on their respective random effect u_{0j}. Further, γ_{01} is the coefficient of the level 2 variable w_j. The distributional assumptions are

$$u_{0j} \sim N(0, \sigma^2_{uoj}) \qquad \text{and} \qquad \epsilon_{ij} \sim N(0, \sigma^2_{\epsilon})$$

which means that random effects and the residual error term are normally distributed with a mean of zero and a variance of σ^2_{uoj} or σ^2_{ϵ}. Further assumptions are that the residuals on both levels are uncorrelated with the predictor ($Cov(x_{ij}, u_j) = Cov(x_{ij}, e_{ij}) = 0$). An important assumption, especially regarding longitudinal multilevel models where it is often violated.

Via substitution of equation (3.4) in (3.3), the simplified two-level model can be written as

$$y_{ij} = \underbrace{\gamma_{00} + \beta_{2j} \times x_{ij} + \gamma_{01} \times w_j}_{\text{Fixed part}} + \underbrace{u_{0j} + \epsilon_{ij}}_{\text{Random part}} .$$

This composite notation allows identifying the fixed (or deterministic) and random (or stochastic) part of the model. However, this notation gets increasingly confusing with every element being added. Therefore, the composite notation is omitted hereafter. The significance of all βs is calculated based on Satterthwaite approximation of degrees of freedom. If not stated otherwise, all models are estimated with the restricted maximum likelihood estimator.

3.3.1 Longitudinal multilevel models: Advantages, problems, solutions

Panel data can be considered as a particular case of multilevel data. Confirming the often-cited phrase that “once you know that hierarchies exist you see them everywhere” (Kreft and Leeuw 1998, 1), multilevel (or random effects) models were used for to analyze panel data a long time by plausibly considering persons as contexts in which their observations are nested. This section merely introduces the essentials of longitudinal multilevel models. More profound information is provided in chapters (Snijders and Bosker 2011, ch. 15; Hox 2010, ch. 5; Goldstein 2011, ch. 5; Raudenbush and Bryk 2002, ch. 6) and textbooks (Hoffman 2015; Long 2012; Singer and Willett 2003) elsewhere.

Most fundamentally, longitudinal analyses should distinguish between time-stable and time-varying variables. For reasons of coherence to the previous section, time-varying predictors are written as z_{ti} (with δs indicating their related coefficients) and time-stable predictors are expressed as x_j (with βs as their related coefficients). Apart from that, the basic notation of multilevel models for longitudinal data is similar to equation (3.3) and (3.4):

$$y_{ti} = \delta_{0i} + \delta_{1i} \times t_{ti} + \delta_{2i} \times z_{ti} + \epsilon_{ti} \quad \text{and} \tag{3.5}$$

$$\delta_{0i} = \beta_{00} + \beta_{01} \times x_j + u_{0j}. \tag{3.6}$$

The first subscript t indicates the dependence on the measurement occasion while the subscript i expresses the belonging to a specific person. In contrast to the introduced multilevel model for cross-sectional data, the formula above has no random slope but a cross-level interaction. A random slope between the within- and between-person level is not possible in this case (without fixing the random intercept to zero). The reason for this is the data analyzed hereafter has only two measurement occasions. To estimate both a random intercept and a random slope would leave no residual variance left. Therefore, it is impossible to distinguish individual differences and residual variance (Hoffman 2015, 252 and ch. 3). However, cross-level interactions allow to include within-person variation.

Further differences are the predictor t_{ti} capturing time. Since the SENSIKO (see Section 4.1) study has two measurement occasions, the coefficients δ_{1i} captures the individual change of fear within 18 months between T_1 and T_2. As discussed above, the low number of measurement occasions allows no random slope of time (in addition to the between-person intercept) and does not call for an investigation of alternative covariance structures (Hoffman 2015, ch. 4, 5). However, a fundamental question remains: How should the effect be interpreted? Unfortunately, there is no easy answer to this question because this within-person effect of time can be both a period or an age effect. Significant age effects on the between-person level are interpreted as an indication that the effect of time is rather an age than a period effect. However, no final interpretation is provided in the following analyses because they are not of core interest for this thesis (see also Brüderl and Ludwig 2015, 351–52).

A decisive advantage of longitudinal multilevel is its treatment of unit nonresponse. It can "readily incorporate all participants who have been observed at least once" (Raudenbush and Bryk 2002, 199; see also Long 2012, ch. 3.8; Hoffman 2015, 566–68; Hox 2010, 106–9). Little (1995) showed that longitudinal multilevel modeling—in contrast to other methods—provides unbiased estimates if data is "missing at random" (where the missing values depend on other variables; for a more elaborate definition see Enders 2010, ch. 1.4; Little and Rubin 1989). This type of missingness is a far less demanding and more realistic assumption than "missing completely at random" (where the missings are independent of all other variables) particularly in longitudinal research where panel attrition increases the likelihood that the missing completely at random assumption is violated. Since maximum likelihood estimation takes all complete cases into account (including the dependent variable of previous measurement occasions) it provides unbiased estimates if observations are missing (Hox 2010, 107). However, this does not extend to missing variables within an observation which are listwise deleted. In this thesis, however, the amount of missing information is considerably reduced by using confirmatory factor analysis with multiply imputed datasets and averaged predictions (Miles 2016; White, Royston, and Wood 2011). If data is "missing not at random" (where the missing values depend on itself), unbiased estimates are unlikely. Since this assumption is not testable due to logical reasons, the author assumes that data is missing at random.

Some scholars argued that conventional multilevel (or random effects) models provide biased estimates compared to fixed effects models (e.g., Brüderl and Ludwig 2015). More technically, the main disadvantages of multilevel modeling for panel data is that it assumes the error terms of both levels to be uncorrelated with the independent variables (i.e., $Cov(x_{ij}, u_j) = Cov(x_{ij}, e_{ij}) = 0$) which is also called the exogenous assumption. Particularly problematic is the coefficient of the time-varying variable δ_{2ij} because it is likely to contain information of the person and the measurement level. On the other hand, fixed effects models have severe disadvantages regarding time-stable variables which would cancel out important between-person and neighborhood-level information. The between-within approach includes the logic of fixed effects models into the random effects framework. This replicates the coefficients of fixed effects models (Bell and Jones 2015) but additionally allows to estimate the time-stable effects (see below).

3.3.1.1 Between-within models

Several authors proposed solutions for the violation of the exogenous assumption (or endogeneity problem) discussed above (Mundlak 1978; Plümper and Troeger 2007; Diez-Roux 1998). More recent literature argued that between-within models (or hybrid models) can successfully decompose the within- and between-person effects in panel data (Allison 2009, 160:23–26; Brüderl 2010; Dieleman 2014; Fitzmaurice, Laird, and Ware 2012, 998:249–52; Bell and Jones 2015; Firebaugh, Warner, and Massoglia 2013). Technically, the underlying logic and procedure is comparable to group-mean centering (Enders 2013) in cross-sectional multilevel modeling, however, on the within- and not the between-person level:

$$y_{ti} = \delta_{0i} + \delta_{1i} \times t_{ti} + \delta_{2i} \times (z_{ti} - \overline{z}_{0i}) + \epsilon_{ti}, \tag{3.7}$$

$$\delta_{0i} = \beta_{00} + \beta_{01} \times x_{0i} + \beta_{02} \times \overline{z}_{0i} + u_{0i}, \tag{3.8}$$

Compared to the basic longitudinal model in equation (3.5), the difference of equation (3.7) is the term $(z_{tij} - \overline{z}_{0ij})$ which replaces z_{tij} on the within-person level and the inclusion of $\overline{z}_{0ij}$ in equation (3.8) on the between-person level. $\overline{z}_{tij}$ is the time-stable person mean of the time-varying variable z_{0ij}. Subtracting $\overline{z}_{tij}$ from the within-person variable z_{0ij} isolates the within-person change (similar to fixed effects regression, however, without demeaning the dependent variable y_{ti}).

Including $\overline{z}_{tij}$ on the between-person level allows capturing the influence of the mean level to explain between-person differences. Simulation studies showed that the within-person coefficients are the same as in fixed effects approach which was long seen as the gold standard in longitudinal regression analysis (Bell and Jones 2015; Dieleman 2014). In addition to fixed effects models, however, between-within models allow estimating between-person differences (which are vital for this study because of the importance of between-person variables like gender and neighborhood characteristics). Furthermore, strongly divergent between- and within-person coefficients ($\delta_{2ij} \neq \beta_{02j}$) signal substantial problems with unobserved heterogeneity in cross-sectional findings (Brüderl 2010, 983–84).

3.3.1.2 Between-within models in neighborhood contexts

Another advantage of multilevel models is their comparatively easy expandability to more than two levels. This expandability is especially interesting for social sciences when (supra-individual) contexts are of interest. The underlying data requires a "pure" hierarchy of the levels (opposed to a cross-classified structure, see Beretvas (2011)). Such an expansion allows investigating, e.g., whether victimization between the measurement occasions has different effects depending on the neighborhood. Adding a third level to equation (3.7) and equation (3.8) can be formalized in the following way:

$$y_{tij} = \delta_{0ij} + \delta_{1ij} \times t_{tij} + \delta_{2ij} \times (z_{tij} - \overline{z}_{0ij}) + \epsilon_{tij} \quad \text{and}$$
$$\delta_{0ij} = \beta_{00j} + \beta_{01j} \times x_{0ij} + \beta_{02j} \times \overline{z}_{0ij} + u_{0ij}.$$

Subscript j is now indicating the belonging of an individual to a neighborhood (or any other higher level). Similar to equation (3.4), the neighborhood level can be expressed as

$$\beta_{00j} = \gamma_{000} + \gamma_{001} \times w_{00j} + u_{00j},$$

where β_{00j} is depending on the neighborhood variable w_{00j}, whearas γ_{000} is the grand mean or average intercept and u_{00j} is the random effect of the intercept on the neighborhood level.

3.3.2 Intra-neighborhood and intra-individual correlation coefficients

Intra-neighborhood ($\mathrm{ICC_n}$) and intra-individual ($\mathrm{ICC_i}$) correlation coefficients are equationally very similar statistics in multilevel modeling which offer intuitive interpretations. The intra-neighborhood correlation coefficient ($\mathrm{ICC_n}$) is defined as

$$ICC_n := \frac{\sigma^2_{uoj}}{\sigma^2_{uoj} + \sigma^2_{uoi} + \sigma^2_{\epsilon}}, \tag{3.9}$$

and used, e.g., as an indicator of inter-rater agreement for ecometric measures (Raudenbush and Sampson 1999, 7) but also to assess the general importance of neighborhood conditions (or other higher units) on a specific outcome (Snijders and Bosker 2011, ch. 3.3). If a measure was assessed only in one wave, $\sigma^2_{uoi} = 0$ in equation (3.9) because it is impossible to distinguish between- and within-person variance. For simplicity, the author only reports $\mathrm{ICC_n}$ based on the null model. By replacing σ^2_{uoj} with σ^2_{uoi} in the numerator of equation (3.9), the intra-individual correlation coefficient ($\mathrm{ICC_n}$) can be calculated as

$$ICC_i := \frac{\sigma^2_{uoi}}{\sigma^2_{uoj} + \sigma^2_{uoi} + \sigma^2_{\epsilon}},$$

where σ^2_{uoi} is the between-person variance, σ^2_{uoj} is the between-neighborhood variance and σ^2_{ϵ} is the residual variance assessed with the unconditional model (that is, with an indicator of the wave as the only predictor). Since, the denominator $\sigma^2_{uoi} + \sigma^2_{uoj} + \sigma^2_{\epsilon}$ is the total variance, the $\mathrm{ICC_i}$ can be interpreted as the percentage of between-person variance. On the other hand, $1 - ICC_i - ICC_n$ is the amount of longitudinal or within-person variance (Hoffman 2015, ch. 3.1). Thus, low values of $ICC_i + ICC_n$ indicate volatile variables while high values of $ICC_i + ICC_n$ indicate time-stable scales or variables.

3.3.3 $\mathbf{R^2}$ and information criteria

R^2 and information criteria are essential tools to evaluate and compare models with the same analytical sample. Listwise deletion is applied hereafter. Therefore, the number of observations differs between most (but not all) models. Hence, only selected analyses provide R^2 and information criteria.

3.3.3.1 $\mathbf{R^2}$ in three-level regression models

R^2 is widely used in single-level regression analysis to investigate the percentage of explained variance model by a regression model and to compare R^2's from different models, e.g., to evaluate the explanatory gain of additional predictors. For multilevel models, e.g., Hox (2010 ch. 4.5) explains in detail how this concept can be applied to each level in multilevel analysis (although some cases require different solutions as discussed by Snijders and Bosker (2011; ch. 7; 1994)). Variance components between the model of interest (m) and the null model (n) with no predictors are compared to calculate the explained variance. Similar to the ICC, the percentage of explained variance is calculated on each level:

$$R^2_{neigh.} := \frac{\sigma^2_{uoj|n} - \sigma^2_{uoj|m}}{\sigma^2_{uoj|n}} \times 100,$$

$$R^2_{between} := \frac{\sigma^2_{uoi|n} - \sigma^2_{uoi|m}}{\sigma^2_{uoi|n}} \times 100,$$

$$R^2_{within} := \frac{\sigma^2_{\epsilon|n} - \sigma^2_{\epsilon|m}}{\sigma^2_{\epsilon|n}} \times 100.$$

3.3.3.2 Information criteria

Information (or fit) criteria are a widely accepted tool for model selection where lower values indicate better models than higher values. In the following, the author will report the Akaike (AIC) and Bayesian (BIC) information criteria. Both are based on the maximum of the likelihood function (L) but penalize the number of parameters (k) differently. In case of the BIC, this penalization is additionally depending on the sample size (n):

$$AIC := 2 \times k - 2 \times \ln(L),$$

$$BIC := \ln(n) \times k - 2 \times \ln(L).$$

While both are similar regarding their equation, the BIC penalizes the number of parameters more strongly as can be immediately seen by comparing the formulas above. All regression models hereafter are complex (with large, medium but also small effects) and based on partly large samples. Therefore, the recommendations of the AIC are preferred when both information criteria disagree (Vrieze 2012). Lastly, the compared models are estimated with maximum likelihood (and not restricted maximum likelihood; see West, Welch, and Galecki (2014), p. 35).

Chapter 4

Data and measurements

This chapter briefly introduces the study and provides more detailed information about the operationalization of the theoretical concepts. More detailed, it discusses the crucial cornerstones of the SENSIKO study as well as the research sites. It pays particular attention to the operationalization of the applied measurements on person and neighborhood level.

4.1 Study

The data stems from the research project “Sicherheit älterer Menschen im Wohnquartier—Analysen und Konzeption des Praxismodells Seniorensicherheitskoordination” (“Safety of older people in their neighborhood—Analyses and Conception of Best Practice Models”). Its acronym “SENSIKO” stands for the German neologism “Seniorensicherheitskoordination” and is used to refer to this study. It was funded by the German Federal Ministry of Education and Research within the security research stream on “Urban Safety,” an extensive and interdisciplinary framework investigating different facets of urban safety like crime, terrorism, and natural disasters. The Max Planck Institute for Foreign and International Criminal Law in Freiburg (PI: Dietrich Oberwittler) and the Technische Hochschule Köln (PI: Herbert Schubert) conducted the SENSIKO project between 2013 and 2016. Its primary focus was the analysis of the security perceptions of older adults with a particular emphasis on their neighborhood and the development of guidelines for social workers to foster it (Schubert et al. 2016).

A centerpiece of the SENSIKO study was the postal panel survey “Zusammenleben und Sicherheit in Köln/Essen” (“Cohabitation and Safety in Cologne/Essen”) which was conducted by the Max Planck Institute. The response rate was 41% in T_1 and 57% (of T_1 participants) in T_2 (Gerstner and Oberwittler 2016; Janssen and Gerstner 2016). The sampling procedure followed a two-stage cluster random sampling approach.[1] On the first stage, neighborhoods were randomly selected from all neighborhoods in Cologne and Essen (separately). Neighborhoods within the highest three poverty deciles within each city had a doubled chance to be sampled. Within those neighborhoods, two equally sized probability samples were drawn with a different target population regarding age (25–59 and 60–89). Besides the well-known sources of nonresponse error, this is an additional reason why the unweighted frequencies shown below are not interpreted as representative for Cologne and Essen but as sample description. Regression analyses, however, control for many known factors influencing unit response and the specific sample characteristics. Additional robustness checks investigate whether neighborhood related findings of this thesis can be found in both cities (see Section 5.6 and 8.4.2). If this requirement is fulfilled, generalizability to other German cities is suggested.

To cover a broader range of topics, the Max Planck Institute applied a split survey design to the differential target populations. In each of the 140 neighborhoods 80 people (25–89 years of age) were sampled who received survey version A, and 40 people (60–89) received survey version B. While large parts of both survey versions were identical core modules, each survey version examines specific topics more closely (see Figure 4.1). Additionally, some questions

[1] Gerstner and Oberwittler (2016) provide a more detailed description of the sampling.

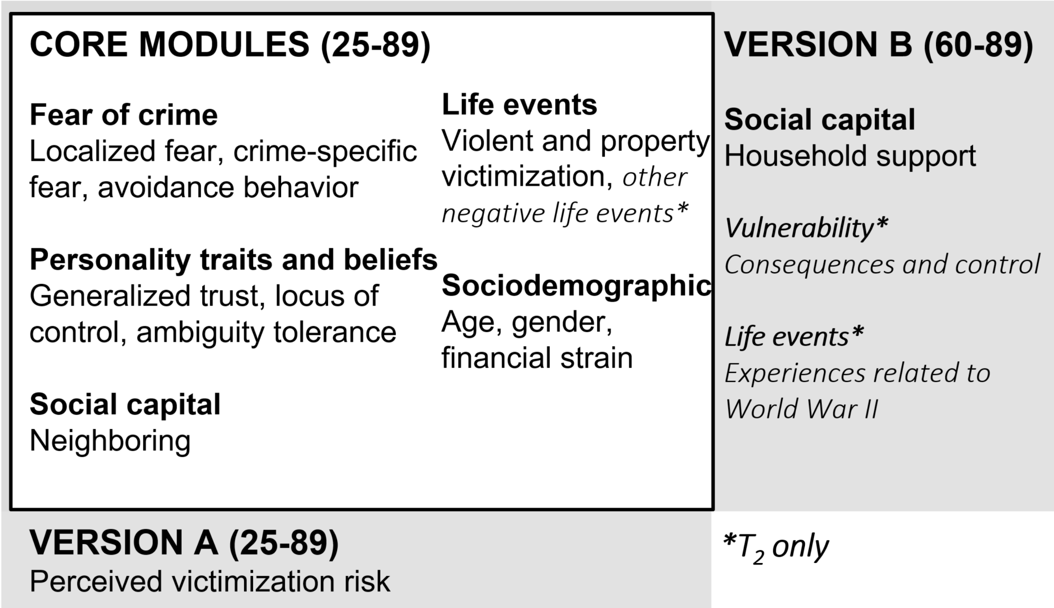

Figure 4.1: Core modules, survey versions, and available concepts for analytic (sub-)samples

were added in T_2. Unfortunately, both limitations (due to survey version or measurement occasion) also affect the analytical sample sizes in regression analyses. To meet the needs of this complexity, Figure 4.1 provides an overview which relevant concepts are available in

a) both versions and waves,
b) both versions but T_2 only,
c) survey version A but both waves,
d) survey version B and T_2, or
e) survey version B but both waves.

This classification above is used to indicate the analytical sample in each regression table in Chapter 5.

The panel design of the postal survey is a rare feature of this study. From an analytical perspective, this is a substantial improvement regarding the informative value of the findings, mainly because unobserved heterogeneity can be mostly ruled out (see Section 3.3.1.1). However, higher statistical and methodological complexity accompany this analytical benefit (Lynn 2009). For example, Sturgis, Allum, and Brunton-Smith (2009) found various effects of panel conditioning (i.e., whether the repeated questioning itself has an independent influence on the respondent's answering behavior) on political attitudes. They found increasing reliability, stability, and a reduction of "don't know" answers but also a slight increase of political interest from T_1 to T_2, however, a subsequent downward trend in the following waves. This trajectory is partly in line with their hypothesis on increasing political interest due to being administered to a panel survey. There might be a similar effect on fear of crime or other variables. However, the existence and size of this effect cannot be unequivocally assessed based on this data (Halpern-Manners, Warren, and Torche 2017; Warren and Halpern-Manners 2012).

Lastly, another strength of the SENSIKO study was its wealth of data sources. Besides the survey, the research team gathered information about neighborhoods from local governments, the police, as well as systematic social observations by trained student research assistants (see Section 4.3.3). Further, the University of Applied Sciences provided 35 semi-structured qualitative interviews with respondents of T_1. Each interview took roughly one hour and aimed at an in-depth investigation of the survey responses. Those interviews were analyzed to develop vulnerability scales for T_2 (see Section 4.4.2).

4.2 Sample characteristics and attrition

Since this is a panel study with split questionnaire design, no single sample is consistently analyzed hereafter. Instead, different research questions allow different samples. The general aim was to include as many cases as possible into the analytical sample. In total, 6,563 respondents returned their questionaries at T_1 and 3,744 at T_2. More detailed, 3,018 people responded only to T_1, and 344 only to T_2. The Max Planck Institut assured that the same person responded in both waves by comparing age and gender in T_1 and T_2. After this verification, the longitudinal sample consisted of 3,401 people who provided longitudinal information.

Table 4.1: Sample characteristics in both waves

	Level	T_1:	n	%	T_2:	n	%
survey version:	a		3,917	59.7		2,231	59.6
	b		2,646	40.3		1,513	40.4
city:	Cologne		4,129	62.9		2,366	63.2
	Essen		2,434	37.1		1,378	36.8
age:	-45		1,371	20.9		600	16.0
	46-59		1,244	19.0		786	21.0
	60-74		2,477	37.7		1,421	38.0
	75+		1,462	22.3		858	22.9
	missing		9	0.1		79	2.1
gender:	men		2,884	43.9		1,689	45.1
	women		3,555	54.2		1,990	53.2
	missing		124	1.9		65	1.7
rent/own:	rent		3,828	58.3		1,810	48.3
	own		2,588	39.4		1,542	41.2
	care home		47	0.7		17	0.5
	missing		100	1.5		375	10.0
family status:	single		1,043	15.9		517	13.8
	partnership		3,991	60.8		2,405	64.2
	divorced		634	9.7		367	9.8
	widowed		745	11.4		408	10.9
	missing		150	2.3		47	1.3
working status:	full time		1,680	25.6		940	25.1
	part time		548	8.3		321	8.6
	marginally		208	3.2		166	4.4
	unemployed		239	3.6		83	2.2
	training		126	1.9		47	1.3
	homemaker		334	5.1		133	3.6
	retired		3,064	46.7		1,960	52.4
	else		155	2.4		80	2.1
	missing		209	3.2		14	0.4
welfare transfer:	not received		5,405	82.4		3,298	88.1
	receiver		961	14.6		390	10.4
	missing		197	3.0		56	1.5
school education:	no degree		195	3.0		46	1.2
	low		2,246	34.2		1,105	29.5
	medium		1,264	19.3		703	18.8
	high		829	12.6		448	12.0
	university		1,523	23.2		922	24.6
	other/missing		506	7.7		520	13.9
ethnicity:	German		4,976	75.8		2,831	75.6
	Turkish		257	3.9		62	1.7
	Polish, Romanian		205	3.1		82	2.2
	Russian		216	3.3		68	1.8

	other European	259	3.9	117	3.1
	non-European	213	3.2	70	1.9
	partly German	265	4.0	151	4.0
	missing	172	2.6	363	9.7
residence:	up to 1 year	319	4.9	151	4.0
	2–5 years	1,244	19.0	593	15.8
	more than 5 years	4,957	75.5	2,645	70.6
	missing	43	0.7	355	9.5

Overall, the attrition rate was 48%. Investigating predictors of attrition, Janssen and Gerstner (2016) found, e.g., a u-shaped effect of age (both younger and older people were less likely to participate again), substantial effects of migration background, education, occupational status, generalized trust, and localized fear but no effect of gender or victimization. This possibly affects descriptive analyses and within-person estimates of the longitudinal regression models. Regarding unit non-response, the author controls, e.g., for victimization, financial strains, and education in later regression models which most likely attenuates attrition effects. Nevertheless, unit non-response and attrition effects cannot be ruled out entirely (see also Chapter 7). Future analyses might use weights to attentuate non-response error (Vandecasteele and Debels 2006).

4.3 Research sites and neighborhood characteristics

The SENSIKO study was conducted in Cologne and Essen. Both cities are in the economically powerful Rhine-Ruhr area in the densely populated German state North Rhine-Westphalia. Cologne is almost twice as big as Essen regarding inhabitants (1,060,582 compared to 582,624 at the end of 2015 (IT.NRW 2017)) and area (405 km^2 vs. 210 km^2). While both cities have unemployment rates considerably above the national average, Cologne had a lower unemployment rate (9.6 %) than Essen (12.4 %) (IT.NRW (2018)). Both cities were massively destroyed in World War II and rebuilt quickly. Therefore, their general cityscape is similar. Economically, both cities are characterized by industry and administration today. However, due to Cologne's large universities, research institutes, and media companies, the city is more progressive, young, and trendy. Compared to Cologne, Essen is more traditional and was strongly affected by the decay of the coal and steel industry but has attracted other industries since then.

As in most larger cities, Cologne and Essen do have socially disadvantaged neighborhoods which are of particular interest for this study. A standard proxy variable for social disadvantage is the percentage of unemployed people in a neighborhood. Localized fear of crime is also of primary interest for this study. Figure 4.2 and 4.3 visualize both variables in Cologne and Essen. This comparison allows investigating the spatial correlation of localized fear and unemployment. Furthermore, it indicates the spatial location of the surveyed neighborhoods.

Technically, those neighborhoods are administrative units. Their boundaries reflect the historical development of city landscapes. The surveyed neighborhoods were randomly sampled with an oversampling by 2 of the most disadvantaged neighborhoods (Gerstner and Oberwittler 2016). The 140 selected neighborhoods were comparatively small (on average .56 km^2) which is beneficial to capture homogenous neighborhood processes (Oberwittler and Wikström 2009).

The remainder of this section investigates key independent neighborhood variables and extract two moderately correlated factors (crime and social disadvantage). In a second step, these components are used to calculate spatially lagged independent variables.

4.3.1 Principal component analysis of selected neighborhood characteristics

Official agencies record a wealth of information about administratively defined neighborhoods. Not all of them are theoretically relevant for this study. As discussed in Section 2.4.5, crime and social disadvantage are the two most essential measurements on neighborhood level which can be derived from official statistics. On closer observation, crime and social

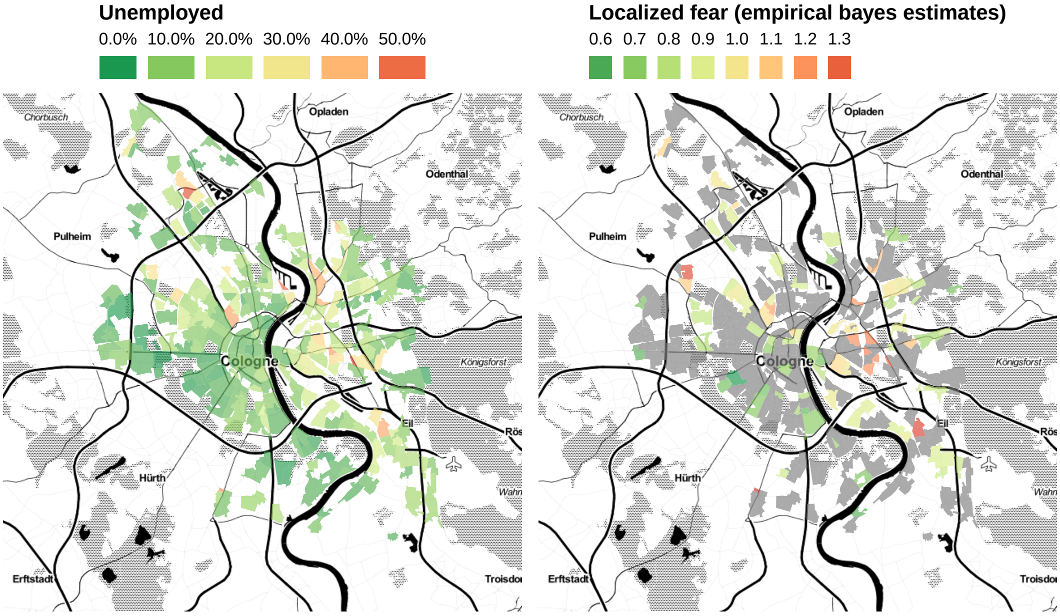

Figure 4.2: Contrasting unemployment and localized fear in Cologne's neighborhoods

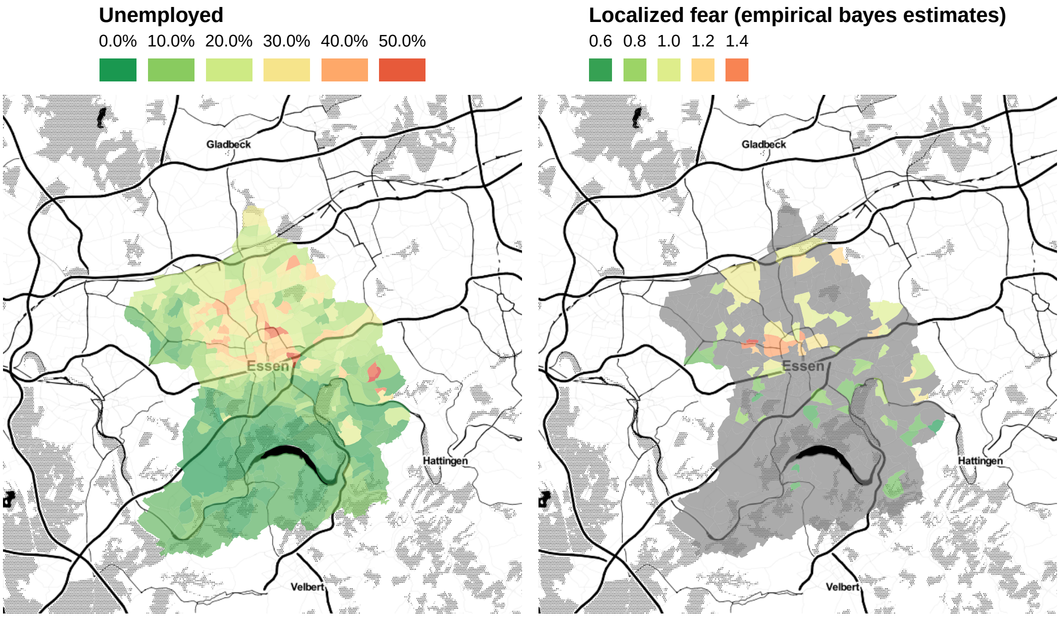

Figure 4.3: Contrasting unemployment and localized fear in Essen's neighborhoods

Table 4.2: Loadings on crime and social disadvantage

Neighborhood characteristic	Crime	Social disadvantage	% extracted
Drug crime (log)	.83		79
Violent crime (log)	.85	.19	90
Property crime (log)	.98	-.16	86
Welfare recipients (%)		.98	92
Non-European foreigners (%)		.88	90

Note: oblique principal component analysis

disadvantage resemble theoretical concepts in survey research which require, however, ex-post operationalization based on secondary data (see Section 3.1 and O'Brien, Sampson, and Winship 2015).

Theory suggests that crime and social disadvantage correlate (Pratt and Cullen 2005; Sampson and Groves 1989). Hence, this section applies a oblique (oblimin) principal component analysis[2] with five selected neighborhood characteristics to derive neighborhood measures of crime and social disadvantage.

More detailed, the author used the percentage of welfare recipients and non-European foreigners per neighborhood at the end of 2013 as well as police recorded crime rates per neighborhood in the years 2012–2014, standardized by 100,000 inhabitants and logarithmized to cope with outliers. Drug crime refers mainly to possession and trading of illegal substances but not acquisitive crime. Violent crime subsumes murderer, coercion, robbery, battery, and sex crimes. Property victimization entails pickpocketing, shoplifting, and burglary. Table 4.2 shows the results of the principal component analysis. Loadings below .15 are suppressed for readability.

Two sufficiently distinct components extracted 87% of the total variance (crime 49% and social disadvantage 38%) from those five neighborhood characteristics. A three-component solution would account for additional 7% of the total variance which is insufficient to justify another neighborhood predictor. The majority of the variance of all variables is extracted. The communalities are not the row sum of the squared loadings because the oblique solution is reported.

One component captures social disadvantage with very high loadings on welfare recipients and non-European foreigners and without any noteworthy cross-loadings on the other component. The latent crime component is strongly influenced by property crime but also has high loadings on drug and violent crime. There are some non-negligible cross-loadings between social disadvantage and violent crime as well as property crime: While violent crime is slightly more often in disadvantaged neighborhoods, property crime is less often conducted in disadvantaged neighborhoods. However, these cross-loadings are comparatively low. Crime and social disadvantage are only moderately correlated with each other (r = .41). Hence, both components are regarded as appropriate representations of crime and social disadvantage on the neighborhood level.

4.3.2 Spatially lagged predictors

Investigating the effects of adjacent neighborhoods allows overcoming the artificially set administrative neighborhood boundaries which do not necessarily fulfill the requirements of the dependent variable (Brunton-Smith and Jackson 2012; Conley, Stein, and Davis 2014; Hipp 2007; Takagi, Ikeda, and Kawachi 2012) with comparatively simple means. Section 2.4.5.1 described the rationale of an investigation of spatial dependence, different methodological approaches, and their differential causal mechanisms. This section describes how the spatially lagged predictors were computed.

Technically, the first step is the computation of a spatial weights matrix. This matrix is subsequently multiplied by the vector of crime or social disadvantage. In general, the spatial weights matrix contains information about which units (respondents or neighborhoods) shall

[2] Since the author expected two distinct factors, exploratory factor analysis would have been the more appropriate technique. However, this led to a Heywood case where a loading after rotation exceeded 1.0. Hence, the author uses principal component analysis.

share their information with which other units and to what percentage the spatially lagged variable should consist of the information of a proximate unit.

According to Bivand, Pebesma, and Gomez-Rubio (2008; ch. 9; Bivand 2016) "neighborhood" (understood as spatial proximity in this paragraph) can be determined based on graphs, contiguity, or distance methods. Contiguity and distance are more common and therefore compared below. The most intuitive way to assess neighborhood is based on contiguity: Spatial units are considered as neighbors when they share at least one point of their boundaries. However, even if a spatial unit is very close to another, but does not share a point with the boundary of another spatial unit (because of, e.g., an unassigned railway), it is technically no neighbor. Centroids-based procedures, on the other hand, circumvent this problem by assessing the distance of the centroids. The analyst chooses how many of the closest neighborhood shall share their information. Unfortunately, this method discriminates larger neighborhoods because their centroids are likely to be farther away compared to smaller neighborhoods.[3]

Furthermore, it is less in line with the theoretical arguments made in Section 2.4.5.1. Hence, contiguity is the more appropriate procedure and was applied to calculate the spatial lags. The author imputed the contiguity-based spatial lags of five neighborhoods with values of the four closest centroids because they did not share a single point of their boundaries with other neighborhoods.

4.3.3 Systematic social observations of incivilities

Incivilities play a long-standing and vital role in criminological neighborhood research (Skogan 2015). Various data sources were exploited to gain information about the amount and severity of incivilities within residential neighborhoods. Survey interviews were the most common source of information about incivilities in fear of crime studies. Telephone hotlines (Boggess and Maskaly 2014; O'Brien, Sampson, and Winship 2015; O'Brien 2016) or even administrative records (Skogan 2015, 474) provide less costly alternatives.

Systematic social observations of incivilities are beneficial in fear of crime research because respondents' incivility assessments might be biased due to simultaneous causality between fear and perceived incivilities as well as implicit biases due to, e.g., stigma, ethnic composition, or poverty. Systematic social observations were applied frequently (see Häfele 2013, ch. 7 for an overview; Brunton-Smith and Sturgis 2011; Oberwittler, Janssen, and Gerstner 2017) and with diverging checklists, effort, and technological means. While most studies relied on the immediate assessments of trained observers, others used video footage and subsequent coding of incivilities (Sampson and Raudenbush 1999). Recently, Grubesic et al. (2018) assessed the usefulness of unmanned aerial systems to sense physical incivilities. Because of their narrow temporal window, however, the validity of systematic social observations for rare and daytime-dependent social incivilities is debated (Skogan 2015, 476).

Systematic social observations for every surveyed neighborhood are also available in the SENSIKO study. Trained observers walked through approximately 40% of all street segments of every neighborhood in 2015 and noted the frequency of 17 physical and social incivilities on an electronic checklist which was based on the study by Sampson and Raudenbush (1999). These frequencies were summed, standardized by the length of the street segment, and logarithmized due to skewness. Some street segments were rated twice to assess inter-rater reliability. The sum scores of these areas are correlated strong enough ($r = .71$) to assume sufficient data quality (Oberwittler, Janssen, and Gerstner 2017).

Previous analyses (not shown) assessed the benefits of distinguishing between physical and social incivilities scores compared to an overall index of incivilities explaining crime-specific fear, avoidance behavior, and localized fear. Both incivility measures behaved remarkably similar regarding their effect strength and interaction with the research site (incivilities significantly increased fear of crime only in Essen but not in Cologne). Due to penalization of additional parameters (see Section 3.3.3.2), models with the overall incivility index were mostly superior to separated physical and social incivility measures. Hence, the author uses the index of all incivilities to reduce the number of coefficients and simplify later analyses.

[3]For an appealing and informative visualization of the different methods to determine neighbors see http://personal.tcu.edu/kylewalker/spatial-neighbors-in-r.html.

Table 4.3: Overview of unstandardized extracted variables

	n	mean	sd	min	max	skew	kurtosis	Ω
crime-specific fear	10,307	0.0	1.0	-1.7	2.3	0.3	-0.5	88.7
avoidance behavior	10,035	2.0	1.9	0.0	6.0	0.5	-1.0	91.1
localized fear	10,267	0.0	1.0	-1.4	3.2	0.7	-0.1	87.3
perceived victimization risk	6,148	0.0	1.0	-1.7	3.2	0.2	0.0	88.4
control (vulnerability)	1,513	0.0	1.0	-2.4	2.4	0.0	-0.5	77.9
consequences (vulnerability)	1,513	0.0	1.0	-2.9	1.8	-0.4	-0.3	89.3
internal locus of control	10,290	0.0	1.0	-4.0	1.6	-0.6	0.5	73.4
external locus of control	10,290	0.0	1.0	-1.7	3.6	0.3	-0.3	60.4
ambiguity tolerance	10,290	0.0	1.0	-1.3	3.5	0.6	0.0	77.9
property victimization	10,194	1.0	1.5	0.0	12.0	2.1	5.6	79.6
violent victimization	10,194	0.3	0.6	0.0	6.0	3.3	13.5	82.5
respondents' life events	3,711	0.5	0.8	0.0	3.0	1.4	1.3	64.8
life events close to respondent	3,712	2.1	1.7	0.0	7.0	0.6	-0.3	72.4
early life events	1,513	2.1	1.8	0.0	6.0	0.6	-0.7	76.9
neighboring	10,307	0.0	1.0	-1.6	1.4	0.0	-1.2	86.8
poverty	10,307	0.0	1.0	-1.5	2.5	0.3	-0.5	84.2

4.4 Operationalization of the theoretical concepts and extraction of variables

Modern survey research relies on existing and tested scales and standard items as well as newly developed or adapted scales. These (groups of) items attempt to capture theoretically defined concepts and constructs[4] and quantify them as variables for statistical analyses (Billiet 2016; Hox 1997). This section describes how the theoretical concepts were operationalized and measured.

The author reports completely standardized solutions (Brown 2015, 116–21) where the latent and observed variables were standardized ($\overline{x} = 0$; $sd = 1$). This eases interpretation since all loadings can be interested as usual correlation coefficients ($-1 \leq r \leq 1$). Further, the author reports non-imputed confirmatory factor analyses for technical reasons. The actual factor scores were multiply imputed using the R packages lavaan, semTools, and mice with 15 imputed data sets and auxiliary variables (Buuren 2012, 127; Buuren et al. 1999). The predictions of these imputed confirmatory factor analyses were averaged (Miles 2016; White, Royston, and Wood 2011) to obtain the final latent variables. Internal consistency reliability (hereafter reliability) was assessed with omega total using variance decomposition and polychoric/tetrachoric correlations (or Revelle's Omega Total; referred to as Ω below) which is superior to previous reliability measures including Cronbach's α (Dunn, Baguley, and Brunsden 2014; McNeish 2017).

Table 4.3 provides an overview of the unstandardized extracted variables and sum scores of the full dataset in the long format. The mean of zero and standard deviation of all latent factor scores is due to their fixed variance. Plausibly, life events (and especially violent victimization) are positively (or right) skewed. Overall, the reliability is sufficiently high to justify the extraction of the latent factor scores except for external locus of control. Section 8.2 of the appendix assesses measurement equivalence across waves.

4.4.1 Fear of crime

As discussed in Section 2.1, fear of crime captures heterogeneous concepts like emotions, cognition, behavior, and beliefs related to crime. This broad conceptualization led to various

[4]Concepts and constructs are closely related and often used interchangeably. Hox (1997, 53) argued concepts and constructs are both theoretical abstractions. However, whereas concepts are derived from generalizations of similar phenomena or attributes, a construct is systematically defined within a theoretical framework (see also Billiet (2016); Vanderveen (2006 ch. 2.1)). According to this definition, fear of crime is a concept while vulnerability to crime is a construct. This small difference, however, results in ambiguous case-by-case decisions. Hence, the author uses the term concept to refer to theoretical abstractions based on similar phenomena and attributes whether or not they are systematically defined within scientific theories.

Table 4.4: Loadings on crime-specific fear

Question	Crime-specific	% extracted
having your home broken into and something stolen?	.77	59.7
being mugged and robbed?	.98	96.2
being physically attacked by strangers?	.86	74.3
being victim of a fraud?	.62	38.6

Note: confirmatory factor analysis; standardized solution

operationalizations which were intensively investigated and debated for decades (Farrall, Jackson, and Gray 2009, ch. 3; Farrall et al. 1997; Ferraro and LaGrange 1987; Kreuter 2002; Noack 2015; Schnell and Noack 2016; Vanderveen 2006). A comprehensive discussion of this debate is beyond the scope of this thesis. However, single aspects are discussed in the respective sections.

4.4.1.1 Crime-specific fear

Crime-specific fear is assessed by asking "How worried are you about…" four offenses (see below) and is applied in this or similar ways in other studies (e.g., Birkel et al. 2014; Brunton-Smith and Sturgis 2011; Kury, Obergfell-Fuchs, and Würger 2000). This operationalization is methodologically less controversial (Ferraro and LaGrange 1987; Kreuter 2002; Noack 2015) and increasingly applied since it takes the criticism of the standard item (see below) into account.

The majority of people are somewhat worried while the second most common answer was "not worried at all." Thus, most people feel safe. There are only minor deviations of this general pattern. There are, e.g., slightly more people afraid of burglary and, contrary, fewer people afraid of being attacked by strangers.

An often-neglected second step is to look at the individual response patterns which reveal how people jointly answered all items. Response patterns provide a more refined picture: 14.2% or 933 respondents answered that they feel somewhat worried about all four offenses. The second most frequent response pattern (6.7% or 437) is feeling "not worried at all" about all offenses. In contrast, a non-negligible number of people (3.2% or 209) reported feeling "very worried" regarding all four offenses. Next, the latent variable is extracted.

Confirmatory factor analysis in Table 4.4 resulted in a good fit (Chi-sq.: 101.9(2)***; CFI: .999; RMSEA: .071; SRMR: .023) without any correlated errors, however, modification indices indicated substantial error terms between "having your home broken into and something stolen?" and "being physically attacked by strangers?" as well as "being physically attacked by strangers?" and "being victim of a fraud?." Since no theoretical or methodological justification for those error covariances was found, they were not allowed to correlate. Contrary to what, e.g., Noack (2015) suggested, distinguishing fear of property and personal crimes did not result in a significantly better solution despite that fear of burglary and fraud have somewhat lower loadings on the single factor.

4.4.1.2 Localized fear

Localized fear asked "How safe do you feel—or would you feel—if you" walking at different daytimes in your neighborhood. Such measurements are called the standard question, item, or indicator as well as a global item because they are used for decades in many general and criminological surveys and do not explicitly target the affective, cognitive, or behavioral component of fear of crime (Ferraro and LaGrange 1987). Other criticisms addressed its 1) implicit reference to (street) crime, 2) the spatially imprecise term neighborhood, 3) its differential meaning for specific groups of the population (e.g., older people might be more afraid of falling down then crime), 4) a low stability and long reactions times (which indicated high cognitive efforts), 5) question order in regard to victimization (Kreuter 2002; Noack 2015), or 6) an extraordinarily high correlation of this item with the behavioral (and less with the cognitive and affective) component of fear of crime (Greve, Leipold, and Kappes 2017).

Should the standard item be abandoned for these reasons? While this measure has limitations,

Table 4.5: Frequencies of avoidance behavior items

Question	yes
... avoid certain streets or places in my neighborhood at dark.	51.3% (n=3,268)
... take the car or a taxi rather than walk in my neighborhood at dark.	43.1% (n=2,754)
... rather stay at home at dark.	36.7% (n=2,336)
... avoid public transport at dark.	33.7% (n=2,133)
... leave the house only in company at dark,	28.6% (n=1,820)
... avoid certain streets or places in my neighborhood during daytime.	11.9% (n=762)

the author agrees with others that its advantages justify its careful use: Since this single item is very cost-effective, it was included in many high-quality general social surveys (Vanderveen 2006, 57). This enables international (Hummelsheim et al. 2011; Vauclair and Bratanova 2016; Visser, Scholte, and Scheepers 2013) and repeated cross-sectional investigations (Koeber and Oberwittler 2019; Reuband 1989). Another advantage is its explicit reference to the residential neighborhood that operationalizes feelings of unsafety in one's immediate living environment. Therefore, it is particularly useful for strongly neighborhood-related research hypotheses (Drakulich 2013; Häfele 2013, 102; Oberwittler 2008; Oberwittler, Janssen, and Gerstner 2017). Taken together, these advantages exceed the methodologic problems in certain situations.

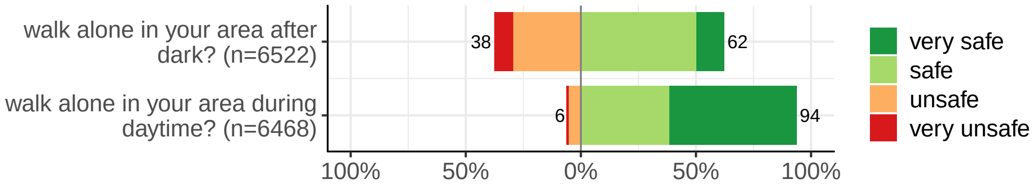

Figure 4.4: Relative item distribution of localized fear

Both items differ strongly regarding their distribution which underlines the non-negligible effect of daytime on perceptions of safety in the neighborhood (see Figure 4.4). In total, almost 40% feel (very) unsafe during the night, in contrast, 6% feel (very) unsafe during the day. Both items correlate considerably. Regarding response patterns, 35.8% or 2348 people answered that they felt safe at night and very safe during the daytime. However, the second most frequent response pattern is feeling unsafe at neigh and safe at daytime (20% or 1309). Since this construct consists of only two items, no confirmatory factor analysis is applied (Brown 2015, 61) but a sum score is calculated (see Table 4.3 for its distribution and reliability).

4.4.1.3 Avoidance behavior

As discussed in Section 2.1, the behavioral component is far less investigated compared to localized or crime-specific fear. This is surprising because such items can be regarded as behavioral costs of crime (Dolan and Peasgood 2007). From a theoretical perspective, avoidance behavior can be seen as reasonable coping mechanisms in the light of passive vulnerability (Greve 1998; Greve, Leipold, and Kappes 2017).

The sum scale of avoidance behavior is based on Lüdemann's (2006) study and subsumes the actions a respondent did to protect oneself from criminal victimization. It was introduced with "To protect oneself against crime, one can take various measures. Please tick which measures you have taken during the last 12 months. To protect me against crime, I. . . " and captured six types of avoidant behavior (see Table 4.5).

Each affirmative answer was regarded as one and summed to a single dependent variable. The resulting sum score is technically a discrete variable ranging from zero (none) to six (all) avoidance behaviors. The most appropriate way to model such a variable is a generalized count model with an appropriate link function (Friendly and Meyer 2016; Hilbe 2011). However, the estimation of such generalized models involves various problems. The regression coefficients cannot be interpreted as marginal effects (as in a linear regression model) because

Table 4.6: Loadings on perceived victimization risk

Question	Risk	% extracted
burglary	.75	56.7
robbery	.97	94.7
physical assault by a stranger	.83	69.2
fraud	.67	44.9

Note: confirmatory factor analysis; standardized solution

their actual strength always depends on other independent effects. Hence, raw coefficients can be compared neither between models with different predictors and the same dependent variable nor different dependent variables and the same predictors (Mood 2010; Tutz 2010). For a related reason, multiplicative interaction effects are more difficult to find and interpret in generalized models (Ai and Norton 2003). Since the comparability between the models as well as the analysis of interaction effects is vital for the following analyses, the author decided to fit linear models to investigate this outcome. However, a robustness check in Section 8.4.1 contrasts the critical findings of the linear models (discussed in Section 5.2) and a generalized linear models (using the negative binomial link function).

4.4.1.4 Perceived victimization risk

Perceived victimization risk is often regarded as the cognitive component of fear of crime (see Section 2.1). However, most studies used it as a predictor of affective fear of crime (Ferraro 1995; Jackson 2009; Häfele 2013). Similar to crime-specific fear, the respondents were asked "How likely do you think you are to be a victim of ... within the next 12 month?".

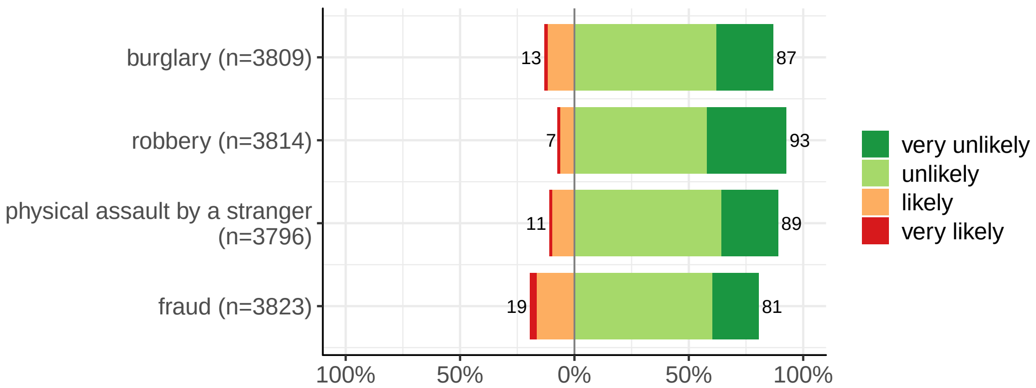

Figure 4.5: Relative item distribution of perceived victimization risk

The vast majority of people regard their victimization as unlikely (see Figure 4.5). Table 4.3 shows that all items correlate sufficiently. Importantly, these items were only surveyed in questionnaire version A (see Figure 4.1). Section 2.2 describes that the usage of this measure as a predictor of other fear measures must be based on the strong assumption that perceived risk predicts fear but not vice versa. Hence, this measure is used only to investigate changing environmental adversity due to victimization in a longitudinal model (controlling for unobserved time-stable heterogeneity).

Table 4.6 presents the standardized solution of the confirmatory factor analysis. Similar to crime-specific fear, perceived victimization risk had an acceptable fit (Chi-sq.: 97.4(2)***; CFI: .999; RMSEA: .08; SRMR: .026) without further rectifications. The modification indices indicate correlated error terms of burglary and assault as well as robbery and fraud. However, due to the absence of theoretical or methodological reasons, these correlations were not allowed. A two-factor solution (personal and property crime) was only marginally better than the one-factor solution (Chi-sq.: 70.6(1)***; CFI: .999; RMSEA: .097; SRMR: .022) and is, therefore, disregarded.

4.4.2 Vulnerability

In comparison to its theoretical importance, vulnerability to crime was rarely operationalized. Adams and Serpe (2000) assessed perceived vulnerability with two items “If someone assaulted me, I could protect myself.” and “If I were physically attacked, I would be seriously injured,” however, both item correlated rather weakly ($r = .37$). Stiles, Halim, and Kaplan (2003, 242) operationalized “perceived vulnerability” remarkably similar to internal locus of control without explicitly mentioning crime (e.g., “You can do very little to change your life”). Liu et al. (2009) assessed vulnerability with a measure of physical strength (“How would you rate your health/strength?”) and self-defense or alertness (“How do you rate your capability for self-defense/alertness about personal safety?”). Jackson (2009) operationalized vulnerability capturing all three of Killias’ (1990) dimensions (exposure to risk, controllability, and consequences) for seven different crimes, each with seven answering possibilities. More detailed, he asked for every offence how likely the respondent thinks it is (definitely not going to happen–certain to happen), if they felt able to control (not at all–to a very great extent), and how much this would affect their lives (not at all–to a very great extent).

Other studies used vignettes to measure vulnerability. Killias and Clerici (2000) asked their respondents to imagine an assault by a young unarmed man on a lonely street. They provided the following answering categories: “I’m sure I’d be able to escape or to defend myself; I’d probably be able to escape or to defend myself; it depends; I’d probably give in; I’m sure I’d give in; don’t know; no answer.” More recently, Studer (2014) asked elderly respondents to imagine that somebody is violently attacking them and asked how he or she would assess their ability to: “successfully run (drive) away?”, “calm down the attacker by talking,” and “prevent the situation by self-confident behavior” which had good reliability ($\alpha = .75$).

Instead of determining in advance what might constitute perceived vulnerability, qualitative interviews (for a short description see Section 4.1) allowed to identify theoretical dimensions based on empirical data. The vulnerability dimensions controllability and consequences of victimization appeared as essential dimensions in these semi-structured interviews, too. Noteworthy, both vulnerability scales are only available in T_2 and questionnaire version B (with a restricted age range of 60–89 years).

Regarding controllability, two more specific dimensions were frequently mentioned: First, controllability was related to physical fight-or-flight capabilities. Second, some respondents also mentioned mental speed, self-confidence, and paralysis which the author subsumed as psychological capabilities. They speculated, e.g., whether they come up with possible ways out of unpleasant situations and behave appropriately regardless of their physical constitution, e.g., by attracting the attention of yet uninvolved others or distracting the offender.

Based on this, a vignette was developed and pretested.[5] The final vignette had the following introduction: “Supposed you walk in the city alone during daytime and encounter two adolescents who look scary and stand in your way. What do you think, could you assert yourself in this situation, or would you be defenseless and at their mercy?”[6] The responses are visualized in Figure 4.6.

Both, psychological (“I would be paralyzed with fear” and “I would behave smartly. . . ”) and physical capabilities (“If necessary I could defend myself . . . ” and “I would be too weak to defend myself”) consisted of a positively and negatively worded (or poled) question. Interestingly, roughly two-thirds assessed their psychological capabilities as sufficient while approximately 45% perceived their physical capabilities as sufficing to evade this situation. This discrepancy is likely due to the advanced age of the respondents.

Three additional vignettes measured the anticipated consequences of victimization. They were introduced with: “Suppose you fell victim of the following crimes: How badly do you reckon would you suffer from the consequences of the offense?”

Figure 4.7 shows a remarkably different picture: In general, more than 50% of the respondents anticipate to suffer very much. The severity of the consequences is most pronounced for the assault in a park with a subsequent injury but only little less for the burglary. Credit card

[5]This pretest was conducted for both operationalization of vulnerability and other new questions for T_2 using LimeSurvey and a convenience sample ($n = 110$). More information are available upon request.

[6]In German: “Einmal angenommen Sie gehen tagsüber alleine in die Stadt und begegnen zwei bedrohlich wirkenden Jugendlichen, die sich Ihnen in den Weg stellen. Was glauben Sie, wie gut könnten Sie sich in dieser Situation behaupten, oder wären Sie ihnen schutzlos ausgeliefert?”

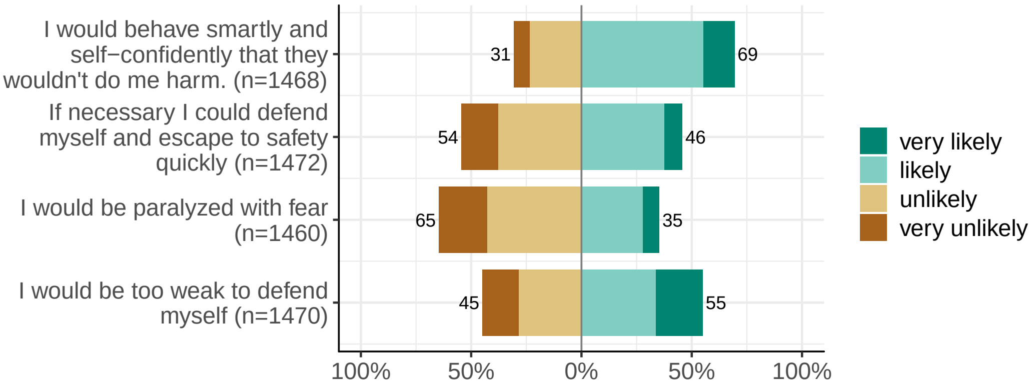

Figure 4.6: Relative item distribution of vulnerability (control)

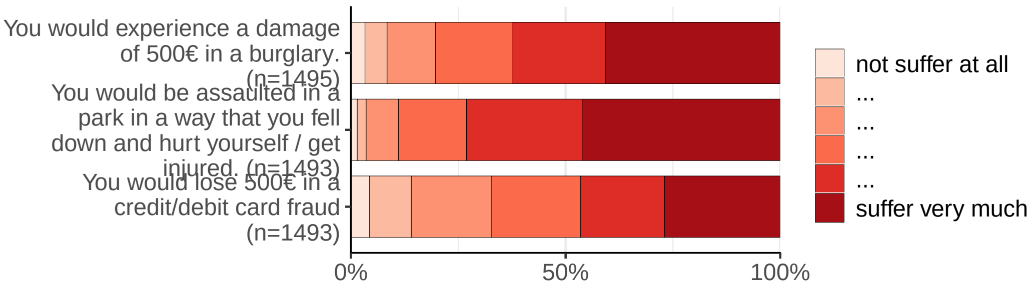

Figure 4.7: Relative item distribution of vulnerability (consequences)

fraud is assessed least consequential. However, almost 50% ticked either the strongest or second strongest suffering category.

Confirmatory factor analysis in Table 4.7 resulted in an acceptable fit (Chi-sq.: 31.3(11)**; CFI: .999; RMSEA: .036; SRMR: .026) after two measurement correlations were allowed. Within the first latent variable (control), "I would behave smartly ... " and "If necessary I could defend myself ... " are both reverse worded items (where a higher self-assessment is related to less vulnerability) and have correlated error terms ($r = .44$). Furthermore, the item "I would behave smartly ... " has a low loading and, hence, little extracted variance. However, it significantly contributes to the factor and has non-negligible inter-item correlation particular with "self-defense and escape" ($r = .64$; which is, of course, partially due to their measurement error) and is thus not removed from the model (Brown 2015, 156). Future studies could improve this item by dropping either "smartly" or "self-confidently."

The second latent variable (consequences) is strongly related to the anticipated effects of being assaulted in a park. While both items on property victimization contribute considerably to the latent factor, both items share a considerable error variance ($r = .64$). This indicates separate latent variables for the consequences of violent and property crime which, unfortunately, cannot be investigated in the absence of a second item measuring the consequences of violent crime.

4.4.3 Personality traits

Personality traits gain increasing attention outside their core field of psychology (Borghans et al. 2008; Mondak 2010; Schoen and Steinbrecher 2013) and have been investigated in the context of fear of crime for decades (see Section 2.4.3.1). According to the extended vulnerability approach, locus of control and ambiguity tolerance measure how people assess their ability to evade or attenuate victimization and cope with the consequences. Due to limited time and space in social surveys, there is a strong need for valid and reliable short scales measuring personality traits and an ongoing debated about their methodological properties (Rammstedt and Beierlein 2014). In this study, locus of control is investigated

Table 4.7: Loadings on vulnerability

Question	Control	Consequences	% extracted
I would behave smartly and self-confidently that they wouldn't do me harm.	-.31		9.5
If necessary I could defend myself and escape to safety quickly	-.61		37.3
I would be paralyzed with fear	0.79		62.4
I would be too weak to defend myself	0.89		78.7
You would lose 500 Euro in a credit/debit card fraud		0.66	43.1
You would be assaulted in a park in a way that you fell down and hurt yourself/get injured.		0.98	95.8
You would experience a damage of 500 Euro in a burglary.		0.74	54.2

Note: confirmatory factor analysis; standardized solution

with a four items short scale where two items assess external, and two items assess internal locus of control (Kovaleva, Beierlein, and Rammstedt 2014) as well as ambiguity tolerance with additional two items (Dalbert 1999). These items were introduced with "To what extent do you think each statement applies to you personally?"

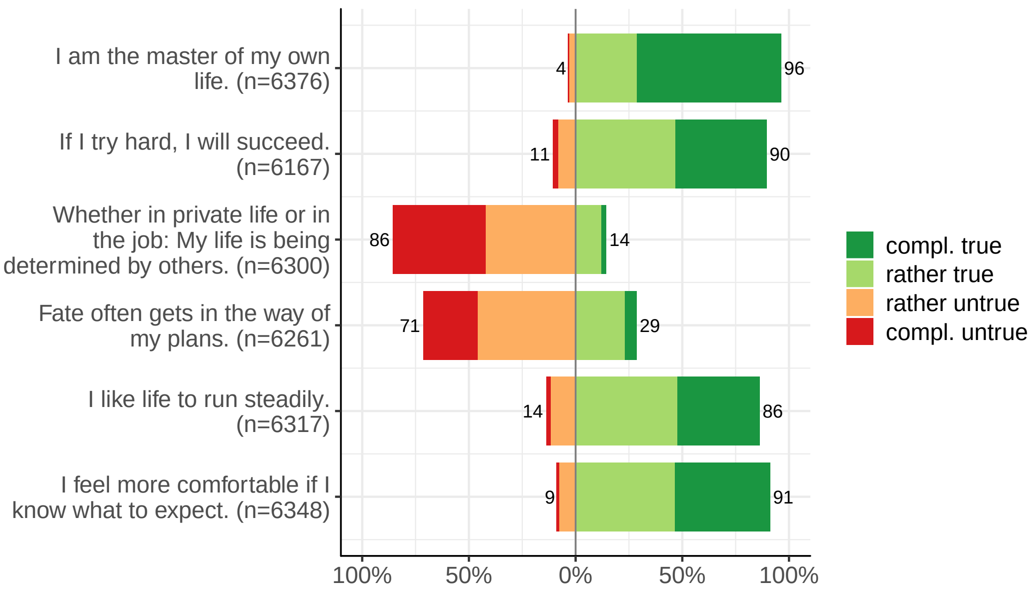

Figure 4.8: Relative item distribution of personality traits

Figure 4.8 shows that all items tend towards high internal/low external locus of control as well as ambiguity tolerance. Such skewed distributions are not unusual for such psychometric scales but methodologically undesirable due to potential floor or ceiling effects (Kovaleva 2012, 65). According to Table 4.3, the reliability of internal locus of control and ambiguity tolerance is acceptable but questionable for external locus of control. The standardized solution of the confirmatory factor analysis can be found in Table 4.8. All latent variables were allowed to correlate.

Overall, the confirmatory factor analysis of personality traits in Table 4.8 had an acceptable fit (Chi-sq.: 94.5(6)***; CFI: .995; RMSEA: .039; SRMR: .026) without any further modifications. However, external locus of control is problematic because of its low reliability and loadings. Therefore, external locus of control will be used with appropriate caution. Further, both items of external locus of control had some noteworthy cross-loadings to ambiguity and internal locus of control which were not allowed for theoretical reasons. Future studies might consider different assessments because this imperfect operationalization of external locus of

Table 4.8: Loadings on personality traits

Question	Int. LoC	Ext. LoC	Ambiguity	% extracted
I am the master of my own life.	.82			67.2
If I try hard, I will succeed.	.52			27.4
Whether in private life or in the job: My life is being determined by others.		.70		49.4
Fate often gets in the way of my plans.		.51		26.0
I like life to run steadily.			.62	38.0
I feel more comfortable if I know what to expect.			.85	72.7

Note: confirmatory factor analysis; standardized solution

control significantly predicted fear of crime.[7]

4.4.4 Beliefs and attitudes

4.4.4.1 Generalized trust

Generalized trust (and trust in general) has a rich history especially in political science, economics, and psychology (e.g., Bauer 2015; Hardin 2006; Lange 2015; Nannestad 2008; Simpson 2007; Twenge, Campbell, and Carter 2014) and is regarded as belief in this thesis (Connors and Halligan 2015). This study utilized a shorter variant of the widely used standard item (Glaeser et al. 2000) which was introduced with "Generally speaking, would you say that most people can be trusted?" and provided eleven answering categories (0 = don't trust at all; 10 = trust completely). It was negatively skewed but approximately normally distributed with a mean of 6.3 at T_1. Hence, most people tended to be trustworthy, however, there is considerable variance.

4.4.4.2 Neighborhood attachment

Neighborhood attachment is adapted from Kasarda et al. (1974) and used only to investigate whether the interaction of age and social disadvantage is attenuated if this item is included in the regression model. It was assessed with "Do you really feel 'at home' in your area?". In T_1 1.9% (of 6,522 valid responses) answered "not 'at home' at all," 9.7% answered "rather not 'at home'," and 44.2% answered "rather 'at home' " or "very much 'at home'."

4.4.5 Negative life events

4.4.5.1 Victimization

While victimization is intuitively the most important life event for fear of crime, revealing its actual effect is a complicated endeavor due to methodological difficulties discussed in Section 2.4.4.1. With its panel design, the SENSIKO study allows determining changes in fear of crime due to victimization (contrary to cross-sectional studies which investigate individual differences in fear between victims and non-victims). Therefore, respondents were asked to report their victimization 24 months before T_1 and in the 18 months between T_1 and T_2. Furthermore, the author distinguished between property and violent victimization. The tables 4.9 and 4.10 provide the frequencies as well as the percentage of victimized people in relation to valid answers of each victimization type and measurement occasion.

The most frequent type of victimization in T_1 and T_2 was property damage followed by theft, burglary, and scams. Overall, property victimization was widespread with nearly half of the respondents being victimized at least once before T_1 and more than one third being victimized at least once between T_1 and T_2 (see also Table 4.11). Violent victimization was less frequent with roughly 15% of all valid answers. Furthermore, the sum score of violent victimization is strongly influenced by the relatively less severe offense harassment. Only a minority of people was beaten or sexually assaulted.

[7] For more information about all surveyed items of these constructs see Oberwittler (2016).

Table 4.9: Frequencies of property victimization

	T_1		T_2	
Question	Once	more than once	Once	more than once
Burglary (attempt)	9.3% (n=595)	3.6% (n=230)	6.6% (n=241)	2.9% (n=108)
Burglary	6.5% (n=413)	1.5% (n=97)	3.5% (n=129)	1% (n=37)
Damaged property	20.1% (n=1,281)	9.3% (n=591)	16.9% (n=618)	5% (n=184)
Theft	15.6% (n=991)	5% (n=318)	10.1% (n=371)	2.2% (n=80)
Fraud	9.1% (n=581)	2.2% (n=141)	7.3% (n=267)	1.4% (n=50)
Scam	4.7% (n=303)	0.6% (n=36)	3.6% (n=134)	0.3% (n=12)

Table 4.10: Frequencies of violent victimization

	T_1		T_2	
Question	Once	more than once	Once	more than once
Physically assaulted	1.9% (n=124)	0.5% (n=33)	1% (n=37)	0.4% (n=14)
Harrassed or threatend	11.6% (n=739)	6% (n=380)	11.7% (n=431)	3.7% (n=135)
Sexually assaulted	0.9% (n=58)	0.3% (n=21)	0.5% (n=19)	0.2% (n=8)

Violent and property victimization was summed with once being equal to one and more than once as two. For analytical purposes (see Figures 5.3–5.6), it is necessary to distinguish between not victimized two years before the survey, only before T_1, only between T_1 and T_2, and before T_1 and between T_1 and T_2 (see Table 4.11).

4.4.5.2 Other negative life events

According to the generalized insecurity approach, victimization is not the only life event which might cause an increase in fear. In the SENSIKO study, the respondents of T_2 were asked about other life events between T_1 and T_2. Due to the absence of information in T_1, life events are only investigated with the cross-sectional sample of T_2 respondents.

The list of life events was inspired by the study of Cutrona et al. (2005) and distinguished life events depending on whom they happened to (personal or friends and relatives). Table 4.12 and 4.13 show their percentages and frequencies.

4.4.5.3 Early negative life events

Section 2.4.4.2 and 2.5.4.2 discussed the importance of life events and social conditions around birth, childhood, and adolescence. Various studies showed the importance of early life events and conditions, e.g., on health and economic success but no study so far investigated early life events due to World War II on fear of crime.

The early life events scale was adapted from the SHARELIFE study (see Table 4.14) which was dedicated to the retrospective assessment of life events (Schröder 2011). It was introduced with: "Many people have experienced war and hard times during their childhood, e.g., during or shortly after World War II. Did you suffer from one of the following events before your 14$^{\text{th}}$ birthday?"

Table 4.11: Frequencies of sum scores of property and violent victimization

	none	once	twice	more than twice
Property (T_1)	52.2% (n=3,384)	19.8% (n=1,282)	12.8% (n=829)	15.2% (n=985)
Property (T_2)	63.1% (n=2,340)	18.4% (n=683)	10.3% (n=381)	8.2% (n=306)
Violent (T_1)	81.9% (n=5,310)	11.1% (n=720)	5.2% (n=335)	1.8% (n=115)
Violent (T_2)	84.2% (n=3,123)	11.4% (n=423)	3.6% (n=135)	0.8% (n=29)

Table 4.12: Frequencies of respondents' life events

Question	Happend
Did you have family or relationship problems?	15.9% (n=587)
Did you have a financial loss or squeeze?	15.8% (n=582)
Did you fall ill badly?	13.1% (n=481)
Did you become unemployed or experienced job insecurity?	7.5% (n=273)
Have you been badly injured in an accident?	3.2% (n=119)

Table 4.13: Frequencies of life events close to respondent

Question	happend
Did somebody very close to you fall ill badly?	41.7% (n=1,538)
Did a close relative or good friend of you die?	38.8% (n=1,431)
Did somebody very close to you become dependent of care?	30.8% (n=1,134)
Did somebody very close to you have family or relationship problems?	29.4% (n=1,079)
Did somebody very close to you become unemployed or experienced job insecurity?	28.3% (n=1,040)
Did somebody very close to you have a financial loss or squeeze?	25.2% (n=924)
Has somebody very close to you been badly injured in an accident?	6.7% (n=246)
Did your spouse or partner die?	6% (n=220)

4.4.6 Individual social capital

4.4.6.1 Neighboring

Neighboring is understood as individual social capital in the residential area. The items draw on the study of Sampson, Morenoff, and Earls (1999) but were developed for the predecessor of SENSIKO study (Oberwittler 2003). It was introduced with "How often during the last 6 months have you done the following with people from your area?" The distributions are as expected: While the majority of respondents discussed personal matters, most respondents did not spend their leisure time together (see Figure 4.9).

Confirmatory factor analysis in Table 4.15 suggests a good fit (Chi-sq.: 11.6(1)**; CFI: 1; RMSEA: .033; SRMR: .012 compared to Chi-sq.: 179.4(2)***; CFI: .994; RMSEA: .095; SRMR: .042) after allowing one error correlation (r = .32) between "did small favors" and "discussed personal matters." Both items assess help (compared to leisure activities) and might, therefore, reflect a slightly different aspect of individual social capital in the neighborhood.

4.4.6.2 Household support

Section 2.5.3.3 suggested that people with no social support are more fearful than others because of the more severe consequences. This was operationalized with a general question on household support in case of illness and introduced with: "Supposed you are ill in bed and need help at home. Could you ask anyone for help?" and allowed three answering categories. Of 2,567 valid answers, 89.7% answered "yes," 3.8% "no," and 6.5% "don't know."

Table 4.14: Frequencies of early life events

Question	happend
Did you experience acts of war directly, e.g., a bombing raid?	36.6% (n=536)
Did your family flee or was expelled or expropriated from your homeland?	33.4% (n=490)
Did your father or a sibling die?	31% (n=454)
Did you suffer from hunger?	28.3% (n=414)
Was your family's home/house destroyed by acts of war?	26.3% (n=383)
Did your mother die, or were you separated from your mother for longer time periods?	17.9% (n=259)
Did your family suffer from persecution or discrimination (for political, religious or reasons of ethnic origin)?	9.7% (n=142)

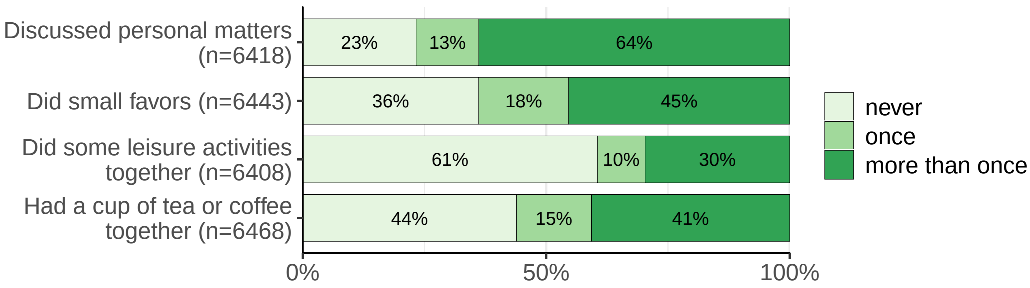

Figure 4.9: Relative item distribution of neighboring

Table 4.15: Loadings on neighboring

Question	Neighboring	% extracted
Had a cup of tea or coffee together	.92	85.4
Did some leisure activities together	.83	68.4
Did small favors	.67	44.9
Discussed personal matters	.66	43.3

Note: confirmatory factor analysis; standardized solution

In previous analyses, these categories were analyzed separately. Since this had no impact on the findings, the author distinguishes only between "yes" and "no/don't know" because the latter also expresses uncertainty in case of future need.

4.4.7 Financial strain

According to Section 2.5.3.3, people with more financial difficulties are more fearful due to, e.g., problems compensating economic consequences of victimization. In T_1, 15.1% (of 6,366 valid answers) received social benefits during the last 12 months. Regarding the second item, 11.3% (of 6,476 valid answers) were unable to pay a bill of 500 Euro while 27.7% could do this only with difficulties. Moreover, 82.4% (of 6,495 valid answers) come along with their monthly income rather well, well, or very well while 2.4% do so very bad, 5% bad, and 10.2% rather bad.

Financial strain is a complex concept which was not operationalized in advance but several related items showed an excellent reliability (see Table 4.3). It was composed by three strongly correlating variables (see Table 4.16) providing information about the financial situation of a respondent's household. Since this three-item one-factor solution is just-identified, no fit statistics can be provided.

Table 4.16: Loadings on financial strain

Question	Financial strain	% extracted
Did you or another member of your household receive one of the following social benefits during the last 12 months? (unemployment benefit, other social security benefit, benefits for paying rent, or none of these benefits)	0.79	62.7
If you immediately had to pay a large bill, e.g. 500 Euro for a new washing machine or a car repair, would you be able to pay this bill?	0.99	97.8
Thinking of your household's total monthly income, does your household make ends meet?	-.67	45.1

Note: confirmatory factor analysis; standardized solution

Chapter 5

Results

The report of results starts with an overview of the models, their designs, and samples. The three-level longitudinal design and the split questionnaire yielded high analytical complexity. As an overview, Table 5.1 summarizes information regarding dependent variables, data limitations, the sections in which they appear, and the lowest level of analysis.

This chapter starts with a visual analysis of bi- and multivariate associations beyond the univariate statistics provided in Chapter 4. Section 5.2 provides between-person and (where possible) within-person estimates of vulnerability factors. Section 5.3 prospectively examines victimization in a methodologically more complex manner than previous analyses. Section 5.4 analyzes life events other than victimization. Section 5.5 investigates whether vulnerability factors are mediated by anticipated controllability and consequences (as two mechanisms of vulnerability). Section 5.6 examines neighborhood characteristics more closely (including spatial lags). Section 5.7 presents interaction analyses of the vulnerability factors and stressors (victimization and neighborhood characteristics).

5.1 Preparatory visual data analyses

Preparatory visual data analyses are essential precursors of inferential statistics. However, they are often absent from social science analyses (Healy and Moody 2014). Data visualization indicates what can be expected from technically sophisticated but more complicated and less intuitive statistical models. According to Tufte (2001, 51) and Ware (2012), good data visualization is almost always multivariate and hence allows a detailed understanding of bi- and multivariate distributions of (in-)dependent variables. Following these insights, this chapter presents selected visual data analyses with a high density of information to prepare for later regression analyses.

5.1.1 Correlations and distributions of fear of crime subtypes

Statistical relationships between components of the fear of crime attracted less attention than, e.g., gender or age differences. Although they are not the focus of this thesis, a short discussion about their (joint) distribution is vital for more methodological considerations, particularly in Section 5.7. Section 8.1 in the Appendix provides an exploratory investigation of longitudinal relationships among the affective, behavioral, and cognitive components of fear of crime that supports the complex claims in Section 2.2.

The scatterplot matrix (Emerson et al. 2012) in Figure 5.1 displays uni- and bivariate distributions of interrelations between z-standardized fear of crime components. The diagonal shows the univariate distributions that are positively skewed: most respondents express little fear of crime and display no avoidance behavior. Such skewed distributions invite floor or ceiling effects as they are less able to capture variance at both ends of the distribution. Fortunately, crime-specific fear as the most frequently investigated outcome in this thesis is the least affected by this issue, however, avoidance behavior—the second-most investigated outcome in this thesis—shows a considerable positive skew that requires methodological refinements (e.g., by including frequent types of avoidance behavior). To assure that the results are not statistical artifacts attributable to this violation of the distributional assumption of

Table 5.1: Overview of the analytical structure

Main category	Analysis	Dependent variable*	Data limitations	Section	Lowest level of investigation
Preparatory	Distribution and correlations of fear of crime components		T^1	5.1.1	Between-person
	Age group differences in fear of crime subtypes		T^1	5.1.2	Between-person
	Longitudinal analysis of fear of crime and victimization		Respondents of T^1 and T^2	5.1.3	Within-person
	Intra-neighborhood and intra-individual correlation coefficients		none	5.1.4	Within-person
	Early life events per birth cohort		T^2, version B	5.1.5	Between-person
Longitudinal	Vulnerability factors	csf, ab	none	5.2	Within-person
	Victimization (main effects and mediation via personality traits and generalized trust)	csf, ab	none	5.3	Within-person
	Victimization (main effects and mediation via perceived risk of victimization)	csf, ab	Version A	5.3	Within-person
Cross-sectional	Vulnerability factors (time-stable; age, gender, education, household support and all means of within-person level)	csf, ab	none	5.2	Between-person
	Early life events (main effect and mediation via vulnerability)	csf	T^2, version B	5.4	Between-person
	Other life events	csf	Version B	5.4	Between-person
	Vulnerability scale (main effects and mediation)	csf, ab	T^2, version B	5.5	Between-person
	Neighborhood effects (including spatial lags)	csf, ab, lf	none	5.7.2	Neighborhood
	Interactions of physical vulnerability factors with victimization	csf, ab	none	5.7.1	Between-person
	Interactions of physical vulnerability factors with neighborhood characteristics	csf, ab, lf	none	5.7	Between-person

Note: *crime-specific fear (csf), avoidance behavior (ab), localized fear (lf) this dependent variable, Section 8.4.1 re-ran the main analyses with the more appropriate negative binomial distribution. The results are nearly identical although the significance level is slightly lower. Therefore, weak significant effects of the linear models should be interpreted with some caution. For comparability between dependent variables, however, the author applies linear regression analysis to this outcome variable.

All correlations between fear of crime variables are strong and highly significant. The question arises as to whether the differences between the correlations are significant.[1] As hypothesized, localized fear correlates more strongly with crime-specific fear—the affective component of fear of crime—than it does with the perceived likelihood of victimization. Contrary to what Ferraro and LaGrange (1987) argued, the affective component of localized fear prevails over the cognitive component according to this correlation analysis.

Further, the correlation between localized fear and avoidance behavior is strong (Greve, Leipold, and Kappes 2017). This result might be explained partly by their explicit reference to respondents' neighborhoods (see Section 3.3.2). A conclusive answer to this question is beyond the scope of this analysis. The assessment of gender, city, and age differences reveals no substantial differences although the likelihood of victimization is slightly less connected to other subtypes of fear in the case of people above age 65.

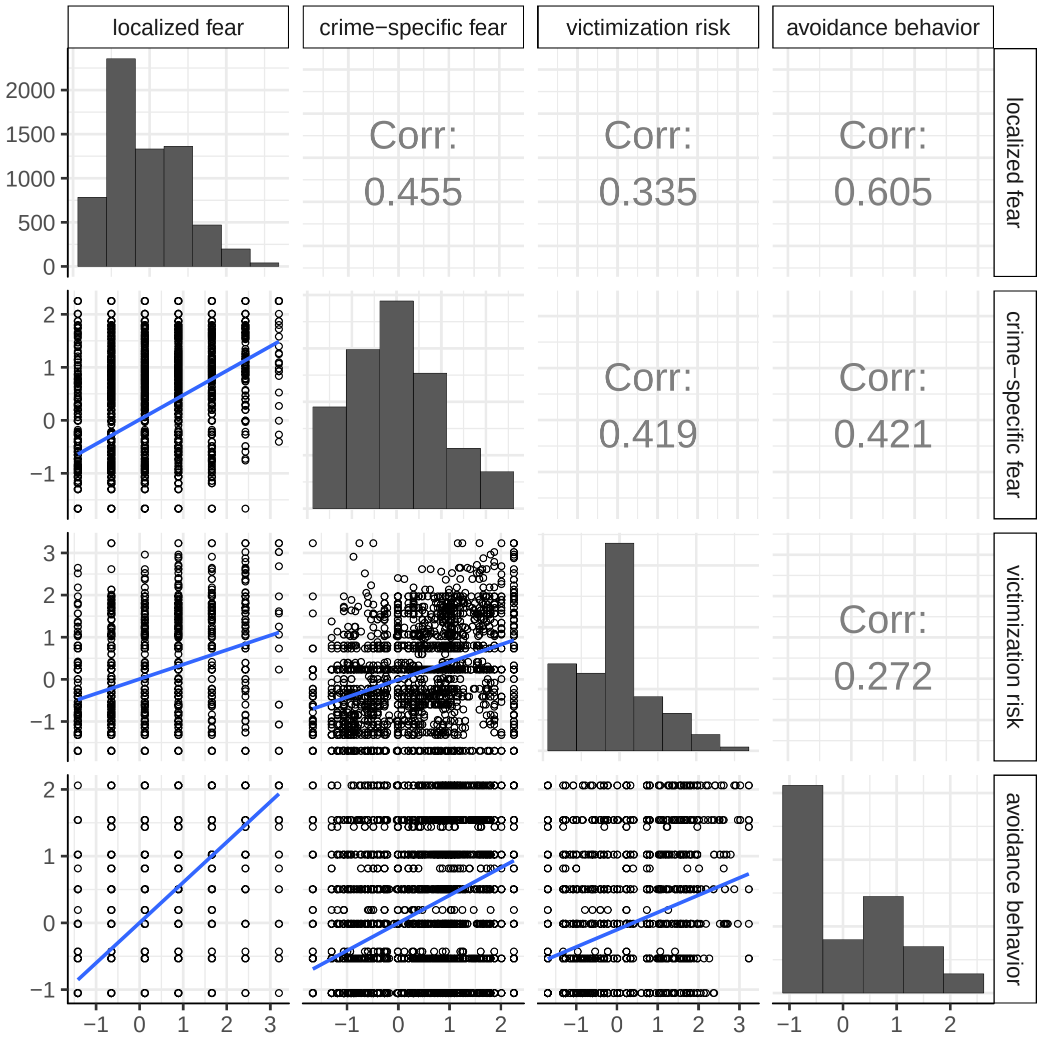

Figure 5.1: Correlations and distributions of fear of crime subtypes

[1]Significance was assessed using the Dunn and Clark's z for overlapping correlations based on dependent groups (Diedenhofen 2015; Hittner, May, and Silver 2003; Zou 2007). Because perceived victimization risk is only available in questionnaire version A the correlation matrix was recalculated based on this cross-sectional subset which resulted in a smaller sample size and a marginally larger difference between the correlation coefficients.

5.1.2 Age group differences for fear of crime

The effect of age on fear of crime is of particular interest. Greve (1998, 292) found that the separate components of fear of crime are differently affected by age. Figure 5.2 reproduces his analysis, and importantly, the pattern of age group differences in fear of crime is almost identical in the SENSIKO sample of Cologne and Essen (in contrast to his larger, nationwide sample two decades earlier).

From this bivariate comparative perspective, older people exhibit only marginally more crime-specific fear. As in Greve (1998, 292), perceived risk declines in the highest age groups. Localized fear and avoidance behavior increase considerably with age. Greve (1998) concluded that older people are not necessarily more alarmed and do not misinterpret the risk of victimization; they respond to their higher vulnerability with foresight, not fright.

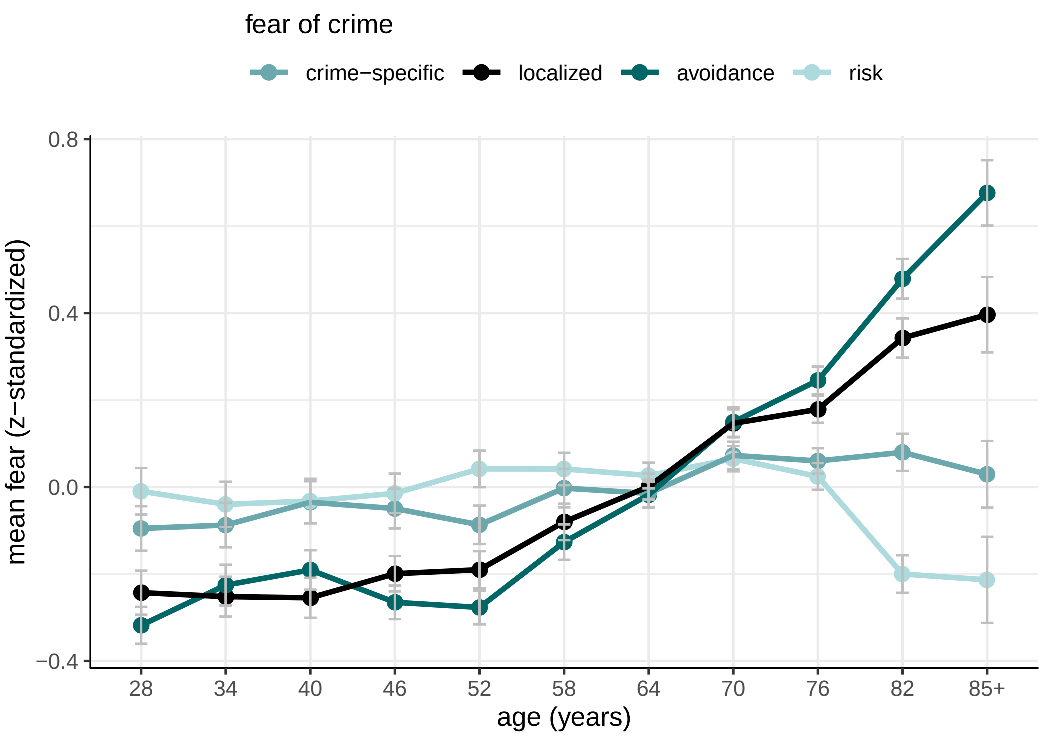

Figure 5.2: Age group means of fear of crime

Studies in German-speaking countries investigated the relationship between age and localized fear. Some found small or negative effects (Görgen 2010, 145; Studer 2014, 110). However, most studies repeatedly found a u-shaped influence of age on localized fear (Birkel et al. 2014; Reuband 1989). These studies rarely investigated the relationship between age and measures of fear of crime other than localized fear.

Studies in the English-speaking world found age–fear relationships different than studies in Germany and Austria. In a comprehensive study of metropolitan areas in the US, Ferraro and LaGrange (1992) mostly found no or negative correlations between several fear measures. Studies analyzing data from the British Crime Survey found that younger people reported more crime-specific fear than did older people (Brunton-Smith and Sturgis 2011; Farrall, Jackson, and Gray 2009, 194). In contrast, Sargeant et al. (2017) found that older people reported more localized fear in Brisbane.

These contradictory findings call for a context-dependent analysis of age differences of fear of crime and are somewhat comparable with differential age effects that are dependent on neighborhood characteristics within cities. This strand of research suggests that positive age effects can be expected in less disorderly, crime-ridden, or disadvantaged areas (see section 2.5.1 and 5.7.2). Furthermore, this ambiguous situation indicates the need for cross-country comparative research into country differences and similarities regarding age effects on fear of crime. Simple literature reviews are limited because of the already discussed particularities of the age–fear relationship: it depends on the investigated component of fear of crime, the control variables, and potential nonlinear effects or interactions with gender (see section 2.4.3.2.3, 2.4.3.2.1 and 5.2.1).

5.1.3 Longitudinal analysis of fear of crime and victimization

As discussed in Section 2.4.4.1, the premise that victimization increases fear of crime is the object of many empirical investigations. However, an overwhelming majority of those studies analyzed cross-sectional data and are consequently limited in their informative value because these findings are likely to suffer from unobserved heterogeneity: victims of crime might differ from non-victims in many ways. As noted in Section 3.3.1.1, longitudinal research controls for time-stable unobserved heterogeneity and provides estimates that are closer to the causal effects of interest.

The logic of ruling out time-stable differences between victims, non-victims, and future victims is applied in figures 5.3–5.6, which investigate crime-specific fear and avoidance behavior among people with different victimization statuses at T_1 and T_2 and provide t-tests above the bars. To compare group means, the sample was restricted to people who participated in T_1 and T_2 and separated for victimization concerning violence and property. As victimization is rare, the error bars of the victimized groups are comparatively wide despite the relatively large sample.

Figures 5.3–5.6 show that people who were not victimized—neither before nor between waves—report slightly below-average crime-specific fear and avoidance behavior at T_1 and T_2 (the dashed line). The increase of avoidance behavior in the absence of victimization can be interpreted as period or age effects or both (see section 3.3.1.1 and 3.3.2).

Victims of violent crime before T_1 but not between T_1 and T_2 report above-average fear at T_1 and slightly less at T_2, not significantly different from the mean. This recovery effect is similar but less pronounced among victims of property crime. The reduced fear is relevant for later analyses because between-within models assume the presence of recovery effects from events (and they are as strong as the increase attributable to victimization between T_1 and T_2; see Table 5.4). However, there is no visible recovery effect for avoidance behavior despite the acknowledgment of positive age or period effects. This called for in-depth analyses (see Section 5.3).

The logic and advantages of between-within modeling are best expressed by the category "between T_1 and T_2" showing increased fear in T_2, which is likely to have been brought about by the detrimental event(s) between the measurement occasions. The effect of violent victimization is slightly stronger than that of property victimization for crime-specific fear but not for avoidance behavior. Importantly, people who were violently victimized between T_1 and T_2 were more fearful already in T_1 than those who were not victimized. This is not the case in property victimization. Perhaps the people in these groups anticipated their violent victimization but not their property victimization. That surmise appears plausible because violence might create a threatening perception of environmental adversity that affects people long before actual victimization. In contrast, property victimization mostly occurs without notable prior indication.

Victims before T_1 and between T_1 and T_2 report above-average fear at T_1 and T_2. This visual analysis, however, can make no statement regarding within-group changes because it is unclear as to how often people were victimized before T_1 and between T_1 and T_2 (unlike all other groups). Hence, the within variable at T_2 (or inversely T_1) can be zero, negative, or positive for this group (see Table 5.4 for an application of between-within transformations for victimization events).

Note that Figure 5.4 suggests that between-person effects are lower for repeated victimization. This is indicated by a comparison of the increase from T_1 to T_2 of both groups that were victimized (again) between T_1 and T_2. The lower increase of the group "before and between" (victimized at least twice, once before T_1 and once between T_1 and T_2) when compared with the higher increase of the group "between T_1 and T_2" suggests a curvilinear effect at the between-person level that declines with repeated victimization (see Section 5.3).

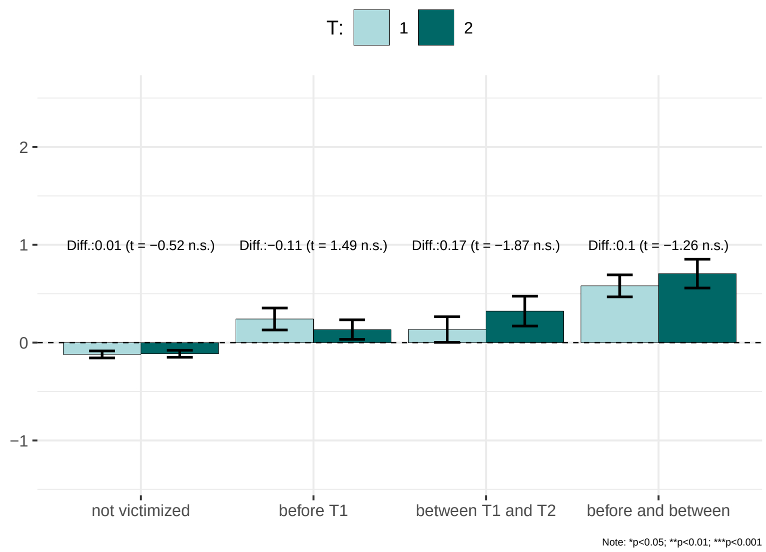

Figure 5.3: Crime-specific fear depending on measurement occasion and violent victimization status

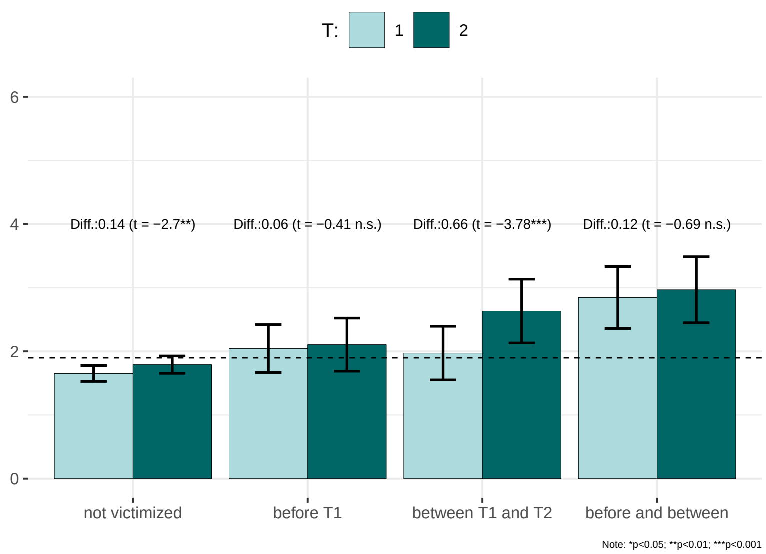

Figure 5.4: Avoidance behavior depending on measurement occasion and violent victimization status

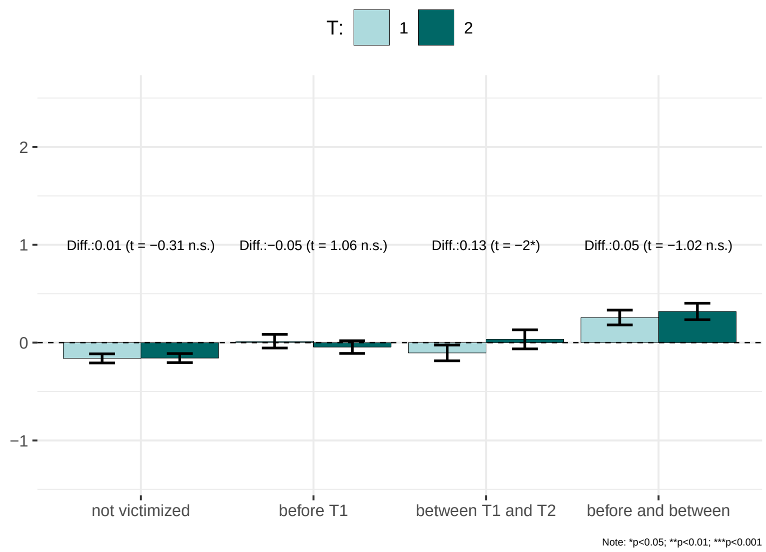

Figure 5.5: Crime-specific fear depending on measurement occasion and property victimization status

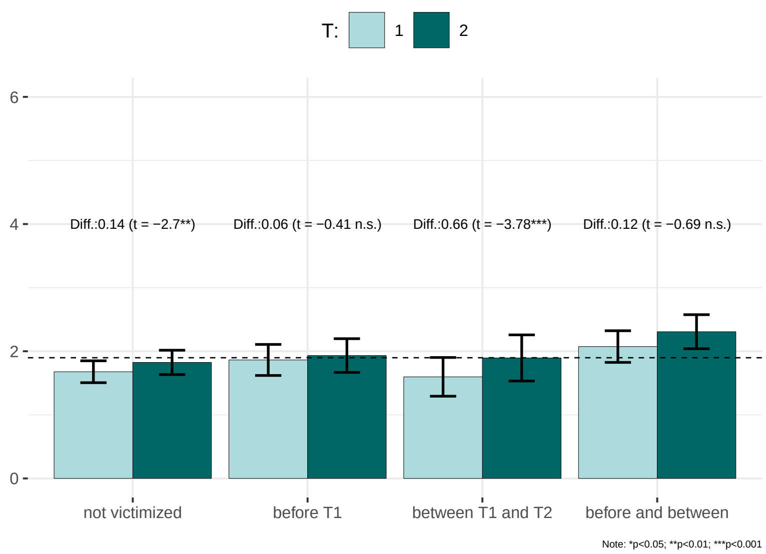

Figure 5.6: Avoidance behavior depending on measurement occasion and property victimization status

5.1.4 Intra-neighborhood and intra-individual correlation coefficients

As introduced in Section 3.3.2, intra-neighborhood, intra-individual, and residual variance imply an intuitive interpretation of the percentage of variance that can be attributed to neighborhood, person, or change (plus measurement error). Hence, high values of $ICC_i + ICC_n$ indicate rather time-stable variables or scales. Figure 5.7 displays these variance components. Therefore, three-level regression models are estimated for each variable with T_2 as the only predictor. The coefficient of T_2 appears in Figure 5.7 alongside variable labels. It is difficult to attribute this effect to age or period (see Section 3.3.1). When the effect of age is strong at the between-person level (e.g., localized fear, avoidance behavior, and health), these within-person effects are likely to be largely the result of aging. For another variable (such as the cognitive fear of crime), period effects might be responsible. All dependent variables were z-standardized for comparison and sorted by the percentage of neighborhood variance or ICC_n.

Localized fear and avoidance behavior have the highest ICC_n. Moreover, 58% of all variance in avoidance behavior is time-stable individual variance. Hence, avoidance behavior is a comparatively stable outcome, which makes the investigation of within-person changes more difficult. Neighborhood explained 4% of all variance in crime-specific fear. This value is numerically lower than those in other studies (Brunton-Smith and Sturgis 2011, 350). However, the ICC_n is not comparable with previous cross-sectional studies because there are three (not two) variance components in this longitudinal study. In other words, this ICC_n expresses the share of neighborhood variance in proportion to between- *and* within-person variance and not (as cross-sectional studies) between-person variance only.

According to Figure 5.7, neighborhood variance in the perceived risk of victimization is surprisingly small (ca. 3%). This finding questions previous studies that argued that neighborhood characteristics predominantly influence perceived risk (e.g., Ferraro 1995). Although this indicates that an investigation of the actual drivers of the perceived risk of victimization would be informative for fear of crime research, an in-depth investigation of this outcome is beyond the scope of this thesis. Interestingly, a considerable percentage of total variance in the perceived risk of victimization is at the within-person level. In addition, there is a substantial effect of the measurement occasion, which, in the absence of cross-sectional age differences (see Section 5.1.2), is considered to be a period effect, potentially the result of an increase in the influx of migrants (Koeber and Oberwittler 2019). In light of this novel perspective on the changes in the components of the fear of crime, a dynamic perspective, particularly on perceived risk, seems to be a valuable extension of previous research, which strongly focused on the neighborhood effects on fear.

Turning the attention to the independent variables of later analyses, several aspects are noteworthy. Contrary to expectations, the locus of control and the tolerance of ambiguity have substantial within-person variance (and partly significant within-person effects), which indicated a non-negligible change in these presumably stable personality traits. Violent and property-related victimization decreased between T_1 and T_2. This can be accounted for by a shorter surveyed victimization period (24 months in T_1 vs. 18 months in T_2). Considering the smaller extent of victimization between the measurement occasions, telescoping seems less likely with the first measurement occasion as a temporal landmark.

5.1.5 Early life events per birth cohort

This study also investigates the importance of early life events on fear of crime. As discussed in Section 2.4.4.2 and 2.5.4.2 and drawing upon cumulative inequality theory (Ferraro and Shippee 2009), the underlying notion is that detrimental early life events have adverse effects throughout life. As older people in our sample experienced World War II and its aftermath (notably the "Hungerwinter" 1946–1947), this section investigates the underlying assumption that an accumulation of these events characterizes the War Generation (i.e., the birth cohorts 1929–1947; see Koeber and Oberwittler (2019)).

Figure 5.8 shows that the birth cohorts between 1925–1947 reported a considerably increased amount of negative early life events (most likely due to World War II). While this accumulation of early life effects might be particularly pronounced in Germany, similar patterns are likely to be found in other countries. Such early life events have been related to long-term

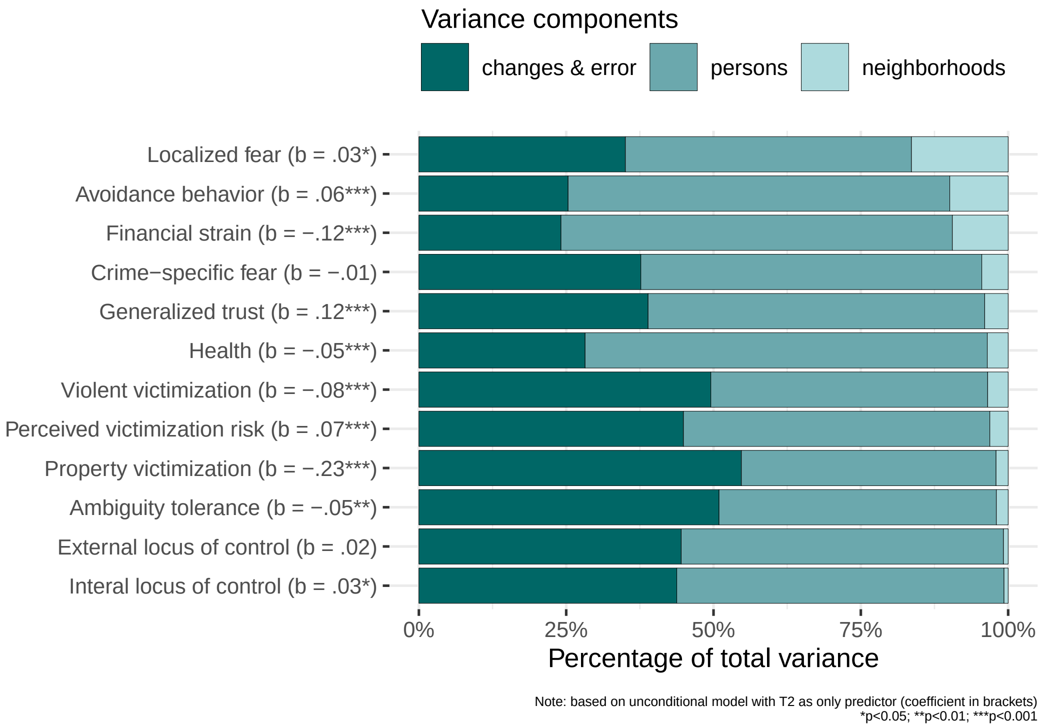

Figure 5.7: Variance components and within-person changes of (in)dependent variables

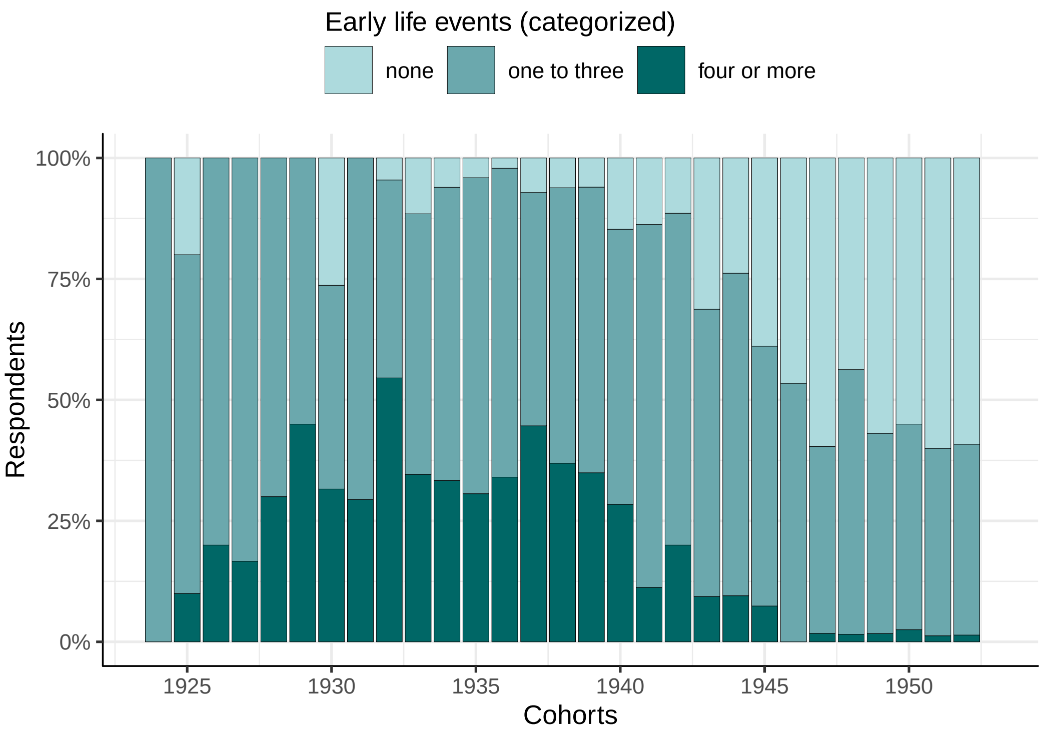

Figure 5.8: Frequency of early life events per cohort

negative consequences (Berg et al. 2010; Berg, Doblhammer, and Christensen 2009; Haas 2008; Hayward and Gorman 2004; Lundberg 1993; Xie and Lagergren 2016). For example, Kesternich et al. (2014) found that experiences during World War II are associated with a higher risk of diabetes, depression, and probably heart disease and are reflected in lower self-rated health. Therefore, it seems reasonable to assume that this War Generation differs from later birth cohorts in many aspects. Section 5.4 investigates the effects and pathways of early life events on fear of crime.

5.2 Vulnerability factors

This section investigates hypotheses of the extended vulnerability approach introduced in Section 2.5. This approach argues that some people are more fearful of crime than others because they differently anticipate their openness to victimization, ability to prevent it, and its consequences. Physical and social factors, personality traits, generalized trust, and the victimization history are hypothesized factors for higher perceived vulnerability. As argued above, the emotional *and* behavioral components of fear of crime are particularly relevant for (passively) vulnerable people. This section investigates crime-specific fear and avoidance.

Numerous studies investigate the relationship between vulnerability factors and fear of crime. However, longitudinal studies in fear of crime research are scarce. No previous study addressed whether changes in vulnerability were related to changes in fear of crime. This section tests this approach longitudinally. It investigates within-person changes in vulnerability factors when possible (victimization, locus of control, ambiguity tolerance, generalized trust, health, financial strain, and neighboring) and between-person differences (age, gender, education, and household support) in addition to the means ($\overline{z}_{0i}$) of the within-person variables (see Section 3.3.1.1). The within-person mediation of victimization is discussed in Section 5.3.1.

Applying random effects between-within models allows the investigation of between-person differences (Are poor people more afraid of crime than affluent people?) and individual changes (Does a worsening financial situation heighten fear?) simultaneously. As more thoroughly introduced in Section 3.3.1, this is advantageous to cross-sectional analyses because it is less affected by unobserved heterogeneity and more rigorously tests the causal effects of vulnerability on fear. When compared with other longitudinal techniques, the between-within approach is preferable to fixed-effects models because it reproduces the same within-person estimates but additionally assesses time-stable between-person differences (Bell and Jones 2015). This is particularly beneficial for this study with its focus on age, gender, and neighborhood characteristics. A disadvantage of the between-within approach is that all time-varying variables have two coefficients: the within-person coefficient is indicated in all tables by the suffix (wi), whereas between-person variables have no indication.

This section fits five structurally equivalent three-level between-within linear models to crime-specific fear and avoidance behavior. Throughout this thesis, the author raises comparative questions (e.g., whether gender is the strongest predictor of fear and whether avoidance behavior is more affected by vulnerability than affective fear of crime). Hence, comparability must be provided within models and across dependent variables. For comparability within models, all continuous variables are standardized with two standard deviations. According to Gelman (2007), doing so allows the comparison of continuous and categorical coefficients of variables, given their similar standard deviations. In addition, all dependent variables are z-standardized for comparability between dependent variables. Standard errors are generally not reported but are available upon request.

With regard to the control variables (bottom of Table 5.2 and 5.3), people report more avoidance behavior (and marginally more crime-specific fear, depending on the control) in T_2. Section 3.3.1 and 3.3.2 argued that this is more likely an age effect than a period effect: strong between-person effects of age, particularly in higher age groups, indicated that this is more likely to be a within-person effect of aging than a period effect. Accordingly, this coefficient is considerably smaller and hardly significant for crime-specific fear. People in Cologne report less fear and avoidance behavior than do people in Essen. In this section, neighborhood social disadvantage, crime, and incivility from systematic social observations (sso) are merely control variables. They are more thoroughly analyzed in Section 5.6.

Table 5.2: Multilevel models of vulnerability factors predicting crime-specific fear

	Dependent variable: crime-specific fear				
	mm1.1	mm1.2	mm1.3	mm1.4	mm1.5
age	.14***	.02	.13***	−.01	.12
gender: female	.17***	.16***	.15***	.15***	.18***
violent vic. (wi)	.04***	.04***	.04**	.04***	.06**
violent vic.	.37***	.35***	.31***	.33***	.43***
violent vic. (sq)	−.06**	−.05**	−.05**	−.06**	−.07
property vic. (wi)	.06***	.06***	.06***	.06***	.07***
property vic.	.36***	.34***	.32***	.35***	.35***
health (wi)		−.001		.002	
health		−.28***		−.20***	
internal loc (wi)			.01		
internal loc			−.08*		
external loc (wi)			.04*		
external loc			.12***		
ambiguity tol (wi)			−.004		
ambiguity tol			−.23***		
trust (wi)			−.04***		
trust			−.35***		
financial strain (wi)				.03*	
financial strain				.13***	
school education: low				.08*	
... high				−.13***	
... no degree				.11	
other/missing				.06	
neighboring (wi)				−.04**	
neighboring				−.10***	
household support: no/don't know					.12*
T: 2	.02	.02	.03*	.03*	−.03
crime	.04	.04	.04	.03	.05
social disadvantage	.31***	.27***	.21***	.19***	.26***
incivilities (sso)	−.05	−.04	−.03	−.05	−.10*
city: Cologne	−.09**	−.08**	−.06*	−.06*	−.07
Constant	−.03	−.04	−.07*	−.06	.01
Respondents	6372	6349	6333	6349	2486
Observations	9,720	9,682	9,632	9,682	3,800

Note: *p<0.05; **p<0.01; ***p<0.001;

Sample: mm1.1–mm1.4: a; mm1.5: e (see Section 4.1)

Table 5.3: Multilevel models of vulnerability factors predicting avoidance behavior

	Dependent variable: avoidance behavior				
	mm2.1	mm2.2	mm2.3	mm2.4	mm2.5
age	.52***	.40***	.50***	.40***	.43*
age (sq)	.36***	.35***	.33***	.36***	.28
gender: female	.54***	.54***	.52***	.53***	.56***
female x age	.13**	.13**	.11**	.11**	.17
violent vic. (wi)	.05***	.05***	.04***	.05***	.05**
violent vic.	.41***	.38***	.34***	.37***	.51***
violent vic. (sq)	−.07***	−.06***	−.05***	−.06***	−.10*
property vic. (wi)	.04***	.04***	.04***	.04***	.01
property vic.	.19***	.17***	.15***	.18***	.15***
health (wi)		−.01		−.01	
health		−.27***		−.20***	
internal loc (wi)			.01		
internal loc			−.04		
external loc (wi)			.03*		
external loc			.11***		
ambiguity tol (wi)			−.01		
ambiguity tol			−.24***		
trust (wi)			−.02*		
trust			−.34***		
financial strain (wi)				.02	
financial strain				.11***	
school education: low				.09**	
... high				−.09**	
... no degree				.09	
other/missing				.01	
neigh contact (wi)				−.01	
neigh contact				−.13***	
household support: no/don't know					.12*
T: 2	.07***	.07***	.08***	.08***	.11***
crime	.04	.05	.05	.04	.07
social disadvantage	.47***	.43***	.37***	.36***	.47***
incivilities (sso)	.16**	.16**	.16**	.15**	.12
city: Cologne	−.21***	−.20***	−.18***	−.18***	−.19***
incivilities x Cologne	−.25***	−.25***	−.23***	−.25***	−.26**
Constant	−.30***	−.30***	−.32***	−.33***	−.32***
Respondents	6259	6243	6226	6243	2419
Observations	9,521	9,493	9,443	9,493	3,679

Note: *p<0.05; **p<0.01; ***p<0.001;
Sample: mm2.1–mm2.4: a; mm2.5: e (see Section 4.1)

5.2.1 Physical factors

Women are significantly more afraid of crime than men. This finding confirms $H1_{\text{physical}}$ and appears in nearly every quantitative fear of crime study. Among the many explanations for this finding, the higher (perceived) vulnerability is the most plausible (Jackson 2009; Smith and Torstensson 1997). What is less widely known is that the strength of this effect depends, again, on the dependent variable: gender differences are stronger for avoidance behavior than they are for crime-specific fear. Accordingly, older women react more with foresight than fright. The careful standardization of all continuous predictors allows numeric comparisons among all variables in the model (Gelman 2007). Accordingly, this data disagrees with the claim that gender is "the strongest predictor of fear" (Cobbina, Miller, and Brunson 2008, 674). Victimization and social disadvantage are stronger predictors of crime-specific fear. Age, attributable to the curvilinear effect, particularly for people above age 50, is also a stronger predicting avoidance behavior.

Age and gender—the most frequently used proxies for physical vulnerability—have a greater impact on avoidance behavior than on crime-specific fear, confirming $H5_{\text{physical}}$. This finding underlines the importance of analyzing different components of fear of crime to investigate the spectrum of consequences of passive vulnerability. Extending Greve's (1998) argument, this finding suggests that older people and women compensate for (perceived) vulnerability less with fright and more with behavioral adaptations (foresight) to avoid victimization.

Age was modeled linearly for crime-specific fear but quadratically for avoidance behavior (and localized fear in later models). The interaction effect, investigating differential age–fear curves for men and women, is not significant for crime-specific fear and is not reported for the models above. However, the linear effect of age on avoidance behavior is significantly stronger in women than it is in men (demonstrated by the "female $\times$ age" interaction effect in Table 5.3).

Furthermore, the effect of age on fear is suppressed by victimization. If model mm1.1 and mm2.1 were estimated without victimization, the coefficients for age would be notably smaller ($\beta_{age} = .46$ and $\beta_{age\,(sq)} = .33$ for avoidance behavior and $\beta_{age} = .08$ for crime-specific fear). This is most probably a suppression effect: the true causal effect of age on fear is underestimated when victimization is not considered because victimization raises fear of crime (Russo and Roccato 2010; Russo, Roccato, and Vieno 2013; Skogan 1987) and older people are less often victimized (Hart 2010; Görgen 2010). This is, to the best of the author's knowledge, a yet unacknowledged aspect of the hotly debated age–fear relationship, with some noteworthy implications for the interpretation of the age effect on fear of crime. When, for example, the age–fear relationship is of interest and the researcher does not have information on the immediate victimization experience (which is often the case in large generic social surveys such as the European Social Survey), the estimated age–fear relationship is lower than the actual causal effect of age on fear. Changing the perspective to the effect of victimization on fear renders age a confounder (with age causally effecting both victimization and fear of crime) of the true effect of victimization on fear. This suggests that age should be controlled for when estimating the causal effects of victimization of fear (not tested). Overall, this finding emphasizes the importance of carefully thinking about the causal mechanisms when estimating causal effects with observational data (Hedström and Ylikoski 2010; Morgan and Winship 2014; Pearl 2000).

Main model 2 (mm1.2 & mm2.2) investigates physical vulnerability in more detail by adding self-rated health. Between-person differences in health significantly predict both dependent variables. However, within-person changes in health are not related to changes in fear or avoidance behavior. Accordingly, people in bad health are more fearful; however, when health changed within the survey period, this was not accompanied by a change in fear of crime. The within-person health effects are not absorbed by controlling for the measurement occasion. Excluding the predictor for T_2 does not alter this finding (not shown). Hence, $H6_{\text{physical}}$ is confirmed only with respect to differences between persons but not regarding changes within a person. This finding somewhat questions the relationship between health and fear (Braungart, Braungart, and Hoyer 1980; Cossman and Rader 2011; Galey and Pugh 1995; McKee and Milner 2000; Stiles, Halim, and Kaplan 2003), which is taken for granted by both epidemiologists and fear-or-crime researchers with, however, opposing causal claims: while epidemiologists claim that fear deteriorates health, fear of crime research argues that people in worse health report more fear. To some degree, this favors the epidemiological view because it could be argued that the deterioration of health due to fear is a more long-term process while—according to the vulnerability approach—health changes are supposed to have a direct link to changes in fear. This finding contributes to the scarce longitudinal evidence on the health–fear relationship (Jackson and Stafford 2009; Stafford, Chandola, and Marmot 2007) and calls for future research.

As hypothesized, health reduces the effect of age, but not gender, on both dependent variables. This mediation is in accordance with the extended vulnerability approach because health is the central mechanism linking age to fear. Regarding avoidance behavior, however, the predictor of age remains significant even when controlling for health. Both age and health are necessary in order to predict avoidance behavior adequately.

To assess whether health is the more informative predictor when compared with age, mm1.1 and m2.1 were rerun with the same respondents but with either age or between-person health. The model fit improved considerably with the use of self-rated health for crime-specific fear (AIC_{age}: 25057 vs. AIC_{health}: 24928; Chisq: 129.5^{***}) and avoidance behavior (AIC_{age}: 22880 vs. AIC_{health}: 22761; Chisq: 118.5^{***}). When compared with age, health is the more predictive predictor of physical vulnerability for both outcomes, likely because it captures perceived frailty better than age. This finding confirms $H7_{physical}$ for both investigated outcomes and suggests that future studies on fear of crime would benefit from surveying some health measures as well because demographic studies suggest that age is an increasingly bad proxy for physical vulnerability (see Section 1.3).

5.2.2 Personality and generalized trust

As outlined in Section 2.5.3.1, the locus of control and the tolerance of ambiguity reflect how people perceive their ability to handle external influences. Generalized trust is theoretically understood as neighborhood-independent environmental adversity or more tangibly as the belief of an individual that unknown others will not harm them. Main model 3 (mm1.3 & mm2.3) adds personality traits and generalized trust to investigate this aspect of vulnerability.

For both dependent variables, all between-person estimates significantly predicted between-person differences in fear (except for the internal locus of control predicting avoidance behavior). Changes in the external locus of control and generalized trust predict changes in crime-specific fear and avoidance behavior. The internal locus of control and the tolerance of ambiguity do not significantly predict changes in both outcomes. Hence, $H1_{pers\&bel}$ and $H6_{pers\&bel}$ are confirmed entirely, whereas $H2_{pers\&bel}$ and $H3_{pers\&bel}$ are only partially confirmed.

Generalized trust has the strongest between-person (and a comparatively strong within-person) effect on crime-specific fear and avoidance behavior and is the most important among this group of predictors. Hummelsheim, Oberwittler, and Pritsch (2014, 431) suggested that fear and generalized trust share a common dimension, which could be a "tolerance of uncertainty and vulnerability." The extended vulnerability approach argues that generalized trust is a major driver of perceived environmental adversity in a holistic view on vulnerability, which is confirmed by this result. Regardless of the theoretical framing, the considerable within-person effects signify a longitudinal correlation between fear and trust, thus giving rise to further research efforts into this relationship.

Ambiguity tolerance has strong between-person effects but no significant within-person effect. Internal and external locus of control relate weakly to both outcomes. Furthermore, the external locus of control exhibits poor reliability (see Section 4.4.3). Investigating the internal and external locus of control separately on both outcomes (not shown) does not substantially alter these results. This analysis suggests that beliefs regarding perceived neighborhood-independent environmental adversity (generalized trust) are much more important for the generation of fear than personality traits that capture individuals' preference for a steady and foreseeable life (ambiguity tolerance) or the controllability of events.

Within-person estimates of personality traits are of particular interest for this study. The number of comprehensive studies investigating personality traits is growing (Adams and Serpe 2000; Guedes, Domingos, and Cardoso 2018; Hirtenlehner 2008; Houts and Kassab 1997; Jackson 2015; Jackson and Gouseti 2015b; Wurff, Van Staalduinen, and Stringer 1989; Wurff and Stringer 1988; Marshall 1991). However, the author is unaware of any longitudinal assessment of these personality traits on fear also because personality traits are generally regarded as time-stable, rendering longitudinal investigation unreasonable. The fact that this assumption is not necessarily met is shown in Section 3.3.2 and other longitudinal studies where some variation was found that could be partly explained by age and life events (Cobb-Clark and Schurer 2013; Cobb-Clark and Schurer 2012; Roberts, Walton, and Viechtbauer 2006). Applying this perspective, Section 5.3.1 investigates whether the effects of victimization on fear are mediated by changes in personality traits. However, the strength of all previously included variables (including victimization) was only slightly reduced, which is the first indication of few mediation effects.

5.2.3 Social factors

Section 2.5.3.3 described the mechanisms of how diverse social vulnerability factors might influence fear of crime. In main model 4 (mm.1.4 and mm2.4), financial strain, formal education, and neighboring were added to the base model. Financial strain is hypothesized to increase fear because of heightened anticipated consequences and more exposure to victimization (e.g., reliance on public transport and inadequately secured homes). Formal education is hypothesized to influence environmental adversity via less differentiated threat assessments and a higher symbolic salience of crime. Active and supportive neighboring might foster neighborhood attachment (reducing perceived environmental adversity) and (independent of context) increases perceived potential support in case of victimization.[2] Section 2.4.3.3 argued that previously found effects of social capital on fear of crime for older people might be spurious because ability and willingness to engage with other people might depend on health. Therefore, mm1.4 and mm2.4 control for subjective health.

The main model 4 (mm1.4 and mm2.4) indicates that the less educated are more afraid of crime, which confirmed $H3_{social}$. They also exhibit more avoidance behavior. People under financial strain also are more fearful. The between- and within-person effects of financial strain are significant for crime-specific fear (controlling for neighborhood characteristics and education). This is among the most important findings of this thesis and provides longitudinal support that financial strain increases perceived vulnerability and thus, for the generalized insecurity approach. According to this view, fear is a " 'sponge,' absorbing all sorts of anxieties about related issues of deteriorating moral fabric, from family to community to society" (Jackson 2006, 261; see also Hirtenlehner and Farrall 2013). The significant within-person effect of financial strain is the first longitudinal support for the positive effect of financial difficulties on crime-specific fear. Numerous studies showed before that financially strained people are more fearful than the wealthy. This analysis adds to the literature that increasing financial strain, e.g., attributable to job loss, welfare cuts, or an economic recession, also increases fear. Vice versa, a favorable economic situation or more generous welfare programs might reduce the fear of crime (Hummelsheim et al. 2011). Although financial strain has substantial effects on between-person differences of avoidance behavior, it does not predict changes in this outcome. Accordingly, $H1_{social}$ is mostly confirmed.

Also, neighboring predicted between-person differences and within-person changes in crime-specific fear. However, only between-person differences in avoidance behavior were significant which largely confirmed $H6_{social}$.[3] Hence, active neighboring—or individual social capital in the neighborhood (Taylor 2002)—exerts a negative and longitudinal influence on crime-specific fear. Importantly, people who reported more neighboring in the second wave also reported less crime-specific fear (the within-person effect). Vice versa, people with fewer neighborhood contacts in T_2 than in T_1 reported more fear. This is interpreted as robust and additional support for the importance of individual social capital in the neighborhood. This analysis was controlled for neighborhood characteristics, financial strain, education, and health and contributes to previous cross-sectional literature (De Donder et al. 2012; Oh and Kim 2009; Oberwittler 2008; Ross and Jang 2000) which additionally strengthens it against objections concerning spurious correlations. Importantly, this finding supports the effectiveness of successful interventions by social workers at the individual level (Schubert et al. 2016).

Similarly, mm1.5 and mm2.5 confirm $H4_{social}$ because no or uncertain household support relates significantly to both outcomes. However, the coefficient is small. In comparison to

[2] The operationalization of neighborhood-independent household support is only available in survey version B and T_1. Hence, it is necessarily regarded as a time-stable between-person variable.

[3] The general stability of this outcome might partially explain the insignificant within-person effects on avoidance behavior (Section 5.1.4).

Table 5.4: Hypothetical victimization patterns and between-within transformations

Respondents	Victim T_1 (x_{T1})	Victim T_2 (x_{T2})	Within T_1 ($x_{T1} - \overline{x}$)	Within T_2 ($x_{T2} - \overline{x}$)	Between ($\overline{x}$)
R_1	1	0	0.5	-0.5	0.5
R_2	0	1	-0.5	0.5	0.5
R_3	1	1	0	0	1

Sacco (1993), this finding provides more solid quantitative support that individual social capital (expressed as potential support) reduces fear. However, the effect of household support on fear is—if there is one at all—rather small.

5.3 Victimization

Despite longstanding interest in how victimization affects fear of crime, the literature shows contradictory findings and few longitudinal studies. Overall, and in contrast to previous studies (Box, Hale, and Andrews 1988; Hindelang, Gottfredson, and Garofalo 1978, ch. 8; Arnold 1991; Skogan and Maxfield 1981, ch. 4; Gibson et al. 2002; Kury and Ferdinand 1998; Denkers and Winkel 1998), recent cross-sectional (Hanslmaier 2013; Hanslmaier, Kemme, and Baier 2016; Jackson and Gouseti 2015b; Tseloni and Zarafonitou 2008) and longitudinal studies (Braakmann 2012; Russo, Roccato, and Vieno 2013; Russo and Roccato 2010; Skogan 1987) confirm $\mathrm{H1}_{\mathrm{events}}$ that victimization increases fear (discussed more thoroughly in Section 2.4.4.1 and 2.5.4.1). The literature has discussed the methodological problems of unobserved heterogeneity regarding victimization (i.e., victims of crime differ from non-victims before victimization occurs) for decades. However, solutions to these problems are rendered infeasible when one relies on cross-sectional data. This section contributes to the scarce longitudinal literature investigating whether victimization has within-person effects on fear of crime, whether they are biased due to missing recovery effects, and whether they are mediated by several vulnerability factors.

This investigation of within-person changes attributable to life events is a technically complex research endeavor. For a more detailed investigation of the findings of the main models 1 (mm1.1 and mm2.1) that, within-person and between-person, victimization increases fear of crime, this section draws upon information scattered throughout this thesis. Section 2.5.2 introduced the intuition of between-within modeling. Section 3.3.1 investigated how such models are algebraically expressed. Descriptive analyses in Section 5.1.3 provided a visualization of group means on the basis of victimization status. The descriptive analyses raised the concern that usual within-person estimates of victimization underestimate the increase of fear that is attributable to the absence of recovery effects. If a respondent was victimized only (once) before T_1, then the regression model would predict the decrease in the outcome (in T_2) to be as strong as the increase (from T_1 to T_2) observed in another respondent who was victimized only (once) between T_1 and T_2. This necessity can be seen in Table 5.4 by applying the formulas of Section 3.3.1 to three hypothetical respondents R_1–R_3. Accordingly, if the decrease is, on average, considerably smaller than the (average) increase, the regression model would underestimate the increase (and overestimate the decrease). Given the technical character of this comparison and the small within-person coefficients of victimization, Table 5.5 reports three digits and standard errors (in brackets).

To investigate this assumption, the author excluded all respondents who were victimized violently only (24 months) before T_1 and investigated changes in the within-estimate of violent victimization in victimization models 2 (vm1.2 and vm.2.2).[4] Thereafter, that logic is applied to property victimization: all people with property victimization experienced only (in the 24 months) before T_1 but not after (in vm1.3 and vm2.3) are excluded. The initial main models (mm1.1 and mm1.2 in the previous section) were estimated only with respondents who participated in T_1 and T_2 (vm1.1 and vm 2.1) for a reasonable comparison. They were estimated without the standardization of victimization because the number of property and violent victimization events are comparable and informative in their natural

[4] Another more complicated solution to this problem would be the introduction of an interaction effect between the within estimate and an indicator of victimization status (victimized before T_1, victimized between T_1 and T_2, before and between).

scale. The concern of downward biased within-person effects is regarded as correct if, e.g., the within-person coefficient of violent crime increases if violent victimizations that occurred only before T_1 were excluded (comparing vm1.1 with vm1.2 and vm2.1 with vm2.2).

Violent victimization, as well as property victimization, exhibits significant within-person and between-person effects on crime-specific fear and avoidance behavior, thereby confirming $H1_{events}$. In addition, there is a quadratic between-person effect of violent victimization (which is significant for crime-specific fear as well in mm1.1, with more respondents at the between-person level). As indicated by the visual analyses in Section 5.1.3, each repeated violent victimization contributes less and less to between-person differences in avoidance behavior (and possibly crime-specific fear). Such a curvilinear effect is not found with regard to property victimization.

The within-person estimate of violent victimization can be interpreted as, e.g., an increase in crime-specific fear and avoidance behavior by a small average amount for people victimized only between T_1 and T_2. Contrarily, people who were victimized before T_1 but not (or less often) between T_1 and T_2 are predicted to report equally less fear in T_2 than T_1. The between-person estimate of violent victimization expresses the overall difference in fear among victims versus non-victims regardless of measurement occasion. Importantly, the coefficient must be interpreted as the between-person effect of two victimizations because it is the untransformed mean of the within-person variable (see Table 5.4).

According to Brüderl (2010, 983–84), strongly divergent within-person and between-person estimates of the same variable indicate unobserved heterogeneity. Notably, the between-person coefficients of violent victimization are considerably larger than the within-person estimates. Hence, cross-sectional studies might have exaggerated the causal effect of violent victimization. Descriptive analyses in Section 5.1.3 suggested that respondents who report no victimization 24 months before T_1 but violent victimization between T_1 and T_2 report higher crime-specific fear and avoidance behavior already in T_1. Accordingly, a possible explanation for the non-negligible unobserved heterogeneity is that people anticipated their violent (but not property) victimization. This conclusion appears to be plausible because violent victimization might cast its shadow long before it happens, given respondents' lifestyle and proximity to violent people, whereas property victimization occurs more suddenly and is less selective in choosing its victims.

The remainder of the section addresses the more technical analysis of attenuated within-person effects that are attributable to (potentially weaker) recovery effects: excluding all respondents who were victimized only before T_1 produced most of the expected changes except for violent victimization and crime-specific fear. However, this attenuation is comparatively small. Excluding those respondents yielded no remarkable increase in the within-person coefficient of violent victimization explaining crime-specific fear (in vm1.2 compared to vm.1.1). However, it yielded a considerable increase in the power of that variable explaining avoidance behavior (in vm2.2 compared to vm2.1). This finding is in accordance with the descriptive analyses in Section 5.1.3, which suggested that avoidance behavior does not decline (on average) in the absence of repeated victimization also between T_1 and T_2. With regard to property victimization, there is a similar increase of roughly one standard error for both dependent variables. Since this effect is negligible for victims of property victimization, respondents who were victimized violently before T_1 are excluded from the next analysis.

5.3.1 Pathways of victimization via personality traits and perceived environmental adversity

Why do victims of crime become more fearful? To answer that question, this section draws on Janoff-Bulman's shattered assumptions theory (1992; 1989; Janoff-Bulman and Frieze 1983). Traumatic experiences can shatter individuals' implicit assumptions about themselves and their environments. They might correct the "illusion of invulnerability, a basic belief that 'it can't happen to me.'" (1989, 116). Hence, within-person effects of victimization on fear of crime could be mediated by the vulnerability factors and perceived environmental adversity or more precisely via personality traits, generalized trust, and the perceived risk of victimization. To test this hypothesis, victimization mediation models vmm1.1–vmm2.3 in Table 5.6 test three pathways of violent and property victimization per outcome. Respondents who report violent victimization only before T_1 are excluded from this analysis because the absence of recovery effects might attenuate the within-person effect of violent victimization

Table 5.5: Multilevel models of victimization on fear of crime

	Dependent variables:					
	crime-specific fear			avoidance behavior		
	vm1.1	vm1.2	vm1.3	vm2.1	vm2.2	vm2.3
violent vic. (wi)	.087	.086	.077	.091	.155	.115
	(.024)***	(.035)*	(.028)**	(.020)***	(.029)***	(.023)***
property vic. (wi)	.049	.050	.060	.031	.030	.040
	(.010)***	(.011)***	(.014)***	(.008)***	(.009)***	(.011)***
violent vic.	.389	.408	.395	.413	.485	.448
	(.056)***	(.064)***	(.063)***	(.054)***	(.061)***	(.061)***
violent vic. (sq)	−.045	−.051	−.049	−.055	−.077	−.065
	(.024)	(.026)	(.025)	(.023)*	(.024)**	(.024)**
property vic.	.152	.156	.149	.069	.074	.068
	(.013)***	(.014)***	(.013)***	(.012)***	(.013)***	(.013)***
Respondents	3399	3040	2605	3391	3033	2598
Observations	6,747	6,079	5,209	6,653	5,993	5,126

Note: *p<0.05; **p<0.01; ***p<0.001;
Controls: age, gender crime, social disadvantage, disorder, measurement occasion, city
Sample: a (see Section 4.1) generally without one-time respondents. Furthermore, all respondents who experienced violent (vm1.2&vm2.2) or property (vm1.3&vm2.3) victimization only in the 24 months before T_1 were excluded.

on avoidance behavior. Figure 5.9 is an overview of the hypothesized causal claims and analyzed variables.

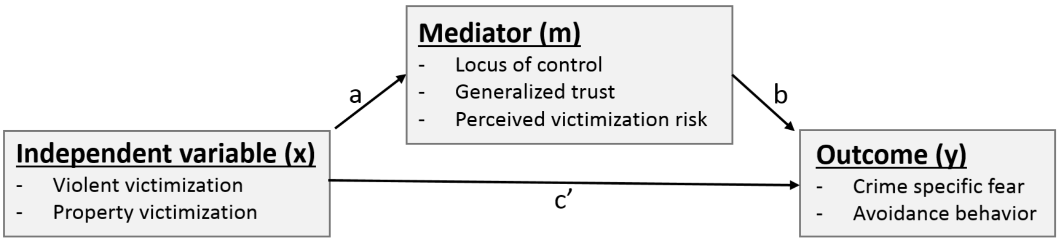

Figure 5.9: Hypothesized pathways of victimization via vulnerability on fear

A technical perspective on mediation was introduced in Section 3.2.2. Paths b and c' appear in Table 5.6. Path a (from the independent variable to the mediator) was estimated in multilevel models by between-person and within-person effects of violence and property victimization in the same model as that with independent variables only. Considering the large number of mediation analyses, a combination of regression tables and visualization presents the results of mediation analyses throughout this thesis, where effects of x on y controlled for m (c') and effects of m on y controlled for x (b) appear in the regression tables. Indirect effects ($a \times b$) and the effects of x on m (a) are presented visually because the considerable amount of information is challenging to process.

The unconventional presentation of the indirect effects of a mediation analysis in Figure 5.10 requires description and justification. This plot is presented to visualize and compare the indirect effects—which are of interest in mediation analysis—and to assess their significance. It also reports the yet-missing path a (from y to m). The x-axis shows the size of the indirect effects, which are the product of paths x to m (a) and m to y (b). Confidence intervals were calculated with the distribution of the product method (MacKinnon et al. 2002). Mediation

Table 5.6: Multilevel mediation models of victimization on fear of crime

	Dependent variables:					
	crime-specific fear			avoidance behavior		
	vmm1.1	vmm1.2	vmm1.3	vmm2.1	vmm2.2	vmm2.3
violent vic. (wi, c')	$.09^{*}$	$.08^{*}$	$.03$	$.16^{***}$	$.15^{***}$	$.09^{**}$
property vic. (wi, c')	$.05^{***}$	$.05^{***}$	$.03^{*}$	$.03^{***}$	$.03^{***}$	$.05^{***}$
internal loc (wi, b)	$.02$			$.02$		
external loc (wi, b)	$.05^{**}$			$.04^{***}$		
trust (wi, b)		$-.05^{***}$			$-.03^{**}$	
risk (wi, b)			$.12^{***}$			$.04^{**}$
Constant	$-.31^{***}$	$-.29^{***}$	$-.33^{***}$	$-.50^{***}$	$-.47^{***}$	$-.50^{***}$
Respondents	3040	3040	1817	3033	3033	1817
Observations	6,071	6,042	3,632	5,985	5,960	3,606

Note: *p<0.05; **p<0.01; ***p<0.001;
Controls: all respective between-person variables, age, gender crime, social disadvantage, disorder, measurement occasion, city
Sample: vmm1.3 and vmm2.3: c; all others: a (see Section 4.1)

is considered to be significant if 95% confidence intervals of the indirect effects do not cross zero (dotted vertical line). On the y-axis, mediators (m) or the independent variables (x) are shown. Figure 5.10 plots the mediators on the y-axis because they outnumber the independent variables. The advantage of this form of presentation lies in its condensation of the presentation of results of numerous related mediation analyses. It aims for "graphical excellence" by providing "many numbers in a small space" and revealing the "data at several levels of detail" (Tufte 2001, 13).

Table 5.6 shows coefficients for paths c' and b. For both outcomes, the locus of control is included in vmm1.1 and vmm2.1. When compared with models vm1.2 and vm2.2 in Section 5.3, coefficients of victimization are not visibly affected. Hence, strong mediation is unlikely. Unlike the external locus of control, the internal locus does not affect either outcome at the within-person level. Generalized trust, introduced into vmm1.2 and vmm2.2, significantly influences both outcomes but again does not alter victimization coefficients. In models vmm1.3 and vmm2.3, perceived victimizaiton risk is included. Unfortunately, perceived risk (or cognitive fear of crime) was available only in questionnaire version A. Therefore, there are considerably fewer observations in this model than there are in earlier models, and victimization coefficients cannot be compared with previous models. Because of its previously discussed proximity, particularly to crime-specific fear (see Section 2.2), it is not surprising that this independent variable strongly connects to both outcomes. Violent victimization is not a significant predictor at the within-person level when perceived risk is included. This finding indicates strong mediation.

Figure 5.10 visualizes complementary results. Most indirect effects are not significant as many confidence intervals cross the dotted line. Mediation by locus of control is not significant (which rejected $H2_{\text{events}}$) irrespective of the type of victimization (color) or the outcome (shape). However, internal locus of control is significantly influenced by violent victimization. This contributes to the research question as to whether personality traits are stable. Cobb-Clark and Schurer (2013) showed that certain life events other than victimization influenced the control perceptions. This effect, importantly, is positive, defying both the hypothesis and the theoretical model: violent victimization increased (not decreased) the internal locus of control on average. Hence, victims of violent crime felt slightly stronger, i.e., they perceived themselves to have more control over the outcomes of events after they experienced victimization presumably because they developed some coping strategies in response to this unwanted event. However, the internal locus of control is not significantly related to changes in fear in model vmm1.1 and vmm2.1. Accordingly, significant indirect effects are unlikely. Inversely, the external locus of control is not influenced by victimization but relates to both outcomes. This finding, again, makes a significant indirect effect unlikely. Accordingly, the effects of victimization on fear are not mediated by the locus of control.

In contrast, perceived environmental adversity (victimization risk and generalized trust)

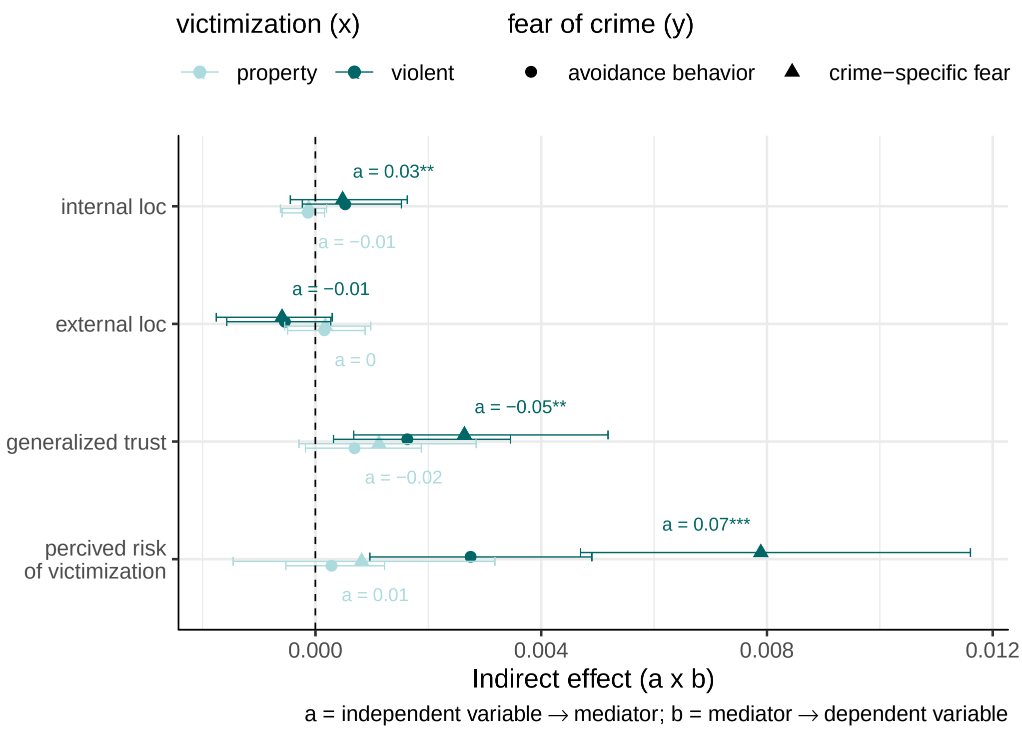

Figure 5.10: Indirect effects of victimization via personality traits, generalized trust, and perceived victimization risk

significantly mediated most effects of violent, but not property, victimization. Accordingly, victims of violent crime perceive their environment as more hostile, which, in turn, increases their fear of crime.

Overall, no mediator is significantly influenced by property victimization. This finding, however, allows only the conclusion that *this sum score of property victimization* does not alter perceived vulnerability. More in-depth analyses could investigate the effects of certain subtypes of property victimization—such as (attempted) burglary—on perceived vulnerability and fear. Violent victimization, on the other hand, does affect all mediators except the external locus of control. However, offense-specific subtype analyses could also unveil differences in the direct and mediated effects. This is, however, beyond the scope of this chapter.

In sum, this section finds no support for the mediation of property victimization. In contrast, within-person effects of violent victimization are mediated by generalized trust and the perceived risk of victimization (confirming $H3_{events}$ and $H4_{events}$) but not internal and external locus of control (rejecting $H2_{events}$). In fact, internal locus of control is increased by violent victimization, which contradicts the model regarding the controllability of future events. However, it supported the second claim of shattered assumptions theory (Janoff-Bulman 1992; Janoff-Bulman and Frieze 1983) in that victims of crime perceive their environments as more adverse, heightening their fear of crime.

The finding that the internal locus of control increased after victimization indirectly supports Winkel's fear–victimization model (1998), which argued that the subjective risk of victimization mediates the effects of victimization. However, Winkel (1998) also argued that victimization lowers the anticipated negative impact of future victimization (with a negative effect on fear of crime). The increase of the internal locus of control can be interpreted as indirect support for the second pathway (see Richter 1997, 16). As underlying data do not allow a consideration of this path, this analysis probably underestimated the (mediated) effects of victims.

This longitudinal perspective called for more complicated analyses with more measurement occasions, shorter intervals, and tailored operationalizations. While impossible to assess with this data, differential trajectories in response to victimization or other potentially traumatic experiences are well known in resilience research (Bonanno, Westphal, and Mancini 2011; Kalisch et al. 2017). Victimology could strongly benefit from the substantial progress made in this field over the past decade. Chapter 7 discusses this issue further.

5.4 Early and recent negative life events other than victimization

Life events other than victimization might influence perceptions of security and behavior. Drawing upon the generalizability approach (Hirtenlehner and Farrall 2013; Jackson 2004), Section 2.5.4 hypothesized that other negative life events are projected onto crime and increase emotional and behavioral responses.

This section investigates whether potentially traumatic experiences early in life attributable to World War II increase fear of crime today among respondents above age 60. The underlying question is whether previously found age effects (attributable to physical, psychological, or attitudinal changes over the life course) are (partially) generational effects. As discussed in Section 2.5.4.2, such generational effects are attributable to the ridden social circumstances during respondents' formative years and the increased likelihood of experiencing potentially traumatic experiences of people born before, during, or shortly after World War II. Section 5.4.2 investigates these generational effects more thoroughly and applies cumulative inequality theory to examine whether health, social status, personality traits, and perceived vulnerability mediate the effects of early life events.

5.4.1 Main effects of cumulated life events

There is little previous knowledge as to whether and how life events other than victimization influence fear of crime (see for a qualitative study Pain 1997). The (early) life events models lem and elem1 (Table 5.7) assess whether the cumulative personal, social, and early (potentially war-related) life events increased the emotional component of fear. Models elem2–elem5 investigate whether early life events are mediated by personality traits, perceived vulnerability, health, and poverty (see Section 2.5.4.2 and 5.4.2). All life events other than victimization are only assessed in T_2. Early life events are surveyed only in T_2 and questionnaire version B. The following analyses of other life events are, unfortunately, restricted to cross-sectional and selective data.

Table 5.7: Multilevel models of cumulated life events other than victimization

	Dependent variable: crime-specific fear					
	lem	elem1	elem2	elem3	elem4	elem5
respondents' life events	$.10^{**}$					
life events close to respondent	.03					
early life events (c')		$.18^{**}$	$.17^{**}$	$.15^{*}$	$.17^{**}$	$.14^{*}$
internal loc (b)			.09			
external loc (b)			$-.20^{**}$			
ambiguity tol (b)			$-.23^{***}$			
controllability (b)				$.26^{***}$		
consequences (b)				$.41^{***}$		
health (b)					$-.22^{***}$	
poverty (b)						$.24^{***}$
gender: female	$.10^{**}$	$.13^{**}$	$.11^{*}$	$-.07$	$.13^{**}$	$.12^{*}$
social disadvantage	$.18^{***}$	$.19^{***}$	$.19^{***}$	$.14^{**}$	$.17^{***}$	$.16^{**}$
Constant	.04	$-.12$	$-.13$	.04	$-.16$	$-.13$
Respondents	3,366	1,369	1,364	1,369	1,368	1,369

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$;
Controls: age, victimization, education, crime, city
Sample: lem: b; elem1–elem5: d (see Section 4.1)

Although personal life events have a significant positive effect on crime-specific fear, adverse life events of close persons do not significantly increase fear (lem1), which confirms H5$_{\text{events}}$. This analysis suggests that personally suffered negative recent life events generated fear, whereas stressful recent life events experienced by people close to the respondent did not.

Early life events such as hunger, dispossession, or acts of war have a comparatively strong effect on crime-specific fear (confirming H6$_{\text{events}}$) as discussed more thoroughly in Section 5.4.2. The size of the effect is strong and comparable with the effects of gender or social disadvantage, which underlines the importance of potentially traumatic experiences in childhood on the affective component of fear and the non-negligibility of generational particularities regarding previously found age effects. Fear of crime research should acknowledge the well-discovered enduring effects of detrimental early life experiences on epidemiological and demographical outcomes (Barker 2004; Berg et al. 2010; Berg, Doblhammer, and Christensen 2009; Haas 2008; Hayward and Gorman 2004; Jürges 2013; Kesternich et al. 2014; Ben-Shlomo and Kuh 2002; Lundberg 1993; Scholte et al. 2017; Xie and Lagergren 2016) and abandon the "life-course fallacy" (Riley 1973) of interpreting age group differences only as age effects. Because of the general absence of war-related experiences, future studies are likely to find older people to be less fearful than those of today because they did not grow up during and shortly after World War II.

Seery (2011) found that small doses of adverse life events are beneficial for various mental health measures. Detrimental effects were only measured if adverse life events occurred heaped. This finding suggests a quadratic influence for life events. Hence, the nonlinear effects of early and recent life events were tested up to a cubic trend; however, no significant higher-order terms were found. Therefore, only linear predictors are reported. The next section discusses the potential pathways of early life events.

5.4.2 Pathways of early life events via personality traits, perceived vulnerability, health, and poverty

Having established the link between early life events and crime-specific fear, the next step for us is to seek the underlying mechanisms. Drawing on cumulative inequality theory (see Section 2.5.4.2), mediation analyses (see Figure 5.11) investigated the pathways of early life events. The data confirmed most of the hypothesized pathways.

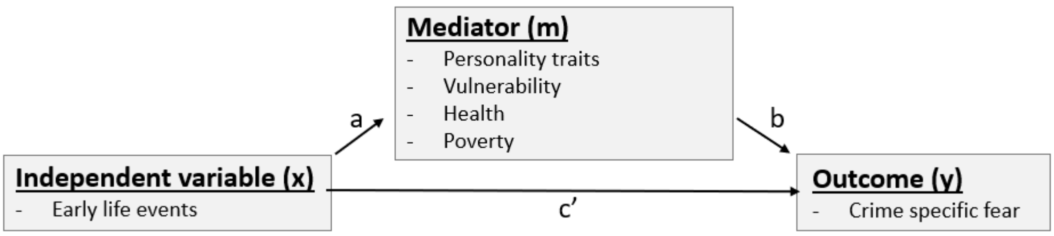

Figure 5.11: Hypothesized pathways of early life events via (proxies of) vulnerability on fear

Four (multiple) mediation analyses based on models elem2–elem5 were calculated. Models elem2–elem5 in Table 5.7 provide the direct effects of the independent variable and the mediator. Figure 5.12 shows the indirect effects and the influence of early life events on the mediator. Section 5.3.1 provides a more detailed explanation of this figure.

Similarly to previous analyses, ambiguity tolerance is an important personality trait in explaining fear of crime. Also, war-related events in childhood adversely influenced ambiguity tolerance but not internal or external locus of control. Hence, early negative life events have a significant indirect effect on crime-specific fear that is mediated by ambiguity tolerance but not on internal and external locus of control. This finding confirms H10$_{\text{events}}$ but rejects H9$_{\text{events}}$.

In addition, people with adverse war-related life events report significantly higher perceived vulnerability (controllability and consequences). Since vulnerability has a strong effect on fear (see model elem3 in Table 5.7), a considerable indirect effect of early life events via vulnerability confirms H11$_{\text{events}}$.

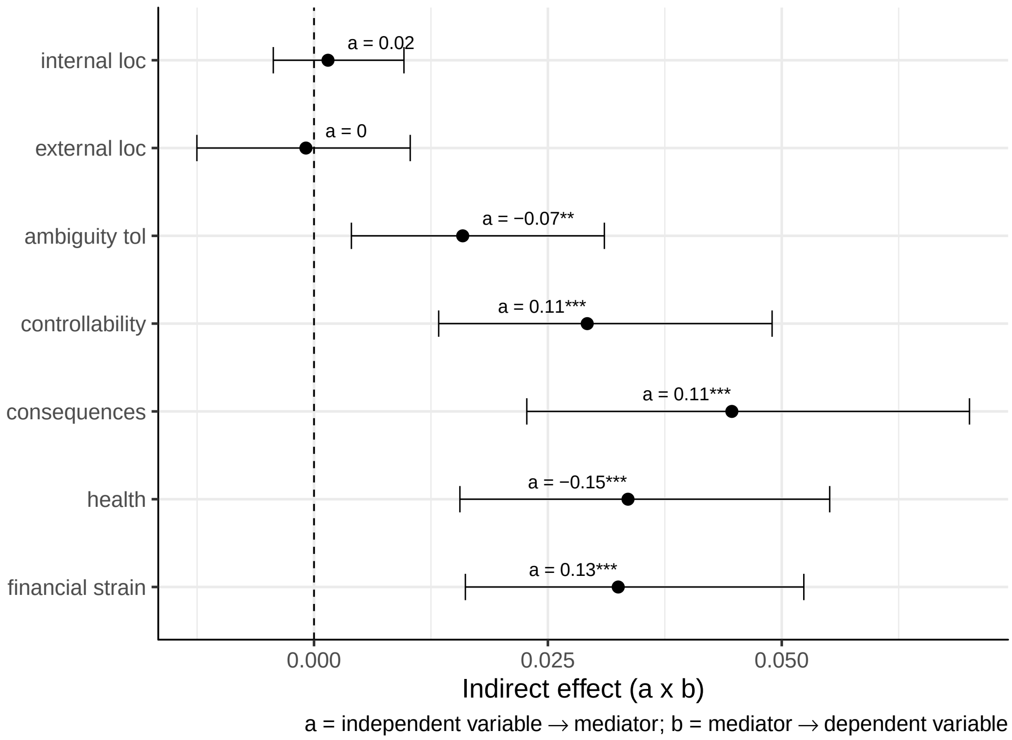

Figure 5.12: Indirect effects of early life events via vulnerability

Respondents who experienced traumatic events in childhood report worse health and more poverty at T_2, which is in accordance with cumulative inequality theory (Ferraro and Shippee 2009; Ferraro, Shippee, and Schafer 2009; Ferraro, Schafer, and Wilkinson 2016) and confirms $H7_{events}$ and $H8_{events}$. As health and financial strain are strong predictors of fear (see models elem4–elem5 in Table 5.7), those variables significantly mediated the effect of early life events. Overall, this analysis suggests that there are multiple pathways of early life events on today's fear of crime.

These findings rely on retrospective data and might be affected by systematic recall bias (Rubin 2006), which could result in reversed causality: people who are economically successful, healthy, ambiguity tolerant, and less vulnerable might not recall early life events. However, there are two arguments against this notion: recall bias might be negligible because early life events were surveyed with reference to the historical period of World War II and its immediate aftermath. Such "temporal landmarks" (Schröder 2011, 14) foster remembering life events. Furthermore, more salient events are recalled more easily (Jürges 2007; Smith 2009). Doubtless, the surveyed life events are sufficiently drastic to be remembered. Hence, recall error might be weak despite the long period. Furthermore, if there was any recall error, its influence might attenuate the findings: recall error was found to be negatively correlated with education (Peters 1988). As health is positively correlated and financial strain is negatively correlated with education, it appears equally likely that the findings above might be slightly underestimated and not overestimated, at least regarding health and financial strain.

5.5 Perceptions of control and consequences of victimization

Despite its theoretical relevance, a majority of studies on fear of crime focus on proxies for vulnerability such as age, gender, health, and social status without investigating the hypothesized mechanisms. This section investigates whether, and how strong, these proxies are mediated by two hypothesized theoretical mechanisms: anticipated controllability and consequences of victimization. In doing so, it follows a reinvigorated development in criminology that distinguishes "correlates" or "markers" (in fear of crime research, e.g., regarding age and gender) from theoretical causal mechanisms (Wikström and Sampson 2006, 2) and if successful provides evidence that the theoretical mechanisms can be reproduced with empirical data.

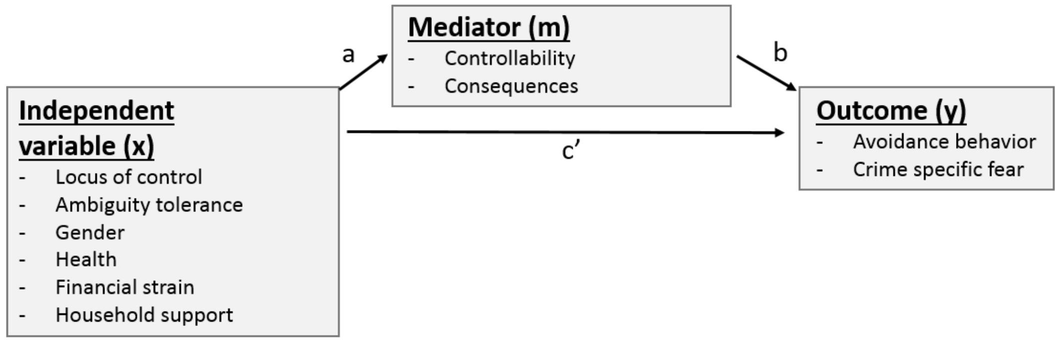

Figure 5.13: Hypothesized pathways of proxy variables of vulnerability via vulnerability (control and consequences) on fear

Such an endeavor requires the operationalization of vulnerability. Few scholars have addressed this issue (see Section 4.4.2). Jackson (2009) conducted mediation analyses to vulnerability and fear of crime. He asked whether the effects of gender and age are mediated by an individual's perceived physical ability to defend themselves, seriousness of consequences, controllability, likelihood, and group-level risk judgment. He found that the effects of gender but not age are mediated by those concepts, predicting the frequency of worry regarding criminal victimization. In what is similar to Jackson (2009), this section investigates whether the controllability and consequences of criminal victimization mediate proxies for vulnerability. The analysis is visualized in Figure 5.13.

Table 5.8: Multilevel mediation models for vulnerability

	Dependent variables:			
	crime-specific fear		avoidance behavior	
	vumm1.1	vumm1.2	vumm2.1	vumm2.2
internal loc (c')	.01	$-.03$	.06	.01
external loc (c')	$-.20^{**}$	$-.18^{*}$	$-.06$	$-.04$
ambiguity tol (c')	$-.22^{***}$	$-.15^{**}$	$-.32^{***}$	$-.25^{***}$
gender: female (c')	$.12^{*}$	$-.04$	$.64^{***}$	$.47^{***}$
health (c')	$-.08$	.04	$-.18^{**}$	$-.05$
financial strain (c')	$.17^{**}$	$.12^{*}$	$.18^{**}$	$.15^{**}$
household support: no (c')	.09	.01	$-.01$	$-.09$
... don't know (c')	$-.06$	$-.04$	.01	.03
controllability (b)		$.21^{***}$		$.35^{***}$
consequences (b)		$.35^{***}$		$.24^{***}$
Constant	.01	.10	.02	.11
Respondents	1,329	1,329	1,299	1,299

Note: *p<0.05; **p<0.01; ***p<0.001;
Controls: victimization, city, crime, social disadvantage, disorder
Sample: d (see Section 4.1)

The first vulnerability mediation model (vumm1.1 and vumm2.1) in Table 5.8 includes predictors reflecting various vulnerability factors. The controllability and consequences of victimization were surveyed only in T_2 and questionnaire version B, reducing the number of respondents and making longitudinal analysis impossible. Further, respondents to questionnaire version B were limited to the age range 60–89 years in the first wave. The influence of the independent variables on the mediators (path a) was assessed without further controls. The indirect effects appear in Figure 5.14 below. The theoretically derived mediators were included in the second model (vumm1.2 and vumm2.2). For both outcomes, $R^2_{between}$ increased by almost 5% when vulnerability was included in the model. $R^2_{between}$ for crime-specific fear rose from 11.7% to 16.7%. $R^2_{between}$ for avoidance behavior rose from 19.9% to 24.6%. Accordingly, self-assessed vulnerability strongly affects fear of crime (Killias and Clerici 2000). Future studies would benefit from capturing vulnerability directly.

A comparison of vumm1.1 and vumm1.2 shows that all vulnerability factors are reduced when mediators are included. This effect is stronger for avoidance behavior (vumm2.1 and vumm2.2), where, e.g., health is no longer significant. However, the majority of the predictors remain significant and not entirely mediated by the mechanisms. Unlike the hypothesized mechanisms of Jackson (2009), those of the present study could not explain the effects of gender on avoidance behavior. However, one key mechanism of vulnerability (perceived openness to victimization) was not operationalized. Although this could explain the remaining effect of financial strain, the openness of the primary causal mechanisms of this vulnerability factor makes it unlikely to contribute to the full explanation of the remaining effect of ambiguity tolerance. This suggests that there are aspects of vulnerability not yet considered or that proxy variables for vulnerability also affected fear of crime through mechanisms outside the theoretical model of vulnerability.

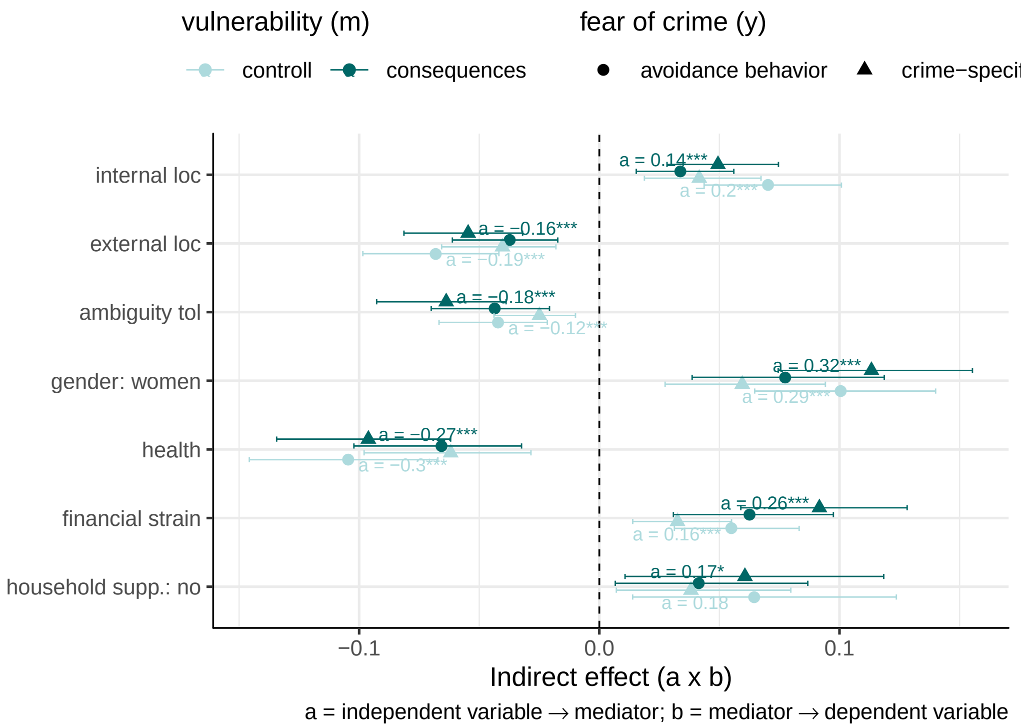

Figure 5.14: Indirect effects of vulnerability proxies via theoretical concepts

A different perspective on mediation—one primarily interested in whether significant mediation paths exist—focuses on indirect effects ($a \times b$). These can be interpreted as the change of fear that is attributable to an increased independent variable (e.g., ambiguity tolerance) because the independent variable affects the mediator (path a). Figure 5.14 shows the results of this analysis. Section 5.3.1 provides a more detailed discussion of the benefits and interpretation of this type of visualization.

All proxies investigated for vulnerability are significantly mediated by the theoretically derived concepts, which confirmed $\text{H2}_{\text{physical}}$, $\text{H8}_{\text{physical}}$, $\text{H4}_{\text{pers\&bel}}$, $\text{H5}_{\text{pers\&bel}}$, $\text{H2}_{\text{social}}$, and $\text{H5}_{\text{social}}$. In other words, all vulnerability factors significantly influence the developed measures of vulnerability, which, in turn, has a strong effect on crime-specific fear and avoidance behavior. This result is essential for the extended vulnerability approach because it supports the underlying theoretical mechanisms. Few differences in the strengths of the indirect effects are found, regarding neither the dependent variable nor the mediator. Perceived control over, and consequences of, victimization significantly mediates all personality traits. Household support is least strongly mediated (the "don't know" response is not mediated at all and is not reported). Financial strain is slightly more strongly mediated by the anticipated consequences, which is also expressed by strong *a* paths in Figure 5.14. This finding is in accordance with the theoretical explanation suggesting people under financial strain are particularly afraid of the material consequences of criminal victimization.

One caveat is that the theoretically derived vulnerability measures do not explain the influence of all proxy variables entirely. With regard to the physical factors of vulnerability, people in poor health and women report considerably less anticipated control but more consequences. The *a* paths (e.g., from gender to perceived consequences) are strongest in the mediation analysis. This, in conjunction with the complete mediation reported in Table 5.8, suggests that the extended vulnerability model best suits the explanation of physical vulnerability factors and to a lesser extent the explanation of social factors and personality traits.

An additional exploratory finding is that the controllability of criminal victimization relates more strongly to avoidance behavior, whereas the anticipated consequences of victimization more strongly predict crime-specific fear. This also influences indirect effects. Accordingly, people who regard themselves as physically or psychologically less capable of responding to an attack try more earnestly to prevent it. Anticipated consequences, on the other hand, arouse greater emotion.

5.6 Neighborhood effects and explained variance

Previous analyses examined individual aspects. This section investigates the spatial context and the amount of explained variance at each level. Neighborhood effects on fear of crime have been studied for decades using sophisticated theoretical approaches and methods (Brunton-Smith and Sturgis 2011; Brunton-Smith and Jackson 2012; Brunton-Smith, Jackson, and Sutherland 2014; Drakulich 2013; Drakulich 2015; Robinson et al. 2003; Taylor 2001; Oberwittler 2008; Wyant 2008). As discussed more thoroughly in Section 2.4.5 and 2.5.5, neighborhood characteristics such as social disadvantage, crime, social disorganization, and incivility are hypothesized to increase fear of crime.

Fear of crime research devotes little attention to the potential importance of adjacent neighborhoods (see however Barton et al. 2017; Brunton-Smith and Jackson 2012; Wyant 2008). As discussed in Section 2.4.5.1, there are reasons to assume that spatial effects of neighborhood problems transcend administrative boundaries, particularly if spatial units are smaller. This section investigates whether spatially lagged predictors are relevant to fear of crime in an urban environment.

As there is a considerable correlation between the independent variables and their spatial lags, the significance level of the lagged predictors is a necessary but insufficient criterion for the evaluation of the importance of adjacent neighborhoods. Simply put, to rule out that a spatial lag is only significant because it absorbs a fraction of the residential neighborhood effect, higher statistical thresholds should be set to confirm the spatial lag hypothesis. To test the overall improvement of the model, the information criteria (AIC and BIC; see sections 3.3.3.2) and $R^2_{neighb.}$ is monitored.

All models in this section are controlled for numerous within-person and between-person variables. The author included between-person and (where possible) within-person predictors of victimization, all three personality traits, and social and physical vulnerability factors in addition to the control variables. There are two reasons for doing so: it ensures that the effect of neighborhood variables could be attributed largely to those variables and not to individual differences among respondents, and it facilitates a comparison of the explained variance at each level when the most important predictors are included. Since vulnerability factors and control variables are discussed in Section 5.2, only neighborhood variables appear in Table 5.9.

The first neighborhood models (nm1.1, nm2.1, and nm3.1) provided information and a benchmark to evaluate improvements in later models. Overall, crime has little influence on all three outcomes. Hence, $\mathrm{H2}_{\mathrm{neighb}}$ is mostly rejected. In contrast, social disadvantage is influential, particularly for avoidance behavior ($\mathrm{ICC}_{\mathrm{n}}$: .10) and localized fear of crime ($\mathrm{ICC}_{\mathrm{n}}$: .16) A considerable amount of total variance is explained by neighborhood characteristics

Table 5.9: Multilevel models for neighborhood characteristics

	Dependent variables:					
	crime-specific fear		avoidance behavior		localized fear	
	nm1.1	nm1.2	nm2.1	nm2.2	nm3.1	nm3.2
crime	0.04	0.03	0.05	0.04	0.08*	0.06
social disadvantage	0.18***	0.16***	0.35***	0.30***	0.46***	0.36***
incivilities (sso)	−0.04	−0.05	0.16**	0.12*	0.17**	0.09
city: Cologne	−0.05*	−0.05	−0.17***	−0.16***	−0.13***	−0.10***
Cologne x incivilities			−0.25***	−0.21***	−0.25***	−0.16*
social disadvantage (lag)		0.05		0.09**		0.20***
R^2_{within}	1.37	1.36	2.69	2.67	2.36	2.35
$R^2_{between}$	20.18	20.17	30.55	30.59	30.26	30.32
$R^2_{neigh.}$	92.69	93.66	92.86	93.84	88.98	92.09
AIC	24406	24406	21812	21807	22622	22597
BIC	24642	24649	22056	22057	22865	22847
Respondents	6311	6311	6210	6210	6305	6305
Observations	9,595	9,595	9,415	9,415	9,574	9,574

Note: *p<0.05; **p<0.01; ***p<0.001;
Controls: age, gender, victimization, education, financial strain, personality traits, neighboring, health, T, city
Sample: a (see Section 4.1)

although crime-specific fear is comparatively less influenced by neighborhood characteristics (ICC_n: .04). This finding confirms $H1_{neighb}$.

People in Cologne fear crime less than people in Essen. Interaction effects between the city and neighborhood characteristics test for city-specific differences in neighborhood processes. The only significant interaction effect of the city (including spatial lag) is for incivilities. Incivilities correlate positively with avoidance behavior and localized crime in Essen but negatively in Cologne. This finding rejects $H3_{neighb}$ in Cologne, but it more generally questions the role of incivility in the fear of crime. An in-depth investigation is beyond the focus of this thesis (Oberwittler, Janssen, and Gerstner 2017). A noteworthy but secondary finding is the inclusion of a spatially lagged social disadvantage variable reduces the city-specific differential effect of incivilities, particularly for localized fear. Its inclusion rendered incivilities insignificant in both cities, but the main and interaction effect for avoidance behavior remained.

The spatially lagged independent variable for social disadvantage is included in nm1.2, nm2.2, and nm3.2 and signified by "lag." The spatially lagged predictor of social disadvantage significantly predicts two of three outcomes and is considerable in size. The coefficient of neighborhood social disadvantage is, as expected, reduced in all three models because of its conclusion but remains larger than the spatial lag.[5] The spatial lag of crime, by contrast, predicts none of the outcomes and is excluded from the analyses (which rejected $H5_{neighb}$). AIC and BIC agree that the model with lagged coefficients for social disadvantage is preferable for localized fear. For avoidance behavior, AIC is considerably lower and BIC[6] is only slightly larger. Although $H4_{neighb}$ is confirmed for both dependent variables, it is rejected for crime-specific fear: the coefficient is not significant, and consequently, neither AIC nor BIC is smaller. A comparison of $R^2_{neigh.}$s for each dependent variable reveals further information regarding the explanatory potential of the lagged variable. The largest improvement in explained variance is for localized fear (3.1%). Spatial lags explain an additional 1% of neighborhood variance in avoidance behavior and 1% of crime-specific fear. Considering the high percentage of explained variance, this is a non-negligible improvement for localized crime and avoidance behavior in the model. Since neighborhood variance in

[5]For a meaningful comparison, spatial lags need to be scaled (again) because they usually occupy a considerably smaller range (due to averaging the values of adjacent neighborhoods) than the original variable. The coefficients of untransformed spatial lags appear disproportionately large at first glance.

[6]As discussed in Section 3.3.3.2, I follow the recommendations of the AIC because the BIC penalizes additional predictors stronger and additionally depends on the number of respondents which is comparatively high in this analysis.

crime-specific fear is comparatively small, a 1% improvement is a negligible explanatory gain.

In other words, both outcomes with considerable neighborhood variation benefit from spatial lags, whereas neighborhood characteristics (including spatial lags) are less important in the case of crime-specific fear. The lagged coefficient is likely a significant improvement with respect to avoidance behavior and localized crime, given the explicit but necessarily imprecise mention of "your neighborhood" in the survey question in combination with administrative borders that residents may be unaware of. Accordingly, the comparatively small neighborhoods (on average .56 km^2) were too small to capture respondents' perceptions of fear-generating neighborhood conditions. Hence, the notion that the smaller the spatial units the higher the risk of missing explanatory potential from adjacent areas is confirmed, assuming constant activity and inhabitants' perceptual radius (see Section 2.4.5.1). This finding might affect the results of other fear of crime studies with small neighborhoods. This analysis suggests that studies with equally small neighborhoods should investigate spatial lags to capture the full explanatory power of neighborhood information. Methodologically, smaller initial neighborhoods and subsequent analytical correction are superior to studies with excessively large spatial units (Conley, Stein, and Davis 2014; Hipp 2007; Groff and Lockwood 2014; Oberwittler and Wikström 2009). This analysis, however, does not indicate how large neighborhoods must be to overlap with respondents' concepts of "neighborhood." To approximate this number, these analyses could be repeated on higher aggregates. Such analysis is, however, beyond the scope of this study.

The second topic of this section was the explained variance at each of the three levels. As discussed, 90% of neighborhood differences are explained by six variables, and two (crime and incivilities) contribute only marginally. Conversely, only 20% or 30% at the between-person level and only 1.4%–2.7% at the within-person level are explained although many theoretically important within-person and even more between-person predictors were included. The considerable discrepancy at the within-person level indicates the need to understand more about within-person changes in the fear of crime.

5.7 Interactions of vulnerability factors with neighborhood characteristics and victimization

As a relational concept (see Section 2.5), vulnerability is naturally prone to interaction analyses. Hence, this thesis accumulated several interaction hypotheses and can contribute to a research area that lacks quantitative support (Brunton-Smith and Sturgis 2011). The relational concept of vulnerability would have allowed for more research hypotheses. However, this section is restricted to the investigation of physical vulnerability so as to keep the extent of the analyses feasible in the face of up to three outcomes. As discussed in Sections 2.4.3.2.1 and 2.4.3.2.3, as well as 2.5.1, the assumption is that (physical) vulnerability factors interact with stressors (victimization experiences or neighborhood characteristics). Vulnerable individuals are expected to suffer more from the same degree of stressors, which would be reflected in a positive interaction term. However, nonsignificant interactions are not regarded as contradictions of the vulnerability model as they mean that personal differences remain constant with varying stressor levels. In contrast, negative interactions invite the rejection of conventional notions of vulnerability and require theory to understand why vulnerable people are less affected by the stressor (see Section 2.5.1).

The author provides case-specific discussions in the respective sections of the literature review. Those are recapitulated here for continuity of understanding: women are regarded as more affected by detrimental neighborhood conditions because they are subjected to more incivilities (Drakulich 2013; Hipp 2010b; Sampson and Raudenbush 2004; but also not differently or even less Jackson et al. 2017; Quillian and Pager 2001) and are more likely to confront potentially aggressive, unemployed men and gang members. In addition, devaluations and mistreatments might be less socially despised in more problematic areas (Cobbina, Miller, and Brunson 2008). When victimized, women and older people might apply neutralization techniques (denial of injury and vulnerability according to Agnew 1985, 233–34) less successfully. Older or dependent (operationalized by health) people might be more reliant on their neighborhood (Lawton and Simon 1968); however, older people could develop an attachment to their neighborhoods that might attenuate the effects of neighborhood problems after living the same place for decades (Wahl and Oswald 2016).

Most of the hypothesized interactions necessarily occurred at the between-person level because both interacting variables are time-stable. This is not the case with victimization, which could have been investigated longitudinally. However, for matters of accessibility[7] and consistency (interaction effects at the within-person and between-person level are not comparable in size or meaning), analyses of victimization were conducted at the between-person level. As mentioned above, the author applied this analysis to the full dataset to include maximum information. This also included repeatedly surveyed respondents (see Section 3.3.1).

The tables 5.10–5.11 initially report all multiplicative interaction terms before selected interactions are visualized. Further insights are provided by plotting selected marginal effects for significant interactions among continuous variables. This selection not only concerned the entire interaction effect but also the choice of the x-axis and the y-axis.[8] This selection is based on analytical criteria and data particularities. The marginal effects of age on crime-specific and localized fear depending on social disadvantage are visualized because they crossed zero, which is impressive because it suggests that the effect of age is reversed in disadvantaged neighborhoods. Interactions with categorical variables such as gender can be interpreted comparatively easily. Hence, plots of these marginal effects are less informative and therefore not visualized. Victimization is plotted on the y-axis because few respondents were victimized twice or more.

The derivative that is necessary for the calculation of the marginal effects and confidence bands becomes increasingly complex as more interactions between polynomials are involved (see Section 3.2.3). Therefore, the author excluded interactions between second-order age and victimization polynomials if the interaction effect of the second-order polynomial is neither significant nor model-improving (Aiken, West, and Reno 1991, ch. 6). No interaction between second-order age or violent victimization polynomials is significant. Even so, they appear in Table 5.9 and 5.10 and are used to predict dependent variables (for computational reasons). They are excluded for the calculation of marginal effects (remaining coefficients of the reduced models differed negligibly).

Further, uncorrelated (orthogonal) polynomials of age and violent victimization are used to isolate the contributions of each polynomial and its interaction term. All models are estimated using maximum likelihood to compare their AIC in addition to the significance level of the predictor.

Section 5.7.1 begins with interactions between physical vulnerability and victimization predicting crime-specific fear and avoidance behavior. Section 5.7.2 discusses interactions between physical vulnerability and neighborhood characteristics. Since this research investigated neighborhood processes, localized fear is analyzed.

5.7.1 Victimization

This part focuses on interactions between victimization and physical vulnerability. Results are in Table 5.5. Interactions of age and victimization were tested in the first victimization interaction model (vi1.1 and vi2.1), for gender and victimization in vi1.2 and vi2.2, and for health and victimization in vi1.3 and vi.2.3. Overall, age does not interact with victimization to explain crime-specific fear although two significant interaction effects explain avoidance behavior. Health does not interact with victimization, which rejects $H11_{\text{physical}}$.

Women's crime-specific fear and avoidance behavior are more affected by property victimization (vi1.2 and vi2.2); however, the effect of violent victimization on avoidance behavior is higher for men (vi.2.2). With the nonsignificant interaction removed, the model fit for crime-specific fear (AIC: 24,676 vs. 24,681 in the base model) and avoidance behavior (AIC: 22,050 vs. 22,053) increased. Given these inconsistent findings, $H10_{\text{physical}}$ could not be confirmed unequivocally. Upon taking a broader perspective, however, this suggests noteworthy gender differences in behavioral reactions to victimization, which is in accordance with findings by Braakmann (2012). Apart from Braakmann (2012), the author found no relevant quantitative empirical literature (there are interesting qualitative studies by Cobbina, Miller, and Brunson 2008; Miller 2008; Bourgois 1996).

[7]Within-person interactions are regarded as less accessible because of the previously discussed problem of (absent) recovery effects. A positive interaction between, e.g., age and victimization on the within-person level would have meant a stronger recovery effect as well.

[8]Whereas selected marginal effects are reported, the author agrees with Berry, Golder, and Milton (2012) about the importance to investigate both directions in the analytical process.

Table 5.10: Multilevel interaction models for victimization

	Dependent variables:					
	crime-specific fear			avoidance behavior		
	vi1.1	vi1.2	vi1.3	vi2.1	vi2.2	vi2.3
violent vic. (wi)	.05***	.05***	.05***	.05***	.05***	.05***
violent vic.	.27***	.28***	.25***	.30***	.34***	.27***
violent vic. (sq)	−.07*	−.08**	−.06**	−.08**	−.09**	−.07***
property vic. (wi)	.05***	.05***	.05***	.04***	.04***	.04***
property vic.	.37***	.31***	.36***	.20***	.16***	.19***
age	.02	.02	−.08**	.38***	.38***	.29***
age (sq)				.17***	.17***	.17***
gender: female	.15***	.15***	.15***	.52***	.52***	.52***
health (wi)			−.002			−.01
health			−.24***			−.22***
violent vic. x age	.05			.12**		
violent vic. x age (sq)				−.05		
violent vic. (sq) x age	−.01			−.03		
violent vic. (sq) x age (sq)				.05		
property vic. x age	−.02			−.12**		
property vic. x age (sq)				−.01		
violent vic. x gender		−.03			−.10*	
violent vic. (sq) x gender		.02			.03	
property vic. x gender		.12**			.09*	
violent vic. x health			.07			.01
violent vic. (sq) x health			−.004			.02
property vic. x health			.02			.002
Constant	−.06	−.06	−.06	−.25***	−.25***	−.25***
R^2_{within}	0.63	0.62	0.53	2.16	2.17	2.16
$R^2_{between}$	16.95	17.11	19.01	28.34	28.14	29.5
$R^2_{neigh.}$	95.93	95.58	94.79	92.56	92.67	93.03
AIC	24686	24680	24596	22047	22052	21969
BIC	24865	24859	24790	22262	22245	22177
Respondents	6319	6319	6319	6219	6219	6219
Observations	9,628	9,628	9,628	9,445	9,445	9,445

Note: *p<0.05; **p<0.01; ***p<0.001;
Controls: crime, social disadvantage, incivilities, city, education, ambiguity tolerance, T, city
Sample: a (see Section 4.1)

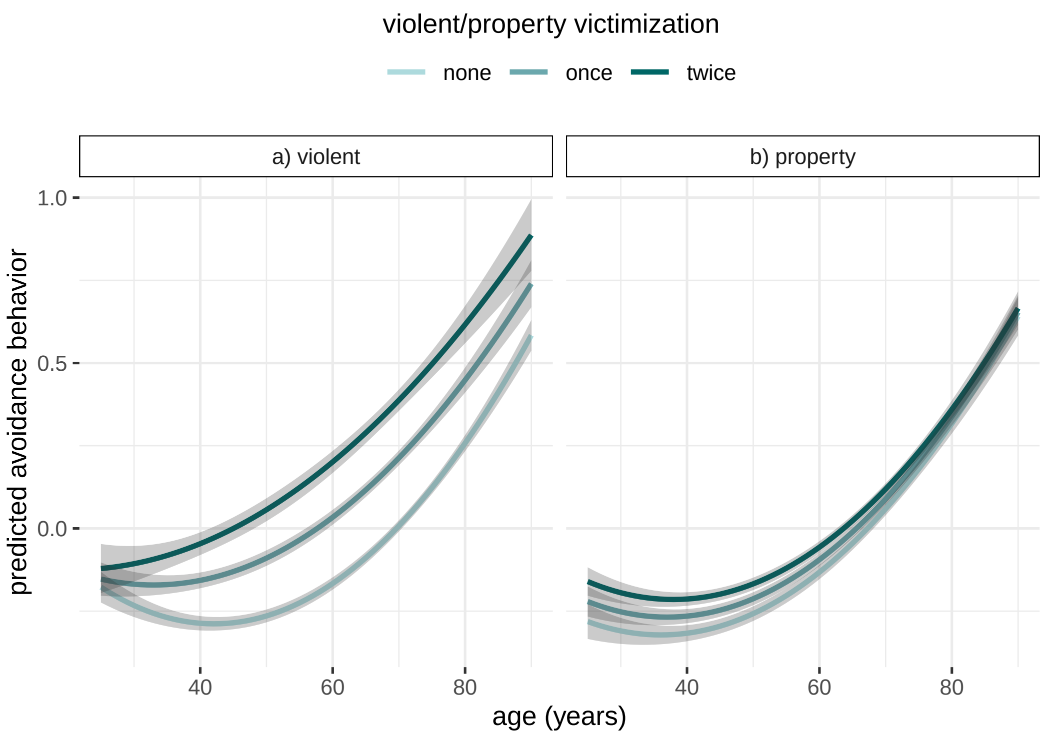

Figure 5.15: Predicted values of fear of crime depending on age and victimization

Good intuition regarding the consequences of victimization × age interactions can be gained by the predicted fear–age curves depending on victimization status. Figure 5.15 a suggests that violent victimization has little influence on the avoidance behavior of people who are below age 35. Younger victims of violent victimization restricted their behavior less than similarly victimized older people did. This difference is more pronounced among people in their forties and fifties but narrows in later life. In contrast, Figure 5.15 b suggests that only people below age 50 react more visibly with avoidance behavior to property victimization.

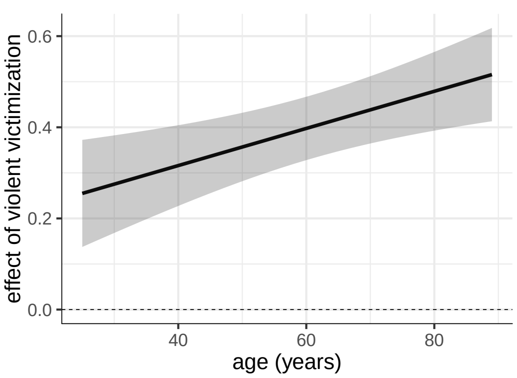

Figure 5.16: Marginal effect of violent victimization on avoidance behavior depending on age

Figure 5.16 shows the estimated between-person effect of violent victimization on avoidance behavior, depending on age. As described above, nonsignificant higher-order interactions are excluded. Although the effect of violent victimization is significant for all age groups, it increases considerably with age. The effect is almost twice as strong in the oldest respondents. This finding is in accordance with theoretical approaches to vulnerability and supports the notion that older people apply neutralization techniques less successfully (Agnew 1985, 233–34) and confirmed $H9_{physical}$. No relevant quantitative empirical literature was found. These analyses suggest that future studies should consider age-dependent differences in victimization effects.

Figure 5.17 shows the declining effect of property victimization with age. Property victimization more strongly affects avoidance behavior among younger people. There are at least two related explanations for this finding. It is important to note that the effect of age on avoidance behavior is comparatively high. At the same time, avoidance behavior is positively skewed. Hence, many younger people do not try to avoid crime at all, whereas older people engage in one or more avoidance behaviors. Perhaps younger victims of property crime were forced to confront crime for the first time. That confrontation might correct their "illusion of invulnerability, a basic belief that 'it can't happen to me' " (Janoff-Bulman 1989, 116). Hence, they might have reacted with small but initial behavioral adaptations. Expressed more technically, the distribution of avoidance behavior suggests that this counterintuitive result arose from a floor effect: many respondents who exhibited no avoidance behavior are young, male, and with no prior victimization experience.

5.7.2 Neighborhood characteristics

This section investigates interactions between physical vulnerability and neighborhood characteristics. The first neighborhood interaction models investigate the differential effects of neighborhood characteristics on age (ni1.1, ni.2.1, ni3.1), gender (ni1.2, ni.2.2, ni3.2), and health (ni1.3, ni.2.3, ni3.3).

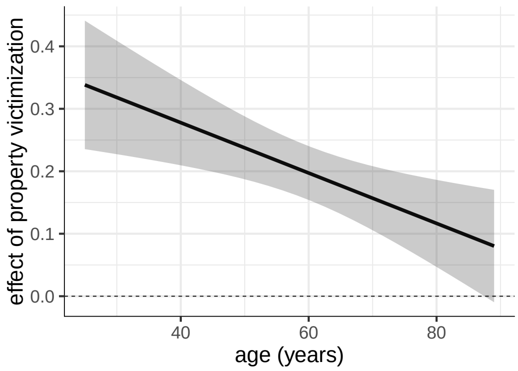

Figure 5.17: Marginal effect of property victimization on avoidance behavior depending on age

Overall, health does not significantly interact with any neighborhood characteristics (which rejects $H13_{\text{physical}}$). Social disadvantage seems less important for older people than it does for younger people (which confirms $H12_{\text{physical}}$ and is discussed below). Social disadvantage exerts stronger effects on women's avoidance behavior (ni2.2) and localized fear (ni3.2), which mainly confirm $H3_{\text{physical}}$.

With regard to $H3_{\text{physical}}$, the overall model fit for localized fear (ni3.2) improved slightly when the nonsignificant interaction of gender and crime was excluded (AIC: 23,081 vs. 23,086 in the base model). The results support the hypothesis that women are more fearful in disadvantaged areas, however, this interaction seems to be rather weak and limited to localized fear. The more surprising finding that women are less affected by incivilities is supported less by the results. There is a weak but significant interaction effect between gender and social disadvantage in predicting avoidance behavior (ni2.2). It does not, however, alter the overall fit of the model. Hence, $H3_{\text{physical}}$ (women react stronger on social disadvantage) is confirmed regarding localized fear. There is further indication that women's localized fear reacts less strongly to independently assessed incivilities. However, with the interaction between gender and social disadvantage removed, this small effect disappeared (not shown). The interaction effect between gender and social disadvantage remains significant.

Social disadvantage negatively interacts with age in explaining crime-specific (ni1.1) and localized fear (ni3.1).[9] These results are supported by an improved overall fit when tested separately (for crime-specific fear 24,668 vs. 24,681 and localized fear 23,080 vs. 23,086). Both interactions warrant closer examination. As a first step, the age curves of both outcomes for low, medium, and high neighborhood social disadvantage are predicted. Figure 5.18 a shows that the positive influence of age on crime-specific fear is reversed in very disadvantaged neighborhoods. Hence, younger people in disadvantaged neighborhoods report more fear than do older people. Figure 5.18 b shows a similar picture for localized fear. However, the quadratic age curve is not reversed but attenuated: although there is a curvilinear effect in low- and medium-disadvantaged neighborhoods, there is a positive, almost linear, effect in very disadvantaged neighborhoods at a much higher mean level.

A more nuanced view considers the effects of the interacting variables that are conditional on each other. With regard to the decreasing effects of age with increasing social disadvantage, figures 5.19 and 5.20 depict the associated marginal effects of age, depending on social disadvantage. For both dependent variables, the effect of age decreases as social disadvantage rises (and vice versa through symmetry of interaction). Although social disadvantage remains

[9] A three-way interaction between social disadvantage, age, and gender was not significant for both outcomes.

Table 5.11: Multilevel interaction models for neighborhood characteristics

	Dependent variables:								
	crime-specific fear			avoidance behavior			localized fear		
	ni1.1	ni1.2	ni1.3	ni2.1	ni2.2	ni2.3	ni3.1	ni3.2	ni3.3
age	.02	.02	−.07**	.38***	.38***	.29***	.25***	.25***	.14***
age (sq)				.18***	.17***	.17***	.08***	.08***	.07***
gender: female	.15***	.15***	.15***	.52***	.52***	.52***	.31***	.31***	.30***
health (wi)			−.002			−.01			−.05***
health			−.24***			−.22***			−.28***
crime	.04	.08	.04	.05	.03	.05	.08*	.08	.08*
social disadvantage	.26***	.20***	.23***	.42***	.36***	.39***	.56***	.49***	.52***
incivilities (SSO)	−.04	−.04	−.04	.15**	.21**	.16**	.17**	.23**	.18**
crime x age	.04			.04			.05		
crime x age (sq)				−.07			.02		
social disadv x age	−.20***			−.05			−.14**		
social disadv x age (sq)				−.08			−.06		
incivilities x age	.03			.03			.02		
incivilities x age (sq)				.04			−.02		
crime x gender		−.07			.03			.01	
social disadv x gender		.10			.10*			.13**	
incivilities x gender		−.01			−.09			−.11*	
crime x health			.04			−.06			−.05
social disadv x health			.10*			.03			.07
incivilities x health			−.08			.04			.01
city: Cologne	−.06*	−.06*	−.06*	−.19***	−.19***	−.18***	−.14***	−.15***	−.14***
incivilities x Cologne				−.25***	−.25***	−.25***	−.24***	−.25***	−.25***
Constant	−.06	−.06	−.06	−.25***	−.25***	−.25***	−.10*	−.09*	−.09*
R^2_{within}	0.65	0.65	0.55	2.18	2.17	2.18	0.83	0.79	1.11
$R^2_{between}$	17.35	17	19.01	28.17	28.08	29.51	24.98	24.91	27.82
$R^2_{neigh.}$	94.49	96.01	94.51	92.66	92.93	93	88.92	89.21	89.14
AIC	24670	24682	24596	22056	22054	21968	23085	23083	22921
BIC	24849	24861	24790	22271	22247	22175	23300	23277	23129
Respondents	6319	6319	6319	6219	6219	6219	6313	6313	6313
Observations	9,628	9,628	9,628	9,445	9,445	9,445	9,610	9,610	9,610

Note: *p<0.05; **p<0.01; ***p<0.001;
Controls: crime, social disadvantage, T, city, education, ambiguity tolerance, victimization
Sample: a (see Section 4.1)

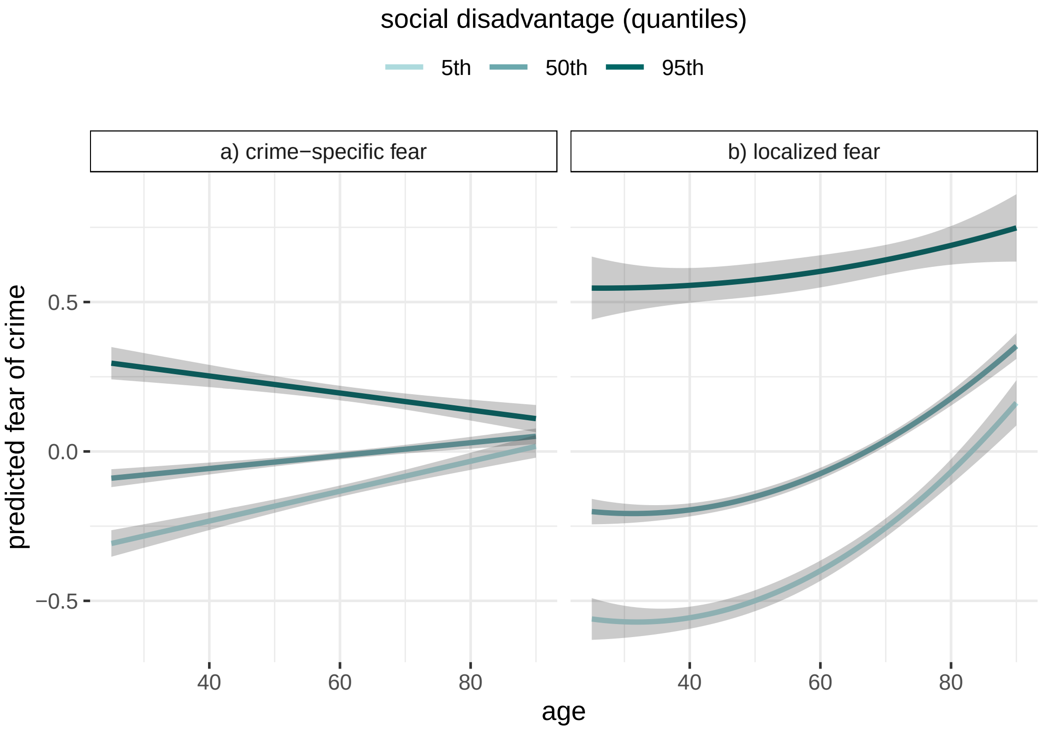

Figure 5.18: Predicted values of fear of crime depending on age and neighborhood problems

a significant age-related predictor for localized and crime-specific fear (not shown), the marginal effects of age depending on social disadvantage requires attention: age increases crime-specific fear only in neighborhoods with little social disadvantage (see Figure 5.19). In all other neighborhoods, age has no, or a negative, effect on crime-specific fear.

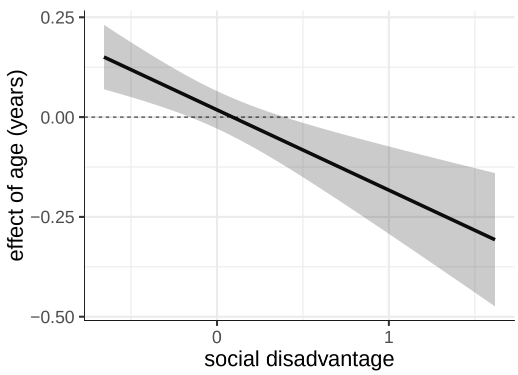

Figure 5.19: Marginal effect of age on crime-specific fear depending on social disadvantage

Since age has a quadratic effect on localized fear in addition to the significant interaction, the coefficient of age depends on social disadvantage and age. The interaction of social disadvantage with the second-order polynomial for age is not significant and exits the model. Consequently, the marginal effects of age decline in parallel depending on social disadvantage and age. Correspondingly, the effects of social disadvantage decline linearly with age (see Section 3.2.3). The left-hand side of Figure 5.20 shows that an additional year of age does not significantly affect localized fear among younger adults (around age 30) regardless of social disadvantage. However, every additional year significantly increases localized fear for older people (see also Figure 5.18). As interaction effects are symmetric (Berry, Golder, and Milton 2012), a complementary perspective on this interaction is provided on the right-hand side of Figure 5.20, which shows the vanishing effect of social disadvantage with age. Contrary to the vulnerability model, social disadvantage has the strongest effect on younger (and not older) people (discussed in the remainder of this section).

These findings contradict the contention that older people and people in worse health are more vulnerable in disadvantaged neighborhoods (Brunton-Smith and Sturgis 2011; Lawton and Simon 1968; Meer, Fortuijn, and Thissen 2008; Ward, Sherman, and La Gory 1988; Ward, Sherman, and La Gory 1988). In contrast, these results are similar to those of Maxfield (1984) and McGarrell, Giacomazzi, and Thurman (1997) with, however, considerably more

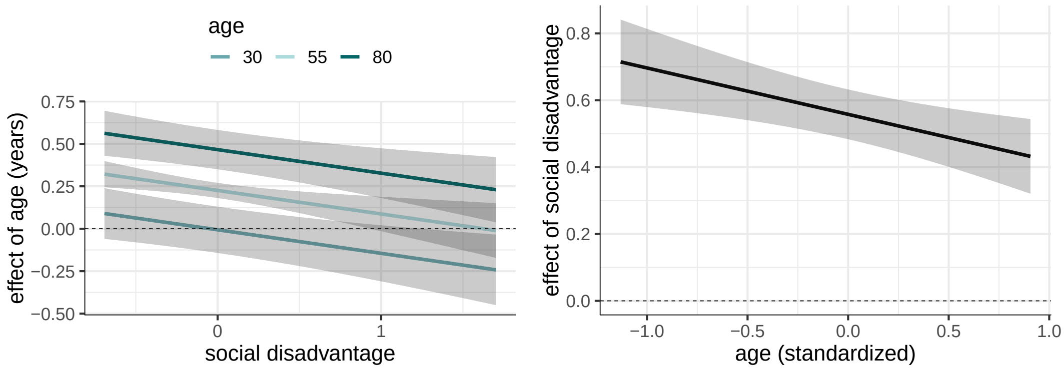

Figure 5.20: Marginal effect of age and social disadvantage on localized fear

comprehensive data (regarding both the number of respondents and neighborhoods). Maxfield (1984) and McGarrell, Giacomazzi, and Thurman (1997) interpreted their findings as "limits of vulnerability," arguing that physical vulnerability plays a minor role in socially disadvantaged neighborhoods; however, they spent little effort to discuss why this should be the case.

Another potential explanation is that older people might perceive fewer incivilities, making them less susceptible to neighborhood disadvantage. Although two studies found that older people perceive less independently measured neighborhood disorder (Hipp 2013; Sampson and Raudenbush 2004), two others, including one based on these data, reached the contrary conclusion (Oberwittler, Janssen, and Gerstner 2017; Jackson et al. 2017). Hence, this explanation is ruled out.

A possible methodological explanation is the existence of ceiling effects: the operationalization of the dependent variable might limit a further increase in localized fear attributable to social disadvantage for older respondents. This explanation is somewhat plausible because the effect of age on localized fear is strong and older people's localized fear is considerably above average. A counterargument is the range of this outcome. The z-transformed scale has a maximum of 3.2, which leaves sufficient room for further increases. However, this maximum requires the skewed item "How safe do you feel—or would you feel—if you walk alone in your area during daytime?" to be answered with "very afraid," which less than 1% did at T_1. A finer-grained operationalization with more (than four) answering categories or more questions would be beneficial in order to investigate this explanation. However, age and social disadvantage interacted similarly, explaining less skewed crime-specific fear. This finding suggests that this methodological explanation is unlikely.

Finally, there is, to the author's knowledge, a hitherto untested hypothesis: different patterns of crime (e.g. more crime among adolescents) within problematic neighborhoods affects younger people more than it affects older people. In contrast to Maxfield (1984) and McGarrell, Giacomazzi, and Thurman (1997), the author interprets these findings differently: instead of proclaiming the "limits of vulnerability," the present study suggests that younger people may be more influenced by social disadvantage than older people and hence are the actual vulnerable group in disadvantaged contexts. It seems reasonable that social disadvantage attracts certain criminal offenses that might be more relevant for younger age groups (e.g., gang crime, molestations, and public sexual harassment). To an extent, this claim is supported by Egan et al. (2012), who found that older people regarded "teenagers hanging around on the streets" as a less serious problem than younger people. Further, this could depend on differential activity patterns: younger people might be more active at night when offenses and social incivilities are more likely. However, an examination of this thesis would require an in-depth investigation of incivilities perceptions, neighborhood crime, activity patterns, and age. This is beyond the scope of this analysis.

Chapter 6

Summary

Fear of crime is a fascinating research topic because of its diverse, complex, and interdisciplinary causes and consequences, its interdisciplinary appeal, as well as its policy relevance. Extensive research has generated a body of literature in over fifty years since the first surveys investigating the fear of crime were published. Despite many valuable contributions, integrated approaches have been rare. The concept of vulnerability aims for such an integrative approach in demanding solid theoretical background on the individual and environmental level. In doing do, vulnerability provides a productive theoretical framework for fear of crime research generating numerous research hypotheses.

6.1 The extended vulnerability approach

At its theoretical core, vulnerability means susceptibility to negative environmental influences. Criminology adopted vulnerability early to analyze differential victimization risks and the fear of crime. Throughout this thesis, the author favored a notion of vulnerability in fear of crime research, according to which some people feel more insecure, given their openness to attack, lower abilities to control victimization, or higher perceived consequences of victimization (Skogan and Maxfield 1981, 69; or similarly Killias 1990). However, four weaknesses of earlier approaches were pointed out: they implicitly focused on static, cross-sectional explanations, they insufficiently separate individual from spatial (or situational) characteristics, they paid little attention to the fact that an individual's own capabilities and environmental threats are roughly estimated using heuristics and are likely to be under- or overestimated, and they insufficiently distinguished among affective, cognitive, and behavioral components of fear of crime.

Therefore, a dynamic, extended vulnerability approach was developed. According to this approach, vulnerability requires two components and an anticipated linkage to generate the fear of crime. At its core are individuals who anticipate three temporally structured dimensions of victimization (openness, controllability, and consequences) and perceive themselves as being more or less vulnerable because of personality traits, beliefs, and physical and social factors, as well as their course of life. Individuals are surrounded by an environment that is interpreted as being more or less adverse. These evaluations are based on availability and representativeness heuristics. Hence, perceived vulnerability to crime might be close to an actual assessment of personal and environmental characteristics but is likely to be under- or overestimated. Accordingly, an individual can either ignore the environmental adversity or roughly assess it on the basis of retrievable information and features of the environment. Similarly, the individual's ability to respond to victimization is assessed on objective criteria such as physical strength but is influenced by less tangible characteristics such as the locus of control.

Figure 2.2 displays the causal structure of the extended vulnerability approach. Individual vulnerability factors, life events, and neighborhood characteristics influence perceptions of environmental adversity, victimization risk, and vulnerability. Perceived environmental adversity and the risk of victimization are influenced by neighborhood characteristics and general assumptions regarding the trustworthiness of other people and according to psychological research (e.g., Loewenstein et al. 2001), possibly fear of crime itself (not tested).

Perceived vulnerability is assessed on the basis of the anticipation of victimization regarding openness, control, and consequences. These perceptions are proximal causes of the fear of crime (crime-specific and localized fear, as well as avoidance behavior).

This thesis stressed that it is insufficient for an in-depth investigation of vulnerability to investigate emotional arousal exclusively. In particular, physically vulnerable people might react initially with behavioral changes (Greve 1998) that have complicated and underexplored consequences for risk perception and emotions. These interrelationships are discussed in Section 2.2.

The extended vulnerability model also draws upon recent theoretical developments and less considered approaches to psychological processes in assessing individual vulnerability and environmental adversity. The older shattered assumptions theory (Janoff-Bulman 1992) argues that traumatizing life events such as victimization might change assumptions regarding the benevolence of the world (interpreted as environmental adversity) and meaningfulness (operationalized as the locus of control). The more recent construal-level theory of psychological distance was applied to fear of crime research by Gouseti and Jackson (2015), and the results suggest that people perceive more recent life events (victimization) as more concrete and neighborhood characteristics in adjacent neighborhoods as less concrete and therefore less important (but still present).

Physical vulnerability factors (particularly gender and age) were most frequently investigated. Although there are other reasonable explanations as to why women fear crime more, all three vulnerability dimensions (openness, controllability, and consequences) were mediating gender effects on fear (Jackson 2009). Age group differences in the fear of crime captured the attention of scholars for a long time; however, the underlying mechanisms and the statistical modeling were often investigated less assiduously. When compared with gender and age, health is a seldom-investigated predictor of fear of crime, and crucially, it is also understood as a consequence and not a cause of fear by epidemiological studies.

Social vulnerability factors contain dissimilar characteristics such as financial strain, education, and individual social capital. People with fewer financial resources might be unable to recoup the material consequences of victimization and have problems in securing their home or obtaining private transportation. Further, less educated people might perceive their environment as being more adverse because of a less differentiated threat assessment and the increased salience of crime (Boers 1991, 218). The frequency and supportiveness of neighborhood social contacts might reduce the fear of crime because their anticipated consequences are attenuated. In addition, frequent and supportive neighborhood contacts might increase neighborhood attachment, which reduces perceived environmental adversity.

Fear of crime research often investigates victimization as an independent subject. Drawing on shattered assumptions theory, potentially traumatic experiences such as victimization might correct the "illusion of invulnerability, a basic belief that 'it can't happen to me' " (Janoff-Bulman 1989, 116) and prompt changes in perceptions of environmental adversity and individual vulnerability. In addition, the author investigated other recent life events, arguing that the resulting diffuse anxieties might be projected onto environmental adversity. Likewise, early life events that are likely attributable to World War II might increase the fear of crime today. Theories on the life course argue that early disadvantages generate lifelong accumulated disadvantages (Ferraro and Shippee 2009).

In contrast to early vulnerability approaches, neighborhoods are regarded as independent explanatory units of fear of crime and are not to be confused with social or situational factors. Social disadvantage is a particularly important neighborhood characteristic for the fear of crime because it is a permanent and comprehensible neighborhood characteristic that drives perceptions of environmental adversity in the neighborhood. Secondary (and weaker) predictors are neighborhood crime and independently assessed incivilities. In addition, the author argued that the smaller the residential neighborhood the higher the risk of missing explanatory potential from adjacent areas, assuming a constant activity and perception radius of people. Hence, neighborhood problems are likely to spread beyond neighborhood borders.

Across neighborhoods, individual vulnerability factors are usually assumed to exert an equally strong influence. Brunton-Smith and Sturgis (2011, 340) noted that most studies that investigated differential individual effects depending on neighborhood characteristics suffered non-negligible shortcomings regarding data and analytical techniques. As a relational concept, however, vulnerability suggests that the effects depend on environmental characteristics. Intuitively, vulnerability factors become more important if stressors increase. With regard to age, however, both empirical findings and theoretical considerations suggest the opposite. Further interactions between physical vulnerability factors and victimization are discussed.

6.2 Empirical findings

This thesis assessed 42 research hypotheses regarding three outcomes at three analytical levels (see Section 3.3.1.2). This complexity might cause problems in comprehending the underlying analytical structure and results. Therefore, two overviews are provided. At the beginning of chapter 5, Table 5.1 showed the overall analytical structure. Table 6.1 in this section lists all research hypotheses, whether confirmed or rejected, and the section where their detailed discussion can be found.

Table 6.1: Summary of empirical findings

Hypothesis	Wording	Section	csf$_{wi}$	csf	ab$_{wi}$	ab	lf
$H1_{pers\&bel}$	External locus of control increases fear.	5.2.2	✓	✓	✓	✓	
$H2_{pers\&bel}$	Internal locus of control lowers fear.	5.2.2	×	✓	×	×	
$H3_{pers\&bel}$	Ambiguity tolerance lowers fear.	5.2.2	×	✓	×	✓	
$H4_{pers\&bel}$	The effect of locus of control on fear is mediated by vulnerability.	5.5		✓		✓	
$H5_{pers\&bel}$	The effect of ambiguity tolerance on fear is mediated by vulnerability.	5.5		✓		✓	
$H6_{pers\&bel}$	Generalized trust lowers fear.	5.2.2	✓	✓	✓	✓	
$H1_{physical}$	Women are more fearful than men.	5.2.1		✓		✓	
$H2_{physical}$	The effect of gender on fear is mediated by vulnerability.	5.5		✓		✓	
$H3_{physical}$	Neighborhood characteristics are more important for women.	5.7.2		×		✓	✓
$H4_{physical}$	Age increases fear of crime.	5.2.1		✓		✓	
$H5_{physical}$	Age and gender has a stronger effect on avoidance behavior than on crime-specific fear.	5.2.1		✓		✓	
$H6_{physical}$	Poor health increases fear of crime.	5.2.1	×	✓	×	✓	
$H7_{physical}$	The effect of self-rated health on fear is mediated by age and is the stronger predictor.	5.2.1		✓		✓	
$H8_{physical}$	The effect of health on fear is mediated by vulnerability.	5.5		✓		✓	
$H9_{physical}$	Victimization increases fear more strongly for older people.	5.7.1		×		✓	
$H10_{physical}$	Victimization increases fear more strongly for women.	5.7.1		×		×	
$H11_{physical}$	Victimization increases fear more strongly for people in poor health.	5.7.1		×		×	
$H12_{physical}$	Age effects depend on neighborhood characteristics.	5.7.2		✓		×	✓
$H13_{physical}$	Health effects depend on neighborhood characteristics.	5.7.2		×		×	×
$H1_{social}$	Financial strain increases fear.	5.2.3	✓	✓	×	✓	
$H2_{social}$	The effect of financial strain on fear is mediated by vulnerability.	5.5		✓		✓	
$H3_{social}$	Education lowers fear.	5.2.3		✓		✓	
$H4_{social}$	Social support lowers fear.	5.2.3		✓		✓	
$H5_{social}$	The effect of social support on fear is mediated by vulnerability.	5.5		✓		✓	
$H6_{social}$	Neighboring lowers fear.	5.2.3	✓	✓	×	✓	
$H1_{events}$	Victimization increases fear.	5.3	✓	✓	✓	✓	
$H2_{events}$	The effect of victimization on fear is mediated by locus of control.	5.3.1	×		×		
$H3_{events}$	The effect of victimization on fear is mediated by perceived victimization risk.	5.3.1	✓		×		
$H4_{events}$	The effect of victimization on fear is mediated by generalized trust.	5.3.1	✓		✓		
$H5_{events}$	Other negative life events increase fear.	5.4.1		✓			
$H6_{events}$	Early life events increase fear.	5.4.1		✓			
$H7_{events}$	The effect of early live events on fear is mediated by financial strain.	5.4.2		✓			
$H8_{events}$	The effect of early live events on fear is mediated by health.	5.4.2		✓			
$H9_{events}$	The effect of early live events on fear is mediated by locus of control.	5.4.2		×			
$H10_{events}$	The effect of early live events on fear is mediated by ambiguity tolerance.	5.4.2		✓			
$H11_{events}$	The effect of early live events on fear is mediated by vulnerability.	5.4.2		✓			
$H1_{neighb}$	Social disadvantage increases fear.	5.6		✓		✓	✓
$H2_{neighb}$	High crime rates increase fear.	5.6		×		×	✓
$H3_{neighb}$	Incivilities increase fear.	5.6		×		×	×
$H4_{neighb}$	Social disadvantage in adjacent neighborhoods increases fear.	5.6		×		✓	✓
$H5_{neighb}$	Crime in adjacent neighborhoods increase fear.	5.6		×		×	×

Note: csf = crime-specific fear; ab = avoidance behaviour; lf = localized fear; wi = within-person

Section 5.2 investigated vulnerability factors. Overall, strong evidence favored the vulnerability model. While gender is a strong predictor of crime-specific fear and avoidance behavior (confirming $H1_{physical}$), it is not the strongest predictor as other studies argued. Older people are more afraid of crime (confirming $H4_{physical}$). However, some nontrivial modeling particularities are relevant. The coefficient of age was suppressed without considering victimization, predicted avoidance behavior (and localized fear) quadratically (not linearly), and interacted with gender (more theoretically driven explanations can also be found in section 2.4.3.2.3). Among the more surprising nonsignificant findings is the within-person estimate of health (partly rejecting $H6_{physical}$). Hence, a recent deterioration in health does not generate an increase in fear that questions the immediateness of this link. Confirming $H7_{physical}$, health is a better predictor of crime-specific fear when compared with age at the between-person level.

Generalized trust (and less ambiguity tolerance) are strong predictors of crime-specific fear and avoidance behavior (confirming $H6_{pers\&bel}$ and partly $H3_{pers\&bel}$). The locus of control has a rather weak influence although the external locus of control predicts changes in crime-specific fear. Hence, $H1_{pers\&bel}$ is completely confirmed although $H2_{pers\&bel}$ is mostly rejected. This outcome contributes to the growing literature on personality traits, beliefs, and the fear of crime (Adams and Serpe 2000; Guedes, Domingos, and Cardoso 2018; Hirtenlehner 2008; Houts and Kassab 1997; Hummelsheim, Oberwittler, and Pritsch 2014; Wurff and Stringer 1988; Marshall 1991).

Controlling for neighborhood characteristics and health, the importance of social factors is generally confirmed. Education and household support were assessed at the between-person level, where they had significant effects in the expected direction, which confirmed $H3_{social}$ and $H4_{social}$. Neighboring and financial strain are significant between-person and within-person predictors of fear of crime (confirming $H1_{social}$ and $H6_{social}$). This provides solid and novel support for the relevance of social vulnerability. These findings were controlled for neighborhood characteristics, health (see Section 2.4.3.3), and at the within-person level, also time-stable unobserved heterogeneity. With regard to social support, this is, to the best of the author's knowledge, the first piece of evidence that social support reduces the fear of crime (beyond specific subgroups (Sacco 1993)).

Fear of crime research has debated the effects of victimization for a long time. Methodological limitations, particularly the scarcity of longitudinal data, led to contradictory findings. Section 5.3 applied between-within modeling to distinguish between-person differences from within-person changes attributable to victimization. Overall, victims of crime are more fearful than non-victims (between-person effect) and the same person becomes more fearful after victimization (within-person effect), which confirmed $H1_{events}$. The effects of violent victimization are considerably larger than those of property victimization. Although studies investigated between-person effects (more recently, e.g., Brunton-Smith and Sturgis 2011; Hanslmaier, Kemme, and Baier 2016; Hanslmaier 2013; Jackson and Gouseti 2015b; Tseloni and Zarafonitou 2008), fewer studies examined within-person effects (Braakmann 2012) or within-person and between-person effects in one coefficient (Russo, Roccato, and Vieno 2013; Russo and Roccato 2010). To the author's best knowledge, this study is the first to separate within-person and between-person estimates and report both. This allows comparisons: considerably larger between-person effects of violent victimization (when compared with within-person effects of the same variable) indicated non-negligible unobserved heterogeneity. This indicates that cross-sectional studies might exaggerate the effects of victimization; victims of violent victimization differ in still unconsidered ways and they anticipate their victimization to an extent.

Within-person effects of violent victimization affect three of four investigated vulnerability mediators (the internal locus of control, generalized trust, and perceived victimization risk). However, only the indirect effects of violent victimization via the perceived risk of victimization on crime-specific fear and avoidance behavior, as well as via generalized trust on crime-specific fear, are significant (partly confirming $H3_{events}$, confirming $H4_{events}$, but rejecting $H2_{events}$). Contrary to the hypothesis, the internal locus of control affects violent victimization positively. Hence, and in contrast to the author's interpretation of shattered assumption theory, victims of violent crime report slightly more robust internal locus of control. This finding indirectly supports Winkel's (1998) fear-victimization model. More in-depth analyses would require more complicated longitudinal investigations (and other operationalized concepts). Such analyses are, however, not possible with the current study design (see Chapter 7).

Life events other than victimization also increase the fear of crime. Potentially traumatizing early life events increase fear decades later. According to cumulative inequality theory, this disadvantage might exert its influence throughout life. The author examined whether such early and recent life events resulted in increased fear and found significant linear effects of cumulated early and recent life events among respondents although none were tied to recent life events of friends and family. In contrast, the most recent life events are insignificant despite the considerably larger sample. Hence, findings suggest that traumatic early life events increase the fear of crime ($H6_{events}$.) However, recent life events are less, if at all, influential in crime-specific fear (partly confirming $H5_{events}$). A mediation analysis also confirmed $H7_{events}$, $H8_{events}$, $H10_{events}$, and $H11_{events}$ but rejected $H9_{events}$: the effects of traumatic early life events are significantly mediated by ambiguity tolerance, perceived vulnerability, health, and financial strain but not the locus of control. Regarding $H6_{events}$, fear of crime research should acknowledge the well-discovered enduring effects of detrimental early life events on epidemiological and demographical outcomes (Barker 2004; Berg et al. 2010; Berg, Doblhammer, and Christensen 2009; Haas 2008; Hayward and Gorman 2004; Jürges 2013; Kesternich et al. 2014; Ben-Shlomo and Kuh 2002; Lundberg 1993; Scholte et al. 2017; Xie and Lagergren 2016) and abandon the "life-course fallacy" (Riley 1973).

Although vulnerability is a frequent theoretical explanation for the fear of crime, most studies forego investigation of the underlying mechanisms and test the influence of vulnerability factors only. This thesis was able to investigate the hypothesized mechanisms because they were operationalized with a subsample of older respondents in T_2. The results strongly support the vulnerability approach: all investigated factors are significantly mediated by the theoretically defined mechanisms (confirming $H4_{pers\&bel}$, $H5_{pers\&bel}$, $H2_{physical}$, $H8_{physical}$, and $H5_{social}$). This adds required and comprehensive support to the little-investigated influence of self-assessed vulnerability (Killias and Clerici 2000) and more importantly to pathways of vulnerability factors via their theoretical mechanisms (Jackson 2009). However, there are noteworthy differences among the vulnerability factors. Although physical factors are strongly and completely mediated, social support is less strongly mediated. The effects of personality traits are significantly and to a considerable extent mediated; however, vulnerability mechanisms do not explain their influence fully. This is partially explained by the missing operationalization of "openness to victimization" as a dimension of vulnerability, but it is indicated that concepts of vulnerability might be overly narrow to explain the effects of personality traits (particularly ambiguity tolerance) on the fear of crime (see Section 7).

Section 5.6 investigated neighborhood predictors more thoroughly. In addition to a discussion of the main effects of social disadvantage, crime, and independently assessed incivilities, an interaction analysis detected city-specific differences in the effects of all neighborhood predictors. Social disadvantage is by far the most important predictor of fear of crime (confirming $H1_{neighb}$). The effects of neighborhood crime are small and mostly below the significance level (contradicting $H2_{neighb}$). The effects of incivilities are small (controlling for crime and social disadvantage) and not significant for crime-specific fear. An investigation of city-specific neighborhood influences revealed significant differences only on incivilities for avoidance behavior and localized fear: incivilities slightly increased avoidance behavior and localized crime in Essen but slightly decreased both outcomes in Cologne. More generally, this finding questions the role of incivilities in explaining the fear of crime. An in-depth investigation is, however, beyond this thesis (Oberwittler, Janssen, and Gerstner 2017). This effect could be reduced by including the spatial lag of social disadvantage. Hence, $H3_{neighb}$ is confirmed in Essen but rejected in Cologne.

The widespread treatment of neighborhoods as isolated islands motivated the investigation of spatial lags. Spatial lags have been investigated by only three studies until now (Barton et al. 2017; Brunton-Smith and Jackson 2012; Wyant 2008), none of which were conducted in Germany (see Section 2.4.5.1 and 5.6). In a joint analysis, the spatial lag of crime turns out to be nonsignificant (rejecting $H5_{neighb}$), whereas the spatial lag of social disadvantage is significant. The $H4_{neighb}$ is confirmed for avoidance behavior and localized fear. It is rejected for crime-specific risk on the basis of the significance of the predictor and a reduced AIC: the spatial lag of social disadvantage explains an additional 1% of the variance in avoidance behavior and 3.1% of the variance in localized fear. Considering the already high percentage of explained variance, this is regarded as a non-negligible model improvement, particularly in relation to the comparatively small effort involved in harnessing this information, which is often collected as a by-product. These analyses suggest that the dependent variables that explicitly refer to the fear of crime in the respondents' neighborhood draw upon spatial characteristics beyond a mean neighborhood size of .56 km^2 (Conley, Stein, and Davis 2014; Hipp 2007; Groff and Lockwood 2014; Oberwittler and Wikström 2009). Hence, fear of crime studies with similarly small neighborhood areas should investigate the effects of adjacent areas.

The relational concept of vulnerability is naturally suited to interaction analyses. Hence, interactions between physical vulnerability, neighborhood characteristics, and victimization experiences at the between-person level were assessed. The vulnerability approach suggested no or positive interactions, while negative interactions require theoretical (and possibly methodological) efforts. Health did not interact at all. Women reacted somewhat more strongly to social disadvantage with avoidance behavior and localized fear, as well as to property victimization with crime-specific fear and avoidance behavior. However, women reacted less strongly than men to violent victimization with avoidance behavior. Older people reacted more strongly to violent victimization with avoidance behavior but less strongly to property victimization. The strongest interaction was found between age and social disadvantage: social disadvantage mattered less to older people than it did to younger people. Controlling for neighborhood attachment reduced this finding. However, a substantial and significant interaction remained. Although some counterintuitive findings might be explained by ceiling and floor effects, the age × social disadvantage interaction seems to be robust. In contrast to similar studies (Maxfield 1984; McGarrell, Giacomazzi, and Thurman 1997), the author argued that this calls for the investigation of perceived (social) incivilities, neighborhood crime, activity patterns, and age because this finding suggests that younger people are the actually vulnerable group in socially disadvantaged neighborhoods. This claim is supported by a study of Egan et al. (2012), which found that perceptions of "teenagers hanging around on the streets" as a serious neighborhood problem is the highest for the youngest age group under age 25 and decreased with age. These analyses underline the importance of theoretically justified interaction analyses between vulnerability factors and stressors, particularly regarding the scarce or unsatisfying quantitative evidence in this area (Brunton-Smith and Sturgis 2011, 340).

Chapter 7

Discussion

This thesis has emphasized the usefulness of the concept of vulnerability for the analysis of fear of crime. This chapter discusses the key findings of this thesis and situates them in a broader context. The chapter starts with highlighting the main results in a nontechnical way and will increasingly evolve into a more technical discussion targeted at the scientific readership by proposing potential methodological improvements for facilitating future research. The final paragraph provides a short conclusion.

Section 5.2 has shown that vulnerability factors (e.g., personality traits, age, gender, physical health, financial strain, and supportive networks) influence crime-specific fear and avoidance behavior. Across the 50 years of research on fear of crime, this study is the first to show the within-person effects of financial strain and social relationships with neighbors on crime-specific fear. While many studies have found those who are poor or not well-connected within their neighborhoods to be more fearful, the within-person effect shown in this study means that *reducing* financial strain and *developing* better contacts with neighbors decreases fear of crime. Thus, both findings provide longitudinal support for substantial relationships between poverty, neighborhood engagement, and fear of crime. By focusing on intra-individual changes—instead of inter-individual differences—the empirical investigation in this study provides much more robust support than most cross-sectional studies that investigate differences between persons only.

There are four essential findings for policymakers, social workers, and the non-scientific readership:

1. This thesis supports the idea that neighborhood cohesion reduces residents' fear of crime. This robust empirical finding underpins the efforts of social workers (Schubert et al. 2016) and active residents in their efforts to nurture social ties and trust among neighbors.

2. This thesis also found that a lessening of financial strain reduces fear of crime. Accordingly, reductions of poverty through a flourishing economy or welfare programs are likely to reduce fear of crime (Hummelsheim et al. 2011). On the other hand, recessions and welfare cuts are expected to increase fear of crime, exacerbating the negative effects of economic insecurity.

3. There is growing evidence partly attributing the higher fear levels of older people to a cohort trend (Koeber and Oberwittler 2019) and a generational effect (see Section 5.4.2). This thesis finds a robust effect of early life events on fear that indicates such a generational effect. One can conclude that previously found age effects were, in part, due to the circumstances of certain birth cohorts and not solely due to biological aging.[1] Hence, future studies will find *ceteris paribus* that age group differences are likely to decline when the War Generation (i.e., the birth cohorts 1929–1947) are replaced by later cohorts (the Baby Boomers), who grew up during more secure, stable, and affluent times. Hence, policymakers and social workers should target the whole population in their efforts to reduce the fear of crime. The graying of Germany (see Section 1.3) will

[1] Potential systematic recall errors were regarded as being unlikely because of the severity of the surveyed early life events, as well as the usage of "temporal landmarks" (Schröder 2011, 14), which facilitates recalling such events.

not lead, in all likelihood, to an increase of fear of crime in equal measure (see Section 5.1.5).

4. While the affective, cognitive, and behavioral components of fear of crime (see Section 2.1) are very well established at a theoretical level, most empirical studies focus on the affective dimension only. This thesis, in contrast, also compares effect strengths between the dimensions of fear. The lesson learned is that physical vulnerability (particularly age and gender but not health) increase avoidance behavior more strongly than affective crime-specific fear of crime. Thus, this study confirms and extends Greve's (1998) observation that older adults react to potential victimization with foresight. This thesis also finds this to hold true in the case of women. Studies that investigate only crime-specific fear might underestimate the day-to-day consequences of crime on physically vulnerable populations. Future studies could continue to identify the different drivers of the emotional, behavioral, and cognitive component of fear of crime.[2]

The interest in vulnerability within fear of crime research has declined over the past two decades, a trend that might be attributed to its *apparently* small relevance for interventions: as policymakers cannot change the age, frailty, or gender of a person, they cannot do anything to lower vulnerable people's fear. Other approaches, such as that involving social capital, offer more straightforward intervention suggestions. This line of argumentation, however, reduces vulnerability to mere differences in the "prevalence of 'fear of crime' in socio-demographic categories" (Vanderveen 2006, 7), which is of little scientific value. The perspective on vulnerability that is advocated in this thesis goes way beyond such simple subgroup differences. As outlined below, it puts the spotlight on the perceptional aspect of the two components of vulnerability (the vulnerable is exposed to an external threat) and asks how it changes and interacts. It invites practitioners to tackle perceptions of vulnerability, i.e., by fostering social capital, improving defense strategies, or attenuating perceived environmental adversity by mitigating perception biases.

By making the *perceptions* of vulnerability toward crime as its central component, the extended vulnerability approach strongly favored a dynamic perspective (see Section 2.5.2) with a focus on within-person changes, e.g., due to victimization. However, this perspective is not limited to victimization experiences. In contrast, there are many possible events and changes (on multiple levels) that can alter the perception of vulnerability without changing tangible vulnerability factors such as health, social support, or the financial situation. For example, perceived environmental adversity might change because of the worsening of neighborhood conditions or the sudden influx of migrants. Such developments might have no—or much weaker—effects on the actual victimization risk but could be perceived more intensely. Turned around, this approach could also be applied to the effects of improved contextual conditions, e.g., does gentrification or the long-term decline of violent crime rates actually decrease perceived environmental adversity?

This thesis also stresses the interdisciplinary character of fear of crime research. Future theoretical developments could draw upon the rich literature on person–environment systems (Magnusson and Stattin 2006) and continue to foster the scientific exchange of theoretical approaches and empirical findings, particularly among criminology, psychology, and sociology, but also among economics, epidemiology, and demography (Coleman 1994; Hedström and Ylikoski 2010; Magnusson 2012; Taylor 2010). For example, the demographic perspective on broad societal changes influenced the investigation of the generational effects of early life events on affective responses to crime. Further, the psychological concept of distance and relevance (see Section 2.3.2) fostered the investigation of neighborhood lags, as well as the discussion on the recovery effect after victimization. It is, supposedly, this amalgamation of different scientific disciplines and analytical levels that makes fear of crime research attractive.

The proposed extended vulnerability approach emphasized the relational nature of vulnerability (i.e., it takes both a vulnerable individual and an adverse environment to make vulnerability relevant) in fear of crime research. Thus, this approach makes the close connection between the individual and contextual level its core element (see Section 2.5) and focuses on research questions regarding vulnerable individuals who encounter adverse environments (see Section 2.5.1). Although the investigated interactions between physical vulnerability,

[2]For example, this study found that the neighborhood is much less important for the perceived risk of victimization than previous studies argued (Ferraro 1995, see Section 5.1.4).

neighborhood characteristics, and victimization support the concept of vulnerability on the whole, a more surprising finding is the negative interaction between age and neighborhood social disadvantage, which persists even after considering the higher neighborhood attachment of older people. This finding calls for further research to explain why younger people's fear of crime is more susceptible to neighborhood characteristics. Possible directions of quantitative investigations are outlined in section 5.7.2, yet qualitative research seems particularly promising for this research question.

The results of the mediation analyses in section 5.5 confirm the causal pathways that the author hypothesizes for individual vulnerability factors for fear of crime. For example, a theoretically driven operationalization of vulnerability fully explains the effect of gender on crime-specific fear, as well as the impact of health on avoidance behavior. These findings contribute to the scarce empirical evidence in this field (Jackson 2009). However, the analysis revealed non-negligible remaining effects; while all proxies of vulnerability are significantly mediated, some considerable direct effects (e.g., ambiguity tolerance and financial strain) remain after controlling for vulnerability. Hence, either more vulnerability factors exist that have not yet been operationalized, or these vulnerability factors influence fear of crime beyond the theoretical concept. Importantly, the vulnerability dimension of "openness to attack" was not assessed in this study despite its theoretical importance, particularly for the effects of financial strain. For instance, less wealthy people might be more open to attack (e.g., from relying on public transportation or being less able to secure their homes). The missing operationalization of "openness to attack" cannot be made responsible for the remaining effect of ambiguity tolerance on fear after controlling for the other dimensions of vulnerability.

The effects of violent victimization are mediated by increased perceived environmental adversity but not by the locus of control. In fact, the internal locus of control increased consequent to violent victimization. This result—and the remarkably low percentage of explained variance at the within-person level—indicates that vulnerability and victimization alone are incapable of explaining within-person changes in fear of crime satisfactorily. Hence, the extended vulnerability approach should abandon shattered assumption theory in favor of more complex theories on how people deal with detrimental life events. In fact, the temporal structure (whether victimization happened before the personality trait and fear were measured), as well as an abundance of more recent psychological research, suggests the importance of other coping patterns. A frequent trajectory is known as resilience, according to which victimizaiton might have (if at all) only short and minor impacts (Bonanno, Westphal, and Mancini 2011; Kalisch et al. 2017). Other trajectories could be more severe deterioration in the beginning but quick and complete recovery or even post-traumatic growth of self-assessed capabilities (Tedeschi and Calhoun 2004; Winkel 1998).

This thesis shows that a spatial neighborhood sizes of .56 km^2 is too small to fully capture the concept of neighborhood of the respondents and discusses and applies analytical corrections. However, this is of course not to say that larger spatial entities are always preferable in order to understand what determines environmental adversity.[3] By contrast, it seems very plausible that small parts of a neighborhood (e.g., certain squares or corners) determine its environmental adversity for many people while other areas remain largely unnoticed (Weisburd, Groff, and Yang 2012). This calls for a profound examination of what environmental adversity is. This thesis was successful in *explaining* most of the neighborhood variance with social disadvantage (a compound of % of unemployment and migrants in the neighborhood). However, this is different from *understanding* what exactly the drivers of environmental adversity are (Roux and Mair 2010). More theoretically driven measures, such as disorder, however, were found to be much less important in studies with the same data (Oberwittler, Janssen, and Gerstner 2017). Accordingly, the question of what exactly environmental adversity is needs to be investigated by future research with innovative means. The very end of this discussion provides a technical discussion on possible statistical advancements.

The longitudinal perspective on fear of crime research—despite its many decades as an intensively investigated topic—is still in its infancy. This study contributes to fear of crime research because even fundamental longitudinal aspects, e.g., that avoidance behavior is comparatively stable, whereas cognitive fear of crime was found to be very volatile (see Section

[3]From a methodological point of view, every dependent variable needs its appropriate level of spatial aggregation (Hipp 2007).

5.1.4), were missing until now. Among the various advantages of a longitudinal perspective on fear of crime and vulnerability is that it allows for the disaggregation of between-person differences from within-person changes (see Section 2.5.2), and if the random effects between-within approach is applied (discussed in section 3.3.1), for a comparison of both coefficients of the same variable at different levels. Section 5.2 showed that each within-person estimate was considerably smaller than its between-person pendant. Hence, all previous cross-sectional studies are likely to overestimate the true causal effects of their predictors because they are technically unable to control for unobserved time-stable heterogeneity.

A surprising and novel longitudinal result in this regard is the low within-person effect of violent victimization when compared with the larger between-person differences. Simple graphical analyses additionally reveal that there is a non-negligible anticipation effect of violent victimization. As the vast majority of studies on the impact of victimization of fear of crime are cross-sectional and the few longitudinal studies until now either report only within-person estimates (Braakmann 2012) or blend between-person and within-person estimates (Russo, Roccato, and Vieno 2013), this study is the first to unveil these temporal dynamics. This perspective has complex implications at both the methodological and substantial levels. The longitudinal investigation of victimization effects would strongly benefit from more than two waves because this would allow for random intercepts *and* random slopes of victimization. The latter is highly plausible because of differential victimization severity, individual sensitivity (a core dimension of vulnerability), and the period of time elapsed since the occurrence of victimization. Therefore, future longitudinal surveys should aim at more than two measurement occasions and should capture when exactly victimization has happend to model recovery effects. These temporarily more complex considerations ultimately point at two critical methodological limitations of this study. Unfortunately, these limitations are even more pronounced in fear of crime research in general: the shortage of (multi-wave) panel datasets. This entails the lack of prior knowledge and question batteries for longitudinal use, which has been made partly responsible for the low explained variance at the within-person level.

The full potential of longitudinal data analysis requires three waves (see, e.g., the recent special issue of SMR 2017 on three-wave panel analysis) and benefits from every additional measurement occasion. As this study had only two waves, it was impossible to, e.g., allow the slope of within-person variables such as time or victimization to vary between persons (in addition to a random intercept; Hoffman 2015, ch. 5). Importantly, these random slopes, e.g., of victimization, could become interesting variables themselves because they indicate the individual sensitivity to a particular external stimulus, which is a core element of resilience according to recent programmatic papers in this field (Kalisch et al. 2017; Scheffer et al. 2018). Furthermore, fear of crime research on the consequences of victimization would benefit from more than two waves. This would allow for latent growth mixture modeling (Muthén and Muthén 2000) to identify differential trajectories of fear and other outcomes (Bonanno, Westphal, and Mancini 2011), as well as full longitudinal mediation models (Little 2013, 298–307), which—given that data has been sampled in appropriate intervals (Dormann and Griffin 2015)—allows the tracing of effects from the independent variable via the mediator to the dependent variable.

Floor and ceiling effects were used to explain some somewhat surprising results of the interaction analyses. The univariate distributions (see Section 5.1.1) indicate the need for further methodological efforts to refine survey instruments capturing the fear of crime, particularly regarding avoidance behavior and localized crime. In addition to more theoretically driven methodological considerations (Vanderveen 2006), statistical requirements such as sufficient variance at both ends of the scale to capture nuanced individual differences throughout the continuum of fear of crime should be considered in future refinements of vulnerability scales. As the distinction between affective, cognitive, and behavioral components is not exclusive to fear of crime research, other research fields might have developed inspiring ways to measure their dependent variables.

Although measurement error and item non-response are considered by the investigation of latent variables of multiply-imputed confirmatory factor analyses, unit non-response, and the sampling error were scarcely considered. Including predictors of unit non-response in regression analyses and applying within-person analyses attenuates potential biases. However, estimates are likely to be affected by sampling and non-response error, mainly due to panel attrition. Weighting requires considerable effort, and it promises rather small improvements to this general problem of (longitudinal) survey research (Vandecasteele and Debels 2006).

Similarly, analyses regarding victimization disregarded whether victimization was randomly assigned to the investigated population. Applying a matching procedure alongside fixed effects regression analysis, Bauer (2015) showed that even within-person estimates might overestimate the actual impact of victimization. Although this study concentrated on the integration of victimization (and other life events) into the vulnerability approach, future in-depth victimization studies could apply more refined techniques to the effects of victimization on the fear of crime (see also Averdijk 2011; Braakmann 2012). Such studies could also assess the timing of the event (Hanslmaier, Kemme, and Baier 2016).

The analysis of the spatial spillover of neighborhood problems assumes that each adjacent neighborhood contributed an equal proportion ($\frac{1}{N_{adj}}$) where N_{adj} is the number of adjacent neighborhoods) of information to the spatial lag. Further, spatial lags are assumed to influence each residential inhabitant equally. These assumptions might, however, be unjustified for at least three reasons: 1) Some adjacent neighborhoods might be more important than others because of the mobility patterns of people. Hence, the modeling of spillover effects of neighborhood problems might be enhanced using, e.g., movement network data (Brockmann and Helbing 2013). The spatial spread of neighborhood problems could further be underestimated. 2) This is because only one adjacent neighborhood is highly problematic, whereas others are not. For such cases, where the less problematic surrounding neighborhoods would absorb the potential spillover effects, edge intensity (Legewie and Schaeffer 2016) might improve future analyses. 3) At the individual level, people living far away from the neighborhood's centroid are likely to be more influenced by nearby neighborhoods and less by distal neighborhoods. Considerations of such individual differences would, however, require the computation of a centroid-based spatial lag for each respondent.

To conclude, the concept of vulnerability facilitates an explanation of the fear of crime because it is compatible with other recent theoretical approaches that integrate levels of analysis, e.g., psychological distance or the generalized insecurity model. The extended vulnerability approach provides an analytical framework that aims at the within-person and between-person level *and* requires an inclusion of the abundant literature on the neighborhood effects on fear of crime. Hence, the extended vulnerability approach constitutes a holistic, dynamic, and interactive explanatory framework that generates research hypotheses with its emphasis on, e.g., the role of life events and the relation between persons and their living environments. The author hopes that this is theoretically useful and empirically stimulating for future interdisciplinary research as "[a]ny model trying to explain fear will include some notion of vulnerability" (Hale 1996, 95). This thesis is dedicated to advance this crucial building block of fear of crime research.

Chapter 8

Appendix

8.1 Cross-lagged panel model of fear of crime components

Since the interrelationship between the fear of crime components was not the focus of this work, this analysis is restricted to a comparatively simple and non-exhaustive structural equation model without, e.g., additional controls or measurement model.

Importantly, this exploratory model indicates that crime-specific fear in T_1 predicts perceived victimization risk in T_2 controlling for avoidance behavior and perceived victimization risk in T_1. This questions the widespread assumption that perceived victimization risk is a unidirectional predictor of crime-specific fear and supports the notion of simultaneous causality (between all components).

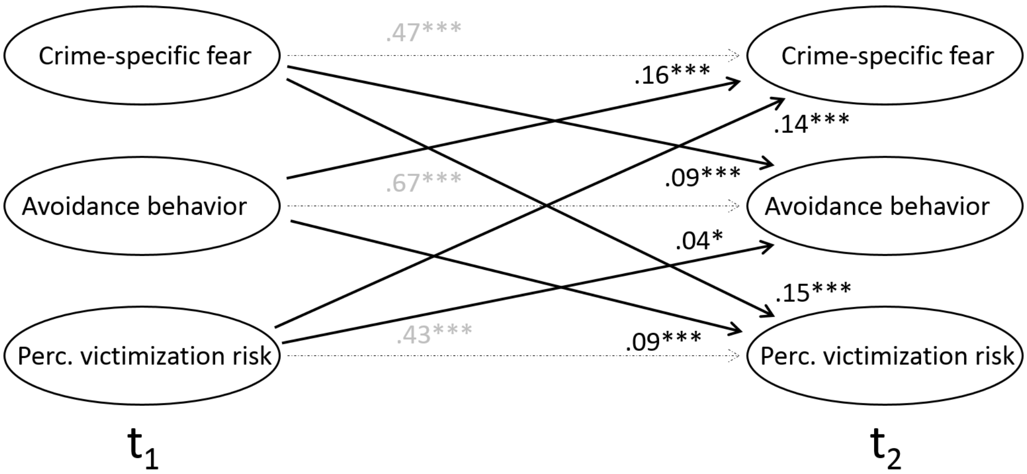

Figure 8.1: Exploratory cross-lagged panel model of fear of crime components

An unexpected finding was that avoidance behavior in T_1 neither reduces crime-specific fear nor perceived victimization risk in T_2. This was especially surprising regarding perceived victimization risk because it seems evident that people behave avoidantly to reduce victimization risk. There are at least two possible explanations for this result. As Liska, Sanchirico, and Reed (1988) argued, there could be a positive escalating loop between avoidance behavior and fear which also increases perceived victimization risk. Another explanation is the differential temporal perspective of both outcomes: While avoidance behavior surveys actions in the *previous* 12 months, perceived victimization risk asks for anticipated risk within the *next* 12 months. Hence, people who were more carefully at T_1 might have worse expectations about the future.

8.2 Measurement invariance of factor scores

A necessary precondition of survey-based longitudinal research is measurement equivalence across waves. While other approaches merely assume that this assumption is fulfilled, one advantage of confirmatory factor analysis was that it allows testing this assumption. If measurement invariance was not assured, within-person changes might be the result of a measurement error. This assumption was tested for all four factor scores. For computational reasons, continues variables were used for testing measurement invariance. Following Little (2013 ch. 5), the author compares configural, weak and strong invariance by sequentially constraining loadings and intercepts across measurement occasions. Measurement errors between the same items at different time points were allowed (Vandenberg and Lance 2000).

Overall, no severe violations were found. The frequency of contact has a marginally significant chi-squared test. A closer look revealed, however, that the intercepts were only negligible deviating between the waves. Thus, the significant chi-square test might be rather the result of the large sample size and does not indicate substantive changes in the latent variable. Poverty is not an actually derived theoretical concept. Therefore, the violation of strong measurement invariance is regarded as less problematic. Longitudinal measurement invariance could not be assessed for the psychological measures because every construct consisted of only two observed variables (Brown 2015, 55–61).

8.3 R-function to calculate and plot conditional marginal effects of multiplicative interactions with polynomial predictors

The author is not aware of any package in R which allows the investigation of marginal effects of multiplicative interactions involving second-order polynomials. Therefore, this function was written and is, for reasons of reproducibility, provided hereafter. The formulas of the respective derivatives and standard errors are obtained from Aiken, West, and Reno (1991, 64).

```
plot_poly_me <- function(reg_model, poly_pred, lin_pred, lin_intera, quad_intera = NULL,
    poly_min, poly_med = 0, poly_max, lin_pred_min = NULL, lin_pred_max = NULL,
    restrict_limits = TRUE, restrict_limits_at = 0.95, pred_quantiles = c(0.1,
        0.5, 0.9), legend_lab = "age (years)", cat_colors = "Set3", linesize_me = 2,
    n_pred = 30, add_histogram = TRUE, orthogonal_poly = FALSE) {

    # extract names
    if ((orthogonal_poly == FALSE)) {
        name_l <- poly_pred
        name_q <- paste0("I(", poly_pred, "^2)")
    } else {
        name_l <- paste0("poly(", poly_pred, ", 2)1")
        name_q <- paste0("poly(age_org, 2)2")
    }

    # extract coefs
    if (class(reg_model) == "clmm") {
        b_poly_lin <- coef(reg_model)[name_l]
        b_poly_quad <- coef(reg_model)[name_q]
        b_lin_pred <- coef(reg_model)[lin_pred]
        b_lin_intera <- coef(reg_model)[lin_intera]
        b_quad_intera <- coef(reg_model)[quad_intera]
    } else {
        b_poly_lin <- fixef(reg_model)[name_l]
        b_poly_quad <- fixef(reg_model)[name_q]
        b_lin_pred <- fixef(reg_model)[lin_pred]
        b_lin_intera <- fixef(reg_model)[lin_intera]
        b_quad_intera <- fixef(reg_model)[quad_intera]
    }

    # restrict prediction limits
    if ((restrict_limits == FALSE)) {
        restrict_limits_at <- 1
    } else {
        restrict_limits_at = restrict_limits_at
    }
```

```
if (is.null(lin_pred_min)) {
    predict_at_lin <- seq(min(reg_model@frame[lin_pred]) * restrict_limits_at,
        max(reg_model@frame[lin_pred]) * restrict_limits_at, length.out = n_pred)
} else {
    predict_at_lin <- seq(lin_pred_min, lin_pred_max, length.out = n_pred)
}

predict_at_poly <- seq(poly_min * restrict_limits_at, poly_max * restrict_limits_at,
    length.out = n_pred)

if ((0 <= pred_quantiles) && (pred_quantiles <= 1) == TRUE) {
    poly_pred_cat <- quantile(reg_model@frame[poly_pred], na.rm = T, probs=pred_quantiles)
} else {
    poly_pred_cat <- pred_quantiles
}

# extract variance estimates
estvar <- vcov(reg_model)
m.vcov <- as.data.frame(as.matrix(estvar))
var.b1 <- m.vcov[name_l, name_l]
var.b2 <- m.vcov[name_q, name_q]
var.b3 <- m.vcov[lin_pred, lin_pred]
var.b4 <- m.vcov[lin_intera, lin_intera]

cov.b1.b2 <- m.vcov[name_l, name_q]
cov.b1.b4 <- m.vcov[name_l, lin_intera]
cov.b2.b4 <- m.vcov[name_q, lin_intera]
cov.b3.b4 <- m.vcov[lin_pred, lin_intera]

# if interaction x2 and z is unimportant
if (is.null(quad_intera)) {

    # case b3 in Aiken, West, Reno (1990, 64)
    me_lin_pred <- b_lin_pred + b_lin_intera * predict_at_poly

    SEs <- rep(NA, n_pred)
    for (i in 1:length(predict_at_poly)) {
        x <- predict_at_poly[i]
        SEs[i] <- sqrt(var.b3 + var.b4 * x^2 + 2 * x * cov.b3.b4)
    }

    me_linear <- data.frame(cbind(x = predict_at_poly, PREDs = me_lin_pred,
        SEs))

    # case 3a in Aiken, West, Reno (1990, 64) outer loop: categories
    for (h in 1:length(poly_pred_cat)) {

        x <- poly_pred_cat[h]
        prediction <- rep(NA, n_pred)
        SEs <- rep(NA, n_pred)

        for (i in 1:n_pred) {
            # inner loop: x-axis

            z <- predict_at_lin[i]

            prediction[i] <- b_poly_lin + 2 * b_poly_quad * x + b_lin_intera *
              z

            SEs[i] <- sqrt(var.b1 + 4 * x^2 * var.b2 + z^2 * var.b4 + 4 *
              x * cov.b1.b2 + 2 * z * cov.b1.b4 + 4 * z * x * cov.b2.b4)
        }
        if (h == 1) {
            prediction_matrix2 <- prediction
            SEs_matrix2 <- SEs
        } else {
            SEs_matrix2 <- rbind(SEs_matrix2, SEs)
            prediction_matrix2 <- rbind(prediction_matrix2, prediction)
        }
    }
} else {
    # if interaction x2 and z is important

    # predict marginal effects for linear predictor extract additional
    # (co-)variance terms
    var.b5 <- m.vcov[quad_intera, quad_intera]
```

```
        cov.b1.b5 <- m.vcov[name_l, quad_intera]
        cov.b2.b5 <- m.vcov[name_q, quad_intera]
        cov.b3.b5 <- m.vcov[lin_pred, quad_intera]
        cov.b4.b5 <- m.vcov[lin_intera, quad_intera]

        # case 4b in Aiken, West, Reno (1990, 64)
        me_lin_pred <- b_lin_pred + b_lin_intera * predict_at_poly + b_quad_intera *
            predict_at_poly^2

        SEs <- rep(NA, n_pred)
        for (i in 1:length(predict_at_poly)) {
            x <- predict_at_poly[i]
            SEs[i] <- sqrt(var.b3 + var.b4 * x^2 + var.b5 * x^4 + 2 * x * cov.b3.b4 +
                2 * x^2 * cov.b3.b5 + 2 * x^3 * cov.b4.b5)
        }

        me_linear <- data.frame(cbind(x = predict_at_poly, PREDs = me_lin_pred,
            SEs))

        # # case 4a in Aiken, West, Reno (1990, 64) outer loop: categories
        for (h in 1:length(poly_pred_cat)) {

            x <- poly_pred_cat[h]
            prediction <- rep(NA, n_pred)
            SEs <- rep(NA, n_pred)

            for (i in 1:n_pred) {
                # inner loop: x-axis

                z <- predict_at_lin[i]  # z = z; x = x

                prediction[i] <- b_poly_lin + 2 * b_poly_quad * x + b_lin_intera *
                  z + 2 * b_quad_intera * z * x

                SEs[i] <- sqrt(var.b1 + 4 * x^2 * var.b2 + z^2 * var.b4 + 4 *
                  x^2 * z^2 * var.b5 + 4 * x * cov.b1.b2 + 2 * z * cov.b1.b4 +
                  4 * x * z * cov.b2.b4 + 4 * x * z * cov.b1.b5 + 8 * x^2 *
                  z * cov.b2.b5 + 4 * x * z^2 * cov.b4.b5)
            }
            if (h == 1) {
                prediction_matrix2 <- prediction
                SEs_matrix2 <- SEs
            } else {
                SEs_matrix2 <- rbind(SEs_matrix2, SEs)
                prediction_matrix2 <- rbind(prediction_matrix2, prediction)
            }
        }
    }

    # data management
    SEs_df <- data.frame(t(SEs_matrix2))
    PREDs_df <- data.frame(t(prediction_matrix2))
    colnames(PREDs_df) <- colnames(SEs_df) <- poly_pred_cat
    df2 <- gather(SEs_df, key = poly_pred, value = "SEs")
    df3 <- gather(PREDs_df, key = poly_pred, value = "PREDs")
    me_poly <- cbind(df3, df2[-1], x = predict_at_lin)
    me_poly[, 1] <- as.factor(me_poly[, 1])
    colnames(me_poly)[1] <- poly_pred

    out <- list(me_linear = me_linear, me_poly = me_poly)
    return(out)
}
```

8.4 Robustness checks

8.4.1 Estimating the main model of avoidance behavior using a negative binomial regression model

8.4.2 Reanalysis of neighborhood interaction models separately by cities

8.4.2.1 Interactions

Table 8.1: Multilevel models of vulnerability factors predicting avoidance behavior (negative binomial regression)

	Dependent variable: avoidance behavior (count)				
	mm2.1	mm2.2	mm2.3	mm2.4	mm2.5
age	.69***	.56***	.66***	.55***	.55**
age (sq)	.32***	.31***	.28***	.32***	.21
gender: female	.63***	.62***	.60***	.61***	.62***
female x age	.11*	.12*	.13**	.15**	.11
violent vic. (wi)	.04**	.04**	.03*	.04**	.03
violent vic.	.43***	.40***	.36***	.38***	.46***
violent vic. (sq)	−.08***	−.08***	−.08***	−.09***	−.12*
property vic. (wi)	.03*	.03*	.03*	.03*	.01
property vic.	.19***	.17***	.15***	.18***	.12***
health (wi)		−.01		−.02	
health		−.30***		−.22***	
internal loc (wi)			.01		
internal loc			−.05		
external loc (wi)			.03*		
external loc			.12***		
ambiguity tol (wi)			−.01		
ambiguity tol			−.28***		
trust (wi)			−.02*		
trust			−.36***		
financial strain (wi)				.02	
financial strain				.13***	
school education: low				.06**	
... high				−.17**	
... no degree				.03	
other/missing				.01	
neigh contact (wi)				−.01	
neigh contact				−.15***	
household support: no/don't know					.13*
T: 2	.06***	.06***	.06***	.07***	.09***
crime	.07	.07*	.07*	.07*	.09
social disadvantage	.51***	.46***	.40***	.39***	.41***
incivilities (sso)	.16**	.16**	.16**	.15**	.12
city: Cologne	−.21***	−.20***	−.18***	−.18***	−.17***
incivilities x Cologne	.19**	.20**	.18**	.20***	.21**
Constant	−.06	−.06	−.05	−.07	−.12***
Respondents	6,259	6,243	6,226	6,243	2,419
Observations	9,521	9,493	9,443	9,493	3,679

Note: *p<0.05; **p<0.01; ***p<0.001;
Controls: crime, social disadvantage, T_2, city, education, ambiguity tolerance, victimization;
Sample: mm2.1–mm2.4: a; mm2.5: e (see Section 4.1)

Table 8.2: Multilevel interaction models for neighborhood characteristics (Cologne)

	COLOGNE ONLY - Dependent variables:								
	crime-specific fear			avoidance behavior			localized fear		
	mmi1.1	mmi1.2	mmi1.3	mmi2.1	mmi2.2	mmi2.3	mmi3.1	mmi3.2	mmi3.3
violent vic. (wi)	.03*	.03*	.03*	.03*	.03*	.03*	.04**	.04**	.04**
violent vic.	.24***	.24***	.23***	.27***	.27***	.26***	.32***	.32***	.31***
violent vic. (sq)	−.08*	−.07*	−.07*	−.09***	−.09**	−.09**	−.06*	−.06*	−.06*
property vic. (wi)	.04**	.04**	.04**	.03*	.03*	.03*	.004	.004	.005
property vic.	.38***	.38***	.37***	.20***	.20***	.19***	.19***	.19***	.18***
age	.03	.04	−.05	.34***	.35***	.28***	.23***	.25***	.15***
age (sq)				.15***	.16***	.15***	.07*	.08**	.07**
gender: female	.14***	.14***	.13***	.53***	.56***	.53***	.30***	.32***	.30***
health (wi)			.0001			−.03*			−.05***
health			−.21***			−.17***			−.24***
crime	.03	.05	.04	.04	.10	.05	.07	.11	.08
social disadvantage	.27***	.21***	.24***	.44***	.36***	.41***	.60***	.53***	.57***
incivilities (SSO)	−.06	−.04	−.06	−.10*	−.03	−.10*	−.09	−.05	−.10*
crime x age	.04			.11			.15*		
crime x age (sq)				.05			.13		
social disadv x age	−.19**			−.10			−.19**		
social disadv x age (sq)				−.11			−.06		
incivilities x age	.04			.02			.02		
incivilities x age (sq)				.04			−.01		
crime x gender		−.03			−.09			−.06	
social disadv x gender		.11			.12*			.12*	
incivilities x gender		−.04			−.12			−.09	
crime x health			−.03			−.16*			−.15
social disadv x health			.07			.03			.09
incivilities x health			−.04			.07			.08
Constant	−.10*	−.10*	−.09*	−.43***	−.45***	−.43***	−.24***	−.24***	−.23***
Observations	6,077	6,077	6,077	5,956	5,956	5,956	6,068	6,068	6,068

Note: *p<0.05; **p<0.01; ***p<0.001; 95% confidence intervals available upon request
Controls: T, education, ambiguity tolerance;

Table 8.3: Multilevel interaction models for neighborhood characteristics (Essen)

	ESSEN ONLY - Dependent variables:								
	crime-specific fear			avoidance behavior			localized fear		
	mmi1.1	mmi1.2	mmi1.3	mmi2.1	mmi2.2	mmi2.3	mmi3.1	mmi3.2	mmi3.3
violent vic. (wi)	.08***	.08***	.08***	.09***	.09***	.09***	.07***	.07***	.07***
violent vic.	.28***	.29***	.27***	.31***	.31***	.29***	.38***	.39***	.36***
violent vic. (sq)	−.08**	−.07*	−.06*	−.06*	−.07*	−.05*	−.06*	−.06*	−.05
property vic. (wi)	.08**	.08**	.08**	.05**	.05*	.05**	.07**	.07**	.07**
property vic.	.35***	.36***	.34***	.20***	.20***	.18***	.25***	.24***	.22***
age	−.02	−.02	−.12**	.43***	.42***	.31***	.24***	.25***	.13***
age (sq)				.17***	.19***	.18***	.06	.07*	.06*
gender: female	.17***	.17***	.16***	.51***	.52***	.50***	.32***	.31***	.31***
health (wi)			−.005			.01			−.04
health			−.27***			−.31***			−.35***
crime	.04	.10	.04	.06	.03	.06	.10	.07	.10*
social disadvantage	.22***	.19*	.19***	.39***	.36***	.36***	.46***	.39***	.43***
incivilities (SSO)	−.002	−.06	−.003	.17*	.17	.17*	.21**	.29**	.20**
crime x age	.05			−.02			−.03		
crime x age (sq)				−.14			−.05		
social disadv x age	−.16			−.02			−.03		
social disadv x age (sq)				−.02			−.04		
incivilities x age	−.08			.14			.01		
incivilities x age (sq)				.02			−.04		
crime x gender		−.11			.07			.06	
social disadv x gender		.06			.04			.14	
incivilities x gender		.11			−.02			−.15	
crime x health			.10			−.005			.08
social disadv x health			.14			.06			.06
incivilities x health			−.15			−.08			−.20*
Constant	−.11	−.09	−.10	−.24***	−.25***	−.24***	−.09	−.08	−.08
Observations	3,551	3,551	3,551	3,489	3,489	3,489	3,542	3,542	3,542

Note: *p<0.05; **p<0.01; ***p<0.001; 95% confidence intervals available upon request
Controls: T, education, ambiguity tolerance;

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