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Income Distribution and the Fear of Crime: Evidence from Germany*

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Abstract

We here explore the link between individual concerns about crime and the distribution of income in Germany. We make use of 1995-2017 microdata from the German Socio-Economic Panel (SOEP) to show that both individual polarization and relative deprivation have statistically-significant effects on reported concerns about crime, while relative satisfaction plays no role. At the aggregate level, the main driver is equally income polarization, whereas the standard measure of inequality, the Gini index, plays no significant role.

Keywords: Concerns about crime, deprivation, inequality, polarization, SOEP.
JEL Classification Codes: I31, I32, D60.

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1. Introduction

Crime is one of the main concerns of both Europeans and Americans. Crime was cited by one in ten EU citizens as one of the two most important issues facing the EU in the 2017 Eurobarometer survey, achieving a double-digit score for the first time since 2010 (European Commission 2017; see Standard Eurobarometer 87). In the past seven years this percentage has never been below 6%. By creating an atmosphere of fear and anxiety that affects individual behavior, mental health and well-being, crime imposes substantial indirect costs on society that go well beyond the direct costs suffered by victims. Understanding the determinants of the fear of crime is therefore crucial in order to consider appropriate policy responses.

We here investigate the relationship between income differences and concerns about crime, building on recent contributions in the measurement of inequality literature that highlight the multi-faceted nature of the latter: individual income differences, which are the building blocks of inequality, can be described in a number of different ways, with different potential correlations with individual well-being, including concerns about crime. The vast majority of work on crime, as briefly surveyed below, only considers the Gini index as a measure of inequality, but there are other aspects of income differences that are not well captured by the Gini. We show that in twenty-two years of German data crime concerns are indeed driven by other characteristics of the income distribution, such as clustering on local means and the hollowing out of the middle-class. We believe that this reveals the misspecification of the models analysed in previous work.

Even though income inequality is not an individual-level concept but rather a measure of income differences in a society, any distribution of income will have individual-level effects via the individual's own income and their standing with respect to those who are richer and poorer, as discussed below. Following Clark and D'Ambrosio (2015), we here consider measures of inequality at the individual and societal level and their associations with fear of crime. At the individual level, we contrast the effect of being poorer or richer than others with that of being different without any further distinction. The societal counterpart of these individual indices will be the well-known Gini index of inequality, and a measure of polarization that captures one particular form of income differences due to the hollowing out of the middle class and the formation of income clusters at various points of the income distribution.

We analyze the relationship between inequality and fear of crime at the individual and aggregate levels, exploiting the variation in income inequality across German Federal States. Our dataset, which we describe in detail in Section 3, allows us to control for a number of individual- and macro-level variables that previous work has suggested may explain the fear of crime. In addition, while other work has, to the best of our knowledge, focused exclusively on the Gini index, we consider a variety of income-distribution measures capturing the different interpretations of this concept.

The analysis of inequality measures at both the individual and aggregate levels is in line with the hypotheses found in the literature on the fear of crime discussed in the next section. At the individual level, the vulnerability hypothesis emphasizes the role of a number of socio-demographic characteristics that increase vulnerability and reduce safety because they affect the individual's perception of their own vulnerability. At the aggregate contextual level, neighborhood and local community characteristics may lead individuals to perceive their immediate environment as threatening; inequality and polarization can affect the individual sense of social isolation and the quality of community life.

The remainder of the paper is organised as follows. Section 2 proposes a brief review of the literature on the determinants of fear of crime, and the indices of individual and aggregate inequality we use appear in Section 3. Section 4 describes our data, while the discussion of the empirical method is in Section 5. Our results then appear in Section 6. Last, Section 7 concludes.

2. The Theoretical Context

The understanding of the determinants of the fear of crime has attracted growing research and policy interest since 1960 (Hale, 1996). This interest reflects a rising awareness of its consequences beyond the individual well-being of the victims concerned. Research into the fear of crime has now become a central area of criminological investigation, as well as a key focus of crime policy.

There are two main approaches to the determinants of the fear of crime in the literature, depending on whether the analysis is at the individual or contextual level (see the references in Vauclair and Bratanova, 2017). The former considers the individual-level predictors and consequences of the fear of crime. The principal argument here is that of vulnerability, according to which some socio-demographic characteristics such as age, gender, physical disability, ethnicity, or socio-economic status predict the fear of crime. Those in these groups (e.g. women, disabled, low educated, living in an urban area etc., see Vauclair and Bratanova, 2017) are thought to feel physically and/or socially more vulnerable faced with crime and are therefore at a greater risk of victimization, producing a heightened fear of crime. An additional role can be played by direct experiences of victimization (see Keane, 1995).

The second strand of research has devoted more attention to contextual factors in the fear of crime. The underlying idea here is that individuals' wider social context helps explain their insecurity and concerns about crime. The great majority of these contributions has focused on the social meso-level, considering neighborhood and local community characteristics (for a review, see Lorenc *et al.*, 2014). One of the main arguments to explain crime and delinquency here is the social disorganization theory of Shaw and McKay (1942). This posits that individuals perceive certain characteristics in the immediate environment as signs of social disorganization and instability, indicating that the community's capacity to regulate individuals' behavior has been impaired. These signals, often referred to as incivilities, such as dirt and garbage, graffiti, and groups of young people hanging out on the streets, may lead to the perception of the immediate environment as threatening, and thus become symbolic cues of a greater victimization risk (Bennett and Flavin, 1994). Anxiety related to deterioration in the local environment, worsening community life, a sense of social isolation and a lack of effective social control is then displaced onto crime. The fear of crime may thus reflect individual unease at the perceived loss of community control over the immediate environment, as well as the government's inability to provide the collective good of safety (LaGrange *et al*., 1992; Scarborough *et al.*, 2010). The effect of the place of residence on the fear of crime has also been connected to the weakening of social ties. This relationship may be mediated by the sense of living in a cohesive and supportive community and integration into local social networks. Social-integration measures have thus also been suggested as predictors of the fear of crime (Gibson *et al*., 2002).

A small number of contributions have carried out empirical analysis of the impact of macro-level variables across macro-units, usually via cross-country comparisons. The macro-level explanatory variables include crime rates, economic characteristics such as unemployment and social-protection expenditure, structural characteristics such as the concentration of immigrants, and social characteristics like social capital. Some of this work (see for example Vieno *et al*., 2013, and Vauclair and Bratanova, 2017) considers inequality, finding the latter to be positively associated with the fear of crime in Europe.

Vieno *et al*. (2013) carry out a multi-level analysis of individuals in 27 countries in the 2006 Eurobarometer. The use of multi-level modelling takes into account the nested structure of respondents within countries and separately assesses the influence of individual and national characteristics, as well as their interactions. The Gini index appears in the country-level regressors as a measure of the degree of income inequality and is positively associated with the fear of crime.

Vauclair and Bratanova (2017) focus more particularly on the link between inequality and fear of crime, using data from the European Social Survey (Round 4, data collected in 2008-2010). Again using the Gini coefficient, they confirm that individuals in more unequal societies are more fearful of crime. Their multi-level modelling approach accounts for both individual- and country-level variables, and explores the role of income inequality as both a predictor of the fear of crime and a moderator of the links between individual characteristics and the fear of crime.

Hummelsheim *et al*. (2011) explore the association between Welfare State regimes and crime insecurity in Europe, via a multi-level analysis of respondents in 23 countries in the 2004/05 wave of the European Social Survey. They include among their country-level controls the Gini index as a measure of income inequality and find it to be positively related to the fear of crime.

We here consider both the individual and contextual perspectives, as inequality can be expected to operate at both levels. At the individual level, consistent with the vulnerability hypothesis, inequality may reduce an individual's ability to cope with their problems, resulting in a heightened fear of crime. On the other hand, greater inequality may reduce the potential benefit of targeting low socio-economic status individuals, putting those of higher socio-economic status at greater risk. At the aggregate level, inequality may reduce social protection, increasing the erosion of social and moral order.

By exploring the link between income inequality and the fear of crime, our work is also related to the literature on the relationship between income inequality and preferences for redistribution. In a recent contribution, Rueda and Stegmueller (2016) argue that the redistributive preferences of the rich depend on inequality. The macro effect of inequality on preferences for redistribution can be explained by a number of different micro-factors. Among these, the fear of crime appears to be the most important, as crime is perceived by individuals as the most visible negative externality of inequality.[1]

3. Measuring Inequality

Even though income inequality is not an individual-level concept, but rather a measure of income differences across society, any distribution of income will have individual-level effects due to changes in the individual's own income and their standing with respect to those who are richer and poorer. Following Clark and D'Ambrosio (2015) we here consider measures of inequality at the individual and societal levels.

Let N denote the set of all positive integers and $\mathbb{R}$ ($\mathbb{R}_+$) be the set of all (all non-negative) numbers. For a population of size $n \in N \setminus \{1\}$, the distinct levels of income are collected in a vector $\boldsymbol{x} = (x_1, x_2, \dots, x_K)$. Let π_j indicate the population share of individuals with the same level of income, x_j. An income distribution is $(\boldsymbol{\pi}, \boldsymbol{x}) \equiv (\pi_1, \dots, \pi_K; x_1, \dots, x_K), x_i \neq x_j$ for all $i, j \in \{1, \dots, K\}$. The space of all income distributions is indicated by Ω. We write $\lambda(\boldsymbol{x})$ for the mean of $\boldsymbol{x}$ and $\bar{\boldsymbol{x}} = (\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n)$ for the illfare-ranked permutation of $\boldsymbol{x}$, that is, $\bar{x}_1 \leq \bar{x}_2 \leq \dots \leq \bar{x}_n$.

[1] A number of other authors (see, for example, Chester, 1976, Stack, 1984, and Fajnzylber *et al*., 2002) have focused on inequality as a determinant of actual crime, which is outside the scope of the current contribution.

While income inequality is usually concerned with differences in the distribution of income in the population, relative deprivation and satisfaction measures focus on one-sided differences only, either with respect to the richer or poorer. One reason for looking at relative deprivation (satisfaction) is that it represents the individual's degree of discontent (contentment): these feelings can affect the perception of one's own ability to cope with adversity and the assessment of the victimization risk, and so influence the fear of crime.

The individual measure of relative deprivation adopted in the analysis follows the seminal paper of Yitzhaki (1979) and is a function $D_i\colon \Omega \rightarrow \mathbb{R}_+$, given by:

$$D_i(\boldsymbol{\pi}, \boldsymbol{x}) = \sum_{j=i+1}^{K} (\overline{x_j} - \overline{x_i})\pi_j$$

for all $(\boldsymbol{\pi}, \boldsymbol{x}) \in \Omega$. The deprivation suffered by individual i is the sum of all income differentials with respect to individuals who are richer than i. Similarly, the measure of relative satisfaction is a function $S_i\colon \Omega \rightarrow \mathbb{R}_+$, given by:

$$S_i(\boldsymbol{\pi}, \boldsymbol{x}) = \sum_{j=1}^{i-1} (\overline{x_i} - \overline{x_j})\pi_j$$

for all $(\boldsymbol{\pi}, \boldsymbol{x}) \in \Omega$. Satisfaction accounts for the income differentials with respect to the individuals who are poorer than i.

If we sum an individual's deprivation and satisfaction we are left with the measure of individual alienation, the function $A_i\colon \Omega \rightarrow \mathbb{R}_+$, defined as:

$$A_i(\boldsymbol{\pi}, \boldsymbol{x}) = \sum_{j=1}^{K} \left|\overline{x_i} - \overline{x_j}\right| \pi_j.$$

While relative deprivation and satisfaction are asymmetric measures, based on comparisons only to the richer or poorer, an individual is assumed to experience alienation with respect to both those who are better off and those who are worse off. The Gini coefficient is the average across the population of this index (generally normalized by mean income). The averages across the population of relative deprivation and, separately, of relative satisfaction are also equal to the Gini coefficient (normalized by mean income) as shown by Yitzhaki (1979) for deprivation. Davies (2016) highlights that $A_i(\boldsymbol{\pi}, \boldsymbol{x})$ provides the basis for an individual inequality index that can further be decomposed into two components, the relative deprivation and satisfaction measures introduced above. The two measures can thus be seen as the individual components of the Gini coefficient, which is what we use as their aggregate counterpart in the empirical analysis. Notice that in the empirical application all indices are normalized by mean income, following Chakravarty (1997), who proposes relative deprivation and satisfaction orderings, that is, deprivation and satisfaction normalized by mean income as preferred method to compare income distributions over time.

Only some particular movements in the income distribution may be relevant for individual concerns about crime. However, these may not necessarily be captured satisfactorily by an index of inequality. The following example illustrates. Consider a society whose income distribution in $ at time 0 is uniformly distributed over the interval [0, 1000]. Now imagine that there is some redistribution of income at time 1 so that all the population between 500$ and 250$ is taxed, with the tax revenue being given to those between 250$ and 0$: all the individuals concerned now have the same income of 250$. A similar process takes place for those between 1000$ and 500$, so that they now all receive 750$. The resulting income distribution has two spikes, with 50% of the population having 250$ and the other 50% 750$. This distribution has less inequality than the first, but more polarization since the middle class has disappeared. A more polarized society is more conflictual (see Esteban and Ray, 1999).

The measure of polarization comes from Esteban and Ray (1994) and is a generalization of the individual alienation index, A_i. The notion of polarization incorporates the role played by identification with individuals who belong to the same income group. Identification is approximated by the population share of each group. The interaction of identification and alienation gives rise to effective antagonism, the function $EA_i\colon \Omega \to \mathbb{R}_+$, defined by:

$$EA_i(\boldsymbol{\pi}, \boldsymbol{x}) = (\pi_i)^{\alpha} \sum_{j=1}^{K} \left|\overline{x}_i - \overline{x}_j\right| \pi_j$$

for all $(\boldsymbol{\pi}, \boldsymbol{x}) \in \Omega$, where $\alpha \in (0, 1.6]$ indicates the degree of polarization sensitivity and is chosen by the researcher. This parameter can be interpreted as the extent to which identification matters to an individual. When there is no identification, that is when $\alpha = 0$, $EA_i = A_i$.

The average effective antagonism across individuals is the polarization index, the function $P\colon \Omega \to \mathbb{R}_+$, given by:

$$P(\boldsymbol{\pi}, \boldsymbol{x}) = \sum_{i=1}^{K} (\pi_i)^{\alpha+1} \sum_{j=1}^{K} \left|\overline{x}_i - \overline{x}_j\right| \pi_j$$

for all $(\boldsymbol{\pi}, \boldsymbol{x}) \in \Omega$. The effective antagonism index can hence be thought of as the individual polarization index. In the empirical application, we make use of the same index defined over a continuous income distribution that was proposed and characterized by Duclos *et al*. (2004), and choose the value of $\alpha = 0.5$

Clearly, the main difference between the Gini coefficient and the polarization index comes from the role played by identification. (See D’Ambrosio and Rodrigues, 2008, for an empirical analysis of the effects of identification.) The minimal level of societal inequality and polarization coincide and is attained when all individuals have the same level of income. In contrast, the upper bounds of the two measures differ. The maximum level of inequality is reached when one individual monopolizes the total income. Polarization is instead maximal when the society is polarized into two equal-sized groups, those possessing income and those not possessing it.

In the empirical section all individual and aggregate measures are normalized by mean income $\lambda(\boldsymbol{x})$, a standard practice in the literature, when comparing the distributions over time.

4. The Data and Descriptive Evidence

Our empirical analysis is based on a very large longitudinal survey, the German Socio-Economic Panel Study (SOEP) (see Goebel *et al*., 2019). The SOEP is a representative longitudinal micro-level study providing a wide range of demographic and socio-economic information on private households in Germany and all household members. The first data was collected in 1984 from a sample of randomly-selected adult respondents in West Germany. Since then, the same private households, families and individuals have been surveyed annually. In 1990 the survey was expanded to include the States of the former German Democratic Republic (GDR). New samples were included later on to collect information on special population groups or boost the sample size. For instance, different immigrant and refugee samples were added in different years in order to account for the changes that took place in the German society since 1984.

The rich set of questions in the SOEP questionnaires allows us to include a number of time-varying characteristics at both the household and individual levels. By using appropriate panel estimators, the longitudinal structure of the data can be exploited to control for individual heterogeneity, that is for individual time-invariant characteristics that are expected to affect the outcome of interest.

The outcome variable is based on a question that was first asked in 1994. The exact wording of the question in the English version of the questionnaire is "*How concerned are you about the following issues?*", with the list of issues including "*Crime in Germany*". All items in the list are answered on a three-point scale: very concerned, somewhat concerned and not at all concerned. We convert this to a binary variable, taking the value of 0 if the answer is either "*Not at all*" or "*Somewhat concerned*" and 1 if the answer is "*Very concerned*". The choice of cut-off to collapse the three answers into two categories is based on the sample average of the original variable, as is common in the empirical literature. The original variable coding is 1 for "*Not at all concerned*", 2 for "*Somewhat concerned*" and 3 for "*Very concerned*". The sample mean is 1.68, with only about 12% "*Not at all concerned*" answers. We thus combine the first two answers in the same category. The estimated model thus shows the effect of the regressors on the probability of shifting from being "*Not at all*" or "*Somewhat concerned*" to "*Very concerned*". We estimate linear-probability models with fixed effects, where the estimated coefficients are the marginal effects. As a robustness check, we alternatively use Chamberlain's estimator for fixed-effects logit models for panel data and the ordered logit model proposed by Baetschmann, Staub and Winkelmann (2015) that allows the separate consideration of three points in the scale.

One clarification is required. We have so far used the term 'fear of crime'; however, it should be noted that there has been substantial debate over the definition and measurement of this concept, in particular regarding the distinction between fear of crime and concerns about crime. Some of the measures that have often been used to measure the fear of crime have been criticized as capturing a more general feeling of worry and insecurity that is not directly related to the fear of being victimized. The question asked in our dataset undoubtedly refers to concerns about crime. As such, our work here contributes to the fear of crime literature. We will here use the two terms, fear and concerns, interchangeably.

All of the individual-level explanatory variables come from the SOEP dataset, and the inequality measures, both at the individual and aggregate levels, are calculated based on the reported household disposable income per person equivalized using the modified OECD equivalent scale.

The additional macro-level control variables are from a number of different sources. The macro-level units considered are the German Federal States, namely the 16 Bundesländer. The regional crime-rate data comes from German police crime statistics (polizeiliche Kriminalstatistik, PKS, Bundeskiminalamt various years). The objective regional crime is defined as the number of offenses committed in the given region, where the offenses include violent crime, bodily harm, criminal threat, theft, burglary, damage to property, and cybercrime. One drawback of the database is that it only contains reported crimes, and thus suffers from unreported crime leading to underestimated actual crime rates. The regional unemployment-rate data is provided by the German Federal Employment Agency (Bundesagentur für Arbeit). Other data at the macro-level is from the German Federal Statistical Office (Destatis) and its Regional Database (Regionaldatenbank Deutschland, see: https://www.regionalstatistik.de/.). Since some of these macro-level variables are not available for 1994 we restrict our sample to 1995-2017. The final longitudinal sample comprises 399,487 person-year observations.

Table 1 displays the sample summary statistics. The percentage reporting to be very concerned about crime in Germany over the whole sample period is 45.6%. Average real individual equivalized income is roughly 22,300 euros. About 48% of observations come from home-owners. Average educational attainment is 12 years and average age 50. Women account for about 51% of observations, and 20% of the sample concerns individuals with either direct or indirect migration background. Most observations come from the married (58%) and the employed (56%). The average Gini index in the sample is 0.26 and average polarization is 0.19. The average crime rate, expressed as the number of registered criminal offenses per 100,000 inhabitants is around 7,650, while the average unemployment rate just above 9%. Since the spatial areas considered are large, namely the German Federal States, the average population is a little below 9 millions, while the average net inflow of people to the region between two consecutive years is 0.3%, as a percentage of the resident population.

5. The Empirical Strategy

The empirical analysis aims to determine the impact of the various inequality measures introduced above, at both the individual and aggregate level, on the fear of crime. Estimation at the individual level is based on the following linear probability model:

$$Concern_{ilt} = \alpha_i + \boldsymbol{X}_{\boldsymbol{ilt}}^{\boldsymbol{T}} * \boldsymbol{\beta_1} + \boldsymbol{Inequality}_{\boldsymbol{ilt}}^{\boldsymbol{T}} * \boldsymbol{\beta_2} + \boldsymbol{Z}_{\boldsymbol{lt}}^{\boldsymbol{T}} * \boldsymbol{\beta_3} + \tau_t + \lambda_l + \varepsilon_{ilt},$$

where $Concern$ is the binary recoding of the answers to the question "How concerned are you about crime in Germany?", with a value of 0 if the answer is either "Not at all" or "Somewhat concerned", and 1 for "Very concerned". The subscript indicates that the answer corresponds to individual i, living in the Federal State (*Land*) l, in year t. The vector $\boldsymbol{Inequality_{ilt}}$ includes our main regressors of interest: the individual inequality measures of relative deprivation, relative satisfaction, and individual polarization. The α_i are individual fixed effects, τ_t year fixed effects, and λ_l *Länder* fixed effects.

The vector $\boldsymbol{X_{ilt}}$ contains a number of individual time-varying characteristics that have been shown to influence the fear of crime in the existing literature. These include the logarithm of real household equivalized income (to reflect its decreasing marginal contribution to concerns about crime), a home-ownership dummy, years of completed education, self-assessed health on a scale from 1 (bad) to 5 (very good), a dummy for married, five labor-force status dummies (employed, unemployed, student, retired and other), the number of household members, the number of children in the household, and four age-group dummies. These latter cover the young (up to age 25), adults in early (26-40) and later (41-65) working life, and the retired (65+). Disposable yearly household income is equivalized using the OECD equivalence scale and is expressed in real terms using the annual consumer price index.

The vector $\boldsymbol{\beta_2}$ contains the parameters of interest, which capture the effect of inequality on the fear of crime. One challenge to the estimation of these parameters is the sorting of individuals into

Federal states, which may lead to a correlation between inequality measures and individual concerns about crime. This correlation may also arise when we focus on individual measures of inequality, since the reference group used to compute these measures consists of all other individuals in the same *Land*. We deal with this problem by introducing both individual and *Länder* fixed effects. We thus exploit within-State and within-individual variation in inequality, eliminating any composition effects resulting from sorting.

The individual-level fixed effects capture time-invariant characteristics, such as personality traits and attitudes, which likely affect individual fear of crime independently of other socio-demographic or environmental factors. To some extent, they may also control for other important unobserved variables that likely vary only sluggishly over time, such as the social network and other lifestyle dimensions. While the SOEP includes many individual-level characteristics, it lacks good proxies for social links, such as relationships with neighbors (which is not available in all observation years, but which would be of interest). In addition, the Länder fixed effects control for any state characteristics that are correlated with both inequality and concerns about crime, such as the quality of institutions or public goods and services. Finally, we include year dummies to capture any common time effect and potential seasonality in people's level of concern about crime.

The vector $\boldsymbol{Z_{lt}}$ includes Länder-level controls. The Federal State unemployment rate controls for the regional economic cycle, which could affect both inequality and concerns about crime. Objective crime rates, the number of offenses committed in a given Federal State per 100,000 inhabitants, are also expected to be correlated with both inequality and concerns about crime. Even though some work has suggested that crime concerns are only little correlated with actual crime rates or victimization (Stafford and Galle, 1984), it does seem reasonable that the two be correlated. The State population may proxy for other relevant State characteristics for which we cannot directly control, such as urbanization. While we cannot control for the share of immigrants, we included the annual net inflow into the Federal State to reflect the degree of regional mobility. When the measure is decomposed into the separate inflows and outflows of Germans and foreigners, the flows of Germans and foreigners are found to be strongly correlated. Finally, since by construction the SOEP induces correlation between respondents in the same household, as some questions are at the household level, we cluster standard errors at the household level.

One potential issue with this estimation strategy is individuals who move across Federal States. If the decision to move to State depends on inequality or crime rate in the previous State of residence, then we have some selection bias in our estimation. However, as the focus of the analysis is on large spatial units (the Federal States), only relatively few respondents change State (around 0.6% of observations in the whole sample). Nonetheless, as a robustness check we also run the analysis on the restricted sample excluding movers: this does not change the results.

We also focus on inequality at the aggregate (Federal State) level. The regression here is:

$$Concern_{ilt} = \alpha_i + \boldsymbol{X}_{ilt}^{\boldsymbol{T}} * \boldsymbol{\beta_1} + \boldsymbol{Inequality}_{lt}^{\boldsymbol{T}} * \boldsymbol{\beta_2} + \boldsymbol{Z}_{lt}^{\boldsymbol{T}} * \boldsymbol{\beta_3} + \tau_t + \lambda_l + \varepsilon_{ilt}.$$

The only difference from the individual model is that inequality measures, $\boldsymbol{Inequality}_{lt}^{\boldsymbol{T}}$, no longer vary at the individual level.

We consider potential differences across groups. The estimation does not allow us to estimate the impact of time-invariant individual characteristics, such as gender or ethnic background, which are all absorbed in the estimated individual fixed effects. The fear of crime literature suggests that gender and ethnic background will matter here, with women and ethnic minorities being more vulnerable and thus expected to report greater fear of crime. We consider heterogeneity by stratifying the sample by gender and ethnicity. We also stratify by the median income by Federal State and year: according to vulnerability theory, poorer individuals should be more likely to perceive victimization risk and express greater fear. On the other hand, according to Rueda and Stegmueller (2016), the richer respond to higher aggregate inequality by changing their preferences for redistribution as a means of preventing the negative externalities of inequality, and in particular crime. We thus ask whether these mechanisms translate into different effects of individual and aggregate inequality for the richer and poorer.

Notice that all continuous variables in the estimated models are standardized to ease interpretation of the coefficients.

6. The Results

Table 2 reports the results from the fixed-effect estimation of the linear probability model introduced in the previous section. The version of this table including all the coefficients on the controls is reported in Appendix Table 1A. The first three columns of Table 2 focus on individual inequality measures: individual polarization, relative deprivation, and relative satisfaction. Both individual polarization and relative deprivation have a statistically significant effect on the fear of crime. The coefficient of individual polarization is positive and statistically significant at the 5% level. A one-standard-deviation increase in individual polarization, namely, effective alienation, is associated with a rise in the probability of being *very concerned* about crime by 0.3 percentage points, which corresponds to 0.6% of a standard deviation of our measure of concern about crime, and 0.7% of the average probability of being *very concerned*. The coefficient of relative deprivation has a negative sign and is also statistically significant at the 5% level. A one-standard-deviation increase in relative deprivation reduces the probability of being *very concerned* by 1 percentage point, corresponding to 2% of a standard deviation in concern about crime. Relative satisfaction has no effect on the fear of crime. While the magnitude of the coefficients may appear small, the effects of our individual measures of inequality are quantitatively similar to those associated with other individual characteristics, as seen in Appendix Table A2. Moreover, the linear probability model assumes homogeneous effects across different groups in the population, while the effect of inequality on the concern about crime may vary across group. We explore this hypothesis in our heterogeneity analysis.

Since relative deprivation reflects how far down the individual ranks, the vulnerability hypothesis would suggest that the more deprived should feel more concerned about crime. However, the negative coefficient of relative deprivation is consistent with other hypotheses outlined in the fear of crime literature, and vulnerability may simply be captured by the polarization and income controls. Ceteris paribus, those who are towards the bottom of the income distribution may be less likely to express concern about crime than those towards the top, as the latter may believe that their higher position exposes them to a greater risk of victimization, especially property crime. The greater the distance to the richer, the lower is the fear of crime: being poorer than others appears to increase the sense of security. Instead, the distance to the poorer seems to play no role in this relationship.

Following the results in the existing literature, which have focused on the Gini index as a measure of inequality, more inequality is expected to produce greater fear. The first set of individual-level estimates suggests that this fear is related to individual polarization, and only relative deprivation among the two components of the Gini coefficient. As Duclos *et al*. (2004) note, the perception of alienation, namely the distance between the incomes of individuals and groups, is *fueled by notions of within-group identity*. Polarization does not simply reflect the distance between incomes, but the clustering of individuals in income groups at local means of the distribution.

The results for aggregate inequality are in the last three columns of Table 2. Contrary to previous research, the Gini coefficient is never significant here, so that at the aggregate level inequality does not affect concerns about crime. This difference from previous research reflects the fact that other studies do not control for polarization, which appears in specifications (4) and (5) of Table 2. The polarization coefficient shows that fear of crime rises with a particular type of inequality that is neglected by the Gini coefficient. This can be explained both by vulnerability and the reasoning in Rueda and Stegmueller (2016). For those at the bottom of the income distribution, polarization may induce feelings of vulnerability and a lack of resources with which to face problems, leading to fear of crime. For those at the top of the income distribution, more polarization can lead to a greater risk of crime, and hence of victimization, as the potential benefit of targeting those of low socio-economic status falls. The magnitude of the coefficient is bigger than the effect associated with individual polarization. A one-standard-deviation increase in aggregate polarization increases the likelihood of being *very concerned* about crime by 0.8 percentage points. This effect is quantitatively similar to the effect of unemployment on the fear of crime. A one-standard-deviation increase in unemployment increases the fear of crime by 0.7 percentage points.

The positive relationship between inequality and fear of crime in the existing literature is thus captured by polarization (the clustering of individuals in income groups distant from each other and the disappearance of the middle class) rather than the Gini index. While the Gini index is constructed using symmetric distances, thus capturing the so-called alienation of individuals and groups, polarization takes into account both alienation and group identity.

Before turning to the heterogeneity analysis and robustness checks, we note the estimated coefficients on the included controls, most of which are in line with those in the existing literature. The full set of results appears in Appendix Table A2. Consistent with the vulnerability hypothesis, a number of individual characteristics are associated with less fear: income, education, home ownership and self-assessed health. Income and health can reduce vulnerability by providing the individual with financial, physical and psychological resources with which to face threats, and education may improve risk-assessment skills. We have no strong *a priori* theoretical expectation regarding the effect of household structure and marital status on concerns about crime. On the one hand, a family and/or partner may be perceived as a safety net, alleviating feelings of insecurity and vulnerability, and reducing concerns. On the other hand, this effect may be outweighed by worries about one's own family and/or partners. While we do not find a statistically-significant effect for the number of family members, there is some evidence of a positive impact of marital status and number of kids: married individuals and those with more children are more concerned about crime. According to the vulnerability hypothesis, older people and the unemployed are expected to be more concerned (as unemployment is a proxy for economic security). However, we here find no significant effect of labor-force status, and it may be that economic stability is already captured by individual income. For age, we do find some evidence that those aged 46-65 are less concerned than those aged over 65.

Moving to the macro-level controls, the coefficient on the objective crime rate is positive and statistically significant at the 1% level, so that subjective concerns do respond to objective crime levels. The objective crime rate here is the number of crimes per 100 inhabitants, and the associated coefficient implies that a one standard-deviation higher objective crime rate (2.3 more crimes per 100 inhabitants) increases the likelihood of being very concerned about crime by 4,9 percentage points, which corresponds to roughly ten percent of the standard deviation of the concern about crime.

We also find a positive and statistically-significant effect for the net inflow of individuals into the region. The net inflow of people into the Federal State can be interpreted as a measure of mobility in the region. At the micro level, greater mobility increases the likelihood of having new neighbors or meeting strangers locally, which in turn can affect insecurity and fear of crime.

According to the vulnerability hypothesis, gender and ethnic identity can also affect the fear of crime: women and ethnic minorities are expected to feel more vulnerable. While empirical analyses tend to confirm that women fear crime more, this is not the case for immigrants and ethnic minorities. As neither gender nor ethnic origin can be estimated in a fixed-effect model, we instead ask whether they affect the relationship with inequality. We thus re-estimate the baseline model on the sub-samples of men and women, Germans and those with either direct or indirect immigration background, and those whose income is either above or below the median income in the region. This last test asks whether income determines how individuals respond to inequality. Under the vulnerability hypothesis, the poorer may be more responsive to inequality; on the other hand, following Rueda and Stegmueller (2016), the richer may be more likely to express concerns about crime, and especially in more unequal areas.

Table 3 shows the results from the heterogeneity analysis. The effect of individual polarization is only statistically significant for men, at the 10% level; while the effect of relative deprivation is only statistically significant for women, at the 5% level. Regarding immigration, the baseline effects continue to hold for Germans, while there is no evidence of an effect of polarization or relative deprivation for immigrants (although we cannot reject that the polarization coefficients are the same for Germans and immigrants). Along with the positive coefficient on polarization and the negative coefficient on relative deprivation, we also find a positive and statistically-significant coefficient of relative satisfaction for the sub-sample of Germans, which is also statistically significant for immigrants but of the opposite sign: only for immigrants does being richer than others appears to increase the sense of protection and lower the fear of crime. Last, the positive effect of polarization, both at the individual and macro level, appears to be driven by individuals under median income, in line with the vulnerability hypothesis. The same holds for the negative effect of relative deprivation.

One worry is that given the binary nature of the dependent variable, the linear-probability model does not constitute a good specification for the relationship between concerns about crime and inequality. As a robustness check we thus estimate a Chamberlain conditional logit model, relaxing the linearity assumption while keeping the fixed effects. The coefficients of this logit model do not have a straightforward interpretation. They can be seen as the partial effects of the regressors on the log odds ratio. Yet, all of the signs and significance levels of the coefficients of interest are the same as those in the baseline linear-probability model. Both the relative-deprivation and individual-polarization coefficients are statistically significant at the 1% level. The results appear in Table 4.

One option to interpret these coefficients would be to report the partial effects and semi-elasticities evaluated at an arbitrary value for the fixed effects, e.g. $\alpha_i = 0$. However, as pointed out by Santos Silva and Kemp (2016), the resulting estimates are not particularly meaningful since the choice of where to evaluate the fixed effects is completely arbitrary. Moreover, their value will depend on how the regressors are measured and not be robust to changes in scale.

However, the average semi-elasticity can be consistently estimated. It captures the average percentage change in the fear of crime for a unit increase in the regressor of interest, and can be evaluated against the coefficients of the baseline linear probability model. Table A3 in Appendix reports the average semi-elasticity for each of the regressors of interest. As in our baseline specification, all included continuous regressors are standardized. The semi-elasticities cannot be directly compared to the coefficients of the linear probability model. The coefficients of the linear probability model give the average percentage-point change in concern about crime for a one-standard-deviation increase in the regressor considered and assume a homogenous effect. However, if we consider the average effect at the mean value of fear of crime (0.456), the percentage change in the outcome variable estimated with the linear probability model is less than half of the average semi-elasticity estimated with the logit model for both individual polarization and relative deprivation (they both correspond to roughly 40% of the estimated average semi-elasticity). Average semi-elasticities consistently suggest a higher magnitude and point towards the presence of heterogeneous effects, which was explored in the heterogeneity analysis. Based on these estimates, a one-standard-deviation increase in individual polarization is associated on average with a rise in the likelihood of being *very concerned* about crime by 1.7%; while a one-standard-deviation increase in relative deprivation on average decrease this likelihood by 5%.

The original outcome variable is coded in an ordinal scale from 1 to 3. Ideally, as a further robustness check one would want to estimate an ordered logit model. However, extensions of ordered non-linear models to a panel data context are complex and far from obvious. For the logit case, a standard approach is to simplify the estimation problem to that of a binary logit model, as we did in the previous robustness check as well as in our baseline regressions. Other estimators proposed in the literature are built around the same idea of reducing the ordered model to a binary one, but aim at exploiting additional information available in the data relative to a simple dichotomization of the dependent variable. Some of these approaches estimate fixed effects logits for every possible dichotomizing cutoff point and then combine the resulting estimates. Thus, as a further robustness check, we implement the approach to the estimation of an ordered logit model proposed by Baetschmann, Staub and Winkelmann (2015).

Results are reported in Appendix Table A4. The outcome variable corresponds to the ordered variable which is based on the original survey question. We recode the variable in increasing order, so that it takes value 1 if the answer was "*Not at all concerned*"; value 2 for "*Somewhat concerned*"; and value 3 for "*Very concerned*". The estimated coefficients combine results from the estimation of the model using the two alternative dichotomizations of the outcome variable. Some caveats apply. First, our choice of dichotomization was motivated by the data, namely by the fact that only 12% of respondents in the whole sample report being "*not at all concerned*" about crime. Second, by shifting the cutoff, we ask whether inequality measures affect the likelihood of shifting from not being concerned to being either *somewhat* or *very concerned* about crime. A priori, the effects may be different. Results from the estimation of the ordered logit are consistent with the results of the logit model estimated based on our chosen dichotomization. For the individual-inequality measures, the magnitude of the coefficients is very similar, but the significance level is lower (from 5 to 10%). The coefficient of aggregate polarization is no longer statistically significant, suggesting that the effect of aggregate polarization may differ depending on the dichotomization considered.

Our empirical strategy, in particular the inclusion of fixed effects, should help address the endogeneity issues related to omitted variables. However, we cannot directly test and dismiss all endogeneity concerns. To provide some suggestive evidence against endogeneity concerns, we carry out a Granger causality test to check whether the lagged values of individual concerns about crime explain current levels of inequality. Were this to be the case, we would be concerned about reverse causality, which is one source of endogeneity. We thus re-estimate the baseline model using as the outcome variables the inequality measures found to have an impact on individual fear of crime. We include among the regressors the lagged values of concerns about crime and check whether the associated coefficient is statistically significant. We repeat the exercise both with and without the other inequality measures as regressors, which produces very similar results. Table 5 reports the results including the other inequality measures in the regressors. As expected, the coefficient on lagged concerns is never statistically significant. This exercise provides suggestive evidence against reverse causality. However, the identification strategy does not allow to rule out the existence of other omitted variables which may confound the relationship between inequality measures and concern about crime.

7. Conclusions

Crime is one of the main concerns of both Europeans and Americans, and understanding the determinants of fear of crime is crucial to understand what the appropriate policy responses may be. The fear-of-crime literature has generally relied on the Gini coefficient as the measure of population income differences. Making use of a panel dataset representative of the German population for twenty-two years, we here suggest that Gini is not the appropriate measure: the fear of crime is driven by other types of individual income comparisons. The two main determinants of fear of crime are income gaps with respect to those who are richer and income differences with respect to everybody interacted with the identification of similar individuals. At the aggregate level, fear of crime is thus related to polarization and not inequality. The analysis underlines the contribution of individual-level inequality measures as well as aggregate measures other than the Gini coefficient to explaining individual concerns about crime. Future research should further investigate the role played by various aspects of inequality in affecting individual preferences and decision making, trying to focus also on the underlying mechanisms, to better understand the far-reaching consequences of inequality.

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Tables

TABLE 1: Summary Statistics

	Mean	SD	Min	Max
Individual-level variables				
Concern	0.456	0.498	0.000	1.000
Individual Polarization	0.191	0.030	0.034	1.490
Relative Deprivation	0.261	0.179	0.000	1.000
Relative Satisfaction	0.269	0.543	0.000	80.812
Annual Eqv. Household Income (thousands, in prices of 2010)	22.314	15.012	0.002	2037.537
Home Ownership	0.478	0.500	0.000	1.000
Education (years)	11.828	2.556	7.000	18.000
Self-assessed Health[1]	3.302	0.968	1.000	5.000
Women (%)	0.514	0.500	0.000	1.000
Migration background (%)	0.195	0.396	0.000	1.000
Age	50.105	17.769	18.000	101.000
Household Size	2.447	1.224	1.000	14.000
Number of Kids	0.316	0.701	0.000	8.000
Married (%)	0.583	0.493	0.000	1.000
Employed (%)	0.562	0.496	0.000	1.000
Unemployed (%)	0.059	0.236	0.000	1.000
Student (%)	0.026	0.159	0.000	1.000
Retired (%)	0.280	0.449	0.000	1.000
Not employed (%)	0.072	0.259	0.000	1.000
Observations	358,983			
Macro-level variables				
Aggregate Polarization	0.191	0.015	0.149	0.225
Gini Index	0.264	0.031	0.167	0.370
Crime Rate[2]	7.626	2.309	4.958	18.569
Population (millions)	8.980	5.730	0.652	18.080
Unemployment (%)	0.093	0.041	0.036	0.2050
Total Net Inflow of People (%)	0.029	0.0387	-0.0533	0.2032
Observations	399,487			

Notes. Summary statistics are computed on the working sample from the baseline regressions of the empirical analysis. The sample includes observations from the German SOEP for the years 1995-2017, for which information is available on all the included characteristics at the macro level; macro-level variables are defined at the level of the *Länder*, namely, the 16 German Federal States. Statistics for individual-level variables are weighted according to SOEP sample weights, so that all observations with zero weight are dropped from the sample. Measures of inequality are computed on the full SOEP sample of respondents. [1]: Measured in a 5-point scale with 1=bad to 5=very good. [2]: Crime rate is defined as the number of crimes per 100 inhabitants.

Table 2: Concern about Crime and Inequality Measures - Baseline Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Individual Inequality					
Individual Polarization	0.0029**	0.0022*				
	(0.0013)	(0.0012)				
Relative Deprivation	-0.0100**		-0.0080*			
	(0.0046)		(0.0043)			
Relative Satisfaction	0.0011		0.0013			
	(0.0015)		(0.0013)			
				Aggregate Inequality		
Aggregate Polarization				0.0082*	0.0058*	
				(0.0046)	(0.0034)	
Gini Index				-0.0025		0.0013
				(0.0031)		(0.0023)
Observations	399,487	399,487	399,487	399,487	399,487	399,487
Adjusted R^2	0.024	0.024	0.024	0.024	0.024	0.024

Notes: Standard errors in parentheses are robust and clustered at the household level; * p<0.1 ** p<0.05 *** p<0.01. Individual-level controls include: the log of real equivalized income, an indicator for house ownership, years of education, self-assessed health, number of household members and number of kids, an indicator for marital status, employment status dummies with employed as reference category, and the age-group dummies with over 65 as reference category; macro-level controls defined at the Länder level include: the objective crime rate, the population in millions, the unemployment rate, and the net inflow of people to the Land. All continuous regressors are standardized. Regressions include Individual, Year and *Länder* fixed effects.

Table 3: Concern about Crime and Inequality Measures - Heterogeneity Analysis

	Women	**Men**	**Germans**	**Immigrants**	**Below median income**	**Above median income**
			Individual-level Inequality			
Individual Polarization	0.0027	0.0030*	0.0029**	0.0027	0.0068**	0.0012
	(0.0017)	(0.0017)	(0.0014)	(0.0028)	(0.0030)	(0.0023)
Relative Deprivation	-0.0116**	-0.0085	-0.0140***	0.0009	-0.0122	-0.0077
	(0.0058)	(0.0059)	(0.0050)	(0.0088)	(0.0080)	(0.0096)
Relative Satisfaction	-0.0003	0.0024	0.0029**	-0.0036***	0.0261	0.0008
	(0.0016)	(0.0017)	(0.0014)	(0.0013)	(0.0516)	(0.0018)
			Aggregate-level Inequality			
Aggregate Polarization	0.0069	0.0100*	0.0051	0.0184	0.0166**	-0.0001
	(0.0057)	(0.0060)	(0.0049)	(0.0119)	(0.0067)	(0.0062)
Gini Index	-0.0016	-0.0037	-0.0019	-0.0031	-0.0013	-0.0031
	(0.0038)	(0.0041)	(0.0033)	(0.0075)	(0.0046)	(0.0042)
Observations	209,922	189,565	316,073	82,644	193,422	206,065
Adjusted R^2	0.025	0.023	0.026	0.017	0.018	0.028

Notes. The outcome variable is the binary variable Concern; the samples are restricted to the category indicated in the respective column; standard errors in parentheses are robust and clustered at the household level; * p<0.1 ** p<0.05 *** p<0.01. These regressions include the same controls as Table 2, with continuous regressors being standardized. Regressions include Individual, Year and *Länder* fixed effects.

Table 4: Concern about Crime and Inequality Measures - Logit Estimates

	Individual Inequality	
Individual Polarization	0.0293***	
	(0.0093)	
Relative Deprivation	-0.0885***	
	(0.0331)	
Relative Satisfaction	0.0106	
	(0.0156)	
		Aggregate Inequality
Aggregate Polarization		0.0694**
		(0.0302)
Gini Index		-0.0220
		(0.0203)
Observations	284,567	284,567

Notes: Standard errors in parentheses are robust and clustered at the household level; * p<0.1 ** p<0.05 *** p<0.01. These regressions include the same controls as Table 2, with continuous regressors being standardized. Regressions include Individual, Year and *Länder* fixed effects.

Table 5. Concern about Crime and Inequality Measures - Placebo Estimates

	Individual Polarization	*Relative Deprivation*	*Aggregate Polarization*	*Gini Index*
Lagged Concern	0.0002	-0.0003	0.0007	-0.0007
	(0.0033)	(0.0010)	(0.0011)	(0.0016)
Individual Polarization		0.0633***		
		(0.0062)		
Relative Deprivation	0.7500***			
	(0.0868)			
Relative Satisfaction	0.0401	0.1681***		
	(0.0778)	(0.0306)		
Aggregate Polarization				0.9785***
				(0.0048)
Gini Index			0.4662***	
			(0.0029)	
Observations	297,691	297,691	297,691	297,691
Adjusted R^2	0.286	0.894	0.904	0.777

Notes. Standard errors in parentheses are robust and clustered at the household level; * p<0.1 ** p<0.05 *** p<0.01. These regressions include the same controls as Table 2, with continuous regressors being standardized. Regressions include Individual, Year and *Länder* fixed effect.

Table A1: Average Annual Inequality Measures

Year	Gini	Relative Deprivation	Relative Satisfaction	Aggregate Polarization	Individual Polarization
1995	0.236	0.236	0.236	0.172	0.172
1996	0.230	0.230	0.230	0.169	0.169
1997	0.231	0.231	0.231	0.169	0.169
1998	0.226	0.226	0.226	0.170	0.169
1999	0.231	0.231	0.231	0.172	0.172
2000	0.234	0.234	0.234	0.176	0.176
2001	0.250	0.250	0.250	0.176	0.176
2002	0.246	0.246	0.246	0.196	0.200
2003	0.255	0.255	0.255	0.192	0.194
2004	0.255	0.255	0.255	0.191	0.194
2005	0.259	0.259	0.259	0.195	0.198
2006	0.271	0.271	0.271	0.197	0.199
2007	0.270	0.270	0.270	0.198	0.200
2008	0.271	0.271	0.271	0.196	0.198
2009	0.269	0.269	0.269	0.196	0.198
2010	0.271	0.271	0.271	0.197	0.196
2011	0.274	0.274	0.274	0.197	0.196
2012	0.277	0.277	0.277	0.197	0.196
2013	0.276	0.276	0.276	0.199	0.196
2014	0.283	0.283	0.283	0.198	0.197
2015	0.277	0.277	0.277	0.195	0.193
2016	0.282	0.282	0.282	0.233	0.217
2017	0.282	0.282	0.282	0.212	0.208

Notes. National average values for aggregate inequality measures are obtained as the mean value across *Länder* in a given year. Average values for individual inequality measures are obtained by first computing the weighted mean at the *Land* level and then averaging across *Länder*.

Table A2: Concern about Crime and Inequality Measures Complete Regressions - Baseline Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Individual Inequality			**Aggregate Inequality**		
Individual Polarization	0.0029**	0.0022*				
	(0.0013)	(0.0012)				
Relative Deprivation	-0.0100**		-0.0080*			
	(0.0046)		(0.0043)			
Relative Satisfaction	0.0011		0.0013			
	(0.0015)		(0.0013)			
Aggregate Polarization				0.0082*	0.0058*	
				(0.0046)	(0.0034)	
Gini Index				-0.0025		0.0013
				(0.0031)		(0.0023)
Log of Income	-0.0097**	0.0000	-0.0084*	-0.0003	-0.0003	-0.0003
	(0.0048)	(0.0015)	(0.0046)	(0.0015)	(0.0015)	(0.0015)
Home Ownership	-0.0052	-0.0051	-0.0056	-0.0054	-0.0054	-0.0054
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Education (years)	-0.0079**	-0.0078**	-0.0080**	-0.0079**	-0.0079**	-0.0079**
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Self-assessed Health	-0.0038***	-0.0038***	-0.0038***	-0.0038***	-0.0038***	-0.0038***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Household Size	-0.0018	-0.0015	-0.0014	-0.0013	-0.0013	-0.0013
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Number of Kids	0.0025	0.0023	0.0025	0.0023	0.0023	0.0023
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Married (%)	0.0108**	0.0108**	0.0106**	0.0106**	0.0107**	0.0107**
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Unemployed	-0.0016	-0.0020	-0.0018	-0.0020	-0.0020	-0.0020
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
Student	-0.0043	-0.0047	-0.0043	-0.0046	-0.0046	-0.0046

	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0059)
Retired	0.0034	0.0035	0.0039	0.0039	0.0039	0.0038
	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)	(0.0048)
Not employed	-0.0024	-0.0026	-0.0024	-0.0025	-0.0025	-0.0026
	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)	(0.0043)
Age Group <26	-0.0072	-0.0076	-0.0075	-0.0079	-0.0079	-0.0078
	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)	(0.0091)
Age Group 26-40	-0.0053	-0.0054	-0.0054	-0.0055	-0.0055	-0.0055
	(0.0068)	(0.0068)	(0.0068)	(0.0068)	(0.0068)	(0.0068)
Age Group 41-65	-0.0069	-0.0071	-0.0072	-0.0073	-0.0073	-0.0073
	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Crime Rate	0.0492***	0.0490***	0.0494***	0.0484***	0.0487***	0.0493***
	(0.0051)	(0.0051)	(0.0051)	(0.0052)	(0.0052)	(0.0051)
Population (millions)	0.2992***	0.2949***	0.2973***	0.3111***	0.3072***	0.2948***
	(0.0619)	(0.0619)	(0.0619)	(0.0620)	(0.0619)	(0.0619)
Unemployment (%)	0.0071	0.0071	0.0069	0.0074	0.0075	0.0071
	(0.0046)	(0.0046)	(0.0046)	(0.0047)	(0.0047)	(0.0047)
Total Net Inflow of People (%)	0.0049*	0.0050*	0.0049*	0.0049*	0.0048*	0.0049*
	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)
Observations	399,487	399,487	399,487	399,487	399,487	399,487
Adjusted R^2	0.024	0.024	0.024	0.024	0.024	0.024

Notes: Standard errors in parentheses are robust and clustered at the household level; * p<0.1 ** p<0.05 *** p<0.01. All continuous regressors are standardized. Regressions include Individual, Year and *Länder* fixed effect.

Table A3: Concern about Crime and Inequality Measures - Average semi-elasticities from Logit Estimates

	Individual Inequality	*Aggregate Inequality*
Individual Polarization	0.0166***	
	(0.0053)	
Relative Deprivation	-0.0503***	
	(0.0188)	
Relative Satisfaction	0.0060	
	(0.0089)	
Aggregate Polarization		0.0394**
		(0.0172)
Gini Index		-0.0125
		(0.0116)
Observations	284,567	284,567

Notes: Standard errors in parentheses are robust and clustered at the household level; * p<0.1 ** p<0.05 *** p<0.01. These regressions include the same controls as Table 2, with continuous regressors being standardized. Regressions include Individual, Year and *Länder* fixed effects.

Table A4. Concern about Crime and Inequality Measures – Ordered Logit Estimates

	Individual Inequality	*Aggregate Inequality*
Individual Polarization	0.0215**	
	(0.0084)	
Relative Deprivation	-0.0789**	
	(0.0317)	
Relative Satisfaction	0.0064	
	(0.0147)	
Aggregate Polarization		0.0127
		(0.0284)
Gini Index		-0.0067
		(0.0180)
Observations	427,400	427,400

Notes: Standard errors in parentheses are robust and clustered at the individual level; * p<0.1 ** p<0.05 *** p<0.01. The outcome variable in this table is the original ordered variable, recoded in increasing order from *not at all concerned (1)* to *very concerned (3)*. The regressions include the same controls as Table 2, with continuous regressors being standardized. Regressions include Individual, Year and *Länder* fixed effect.