ONLINE APPENDIX FOR "BREAKING BAD: HOW HEALTH SHOCKS PROMPT CRIME"

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This document includes the following appendices for online publication:

APPENDIX A: INSTITUTIONAL DETAILS

This section provides additional information on the income insurance Danes are eligible for when diagnosed with cancer. Income insurance in Denmark consists broadly of three parts. First, short-term sick pay and, depending on the occupation, employer-based policies (lump sum payment for critical illness). Short-term coverage is then followed by state-funded sickness benefits. When state-funded sickness benefits run out, individuals are eligible to either nothing or some social insurance, early retirement programs, or permanent Social Disability Insurance.

Regarding the first component, workers are eligible to full pay during an initial period of absence due to sickness. Coverage termination depends on the employee's contract and on whether the employer lets the employee go after the contractual obligation to retain her expires. Additionally, employer-based insurance policies and private pension plans have become standard, and these provide a lump sum source of income to those who experience critical health shocks.

Second, when employment is terminated, or the employment contract does not include full wage insurance during sickness, the employee can apply for state-funded sickness benefits at the municipality of residency. Sickness benefit duration varies somewhat over the period of interest, and as of 2019, lasts for a maximum of 22 weeks, though extended coverage is negotiable with the municipality if certain conditions are met. The sickness benefits amount to a maximum of 4,355 Danish kroner (DKK) per week in 2019 ($702).

In the final stage, when an individual is permanently unable to work, she can apply for a disability pension with her municipality of residence. Different municipalities administer both sick leave benefits and disability benefits to some degree differently. Approved applicants receive benefits that, in 2019, amounted to DKK 192,528 ($31,053) per year for married or cohabitating individuals and DKK 226,500 ($36,532) for singles.[1]

[1] At older ages, individuals can choose to go into early retirement, depending on contributions, either at age 60 through the Voluntary Early Retirement Pension (VERP), or depending on the time period, through an old-age pension at ages 65–67.

APPENDIX B: COMPARISON OF INDIVIDUALS DIAGNOSED IN DIFFERENT PERIODS

To further validate our approach, we conduct an exact matching between pre-diagnosis individuals who, in the same (calendar) year, are of the same age and gender but are diagnosed as far apart as possible.[2] Namely, they are either in event year $\tau = -1$ (the year before diagnosis) or $\tau = -10$ (10 years before diagnosis). We then compare the distribution of three key covariates (income, financial wealth, and education) between people who will be diagnosed in 1 year and people who, in the same year, are of the same age and gender but will be diagnosed only 10 years later, which is the longest gap available by construction.

Results in Figure J.1 show that these individuals are ex ante observationally equivalent in terms of the distribution of the covariates, thereby supporting the claim that the cancer diagnosis's timing is as good as random for the purpose of our analysis.

APPENDIX C: EFFECTS OF ATTRITION AND MISSPECIFICATION OF THE CHOICE MODEL

We attempt to quantify in a simulated dataset the effects of i) selective attrition, and ii) using linear probability (rather than non-linear) estimation models. We employ the following procedure. First, we simulate N individuals with a uniformally distributed age between -20 and 60 and set half of them as women. We then generate individual (normally distributed) fixed effects for the probabilities of i. being diagnosed with cancer, ii. committing a crime, and iii. exiting the sample due to death. We then expand the dataset to the number of years in our data, 40, and exclude from the sample any individual of age below 18 or above 62. Next, we simulate the binary events of i. being diagnosed with cancer, ii. committing a crime, and iii. dying by assuming Bernoulli processes:

$$y|x \sim Bernoulli(p(x, \beta)), \tag{1}$$

[2]Note that in our baseline specification these comparability requirements are addressed by including year-by-age and person fixed effects.

$$p(x, \beta) = \frac{e^{x^T \beta}}{1 + e^{x^T \beta}}, \tag{2}$$

where x is a vector that includes individual and time fixed effects as well as demographics, β measures the magnitude of the effect on probability, and p is the probability of the events above.

We follow basic insights from our data and specify the probability of being diagnosed with cancer, p_{cancer}, as increasing in age and over time and being higher for women. We then simulate each year whether individuals are diagnosed with cancer. For diagnosed individuals, we define the first year of diagnosis as event time zero and label the following years as post-treatment period.

We specify the baseline probabilities of committing a crime when healthy, p^H_{crime}, and dying, p^H_{death}, in a similar way. We assume that the probability of committing a crime is declining with age, higher for males, and decreasing over time. Furthermore, we assume that the death probabilities increase in age, are lower for women, and decrease over time. The average treatment effect of interest is the increase in the conditional probability of committing crime given cancer, p_{crime}, which we specify as $p_{crime} = p^H_{crime} + 0.02 * post\ treatment$. In each period, we then simulate whether individuals commit a crime or not. We also account for the effect of cancer diagnoses on life expectancy by setting the conditional probability of dying given cancer as $p_{death} = p^H_{death} + 0.02 * post\ treatment$. To obtain our final sample, we first remove people who are never diagnosed with cancer, and observations outside of the -10 to +10 event window. Finally, we randomly sample 350,000 individuals in each simulation to mimic the size of our sample. To examine the assumption of linearity, we simulate the model and estimate the average treatment effect with our standard empirical procedure. We then compare the estimated ATE to the "real" average treatment effect. We find no statistical bias in our estimates – probably due to the sheer size of the sample.

To examine whether and how seriously the correlation between death and crime propensity biases our estimates we additionally set $p_{death} = p^H_{death} + 0.02 * post\ treatment + \alpha * p_{crime}$. By varying α across different simulations, we can quantify the effect of attrition on

our estimates. We report in Figure J.8 the bias for different correlations between crime and death probabilities. Overall, the bias appears to be negligible.

APPENDIX D: ALTERNATIVE TESTS OF THE ASSUMPTION OF PARALLEL TRENDS

We propose a number of alternative tests of the hypothesis that crime rates run parallel for control and treated individuals before the latter are diagnosed. Following Borusyak, Jaravel, and Spiess (2021) we test for anticipation on untreated observations only ($\tau < 0$), thereby explicitly separating testing from estimation. Specifically, we estimate lead coefficients for the five periods immediately before treatment, with periods more than five years before treatment serving as the reference group. Online Appendix Figure J.2 Panel B shows insignificant coefficients for each lead. We cannot reject the null hypothesis that the pre-event coefficients are jointly equal to zero (F-statistic $= 0.57$, p-value=0.75). We also test for parallel trends violations recovering lead coefficients as linear combinations of different cohort effects (following Sun and Abraham 2021). Furthermore, we employ the methodology of De Chaisemartin and D'Haultfœuille (2020, 2021) to estimate placebo effects. Also in these cases, we find no evidence of pre-trends (see Online Appendix Figure J.2 Panels C and D).

Finally, we employ the R package HonestDiD accompanying Rambachan and Roth (2021) to examine the sensitivity of our estimates to the presence of non-linear differences in trends. Online Appendix Figure J.3 compares the confidence intervals for treatment effects from our modified specification[3] to those obtained after allowing per-year deviations from a linear trend up to an arbitrary value M. In our setting, it is not apparent how to choose the maximum value of M, as there is no evidence of violations of the parallel trend assumption (the lead coefficients are insignificant, the confidence intervals of the leads are narrow, and there is no apparent pre-trend) and our economic context does not inform us on the shape or sign of a potential violation. To be conservative, we set the maximum value for M equal to the mean of the absolute deviations from the linear trend in the pre-treatment

[3]We omit only period $\tau = -1$ and estimate a lead coefficient for $\tau < -5$ to be able to employ the R package HonestDiD accompanying Rambachan and Roth (2021).

period.[4] This yields a value of $M = 0.0032$. To put this number into perspective, note that the slope of the linear trend is 0.0026, which means that the maximum value of M allows for a more than 100% ($\frac{0.0032}{0.0026} \approx 125\%$) change in the slope of the differential trend between consecutive periods, which accumulates to a more than 400% deviation after four years ($\tau = 3$). Online Appendix Figure J.3 shows that, for $\tau = 3$, the "breakdown" value at which we can no longer reject the null hypothesis is 0.0033 and 0.0015 for $\tau = 10$.

APPENDIX E: MAGNITUDE OF THE IMPACT OF CANCER ON CRIME

In the paper, we report that each thousand cancer diagnoses cause 14 additional crimes each year. In this section, we elaborate on how we estimate this number. The information needed are obtained from the *Danish Central Crime Registry* and the *National Patient Registry* from Statistics Denmark. Importantly, we assume that cancer patients commit as many crimes per conviction as the average Danish criminal. We find that a cancer diagnosis increases the likelihood that a cancer patient or her spouse is convicted of a crime by 0.11 percentage points (Table II, Column 3 of the paper). Given that each year there are 71,920 individuals who are themselves (or whose spouse is) in the post diagnosis 10-year window, this means that each year there are 79 additional convicted criminals in response to cancer diagnoses (71,920 $\times$ 0.11%). Annually, 9,650 people are diagnosed with cancer, thus each 1,000 diagnoses lead to 8.2 more criminal convictions annually. On average, a criminal gets convicted of 1.7 crimes. Therefore, this leads to 14 additional crimes per year each 1,000 cancer diagnoses. Notably, this number includes only solved crimes. If one considers that only 10.6% of crimes are solved on average, 1,000 cancer diagnoses could induce 131 more crimes.

[4] Note that the average of the pre-trend coefficients is positive even though statistically non-different from zero.

APPENDIX F: STYLIZED FRAMEWORK

We present a simple framework that outlines how health shocks may induce criminal behavior. We consider three main channels that prompt crime through changes in (i) the ability to earn legal income, (ii) survival probabilities, and (iii) preferences.[5]

F.1. *Model setup*

An individual lives for a maximum of two periods, a working period, from $t = 0$ to $t = 1$, and a retirement period, from $t = 1$ to $t = 2$. At the start of the working period, the individual receives information on her health state $J \in \{S, H\}$. We superscript the state of the world in which she is sick with an S, and the state in which she is healthy with an H. After observing the state of the world, she chooses to allocate a share, κ^J, of her labor supply to illegal activities, and the residual share, $1 - \kappa^J$, to legal activities. For simplicity, we assume that the discount rate is zero, such that the individual maximizes lifetime utility defined as:

$$U(c_1^J, c_2|\kappa^J) \equiv g\big(c_1^J(\kappa^J)\big) + \rho^J g(c_2) - \rho^J b(\kappa^J),$$

where $g(\cdot)$ represents the per-period utility of consumption (c_1^J and c_2) which is increasing and concave in consumption (i.e., $g'(\cdot) > 0$ and $g''(\cdot) < 0$). The survival probability to the retirement period is denoted by ρ^J. The last term, $b(\kappa^J)$, is the expected disutility of crime, which we assume is globally increasing and weakly convex in crime to reflect that both the likelihood of getting caught and the size of the penalty increase with the share of labor supply allocated to crime (i.e., $b'(\kappa^J) > 0$ and $b''(\kappa^J) \geq 0$). We assume that the disutility of crime in the first period is zero. This simplifying assumption reflects that criminals are

[5] Our framework builds on the models by Dobkin, Finkelstein, Kluender, and Notowidigdo (2018) and Ehrlich (1973). As our focus is on examining the effect of health shocks on criminal activity, we remove several features from the Dobkin, Finkelstein, Kluender, and Notowidigdo (2018) model of health and add others from Ehrlich (1973). Specifically, we remove savings behavior and out-of-pocket medical expenses (as these are negligible in Denmark). By contrast, we add the decision to commit criminal activity and the possible consequences, as well as the change in survival probability due to the health shock.

usually apprehended and convicted with a delay and implies that survival probabilities matter when choosing the fraction of labor supply to allocate to criminal activity.

To explore the tradeoff between illegal and legal activity, we define the income process as follows: the labor supplied to the legal market earns a wage w and the labor supplied to the illegal market earns a wage normalized to one. Importantly, we assume $w < 1$, which ensures compensation for the additional expected disutility of crime, and thus a positive supply of criminal activity (in line with Ehrlich 1973 and Freeman 1999).[6] A health shock reduces human capital, which translates into lower productivity, and, in turn, results in lower compensation for legal activity. More generally, reducing legal wages can be interpreted as a worse career trajectory due to illness. We model the fall in productivity by assuming that the legal wage declines by a fraction $\alpha \in]0, 1[$ in the sick state.

Furthermore, the welfare system only partially compensates for the reduction in legal earnings. We model sickness benefits by assuming that the welfare system compensates a fraction $\lambda \in [0, 1[$ of the legal wage decline, α. For simplicity, we assume that there is no possibility to save so that in each period the individual consumes her entire income. Furthermore, we assume that, in the retirement period, the individual consumes exogenously fixed retirement benefits c_2. Consumption in the working period in the two different states is as follows

$$c_1^S = (1 - \kappa^S)\iota w + \kappa^S,$$
$$c_1^H = (1 - \kappa^H)w + \kappa^H,$$

where $\iota = [1 - \alpha[1 - \lambda]]$, $0 < \iota \leq 1$ reflects the fraction of legal income including sickness benefits maintained in the sick state.

To explore the impact of an adverse health event on criminal activity through changes in survival probabilities, we specify the probability of being alive in the second period for each health state. In a healthy state, a person's survival probability is $\rho^H = \rho$, while in a

[6] Notably, this setting can be easily extended to non-economic crimes by interpreting w as non-monetary utility from criminal activity.

sick state a person's survival probability is lowered by ϱ, thus $\rho^S = \rho - \varrho$, where $\rho \in [0, 1]$ and $\varrho \in]0, \rho]$.

Maximizing lifetime utility with respect to κ^J yields the following indifference conditions, which equate the marginal benefit with the marginal cost of crime in each state:

$$\frac{\partial g(c_1^H(\kappa^{H*}))}{\partial c_1^H} \times [1 - w] = \rho \frac{\partial b(\kappa^{H*})}{\partial \kappa^H}, \tag{3}$$

$$\frac{\partial g(c_1^S(\kappa^{S*}))}{\partial c_1^S} \times [1 - \iota w] = [\rho - \varrho] \frac{\partial b(\kappa^{S*})}{\partial \kappa^S}, \tag{4}$$

with Equation (3) for the healthy and Equation (4) for the sick state. The left-hand side of each equation represents the marginal utility of obtaining extra income when replacing legal with illegal work—that is—the marginal benefit of crime, $MB(\kappa)$. The right-hand side of each equation represents the marginal disutility when replacing legal with illegal work—that is—the marginal cost of crime, $MC(\kappa)$. The framework allows us to explore how the incentive to commit crime changes as marginal costs and benefits differ between the healthy and the sick states.[7]

We further allow for the possibility that the health state influences a person's preferences: in particular by assuming that, in the sick state, absolute risk aversion is lower. We define absolute risk aversion as $A^J(c_1^J(\kappa^J)) = -g^{J\prime\prime}(c_1^J(\kappa^J))/g^{J\prime}(c_1^J(\kappa^J))$ and consider the possibility that $A^S(\cdot) < A^H(\cdot)$. In words, we allow for the health shock to reduce the absolute risk aversion of the individual.[8] The propositions below follow:

[7]Equations (3) and (4) are only necessary (first-order) conditions for maxima. To ensure a global utility maximum in the domain of interest, $0 < \kappa^J < 1$, we further assume $b(0) = 0$, $g(0) = 0$, and $\lim_{\kappa^J \to 1} b'(\cdot) = \infty$. A richer model could allow for corner solutions by, for example, adding present bias preferences or entry costs into the illegal labor market.

[8]Note that we assume that health shocks decrease risk aversion to explain the increase in the propensity of committing a crime. Under more stringent conditions, it is possible to show that an increase in risk aversion can also lead to more crime (see Proposition F.3 below).

F.2. *The impact of health shocks*

PROPOSITION F.1: *If $\iota < 1$ and $\varrho = 0$ then $\kappa^{S*} > \kappa^{H*}$. That is, a health shock that reduces total legal income generates an increase in the labor supply of illegal activities.*

Thus, individuals suffering a health shock that decreases their legal wage, which is not fully compensated by sickness benefits, will have a higher marginal benefit from committing crime. This will increase the labor supply to illegal activities.

PROOF: To understand how a lower legal wage in the sick state compared to the healthy state affects the supply of illegal activity κ, we assume that the survival probability across health states is constant, thereby fixing the marginal cost of criminal activity.

The optimal choice for κ^S is given by the following indifference condition which equates the marginal benefit of additional labor supplied to crime to its marginal cost:

$$\frac{\partial g(c_1^S(\kappa^{S*}))}{\partial c_1^S} \times [1 - \iota w] = \rho \frac{\partial b(\kappa^{S*})}{\partial \kappa^S}.$$

The left-hand side presents the marginal utility of an additional unit of consumption multiplied by the wage differential between illegal (1) versus legal work ($\iota w < 1$). The right-hand side presents the probability of surviving to the second period times the marginal expected disutility of punishment for an additional unit of labor supply to crime.

The optimal choice for κ^H is given by

$$\frac{\partial g(c_1^H(\kappa^{H*}))}{\partial c_1^H} \times [1 - w] = \rho \frac{\partial b(\kappa^{H*})}{\partial \kappa^H}.$$

Note that the marginal cost per unit of criminal activity remains constant in both health states. However, the marginal benefit of criminal activity increases in the sick state, as $1 - \iota w > 1 - w$. Then the result follows from the fact that $g(\cdot)$ is increasing and concave in κ and $b(\cdot)$ is increasing and convex in κ. *Q.E.D.*

COROLLARY F.1: *If sickness compensation (λ) is smaller or if the negative impact on earnings (α) is larger, then the health shock increases the labor supply to criminal activity more.*

The marginal benefit of crime increases more if the health shock results in a larger decrease in the legal income including sickness benefits. This increases the labor supply to illegal activities.

PROPOSITION F.2: *If $\iota = 1$ and $\varrho \in]0, \rho]$ then $\kappa^{S*} > \kappa^{H*}$. That is, a health shock that reduces survival probabilities generates an increase in the labor supply of illegal activities.*

Individuals suffering from a health shock that decreases their survival probability face a lower marginal cost of crime. This is because the health shock increases the discount rate of future consumption and punishment. This, in turn, increases the labor supply of illegal activities.

PROOF: To understand how a decrease in survival probability affects the supply of illegal activity κ, we assume that the ability to generate income across health states is constant, thereby fixing the marginal benefit of criminal activity at identical levels across health states. The optimal choice for κ^{H*} and κ^{S*} are given by

$$\frac{\partial g(c_1^H(\kappa^{H*}))}{\partial c_1^H} \times [1-w] = \rho \frac{\partial b(\kappa^{H*})}{\partial \kappa^H},$$
$$\frac{\partial g(c_1^S(\kappa^{S*}))}{\partial c_1^S} \times [1-w] = [\rho - \varrho] \frac{\partial b(\kappa^{S*})}{\partial \kappa^S}.$$

The health shock decreases the marginal cost per unit of crime, as $\varrho \in]0, \rho]$. A decline in survival probability corresponds to a downward shift of the marginal cost curve, as the cost of an additional hour of illegal work becomes comparatively lower since the probability of paying the penalty for crime is lower. Since $\rho - \varrho < \rho$, the result follows from the fact that $g(\cdot)$ is increasing and concave in κ and $b(\cdot)$ is increasing and convex in κ. *Q.E.D.*

PROPOSITION F.3: *If $\iota = 1$, $\varrho = 0$, and $A^S(\cdot) < A^H(\cdot)$ then $\kappa^{S*} > \kappa^{H*}$ when $|g^{S\prime\prime}(\cdot)| \geq |g^{H\prime\prime}(\cdot)|$. That is, under specific assumptions on the shape of the utility function, a health shock that reduces risk aversion generates an increase in the labor supply of illegal activities.*

Individuals suffering from a health shock may face changes in their preferences potentially resulting in a higher marginal benefit of crime. This increases the labor supply of illegal activities.

PROOF: To understand how a change in preferences elicits an increase in the labor supply of illegal activities, we fix the legal wage and the survival probabilities at identical levels across health states. In this way, we investigate the implications of a change in the curvature of the utility function $g(\cdot)$.

We rewrite the FOCs as:

$$-g^{H\prime\prime}(c(\kappa^*))/A^H(c(\kappa^*)) \times (1-w) = \rho b'(\kappa^*),$$
$$-g^{S\prime\prime}(c(\kappa^*))/A^S(c(\kappa^*)) \times (1-w) = \rho b'(\kappa^*),$$

then, we have two scenarios to consider:

1. If $|g^{S\prime\prime}(\cdot)| \geq |g^{H\prime\prime}(\cdot)|$ then, as $A^S(\cdot) < A^H(\cdot)$, function $g(\cdot)$ is concave and increasing in κ^J and $b(\cdot)$ is increasing and convex in κ^J, we have that the marginal benefit of crime is higher in the sick state and, therefore, $\kappa^{S*} > \kappa^{H*}$.
2. If $|g^{S\prime\prime}(\cdot)| < |g^{H\prime\prime}(\cdot)|$ then whether the marginal benefit of crime is higher or lower in the sick state depends on the functional form of $A^J(\cdot)$ and $g^J(\cdot)$.

Q.E.D.

APPENDIX G: 5-YEAR SURVIVAL RATE ESTIMATION

We estimate the decline in the 5-year survival probability due to cancer in three steps. We first use matching to select a set of cancer treated as well as undiagnosed control individuals. We then estimate the 5-year death probability for each individual in our sample. Finally, we define as having low survival probability those individuals who, in the diagnosis year, face an above-median increase in death probability conditional on their gender.

To select the set of control individuals, we rely on exact matching. Specifically, for each diagnosed individual in our baseline sample, we consider only those individuals in the population who, in the same year (our reference year is the year before the diagnosis), are of the same age, have the same marital status, the same gender, and are in the same ventile

of income and quintile of years of education. Treated and control observations without a match are dropped. Out of all available matches, we select ex post a maximum of ten control individuals who exhibit the smallest difference in total income.

We then estimate the 5-year death probability of individuals between the age of 18 and 62 in the years from 1980 to 2013. Notably, we do not include data from 2014–2018, as we cannot establish whether people will die within 5 years (as our sample ends in 2018). The estimation sample consists of people who are diagnosed with cancer between 1980 and 2013 and a control sample extracted from the entire population. We estimate a logit model whereby p is the probability that person i has 5 years or less left to live:

$$\log\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = \beta_t + \sum_{\nu=0}^{15}\theta_\eta \mathbb{1}\{\eta_{i,t}=\nu\} + \sum_{\nu=0}^{15}\gamma_\eta \mathbb{1}\{\eta_{i,t}=\nu\}A_{i,t} + \zeta A_{i,t} + \vartheta \mathbb{1}\{Post\ cancer\} + \lambda Z_{i,t},$$

where $\eta_{i,t}$ takes a value from 0 to 15, where every number from 1 to 14 corresponds to a different type of cancer diagnosed in year t, and 0 indicates that the person has not been diagnosed with cancer in year t. The index of 15 is reserved for individuals diagnosed with multiple types of cancer. $A_{i,t}$ is a vector containing a fourth-order polynomial of age. $\mathbb{1}\{Post\ cancer\}$ is an indicator variable that takes a value of 1 if a person has been diagnosed with cancer in the past, excluding the diagnosis year. $Z_{i,t}$ includes gender and married controls. β_t are calendar year fixed effects. We estimate this equation separately on three different periods, 1980–1992, 1993–2003, and 2004–2013, to account for the effect of advances in cancer treatment that can alter the coefficients above.

We then proceed in three steps. We first rely on the estimates above to predict the probability that treated observations will die within five years of the diagnosis ($\hat{p}$). Second, we predict the counterfactual probability of being dead in five years in the case the person had not been diagnosed with cancer (we impose $\eta_{i,t} = 0$). We define the difference between these two probabilities as the decline in survival probability due to cancer. Finally, we sort individuals based on their survival probability decline, conditional on their gender. Men

(respectively women) with above median decline in survival probability are included in the low-survival probability group.

Figure J.7 shows the predicted and actual death rates by type of cancer.

APPENDIX H: ESTIMATING THE GENEROSITY OF MUNICIPALITIES

The analysis on the effects of the 2007 Danish municipality reform presented in Section 5.4 is conducted in two steps. First, we estimate the change in social support to cancer patients induced by the reform. Second, we explore how the sensitivity of crime to cancer changes for people who face the largest decrease in social support from their municipality due to the reform. In this section, we describe in detail the first step. Details on the second step and the results are presented in the paper.

Step 1: Estimating the change in municipalities' generosity. As we do not observe directly the social policies put in place by each municipality, we infer the variation in welfare's generosity from the data. We expect that more generous social policies will mitigate to a greater extent the adverse impact on total income (labor income and social transfers) and thus will be reflected into a lower income decline caused by cancer (Corollary F.1 of the model). Note that we also consider labor income besides social transfers because a number of welfare policies consist of re-integrating people with disabilities in a work environment. If those policies are prevalent, a municipality's "generosity" will be reflected into a relatively higher share of labor income preserved post cancer rather than into larger income transfers. In sum, our approach defines as generous those municipalities that minimize the average loss of income streams induced by the local population's health shock with respect to pre-cancer levels.

To estimate the practical implications of the municipality reform for income, we first run the following specification:

$$\Delta Income^R_{i,t} = K^R_m + \lambda Z^R_{i,t} + \beta^R_t + \epsilon^R_{i,t},$$

where $\Delta Income^R_{i,t}$ is the percentage change in the sum of labor income and additional income transfers earned by person i in year t after the cancer diagnosis, with respect to the

average over the five years before the diagnosis.[9] $\Delta Income^R_{i,t}$ is thus only defined in the years *after* the initial diagnosis. To generate this variable, we exclude individuals who have been diagnosed with cancer between 2004 and 2006, to remove the effect of the runup to the municipality reform. K^R_m are municipality fixed effects that capture the average change in income after cancer *at the municipality level* net of the effects of individual-specific characteristics ($Z_{i,t}$) and time trends (β_t). The vector $Z_{i,t}$ includes age fixed effects and a third order polynomial of income rank in the year before the diagnosis. We include controls based on income because welfare support in Denmark is allocated progressively. Therefore, high-net worth individuals will experience a comparatively higher decline in income (or, equivalently, will receive lower social support) regardless of the municipality's generosity. Notably, the superscript $R \in \{0, 1\}$ indicates whether the equation is estimated on the sub-sample that includes the calendar years before the reform (1987–2006) or after the reform (2007–2018). Note that we only include years from 1987 onwards because, to generate the variable $\Delta Income_{i,t}$, we need five years of income data before the diagnosis. K^0_m (K^1_m) are pre-reform (post-reform) municipality fixed effects.

We then obtain the change in generosity as $\Delta G_m = K^1_m - K^0_m$. We define as treated those individuals who live in municipalities that become stingy, defined as municipalities in which the difference between pre- and post-reform income replacement for cancer patients falls below the sample median. $S_{t,m}$ is an indicator equal to one from 2007 onwards if the individual is treated.

Step 2: Estimate the change in sensitivity of crime to cancer due to a change in welfare generosity. This step is presented in the paper.

APPENDIX I: DIFFERENCE-IN-DIFFERENCES APPROACH À LA FADLON AND NIELSEN

We replicate our analysis employing a difference-in-differences approach that follows closely the methodology of Fadlon and Nielsen (2019, 2021). Using this approach, the

[9] The choice of a five-year window minimizes the effect of noise in our measurement of pre-cancer income levels. Results for alternative lengths are in any case qualitatively similar.

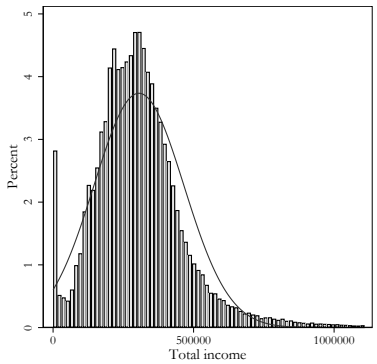
crime choices of individuals diagnosed with cancer at time s (treatment group) are compared to those who are diagnosed with cancer at time $s+\Delta$ (control group). We fix the time interval between treated and control observations to $\Delta = 6$ years. Individuals in the control group are assigned a placebo shock at time s, since they are actually diagnosed with cancer only at time $s+\Delta$. As in Fadlon and Nielsen (2019), the same individual can appear both in the treatment group and in the control group, but is never used as a control to himself.

We can then estimate the effect of cancer on crime for $\Delta - 1$ time periods using a difference-in-differences estimator. For more details, Druedahl and Martinello (2020) explicitly compare this approach to our baseline methodology in Online Appendix C of their paper. The regression specification is as follows:

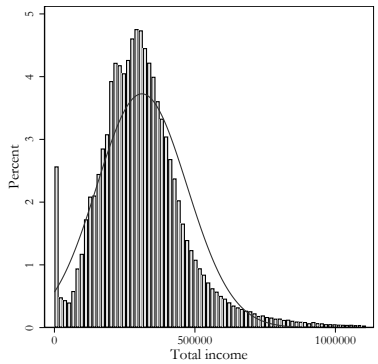
$$C_{i,t} = \beta_{t,a} + \theta\, treat_i + \sum_{\tau \neq 1; \tau = -4}^{5} \eta_\tau \mathbb{1}\{T_{i,t} = \tau\}$$
$$+ \sum_{\tau \neq 1; \tau = -4}^{5} \gamma_\tau \mathbb{1}\{T_{i,t} = \tau\} \times treat_i + \lambda X_{i,t} + \epsilon_{i,t},$$

where i indexes individuals, t the calendar year, a the age, and τ the event time (i.e., the calendar year minus the diagnosis year). $C_{i,t}$ is an indicator that takes a value of one if individual i is convicted of a crime committed in year t, and $\mathbb{1}\{T_{i,t} = \tau\}$ are indicator variables for time relative to the year of diagnosis. $treat_i$ is an indicator that takes a value of one if the person is part of the treatment group. γ_τ therefore captures the effect of cancer on crime at event time τ. The vector $X_{i,t}$ includes $In\ prison$, and $Cancer\ recurrence$ fixed effects. Person fixed effects cannot be included since they would be collinear with the treatment variable. The standard errors are clustered at the person-treatment group level.

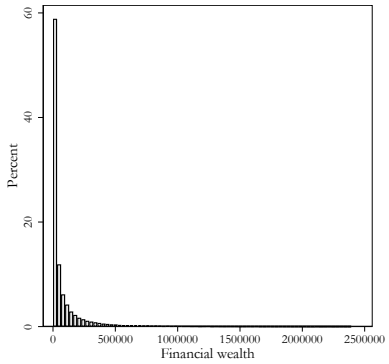
APPENDIX J: ADDITIONAL FIGURES AND TABLES



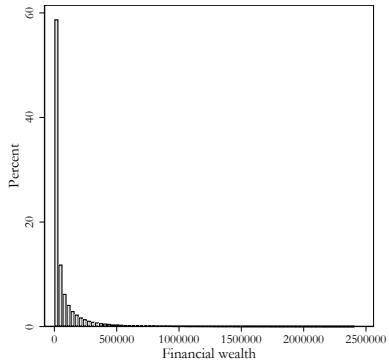
(a) Total income at $\tau = -1$



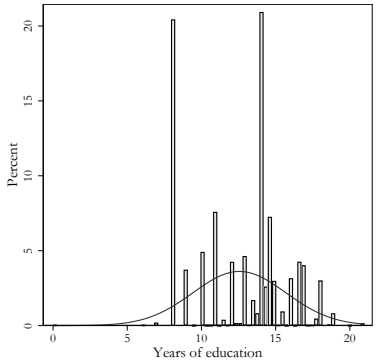
(b) Total income at $\tau = -10$



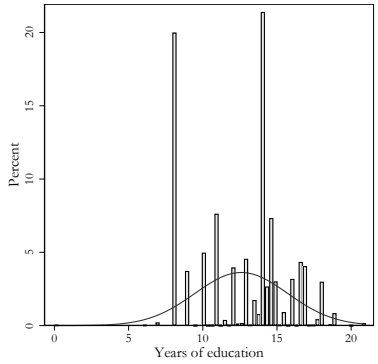
(c) Financial wealth at $\tau = -1$



(d) Financial wealth at $\tau = -10$

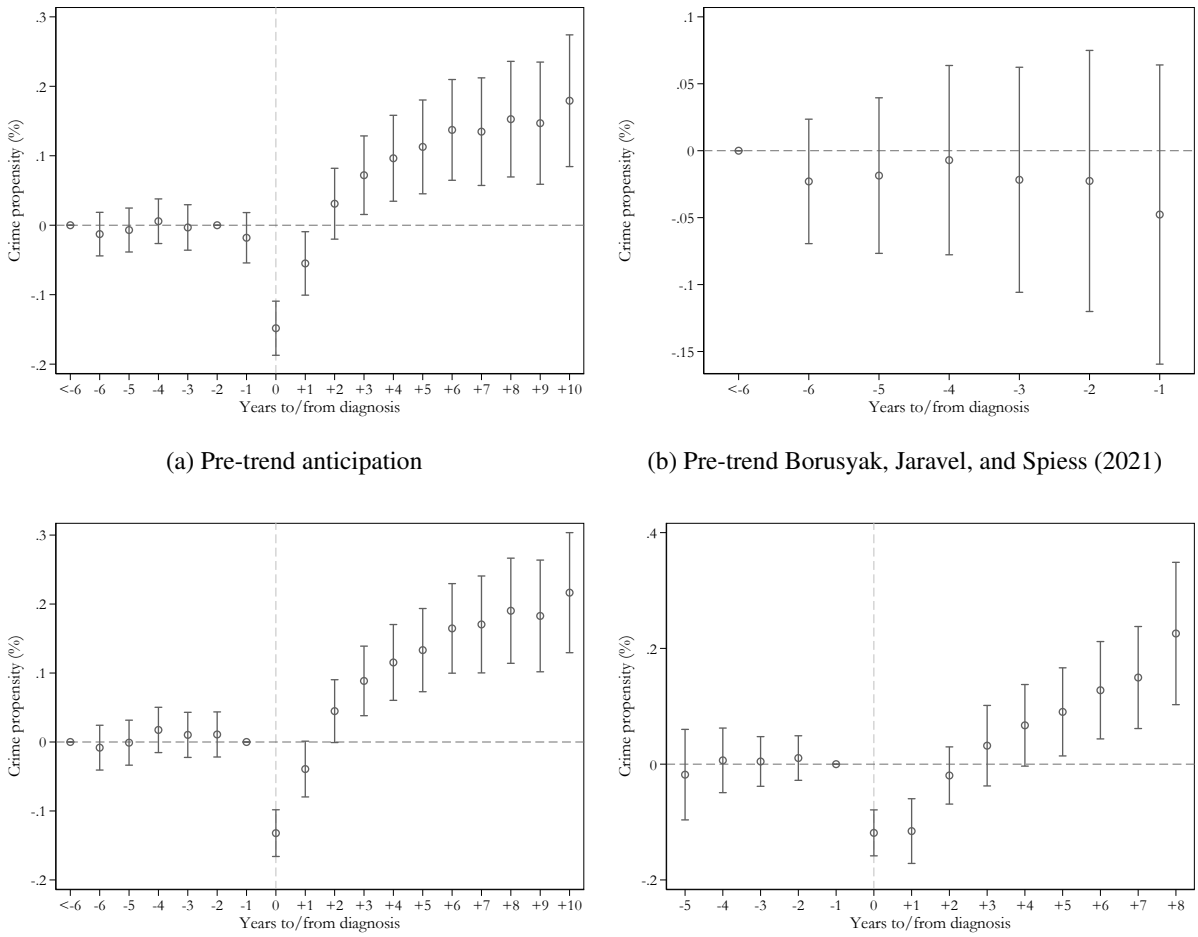


(e) Education at $\tau = -1$



(f) Education at $\tau = -10$

FIGURE J.1.—Comparison across individuals treated at different times. *Notes*: This table compares total income, financial wealth, and education of individuals in the year before cancer diagnosis and counterfactual individuals who, in the same year, are of the same sex and same age, but will be diagnosed with cancer 10 years later.



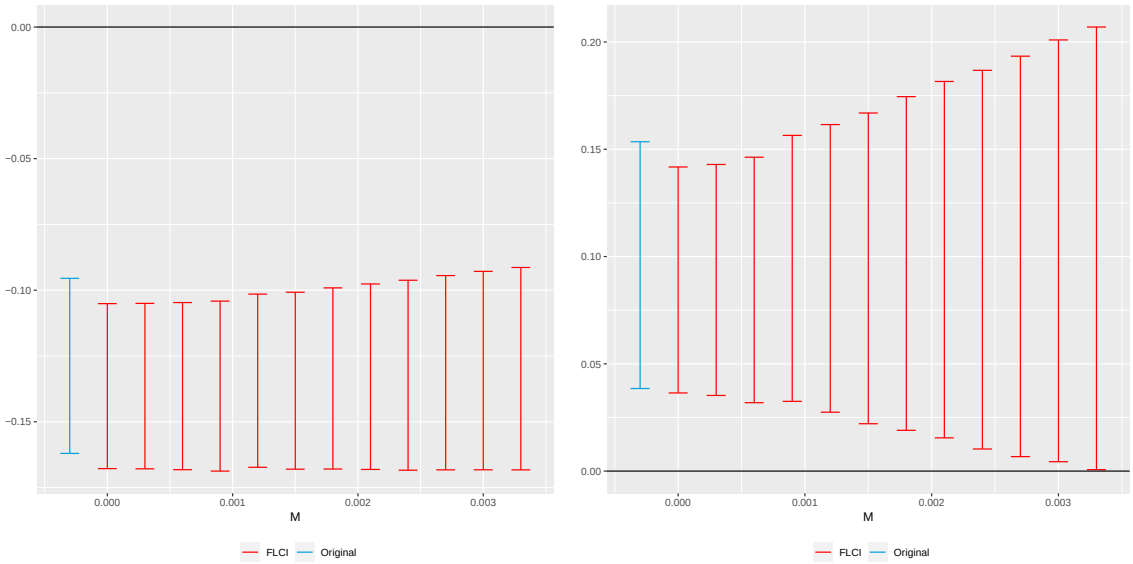
(a) Pre-trend anticipation

(b) Pre-trend Borusyak, Jaravel, and Spiess (2021)

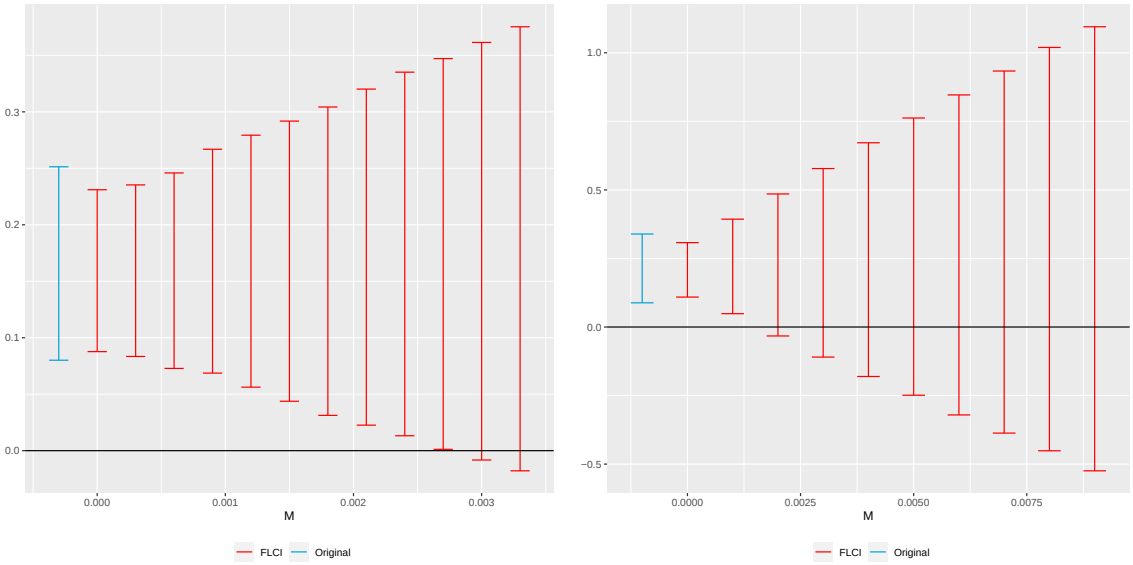
(c) Pre-trend Sun and Abraham (2021)

(d) Pre-trend Chaisemartin and D'Haultfœuille (2020,2021)

FIGURE J.2.—Robustness tests for pre-trends. *Notes*: This figure reports event study estimates for criminal activity changes in response to cancer diagnoses. In panel A, event time $\tau = -2$ (rather than event time $\tau = -1$) is excluded. In panel B, the event study estimates are obtained using the methodology developed by Borusyak, Jaravel, and Spiess (2021), which uses only observations before treatment. In panel C, the event study estimates are obtained using the methodology developed by Sun and Abraham (2021). In panel D, the event study estimates are obtained using the methodology developed by De Chaisemartin and D'Haultfœuille (2020, 2021). The figures plot the estimated coefficients along with their 95% confidence interval. The x-axis denotes time with respect to the year of diagnosis. The y-axis denotes crime propensity in percentage points. The empirical model includes person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the person level.



(a) $\tau = 0$ (b) $\tau = 3$



(c) $\tau = 6$ (d) $\tau = 10$

FIGURE J.3.—Sensitivity estimates based on Rambachan and Roth (2021). *Notes*: This figure reports sensitivity estimates for criminal activity changes in response to cancer diagnoses to potential violations of parallel trends based on Rambachan and Roth (2021). The blue bars (far left bar in each figure) represents the 95% confidence intervals of the event study estimates for relative time τ of our modified specification in which we omit the lead variable $\tau = -1$ and estimate the lead coefficient $\tau < -5$. The red bars represent the 95% confidence intervals when allowing for per-year violations of parallel trends up to a value M. $M = 0$ allows for violations of parallel trends that have to be exactly linear. All coefficients are multiplied by 100.

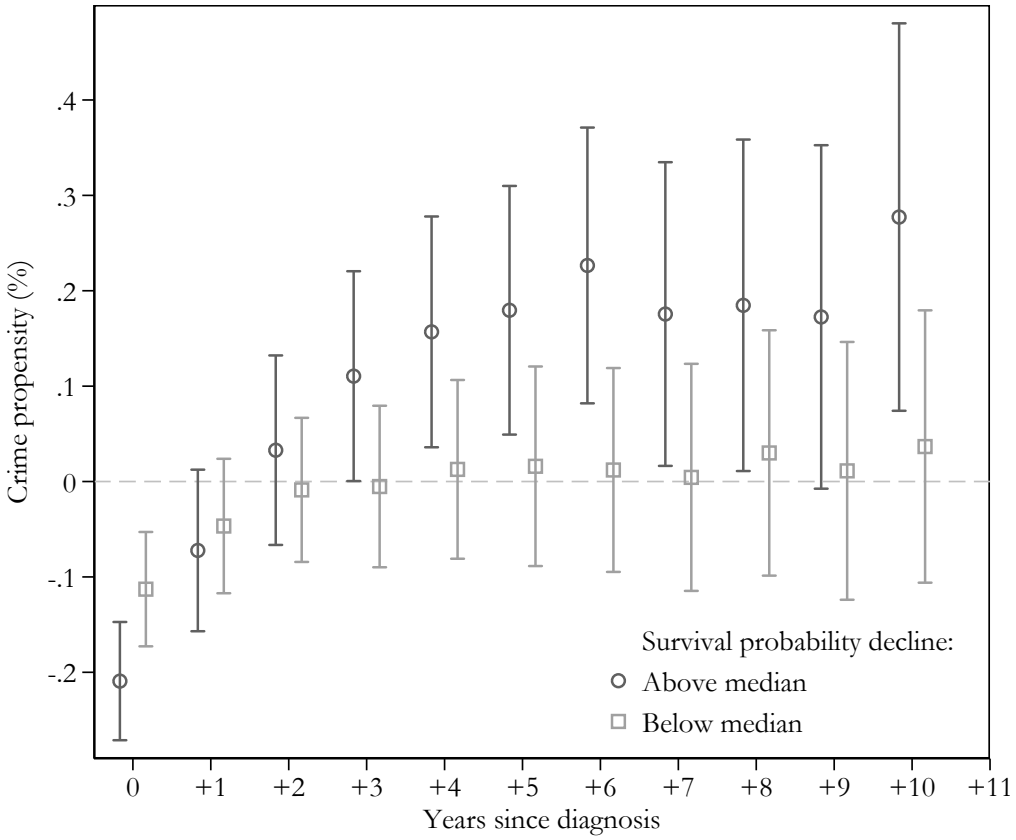


FIGURE J.4.—Survival probabilities mechanism—bootstrapping. *Notes*: This figure reports event study estimates for criminal activity changes in response to cancer diagnoses. The figure plots the estimated coefficients along with their 95% confidence interval. Individuals are sorted on the basis of whether they face an above- (respectively below-) median decline in survival probability due to cancer. The x-axis denotes time with respect to the year of diagnosis. The y-axis denotes crime propensity in percentage points. The empirical model includes income controls (total income and a rank variable of total income), person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients are multiplied by 100. Standard errors are calculated through 1,000 random draws of individuals.

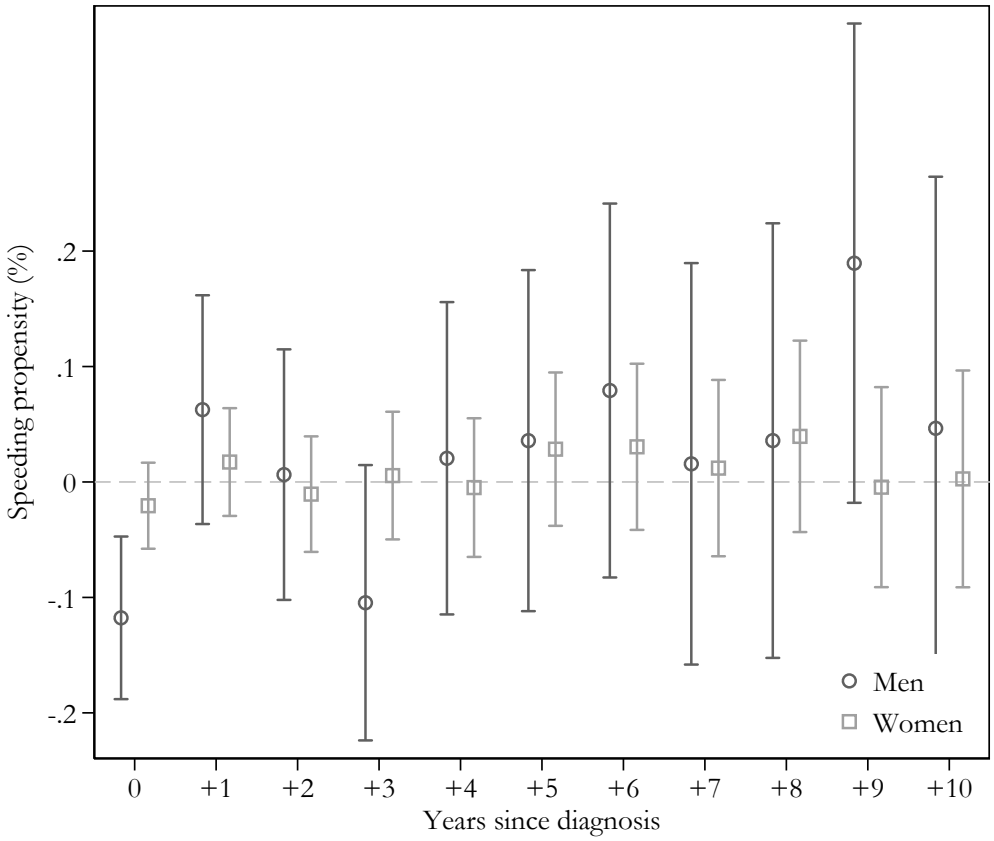


FIGURE J.5.—The relation between cancer and speeding. *Notes*: This figure reports event study estimates for speeding violations in response to cancer diagnoses. The figure plots the estimated coefficients along with their 95% confidence interval. The x-axis denotes time with respect to the year of diagnosis. The y-axis denotes speeding propensity in percentage points. The empirical models include person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the person level.

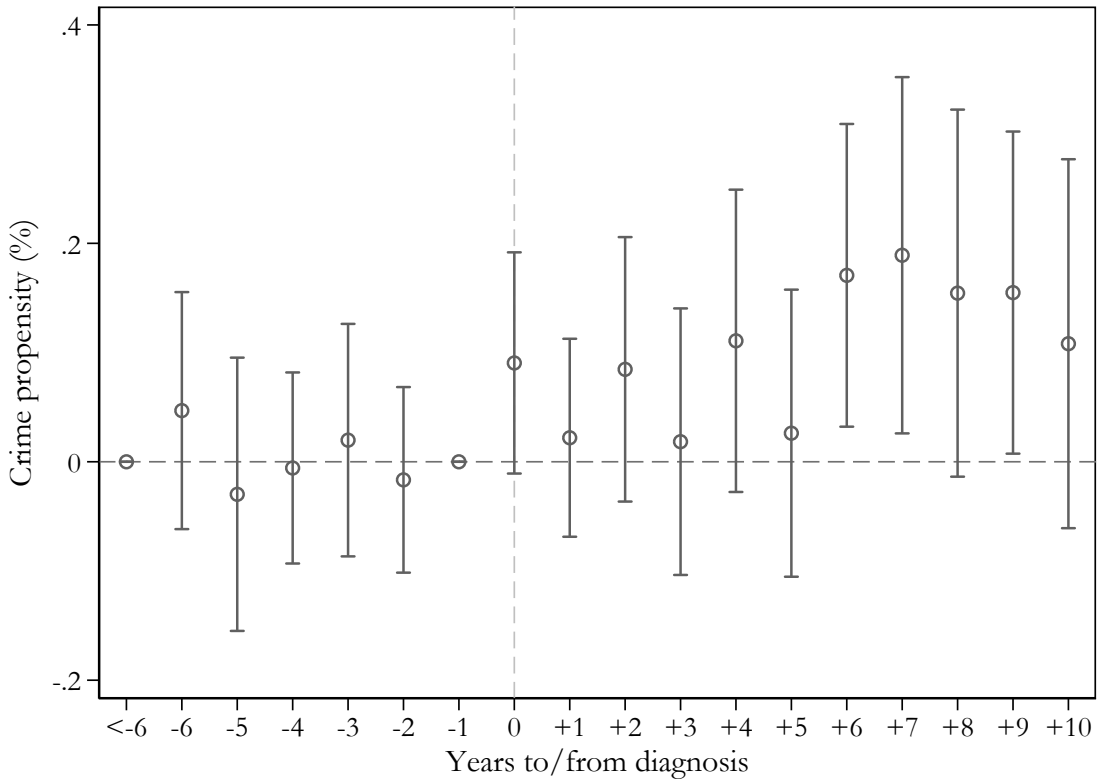


FIGURE J.6.—Pre-trends in treated municipalities. *Notes*: This figure reports event study estimates for criminal activity changes in response to cancer diagnoses interacted with the variable $S_{t,m}$. $S_{t,m}$ is a dummy variable that takes a value of one from 2007 onwards for municipalities that become stingy, defined as municipalities in which the difference between pre- and post-reform income replacement for cancer patients falls below the sample median. The empirical model includes person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the municipality level.

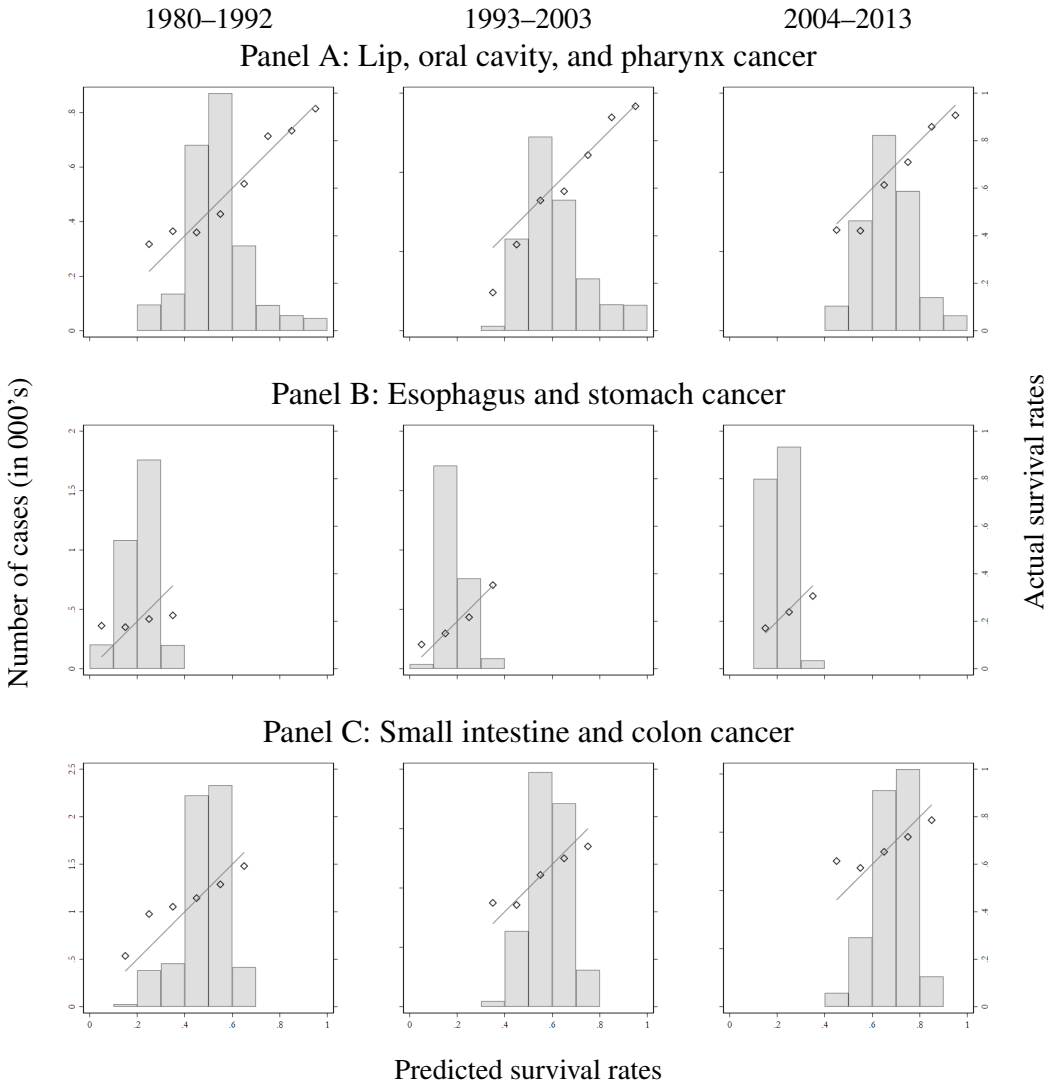


FIGURE J.7.—Expected 5-year survival rates. *Notes*: These figures report the predicted 5-year survival probabilities for three different types of cancer over three different time periods. The estimation methodology is described in detail in Online Appendix G. The x-axis divides the predicted 5-year survival probabilities in 10 buckets of equal size. The gray bars indicate the number of cancer diagnoses in each bucket (reported in thousands on the left hand side y-axis). The diamonds indicate the average actual survival rate in each bucket (reported on the right hand side y-axis) and the difference between the diamonds and the 45-degree line represents the average prediction error. Panel A shows values for lip, oral cavity, and pharynx cancer. Panel B shows values for esophagus and stomach cancer. Panel C shows values for small intestine and colon cancer.

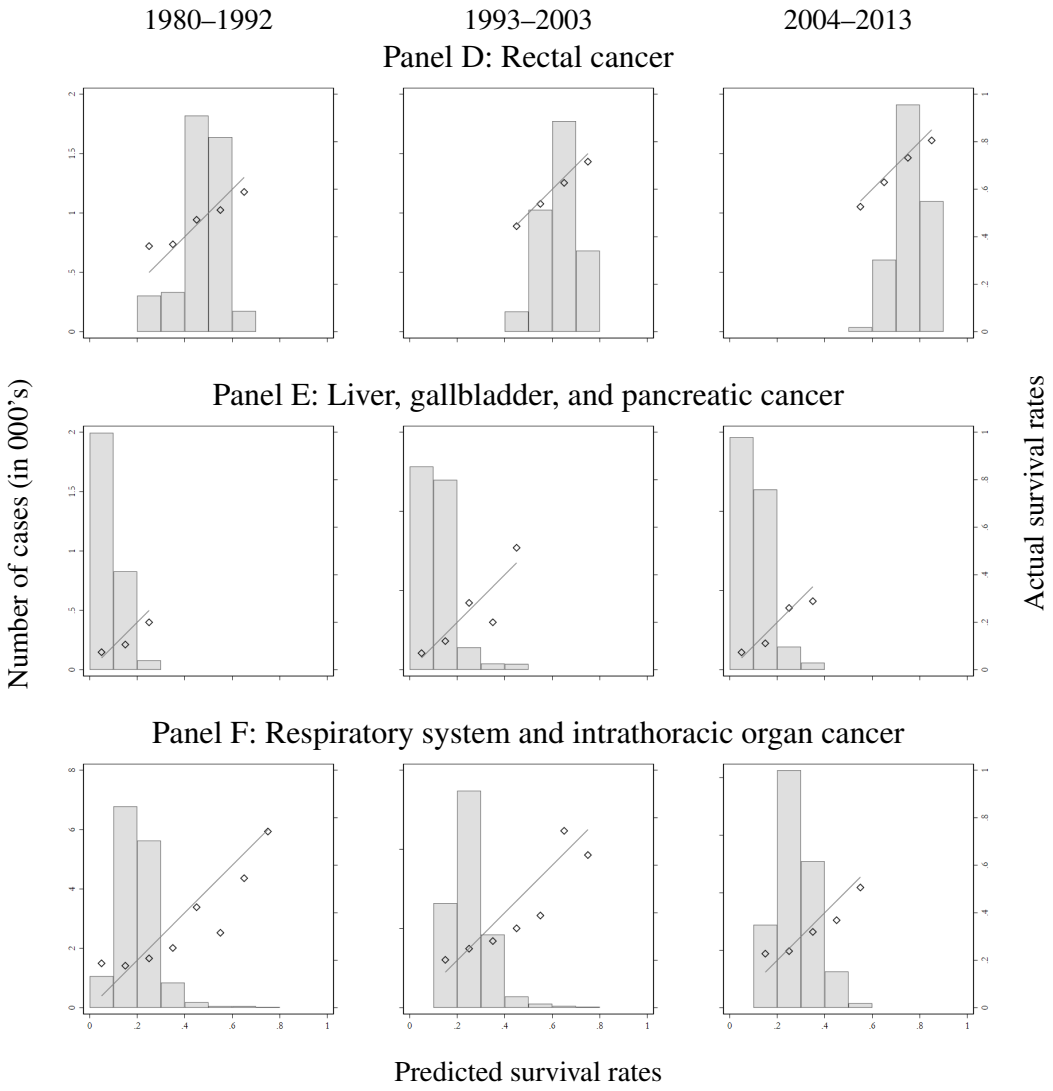


FIGURE J.7.—Expected 5-year survival rates - Continued. *Notes*: These figures report the predicted 5-year survival probabilities for three different types of cancer over three different time periods. The estimation methodology is described in detail in Online Appendix G. The x-axis divides the predicted 5-year survival probabilities in 10 buckets of equal size. The gray bars indicate the number of cancer diagnoses in each bucket (reported in thousands on the left hand side y-axis). The diamonds indicate the average actual survival rate in each bucket (reported on the right hand side y-axis) and the difference between the diamonds and the 45-degree line represents the average prediction error. Panel D shows the estimates for rectal cancer. Panel E shows the estimates for liver, gallbladder, and pancreatic cancer. Panel F shows the estimates for respiratory system and intrathoracic organ cancer.

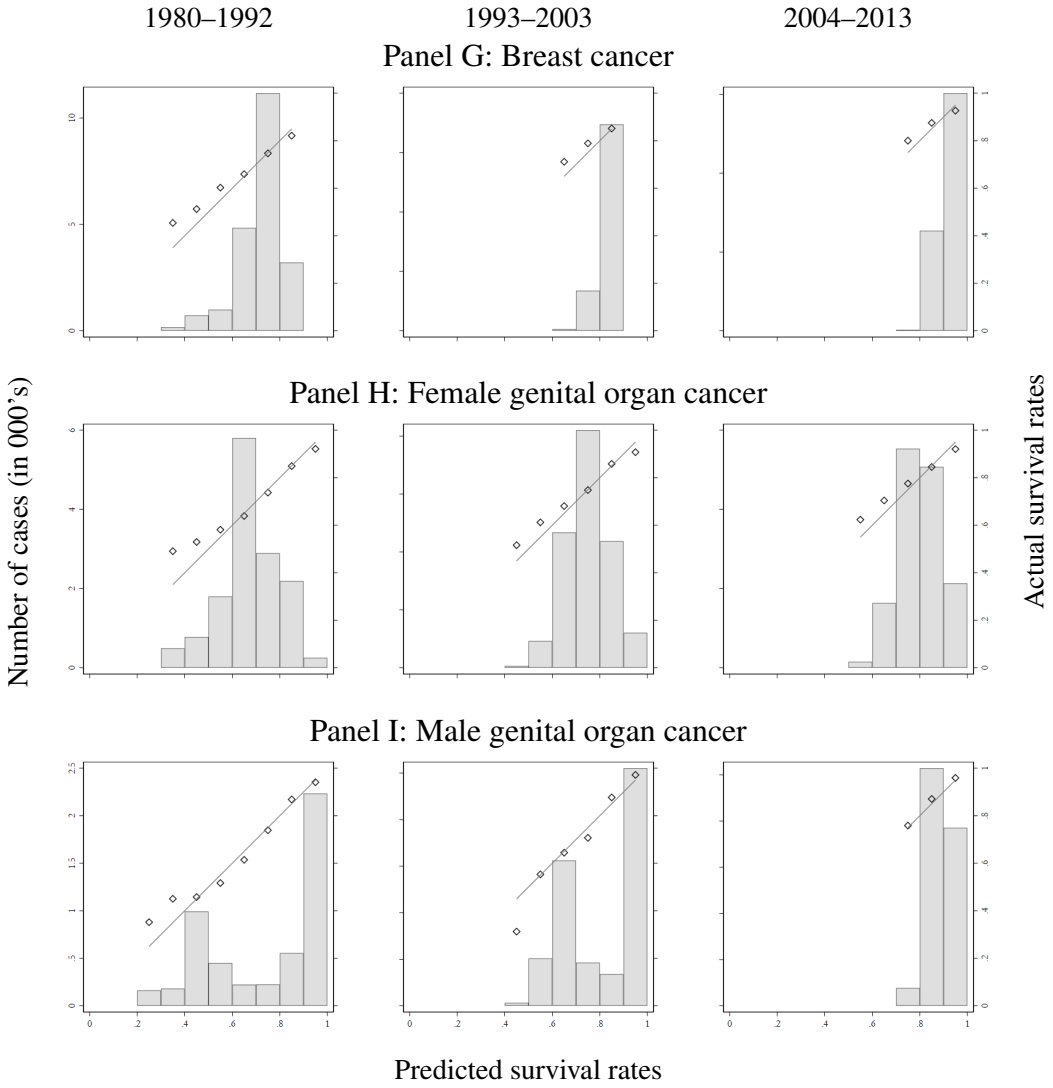


FIGURE J.7.—Expected 5-year survival rates - Continued. *Notes*: These figures report the predicted 5-year survival probabilities for three different types of cancer over three different time periods. The estimation methodology is described in detail in Online Appendix G. The x-axis divides the predicted 5-year survival probabilities in 10 buckets of equal size. The gray bars indicate the number of cancer diagnoses in each bucket (reported in thousands on the left hand side y-axis). The diamonds indicate the average actual survival rate in each bucket (reported on the right hand side y-axis) and the difference between the diamonds and the 45-degree line represents the average prediction error. Panel G shows the estimates for breast cancer. Panel H shows the estimates for female genital organ cancer. Panel I shows the estimates for male genital organ cancer.

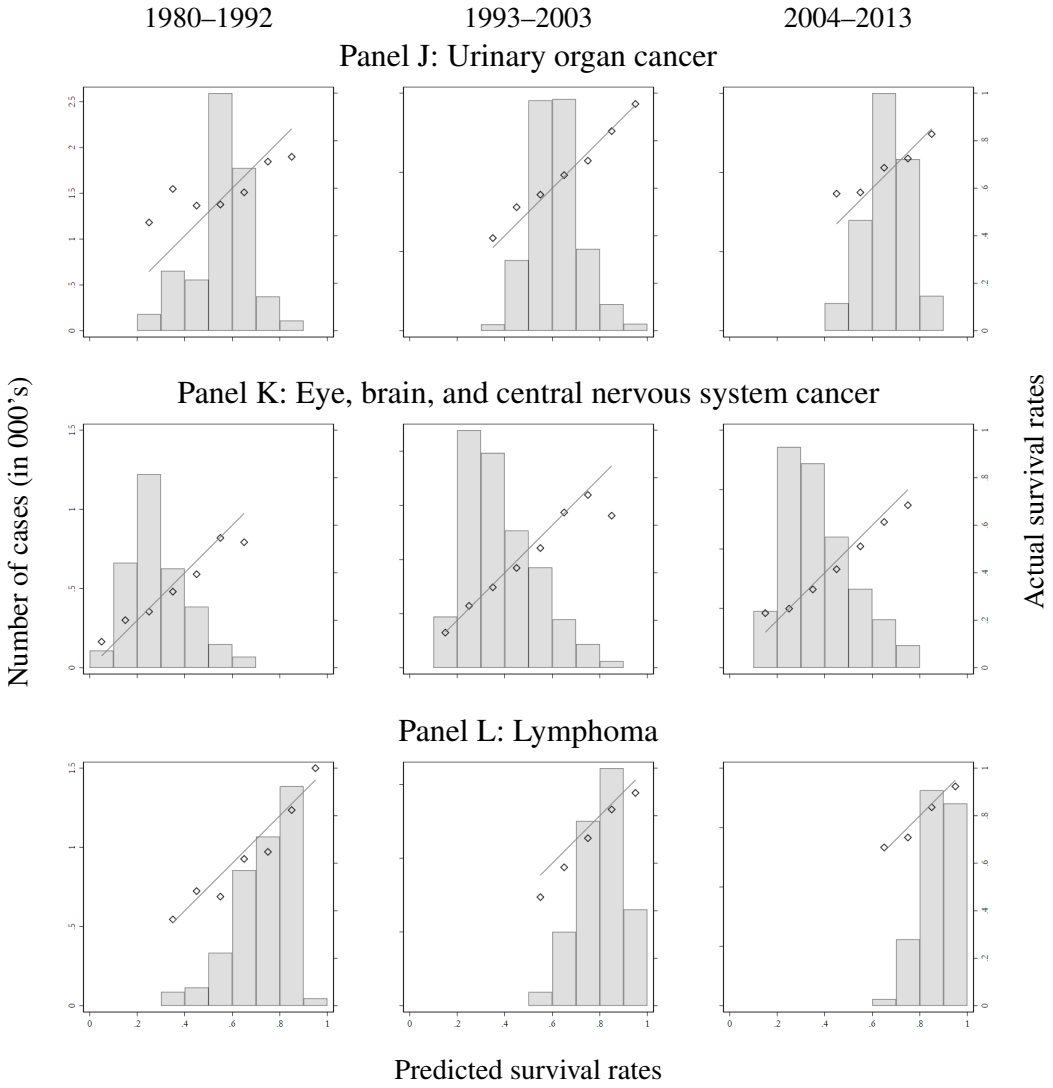


FIGURE J.7.—Expected 5-year survival rates - Continued. *Notes*: These figures report the predicted 5-year survival probabilities for three different types of cancer over three different time periods. The estimation methodology is described in detail in Online Appendix G. The x-axis divides the predicted 5-year survival probabilities in 10 buckets of equal size. The gray bars indicate the number of cancer diagnoses in each bucket (reported in thousands on the left hand side y-axis). The diamonds indicate the average actual survival rate in each bucket (reported on the right hand side y-axis) and the difference between the diamonds and the 45-degree line represents the average prediction error. Panel J shows the estimates for urinary organ cancer. Panel K shows the estimates for eye, brain, and central nervous system cancer. Panel L shows the estimates for lymphoma.

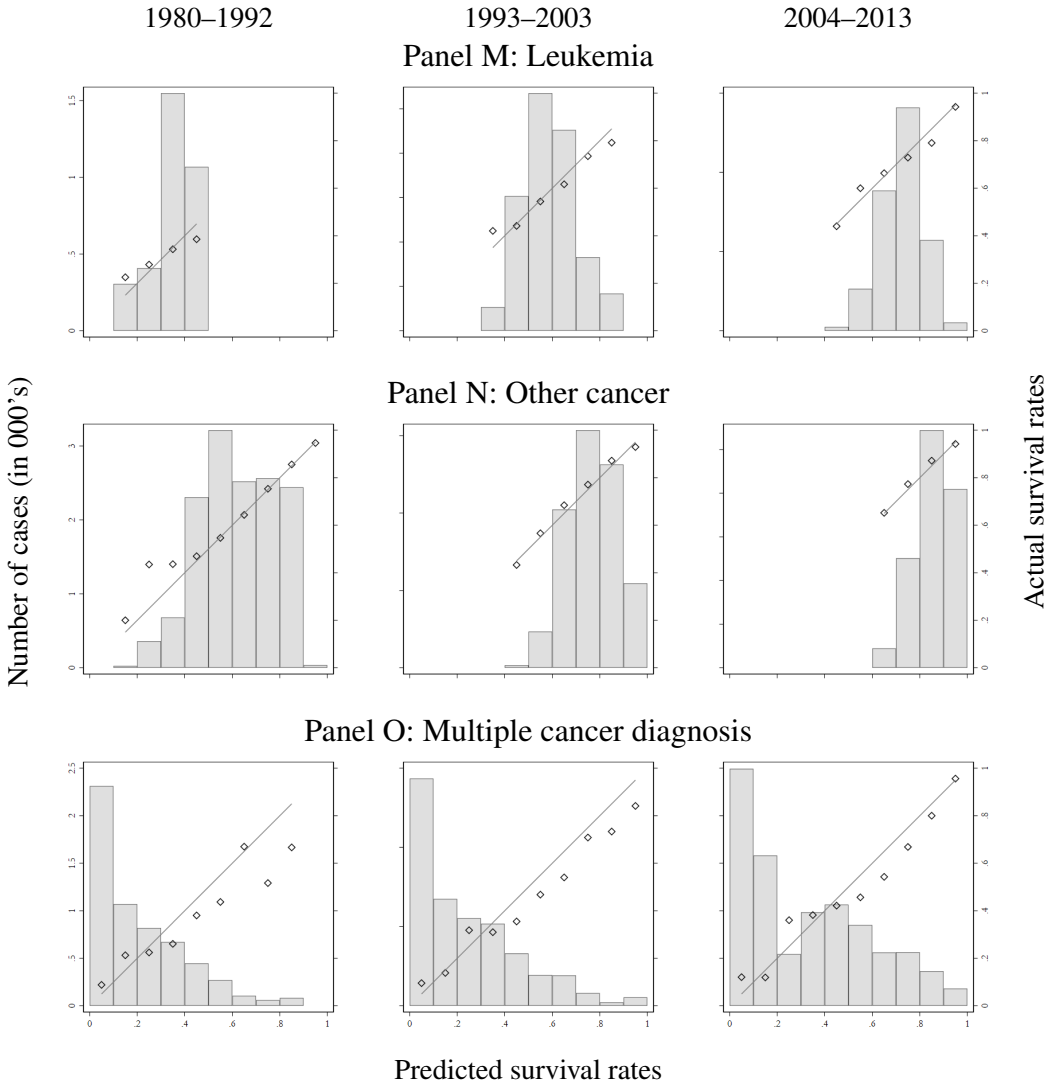


FIGURE J.7.—Expected 5-year survival rates - Continued. *Notes*: These figures report the predicted 5-year survival probabilities for three different types of cancer over three different time periods. The estimation methodology is described in detail in Online Appendix G. The x-axis divides the predicted 5-year survival probabilities in 10 buckets of equal size. The gray bars indicate the number of cancer diagnoses in each bucket (reported in thousands on the left hand side y-axis). The diamonds indicate the average actual survival rate in each bucket (reported on the right hand side y-axis) and the difference between the diamonds and the 45-degree line represents the average prediction error. Panel M shows the estimates for leukemia. Panel N shows the estimates for other and ill-defined cancer. Panel O shows the estimates for multiple cancer diagnosis.

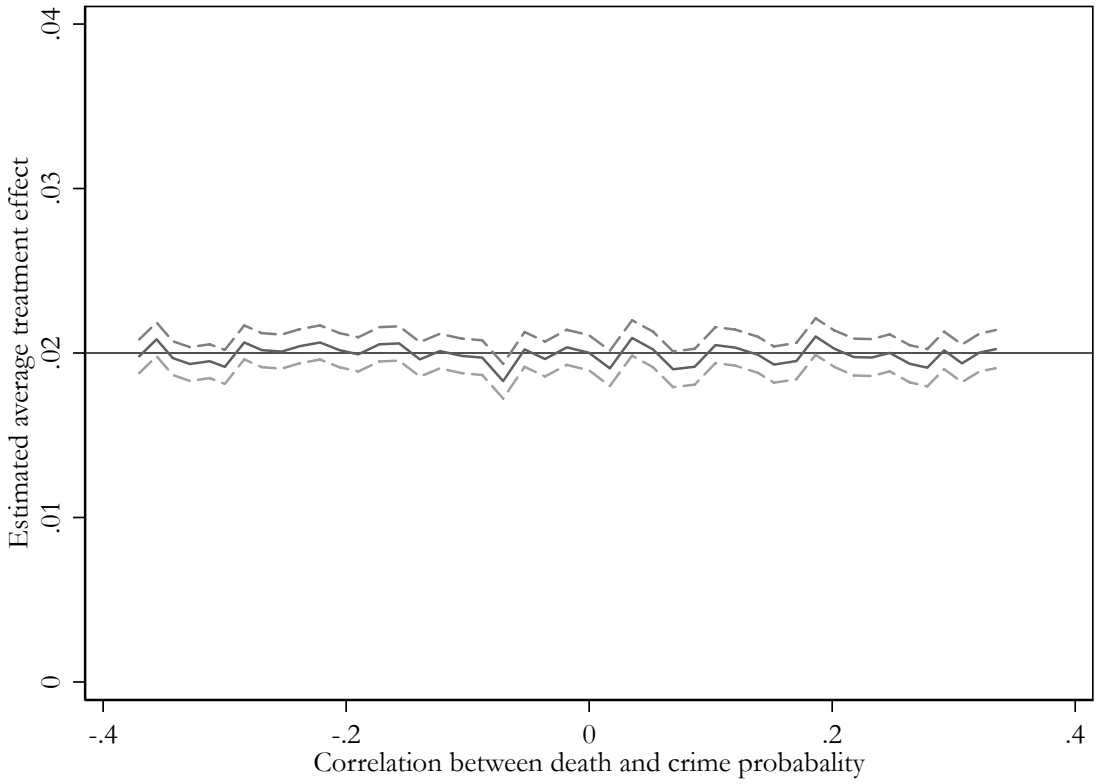


FIGURE J.8.—Effect of attrition on event study estimates. *Notes*: This figure reports the estimation bias due to selective attrition in a simulated dataset. The x-axis denotes the correlation between death and crime probability. The y-axis denotes the average treatment effect. The methodology is described in detail in Online Appendix C.

TABLE J.I

TYPES OF CRIME[a]

Type of crime	% of total crime (1)	Classification economic/ non-economic (2)	Classification property/ sexual/violent (3)
Forgery	0.634	Economic	Property
Forgery with check	0.397	Economic	Property
Burglary of bank/business	2.162	Economic	Property
Burglary of house	1.039	Economic	Property
Burglary of uninhabited building	0.324	Economic	Property
Theft from car, boat, etc.	0.665	Economic	Property
Store theft	9.458	Economic	Property
Theft other	3.598	Economic	Property
Theft indoor vehicle	1.600	Economic	Property
Theft of motorcycle	0.401	Economic	Property
Theft of bicycle	0.691	Economic	Property
Other theft	0.254	Economic	Property
Illegal handling of lost goods	0.419	Economic	Property
Embezzlement	0.315	Economic	Property
Fraud	1.870	Economic	Property
Check fraud	0.211	Economic	Property
Breach of trust	0.125	Economic	Property
Extortion and usury	0.058	Economic	Property
Fraud against creditors	0.094	Economic	Property
Possession stolen goods	1.577	Economic	Property
Robbery	0.709	Economic	Property
Serious tax fraud	0.061	Economic	Property
Negligent possession of stolen goods	0.102	Economic	Property
Wealth offenses, such as insider trading, bribery	0.210	Economic	Property
Counterfeiting money	0.141	Economic	Unclassified
Sale of drugs	0.385	Economic	Unclassified
Drug smuggling	0.128	Economic	Unclassified
Illegal occupation	0.053	Economic	Unclassified
Taxes and excise laws	0.550	Economic	Unclassified
Sales drugs	0.385	Economic	Unclassified
Prostitution, fornication	0.063	Economic	Sexual
Incest	0.033	Non-economic	Sexual
Rape	0.179	Non-economic	Sexual
Heterosexual offenses with children under 12	0.059	Non-economic	Sexual
Sexual crime against children under 12	0.012	Non-economic	Sexual
Heterosexual offenses otherwise	0.078	Non-economic	Sexual
Sexual crime against children under 15	0.014	Non-economic	Sexual
Sexual crime otherwise	0.011	Non-economic	Sexual
Homosexual offenses with children under 12	0.008	Non-economic	Sexual
Homosexual offenses otherwise	0.009	Non-economic	Sexual
Unwanted touching	0.116	Non-economic	Sexual

[a]Continues in next table

TABLE J.I

TYPES OF CRIME—CONTINUED[a]

Type of crime	% of total crime (1)	Classification economic/ non-economic (2)	Classification property/ sexual/violent (3)
Indecent exposure	0.082	Non-economic	Sexual
Indecency other	0.147	Non-economic	Sexual
Crimes against life and body, such as help with suicide	0.130	Non-economic	Violent
Violence against homeless	0.517	Non-economic	Violent
Arson	0.237	Non-economic	Unclassified
Vandalism	2.395	Non-economic	Unclassified
Family crimes	0.027	Non-economic	Unclassified
Involuntary manslaughter accident	0.220	Non-economic	Unclassified
Unknown	0.009	Unclassified	Unclassified
Violence against official authority	0.873	Unclassified	Violent
Riot/disturbance against official authority	0.032	Unclassified	Violent
Murder	0.034	Unclassified	Violent
Attempted murder	0.053	Unclassified	Violent
Simple violence	3.472	Unclassified	Violent
Serious violence	0.689	Unclassified	Violent
Particularly serious violence	0.018	Unclassified	Violent
Intentional bodily harm	0.199	Unclassified	Violent
Severe intentional bodily harm	0.017	Unclassified	Violent
Negligent manslaughter/bodily harm	0.019	Unclassified	Violent
Crimes against personal freedom	0.099	Unclassified	Violent
Threats	0.759	Unclassified	Violent
Terrorism, spying, treason, etc.	0.520	Unclassified	Unclassified
Offense by public employee	0.020	Unclassified	Unclassified
Perjury	0.088	Unclassified	Unclassified
False statement, withholding information	0.601	Unclassified	Unclassified
Public harm	0.088	Unclassified	Unclassified
Received request, received, or violated order	0.154	Unclassified	Unclassified
Data exploitation, defamation, etc.	0.369	Unclassified	Unclassified
Arms act	2.027	Unclassified	Unclassified
Health and social law	0.422	Unclassified	Unclassified
Building and housing law	0.053	Unclassified	Unclassified
Environmental law	0.584	Unclassified	Unclassified
Employment protection act, etc.	0.844	Unclassified	Unclassified
Company law	0.175	Unclassified	Unclassified
Military law	0.774	Unclassified	Unclassified
Electricity and gas law, etc.	0.087	Unclassified	Unclassified
Other special legislation	0.022	Unclassified	Unclassified
Holding drugs	6.681	Unclassified	Unclassified

[a]This table shows crime statistics and classifications. Column (1) reports the percentage of each type of crime out of total crime. Column (2) reports the classification of crime into economic and non-economic crime. Column (3) reports the classification of crime into property, sexual, and violent crime based on the system used by Statistics Denmark. The total number of crimes in the population is 4,732,529 from 1980 to 2018.

TABLE J.II

PREDICTING THE TIMING OF THE DIAGNOSIS[a]

	Diagnosis in 1 year (1)	Diagnosis in 2 years (2)	Diagnosis in 3 years (3)
F-statistic	1.528	0.575	0.301
P-value	(0.164)	(0.750)	(0.937)
Observations	2,926,697	2,926,697	2,926,697

[a]This table reports *F*-statistics for the hypothesis that is possible to predict the timing of the cancer diagnosis using the variables $Total\ income$, $Financial\ wealth$, $Mortgage\text{-}to\text{-}income\ ratio$, $Homeowner$, $Married$, and $In\ prison$. The dependent variable is a dummy that takes a value of one if a person is diagnosed with cancer within one, two, or three years, respectively. Only people who will develop cancer within 10 years are included. The empirical model includes person and year-by-age fixed effects. P-values are presented in parentheses.

TABLE J.III

TESTS ON PRE-TRENDS[a]

Specification	F-statistic (1)	P-value (2)
Partner's crime	0.702	0.622
Household's crime	0.726	0.604
First crime	1.696	0.132
Reoffenders	0.377	0.865
Economic crimes	0.330	0.895
Non-economic crimes	1.265	0.276
Property	0.447	0.816
Sexual	0.753	0.584
Violent	1.931	0.086
Low survival probability	0.705	0.620
High survival probability	0.670	0.646
High income	1.379	0.229
Low income	1.474	0.195
High income decline	0.802	0.548
No income decline	0.520	0.761
Homeowner	0.131	0.985
No homeowner	0.486	0.787
Wealthy	0.440	0.821
Not wealthy	0.276	0.926
Men	0.282	0.923
Women	0.857	0.509
Young	0.346	0.885
Old	1.061	0.380
High education	0.926	0.462
Low education	1.087	0.365
Married	0.587	0.710
Single	0.678	0.640
Criminals in family	0.891	0.486
No criminals in family	0.058	0.998
Ability controls	0.255	0.938
Balended DiD	1.801	0.145
Idle hands	0.505	0.773
Muni FEs	0.347	0.884
Muni x Year FEs	0.335	0.892
Charges	0.550	0.739

[a]This table reports F-tests on pre-trend coefficients for the specifications used in the main paper.

TABLE J.IV

EFFECTS OF CANCER ON CRIME BY DIAGNOSIS COHORT [a]

	Diagnosis in 2002 or after (1)	Diagnosis before 2002 (2)
ATE	0.099***	0.056*
	(0.026)	(0.031)
Observations	2,606,852	2,400,835

[a]This table reports the average treatment effects for criminal activity changes in response to cancer diagnoses. Column (1) presents the effect of cancer on crime for people who are diagnosed in or after 2002. Column (2) presents the effect of cancer on crime for people who are diagnosed before 2002. ATEs are obtained as linear combinations of the treatment effects for each post-diagnosis event year, weighted by the relative size of the treatment group. The empirical models include person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the person level and presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE J.V

ECONOMIC MECHANISM—NON-OVERLAPPING CRIMES[a]

Years from diagnosis	Economic (1)	Non-economic (2)
0	-0.097***	-0.004
	(0.011)	(0.004)
+1	-0.019	0.001
	(0.014)	(0.005)
+2	0.032**	0.010*
	(0.016)	(0.006)
+3	0.051***	0.006
	(0.017)	(0.006)
+4	0.068***	0.012*
	(0.019)	(0.006)
+5	0.086***	0.011
	(0.021)	(0.007)
+6	0.079***	0.014*
	(0.022)	(0.008)
+7	0.090***	0.028***
	(0.024)	(0.009)
+8	0.091***	0.022**
	(0.026)	(0.009)
+9	0.084***	0.033***
	(0.027)	(0.010)
+10	0.118***	0.028***
	(0.030)	(0.010)
ATE	0.052***	0.013**
	(0.015)	(0.005)
Observations	5,007,687	5,007,687

[a]This table reports event study estimates for changes in different categories of crime in response to cancer diagnoses. Column (1) shows results for economic crimes that did not coincide with a non-economic crime. Column (2) shows results for non-economic crimes that did not coincide with an economic crime. At the bottom of each column the average treatment effects (ATEs) are reported. ATEs are obtained as linear combinations of the treatment effects for each event year post-diagnosis, weighted by the relative size of the treatment group. The empirical models include person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the person level and presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE J.VI

PSYCHOLOGICAL DISTRESS CHANNEL[a]

	Panel A	Panel B	
Dependent variable:	Psychological distress	Crime	Crime
		Subsample: in psych. distress	Subsample: not in psych. distress
Years from diagnosis	(1)	(1)	(2)
0	0.019***	0.088	-0.162***
	(0.000)	(0.056)	(0.018)
+1	0.029***	0.094	-0.071***
	(0.001)	(0.062)	(0.021)
+2	0.015***	0.105	0.022
	(0.001)	(0.067)	(0.024)
+3	0.007***	0.173**	0.074***
	(0.001)	(0.076)	(0.027)
+4	0.004***	0.227***	0.083***
	(0.001)	(0.085)	(0.029)
+5	0.003***	0.096	0.111***
	(0.001)	(0.087)	(0.032)
+6	0.002**	0.120	0.145***
	(0.001)	(0.093)	(0.034)
+7	0.001	0.320***	0.097***
	(0.001)	(0.109)	(0.036)
+8	0.000	0.297**	0.133***
	(0.001)	(0.117)	(0.040)
+9	-0.000	0.229*	0.140***
	(0.001)	(0.124)	(0.042)
+10	-0.000	0.105	0.200***
	(0.001)	(0.128)	(0.045)
ATE	0.010***	0.166**	0.066***
	(0.000)	(0.068)	(0.024)
Observations	3,969,869	444,061	3,525,808

[a]Panel A reports event study estimates for changes in psychological distress in response to cancer diagnoses. Panel B reports event study estimates for criminal activity changes in response to cancer diagnoses. Column 1 (Column 2) shows the coefficients for people in (not in) psychological distress during one of the years following the cancer diagnosis. Psychological distress is proxied by having received treatment by a psychologist or psychiatrist. At the bottom of each column the average treatment effects (ATEs) are reported. ATEs are obtained as linear combinations of the treatment effects for each event year post-diagnosis, weighted by the relative size of the treatment group. The empirical model includes person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients in Panel B are multiplied by 100. Standard errors are clustered at the person level and presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE J.VII

CHANGE IN WELFARE GENEROSITY AND THE EFFECT OF CANCER ON CRIME—EXCLUDING MOVERS[a]

Years from diagnosis	Years from diagnosis indicators (1)	Years from diagnosis indicators $\times S_{t,m}$ (2)
0	-0.128***	0.111**
	(0.029)	(0.053)
+1	-0.047**	0.072*
	(0.020)	(0.041)
+2	0.014	0.107*
	(0.025)	(0.055)
+3	0.074***	0.056
	(0.022)	(0.055)
+4	0.078***	0.163**
	(0.027)	(0.063)
+5	0.082***	0.128*
	(0.029)	(0.070)
+6	0.099***	0.162***
	(0.031)	(0.059)
+7	0.125***	0.191***
	(0.030)	(0.070)
+8	0.120***	0.138
	(0.036)	(0.083)
+9	0.121***	0.130*
	(0.037)	(0.076)
+10	0.144***	0.123
	(0.038)	(0.088)
ATE	0.054***	0.115***
	(0.018)	(0.040)
Observations	3,816,549	—

[a]This table reports event study estimates for the effect of the 2007 municipality reform on the relation between cancer and crime. *Individuals who relocate to a different municipality are excluded.* $S_{t,m}$ is a dummy variable that takes a value of one from 2007 onwards for municipalities that become stingy, defined as municipalities in which the difference between pre- and post-reform income replacement for cancer patients falls below the sample median. Columns (1) and (2) report coefficients for two different sets of independent variables obtained from the same estimation. The independent variables in Column (1) are the years from diagnosis indicators and the independent variables in Column (2) are the years from diagnosis indicators interacted with the variable $S_{t,m}$. At the bottom of each column the average treatment effects (ATEs) are reported. ATEs are obtained as linear combinations of the treatment effects for each post-diagnosis event year weighted by the relative size of the treatment group. The empirical model includes person, year-by-age, in prison, and cancer recurrence fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the post-reform municipality level and presented in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE J.VIII

TIME TO APPREHENSION[a]

Years since diagnosis	(1)
0	0.073
	(0.081)
+1	-0.031
	(0.101)
+2	-0.146
	(0.108)
+3	-0.023
	(0.112)
+4	0.074
	(0.124)
+5	-0.058
	(0.132)
+6	0.024
	(0.137)
+7	0.007
	(0.149)
+8	-0.236
	(0.166)
+9	-0.049
	(0.185)
+10	0.179
	(0.191)
ATE	-0.035
	(0.088)
Observations	21,369

[a]This table reports event study estimates for changes in the time from offense to apprehension as a response to cancer diagnoses. The dependent variable is the time in days between when a crime is committed and when the perpetrator is apprehended. If a person commits multiple crimes in a year, the variable equals the median time. Only observations in the year of the offense are included. The ATE is obtained as linear combinations of the treatment effects for each event year post-diagnosis, weighted by the relative size of the treatment group. The empirical model includes person, year-by-age, and cancer recurrence fixed effects. Standard errors are clustered at the person level and presented in parentheses.

TABLE J.IX

DO CANCER RATES RELATE TO THE RATE OF CRIMES SOLVED IN A MUNICIPALITY?[a]

	Rate of crimes convicted (1)	Rate of property crimes convicted (2)	Rate of crimes charged (3)	Rate of property crimes charged (4)
Rate of cancer	0.711	0.358	0.634	0.264
	(0.439)	(0.279)	(0.676)	(0.684)
Observations	5,587	5,587	5,587	5,587

[a]This table reports estimates for the relation between the rate of cancer by municipality and the rate of crimes solved by municipality. The analysis is at the municipality level. The independent variable is the rate of cancer diagnoses in the population by municipality. The dependent variables are the *Rate of crimes convicted* out of all crimes reported (Column 1), the *Rate of property crimes convicted* out of all crimes reported (Column 2), the *Rate of crimes charged* out of all crimes reported (Column 3), and *Rate of property crimes charged* out of all crimes reported (Column 4). The empirical model includes municipality and year fixed effects. Standard errors are clustered at the municipality level and presented in parentheses.

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