ONLINE APPENDIX FOR “BREAKING BAD: HOW HEALTH SHOCKS PROMPT CRIME”

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APPENDIX A: 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.[1]

A.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

[1] Our framework builds on the models by Dobkin et al (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 et al (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).[2] 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

[2] 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:

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

$$\frac{\partial g(c_1^S(\kappa^{S*}))}{\partial c_1^S} \times [1 - \iota w] = [\rho - \varrho] \frac{\partial b(\kappa^{S*})}{\partial \kappa^S}, \tag{2}$$

with Equation (1) for the healthy and Equation (2) 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.[3]

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.[4] The propositions below follow:

[3] Equations (1) and (2) 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.

[4] 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 A.3 below).

A.2. *The impact of health shocks*

PROPOSITION A.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 A.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 A.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 A.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 B: COMPARISON OF INDIVIDUALS DIAGNOSED IN DIFFERENT PERIODS

Our methodology requires us to compare similar individuals who are, however, diagnosed in different years. This empirical design implies a tradeoff between the comparability amongst units of observation and the analysis horizon. Note that due to the inclusion of year fixed effects and to the choice of considering only the $[-10, +10]$-year interval around cancer, our baseline specification never compares individuals who are diagnosed with cancer more than 20 years apart. To further validate this 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.[5] Namely, they are respectively in event year $\tau = -1$ or $\tau = -10$. We therefore compare the distribution of three key covariates (income, education, and financial wealth) for 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 G.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: INCOME SUBSIDY RECUPERATION ESTIMATION

For our back-of-the-envelope calculation of welfare effects, we need estimates of: (i) the total cost of crime in Denmark, (ii) the total cost of income subsidies if everyone with an income loss following cancer were compensated, and (iii) the reduction in crime due to these income subsidies. The total economic cost of crime is notoriously difficult to estimate. Intangible costs (for instance, fear of crime, pain and suffering) and some tangible costs (for instance, loss of productivity, expenditures to prevent crime) are challenging to determine. Additionally, crime tends to be underreported. To the best of our knowledge, no estimates for the total cost of crime are available for Denmark. Therefore, we rely for guidance on estimates from the United Kingdom and the United States. These estimates put the total cost of crime in the range between $1,300 and $10,700 per capita per year, depending on the source (Anderson 2012, Brand and Price 2000, United States Government Accountability Office 2017). Second, we need an estimate of the total cost of income subsidies. To that end, we estimate the total number of people that face an income decline due to cancer (around 26,000 per year) times the median income decline (34,000 DKK). Third, we need an estimate for the reduction in crime due to income subsidies assigned to people diagnosed with cancer. We assume that, when everyone gets compensated for their income loss following cancer, the incentive to commit crime drops as predicted by

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

the average treatment effect estimates reported in Figure 2 (0.098 and 0.017), allowing us to calculate the fraction of crime prevented. Finally, we divide the multiplication of the percentage of crime prevented times the total cost of crime by the total income subsidies to obtain a range between 2% and 18%.

APPENDIX D: 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 finally 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 intervals of years to account for the effect of advances in cancer treatment that can alter the coefficients above: 1980–1992, 1993–2003, and 2004–2013.

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

APPENDIX E: 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 and present the results from an alternative empirical approach. 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 A.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 more into a relatively higher share of labor income preserved post-cancer 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:

$$\Delta Income_{i,t}^{R} = K_m^R + \lambda Z_{i,t}^R + \beta_t^R + \epsilon_{i,t}^R,$$

where $\Delta Income_{i,t}^{R}$ 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.[6] $\Delta Income_{i,t}^{R}$ 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_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). 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_m^0 (K_m^1) are pre-reform (post-reform) municipality fixed effects. The vector $Z_{i,t}$ includes age fixed effects and a third order polynomial of income

[6] 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.

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.

We then obtain the change in generosity as $\Delta G_m = K_m^1 - K_m^0$. We define as treated those individuals who are part of a municipality that falls in the bottom half of K_m^1 post-reform, conditional on them not being in the bottom half of K_m^0 pre-reform. In this way, we make sure that we focus on individuals who went from a situation of generous social welfare pre-reform to a (comparatively) stingy regime.

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

Alternative empirical approach. Note that in the main paper, we run a regression that augments our baseline specification with the treatment variable $Stingy\ muni_{t,M}$. We rely on this specification to be consistent with the previous analyses conducted in the paper. An issue that we face is, however, that a change in municipality-level welfare policies may also affect through a different channel people not yet diagnosed (e.g., through a reduction of other subsidies that do not affect cancer patients such as, for example, maternity support). In other words, our control group may be treated as well (even though arguably at a different intensity). We therefore run an alternative specification on a more homogeneous sample that only includes individuals after they have been diagnosed with cancer:

$$C_{i,t} = \beta_t + b \times Stingy\ muni_{t,m} + \lambda X_{i,t} + K_m^1 + \epsilon_{i,t},$$

where $Stingy\ muni_{t,m}$ is a variable that takes a value of 1 during the post-reform period for people residing in an area that became part of a stingy municipality (while not being part of a stingy municipality before the reform). The coefficient b measures the effect of a reduction of welfare generosity on the crime rate *among the fraction of the population who has been diagnosed with cancer*. The vector $X_{i,t}$ includes Age, $In\ prison$, and $In\ hospital$ fixed effects. The results are reported in Online Appendix Table G.IV and are in line with our main municipality-generosity specification in Equation (3).

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

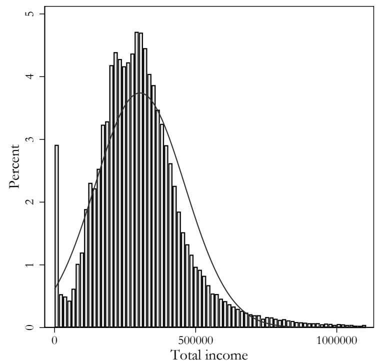
We replicate our analysis employing a difference-in-differences approach that follows closely the methodology of Fadlon and Nielsen (2019, 2021). Using this approach, the crime choices of individuals diagnosed with cancer at time s (treatment group) are compared to those who are diagnosed with cancer 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

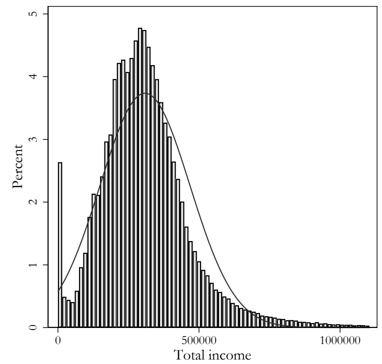
$$C_{i,t} = \beta_t + \theta\, treat_i + \sum_{\tau \neq 1; \tau=-4}^{5} \eta_\tau \mathbb{1}\{T_{i,t} = \tau\} + \sum_{\tau \neq 1; \tau=-4}^{5} \gamma_\tau \mathbb{1}\{T_{i,t} = \tau\} \times treat_i + \lambda X_{i,t} + \epsilon_{i,t},$$

where i indexes individuals, t the calendar year, 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 Age, $In\ prison$, and $In\ hospital$ 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.

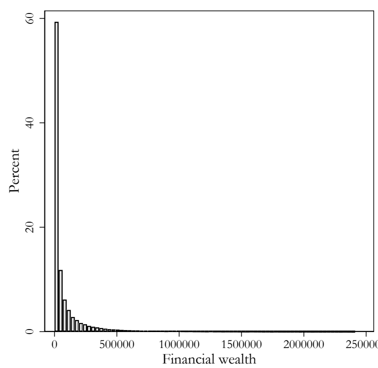
APPENDIX G: ADDITIONAL APPENDIX FIGURES AND TABLES



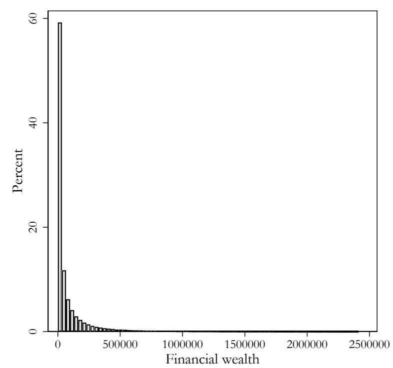
(a) Total income at $\tau = -1$



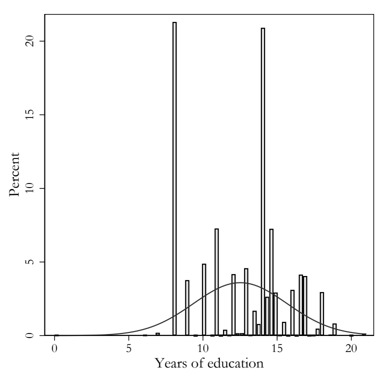
(b) Total income at $\tau = -10$



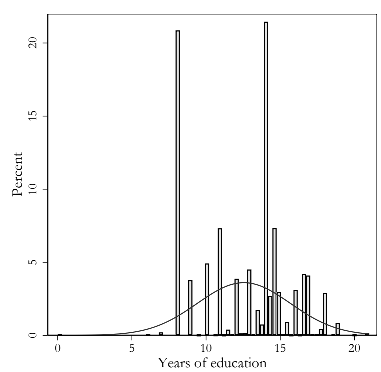
(c) Financial wealth at $\tau = -1$



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



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



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

FIGURE G.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.

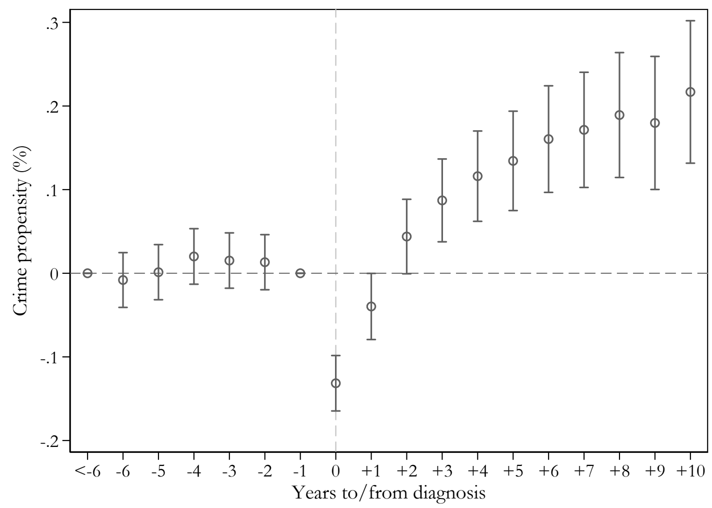


FIGURE G.2.—Test for pre-trends with heterogeneous effects by diagnosis-cohort. *Notes*: This figure reports event study estimates for criminal activity changes in response to cancer diagnoses. The specification allows the treatment effects to differ across diagnosis-cohorts. The coefficients are obtained using a weighted average across cohorts (see Equation (2) in the paper). 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 crime propensity in percentage points. The empirical model includes person, year, age, in prison, and in hospital fixed effects. Standard errors are clustered at the person level. The number of observations is 4,897,472.

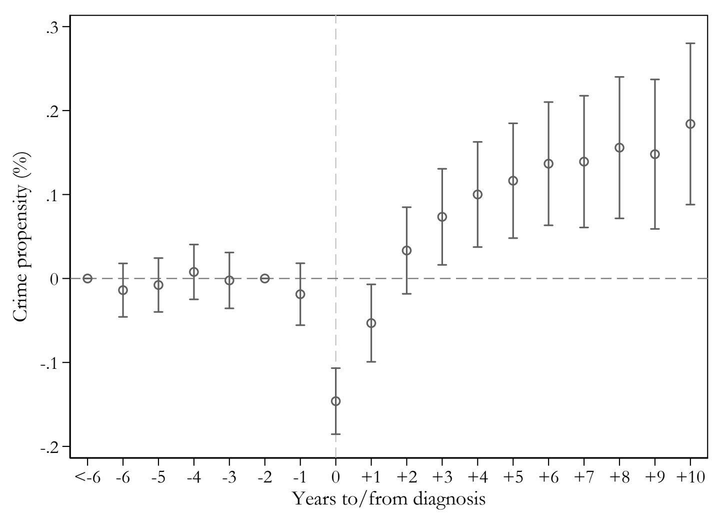


FIGURE G.3.—Alternative test for pre-trends—different event time excluded. *Notes*: This figure reports event study estimates for criminal activity changes in response to cancer diagnoses. The figure plots the estimated coefficients along with their 95% confidence interval. Event time $\tau = -2$ (rather than event time $\tau = -1$) is excluded. 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, age, in prison, and in hospital fixed effects. Standard errors are clustered at the person level. The number of observations is 4,897,472.

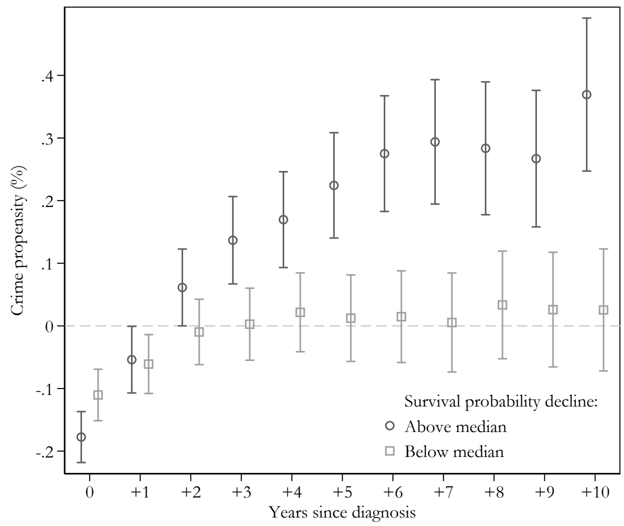


FIGURE G.4.—Survival probabilities channel—income controls. *Notes*: This figure reports event study estimates for criminal activity changes in response to cancer diagnoses. Income controls added are total income and a rank variable of total income. The figure plots the estimated coefficients along with their 95% confidence interval. Individuals are sorted based on whether they face an above- (respectively below-) median decline in survival probability due to cancer, using a different median threshold for men and women. 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, age, in prison, and in hospital fixed effects. Standard errors are clustered at the person level.

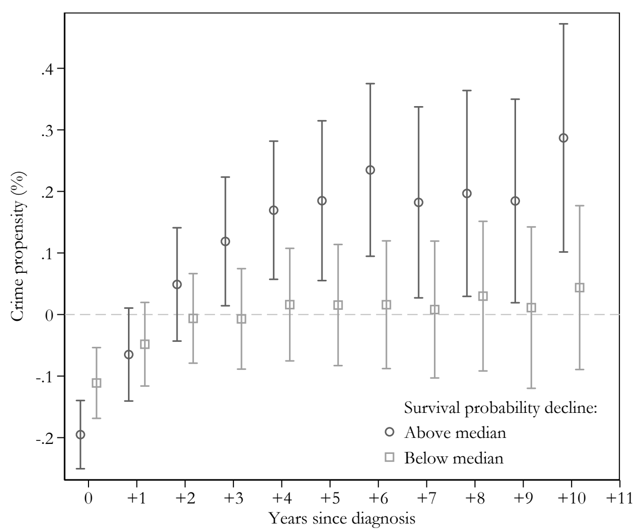


FIGURE G.5.—Survival probabilities channel—bootstrapping. *Notes*: This figure reports event study estimates for criminal activity changes in response to cancer diagnoses. The figure plots the estimated coefficients along with their 95% confidence interval. Individuals are sorted on the basis of whether 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 person, year, age, in prison, and in hospital fixed effects. Standard errors are calculated through block bootstrapping by 500 replications of the two-stage procedure.

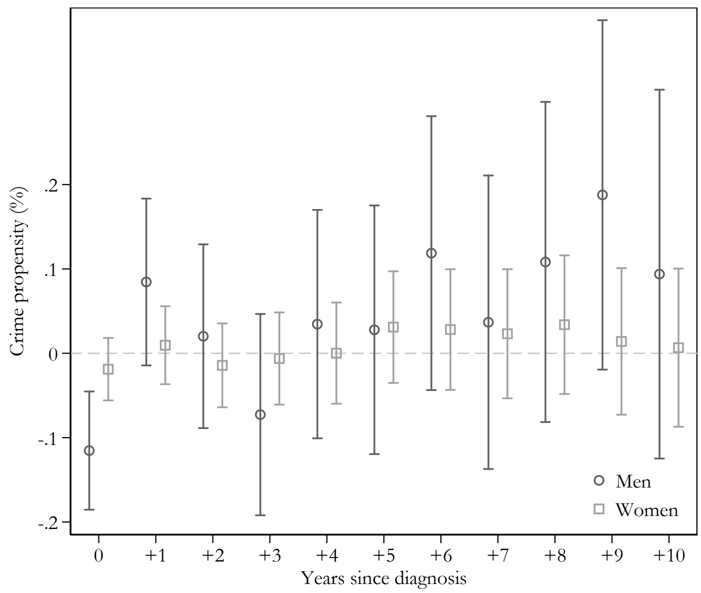


FIGURE G.6.—The relation between cancer and speeding. *Notes*: This figure reports event study estimates for speeding violations in response to cancer diagnoses. The figure plots the estimated coefficients along with their 95% confidence interval. The empirical models include person, year, age, in prison, and in hospital fixed effects. Standard errors are clustered at the person level.

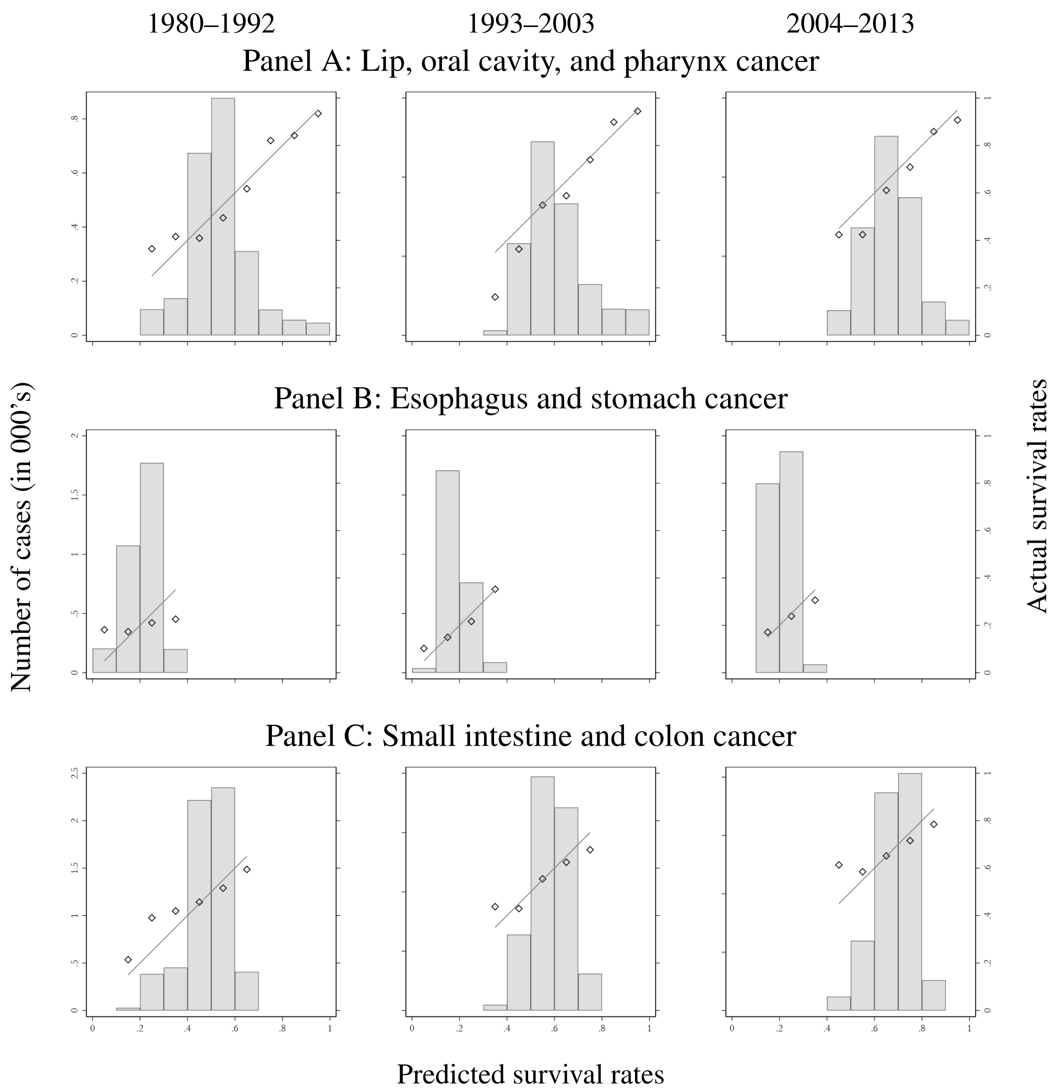


FIGURE G.7.—Expected 5-year survival rates. *Notes*: These figures report the predicted 5-year survival probabilities for three different types of cancer over three different time periods. The estimation methodology is described in detail in Online Appendix D. The x-axis divides the predicted 5-year 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.

TABLE G.I

TYPES OF CRIME[a]

Type of crime	% of total crime (1)	Classification economic/ non-economic (2)	Classification property/ sexual/violent (3)
Forgery	0.635	Economic	Property
Forgery with check	0.397	Economic	Property
Burglary of bank/business	2.166	Economic	Property
Burglary of house	1.041	Economic	Property
Burglary of uninhabited building	0.325	Economic	Property
Theft from car, boat, etc.	0.666	Economic	Property
Store theft	9.448	Economic	Property
Theft other	3.601	Economic	Property
Theft indoor vehicle	1.603	Economic	Property
Theft of motorcycle	0.402	Economic	Property
Theft of bicycle	0.691	Economic	Property
Other theft	0.253	Economic	Property
Illegal handling of lost goods	0.419	Economic	Property
Embezzlement	0.315	Economic	Property
Fraud	1.872	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	0.095	Economic	Property
Possession stolen goods	1.579	Economic	Property
Robbery	0.711	Economic	Property
Serious tax fraud	0.061	Economic	Property
Negligent possession of stolen goods	0.102	Economic	Property
Wealth offences, such as insider trading, bribery	0.210	Economic	Property
Counterfeiting money	0.141	Economic	Unclassified
Sale of drugs	0.386	Economic	Unclassified
Drug smuggling	0.128	Economic	Unclassified
Illegal occupation	0.053	Economic	Unclassified
Taxes and excise laws	0.547	Economic	Unclassified
Sales drugs	0.489	Economic	Unclassified
Prostitution, fornication	0.063	Economic	Sexual
Incest	0.033	Non-economic	Sexual
Rape	0.180	Non-economic	Sexual
Heterosexual offences with children under 12	0.059	Non-economic	Sexual
Sexual crime against children under 12	0.012	Non-economic	Sexual
Heterosexual offences 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 offences with children under 12	0.008	Non-economic	Sexual
Homosexual offences otherwise	0.009	Non-economic	Sexual
Unwanted touching	0.116	Non-economic	Sexual

[a]Continues in next table

TABLE G.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	0.518	Non-economic	Violent
Arson	0.23	Non-economic	Unclassified
Vandalism	2.398	Non-economic	Unclassified
Family crimes	0.027	Non-economic	Unclassified
Involuntary manslaughter accident	0.221	Non-economic	Unclassified
Unknown	0.009	Unclassified	Unclassified
Violence against official authority	0.875	Unclassified	Violent
Riot/disturbance against official authority	0.032	Unclassified	Violent
Murder	0.034	Unclassified	Violent
Attempted murder	0.053	Unclassified	Violent
Simple violence	3.479	Unclassified	Violent
Serious violence	0.690	Unclassified	Violent
Particularly serious violence	0.018	Unclassified	Violent
Intentional bodily harm	0.200	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	0.761	Unclassified	Violent
Terrorism, spying, treason, etc.	0.520	Unclassified	Unclassified
Offence by public employee	0.020	Unclassified	Unclassified
Perjury	0.088	Unclassified	Unclassified
False statement, withholding information	0.602	Unclassified	Unclassified
Public harm	0.089	Unclassified	Unclassified
Received request, received, or violated order	0.154	Unclassified	Unclassified
Data exploitation, defamation, etc.	0.369	Unclassified	Unclassified
Arms act	2.022	Unclassified	Unclassified
Health and social law	0.420	Unclassified	Unclassified
Building and housing law	0.053	Unclassified	Unclassified
Environmental law	0.581	Unclassified	Unclassified
Employment protection act, etc.	0.839	Unclassified	Unclassified
Company law	0.175	Unclassified	Unclassified
Military law	0.749	Unclassified	Unclassified
Electricity and gas law, etc.	0.087	Unclassified	Unclassified
Other special legislation	0.022	Unclassified	Unclassified
Holding drugs	6.657	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 4,723,300 from 1980 to 2018.

TABLE G.II

EFFECTS OF HEALTH SHOCKS ON TOTAL INCOME[a]

Sample: Years from diagnosis	All (1)	Income decline>0 (2)
0	–21,658	–32,889
	(645)	(490)
+1	–28,373	–71,317
	(834)	(673)
+2	–22,408	–76,137
	(1,015)	(732)
+3	–18,508	–83,539
	(751)	(822)
+4	–17,518	–90,854
	(820)	(930)
+5	–15,327	–96,761
	(883)	(1,037)
+6	–14,160	–100,177
	(1,547)	(1,143)
+7	–13,688	–95,017
	(934)	(1,244)
+8	–12,341	–94,202
	(1,225)	(1,807)
+9	–11,175	–93,656
	(1,192)	(1,559)
+10	–12,099	–96,042
	(1,191)	(1,583)
ATE	–18,836	–85,569
	(762)	(827)
Observations	4,897,472	2,096,890

[a]This table reports event study estimates for income changes in response to cancer diagnoses. The dependent variable is total income (in DKK). Column (1) is estimated on the full sample. Column (2) is estimated on the subset of cancer patients who face a decline in income following the cancer diagnosis (defined as the average income in the six years following cancer being lower than the income in the year before the cancer diagnosis). 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, and age fixed effects. Standard errors are clustered at the person level and presented in parentheses.

TABLE G.III

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 $\times Stingy\ muni$ (2)
0	–0.125	0.108
	(0.030)	(0.051)
+1	–0.044	0.074
	(0.020)	(0.040)
+2	0.017	0.112
	(0.025)	(0.053)
+3	0.075	0.053
	(0.022)	(0.052)
+4	0.082	0.168
	(0.028)	(0.061)
+5	0.086	0.133
	(0.031)	(0.069)
+6	0.102	0.136
	(0.030)	(0.057)
+7	0.128	0.185
	(0.030)	(0.068)
+8	0.125	0.130
	(0.035)	(0.082)
+9	0.124	0.131
	(0.036)	(0.076)
+10	0.150	0.120
	(0.036)	(0.087)
ATE	0.057	0.114
	(0.019)	(0.038)
Observations	3,726,766	

[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.* $Stingy\ muni$ takes a value of one for people residing in an area that became part of a stingy municipality in 2007, while not being part of a stingy municipality before 2007. 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 $Stingy\ muni$. 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, age, in prison, and in hospital fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the post-reform municipality level and presented in parentheses.

TABLE G.IV

CHANGE IN WELFARE GENEROSITY AND THE EFFECT OF CANCER ON CRIME—ALTERNATIVE SPECIFICATION[a]

Sample:	Diagnosed patients only
	(1)
Stingy muni	0.134
	(0.037)
Observations	1,430,908

[a]This table reports estimates for the effect of the 2007 municipality reform on the relation between cancer and crime. The specification includes only people who have already been diagnosed with cancer ($Event\ time > 0$). *Stingy muni* takes a value of one after 2006 for people residing in an area that became part of a stingy municipality in 2007, while not being part of a stingy municipality before 2007. The empirical model includes port-reform municipality, year, age, in prison, and in hospital fixed effects. All coefficients are multiplied by 100. Standard errors are clustered at the post-reform municipality level and presented in parentheses.

TABLE G.V

TIME TO APPREHENSION[a]

Years since diagnosis	(1)
0	0.117
	(0.077)
+1	–0.012
	(0.098)
+2	–0.127
	(0.106)
+3	0.008
	(0.109)
+4	0.071
	(0.120)
+5	0.014
	(0.129)
+6	0.070
	(0.131)
+7	0.049
	(0.146)
+8	–0.112
	(0.162)
+9	–0.020
	(0.180)
+10	0.139
	(0.183)
ATE	–0.003
	(0.087)
Observations	20,929

[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 a crime is committed and 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, age, and in hospital fixed effects. Standard errors are clustered at the person level and presented in parentheses.

TABLE G.VI

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	0.703	0.367	0.634	0.264
	(0.433)	(0.277)	(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 total crimes (Column 1), the *Rate of property crimes convicted* (Column 2), the *Rate of crimes charged* (Column 3), and *Rate of property crimes charged* (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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