CReAM
Centre for Research & Analysis of Migration

Discussion Paper Series

CPD 05/18

Child's Gender, Young Fathers' Crime, and Spillover Effects in Criminal Behavior

Christian Dustmann and Rasmus Landersø

Centre for Research and Analysis of Migration
Department of Economics, University College London
Drayton House, 30 Gordon Street, London WC1H 0AX

www.cream-migration.org

Child’s Gender, Young Fathers’ Crime, and Spillover Effects in Criminal Behavior

Christian Dustmann[*] and Rasmus Landersø[†]

May 2018

Abstract

This paper studies whether an exogenous reduction in the criminal activity of one individual lowers crimes committed by other young men who live in the immediate neighborhood. Using the randomness of a child’s gender, we first show that men who father their first child at a very young age are convicted of significantly fewer crimes in the first years after the birth if the child is a son rather than a daughter. We next show that this leads to behavioral spillovers that significantly reduce criminal convictions among other young men living in the same neighborhood as the father at the child’s birth, as well as victimization rates, for at least five years after birth. Evaluating our estimates within a structural model shows that spillovers in crime generate crime multipliers that continue to increase even after the primary impact of the initial shock on the focal individual has dissipated. From the model we further illustrate that crime prevention policies that target high crime individuals at an early stage of their lives are likely to lead to far larger reductions in the cost of crime than suggested by the primary effects alone.

[*] Department of Economics, University College London and Centre for Research and Analysis of Migration (CReAM), c.dustmann@ucl.ac.uk

[†] Rockwool Foundation Research Unit, Copenhagen, rl@rff.dk

1. Introduction

Understanding which mechanisms lead to within-group spillovers in criminal behavior is essential for the optimal design and cost effectiveness of crime prevention policies. Yet, in any such analysis, the researcher must overcome several obstacles, among others the non-random selection into groups (Blume et al., 2015). This is in essence the selection problem studied by Heckman (1979) and Heckman and Robb (1986). It has been addressed in previous work by examining whether crime of one individual varies with crime in a quasi-random reference group in research designs based on (re-)allocation experiments (e.g., Ludwig and Kling, 2007, Damm and Dustmann, 2014).[1] However, these designs do not establish whether an individual's behavior is influenced by the *behavior* or by the *characteristics* of other group members.[2] Identifying these mechanisms separately is, nevertheless, crucial as only the former gives rise to multiplier effects, which are fundamental for group dynamics studied in economics (e.g., Glaeser et al., 1996; 2003), sociology, and criminology.[3]

In this paper, we propose a novel design to estimate the spillovers from criminal behavioral interactions. The basic idea that underlies our identification is to reverse the experiment: rather than studying how variation in the composition of the reference group affects an individual's behavior, we study how an exogenous change to one focal

---

[1] See also Case and Katz (1991) for an early non-experimental study, and Carrell and Hoekstra (2010), Deming (2011), Sacerdote (2001), Kremer and Levy (2008), Drago and Galbiati (2012), and Billings et al. (2016) for related work.

[2] These two distinct reasons for spillovers are often labelled *endogenous* and *exogenous/contextual* social interactions (Manski 1993, 2001), respectively. In contrast, *correlated* effects are not based on social interactions but on group members facing the same environment.

[3] See e.g., the Social Bond Theory (Hirsch, 1963), the Social Control Theory (Gottfredson and Hirschi, 1990), and studies of group dynamics in crime (Thrasher, 1927; Short and Strodtbeck, 1965; Papachristos, 2009).

individual's criminal behavior in a fixed group affects the other group members. Any response of other individuals in the group following one individual's exogenous change in criminal behavior must then be due to behavioral interactions.

The key challenges in implementing such a design are to identify exogenous variation in the criminal behavior of one individual, and to measure the impact this has on peers. Based on administrative data from Denmark, our research design uses the gender of a firstborn child as an exogenous event that induces variation in young fathers' criminal behavior.[4] Our study focuses on males who father a child between the ages of 15 and 20, an age range in which crime rates peak. Fathering a child at such young age is unusual and signals both adverse characteristics related to risky behavior and a general disadvantaged background, and these young males are a particularly high crime group.

We find sizeable and significant effects of having a son vs. a daughter on young fathers' crime, measured either as convictions or charges for crimes committed in the years after the child's birth. Specifically, the probability of being convicted for a crime is about 19% lower for fathers of boys than girls in the first year after the child's birth, an effect that remains significant for three years after becoming a parent.

Having identified a response to child gender from the young fathers, we then investigate whether birth of a son rather than a daughter leads to changes in the criminal

---

[4] Several papers find that parents respond to child's gender. Bennedsen et al. (2007) use gender of first born to instrument CEO family successions in Danish firms. Warner (1991), Warner and Steel (1999), and Oswald and Powdthavee (2010) show that parents sympathize more with female rights and vote more liberal when they have a girl rather than a boy. Washington (2008) shows that legislators' number of daughters affects voting behavior, particularly on reproductive rights. Dahl and Moretti (2008), Lundberg and Rose (2002, 2003), Mammen (2008), and Morgan et al. (1988) show that young men who father a boy behave differently along various dimensions. Maurin and Moschion (2009) use children's gender composition as exogenous variation in female labor force participation to study spillovers of labor force participation between neighbors.

behavior of a father's neighborhood peers, defined as all young men within an age range of ± 3 years from the father's age who lived in the father's immediate neighborhood before the child is born.[5] While there are no differences in peers' crime before the child is born, we show that the birth of a boy rather than a girl reduces the probability of a crime conviction for peers from 6.29% to 5.85% in the first year after childbirth (7.3% relative to the sample mean). The effect increases (and remains significant) for at least five years after birth. We further demonstrate that the child gender effect is driven by fathers with pre-birth characteristics that are highly predictive for crime, and that peers' responses are similarly concentrated in the neighborhoods of fathers with these characteristics. We also show that, apart from criminal behavior, peers' behavior is unrelated to child's gender, implying that the spillovers do run through crime.

Moreover, we analyze victimization rates constructed from individual crime reports. Victimization is a more robust measure of crime, as crime convictions and charges only record crimes for which the offender is identified. There are no differences in the *pre-birth period* between victimization rates in neighborhoods of young men who father a boy and a girl but significant gaps emerge post-birth. We also study responses to child gender for fathers who are between 21 and 25 years old when their first child is born. Contrary to very young fathers, the observable characteristics of fathers between 21 and 25 are similar to males within the same age range in the general population. We find no effect of child gender on neither their crime nor on their labor market outcomes. This non-response

[5] Our findings are robust to alternative definitions of the peer group. For instance, effects are similar when we define peers as males who are age 14-25 at the time of childbirth and live in the father's neighborhood at child's birth.

provides us with a “placebo” test by studying whether there are any associations between child gender and peers’ crime or victimization rates for this group of fathers. We find none.

In a last step, we use a structural model of social interaction to interpret our estimates, complementing the frameworks from Blume et al. (2011), Blume et al. (2015), Bramoullé et al. (2009), and Glaeser et al. (2003). We show that the *social multiplier* equals a Wald estimator with the direct response of one focal individual to an exogenous event as first stage in the denominator and the aggregate response on group level in the numerator. We estimate the social multipliers in crime in years 2 and 3 after childbirth in the range of 4.7-5.4. Hence, a reduction in a young father’s crime by one crime will in the following years result in a total of 5 fewer crime convictions to him and his peers because the effects of the initial reduction continue to bounce back and forth between peers. These multipliers are in the range of those estimated by Glaeser et al. (2003). We use our estimates to quantify the potential benefits, including those from social interactions, of reducing the crime of young males with risk-markers that are often observable to policy-makers, police, and social workers. Evidence in Heckman et al. (2010) and Elango et al. (2015) illustrates large benefits from early childhood interventions to children with disadvantaged backgrounds, among others due to later crime reductions. We add to that, by showing that social multipliers substantially increase the benefits of crime reductions, and lead to larger reductions in the costs of crime than suggested by the primary effects alone. For individuals with a similar disadvantaged background as the young fathers in our sample, the total benefits accumulate to almost $140,000 per crime avoided within the first five years.

The paper’s main contribution is to the literature on spillovers in delinquent behavior. Our design allows us to establish the existence of *behavioral* social interactions in crime - a fundamental prerequisite for the existence of social multipliers in crime, which to our knowledge has not been empirically established previously.[6] We further complement previous frameworks describing spillovers in social networks (see Blume et al. 2010, Blume et al. 2015, Bramoullé et al. 2009) by outlining a model of spillovers in crime and estimating the key parameters, on the basis of which we simulate the potential benefits from crime avoidance programs aimed at individuals with circumstances that predict a high likelihood to offend later in life. Our analysis speaks furthermore to the literature on crime networks (see e.g. Ballester et al., 2006, 2010; Lindquist and Zenou, 2014). We show that the core assumed mechanism here, the spillover of one individual's *behavior* onto that of other agents, is indeed present in crime networks.

The paper is structured as follows: In Section 2 we describe the institutional settings of criminal justice in Denmark, as well as our data and samples. In Section 3 we outline our empirical approach to identify the effects of child gender. In Section 4 we first confirm the randomness of child gender using balancing tests. We then present the effects of child gender on the father's crime, peers' crime, and victimization rates. In Section 5 we outline a model of spillovers in crime to identify social multipliers. Section 6 concludes the paper.

[6] Yet a few studies claim to do so. We discuss these claims in relation to our framework in the Appendix.

2. Background, Data, and Descriptives

2.1 Criminal Justice and Youth Crime in Denmark

The age of criminal responsibility in Denmark is 15, after which adolescents are considered fully responsible and subject to imprisonment, albeit in different facilities than adults.[7,8] We measure crime based on charges or convictions for offenses against the criminal code. Convictions, our preferred crime measure, are court rulings that a suspect is guilty.[9] Arrests, a common measure of crime in the US, are not frequent in Denmark, but Figure A1 shows that charge rates in Denmark follow the same age pattern as arrest rates in the US in both 1995 and 2000.

The Central Police Register categorizes crimes by type (see Table A1 for a detailed breakdown). Throughout the analysis, we omit traffic offenses.[10] We always relate charges and convictions to the date of crime. Figure 1 shows the probability of receiving a crime conviction by age, which peaks around age 19 to 20.

---

[7] This is high by international standards. The UK, in comparison, sets the age of criminal responsibility at 10, while only a few U.S. states have any limit, usually set between 6 and 12 years (see http://www.unicef.org/pon97/p56a.htm for more detail).

[8] See the Danish Service Act (https://www.retsinformation.dk/Forms/R0710.aspx?id=167849, accessed 02-25-2015). For an extensive overview of the youth crime justice system in Denmark, see Kyvsgaard (2003).

[9] We observe all charges and convictions even after deletion of the criminal record from the individual's file.

[10] We also define three subcategories of crime: 'property crime', 'violent crime', and the residual 'other crime' (see Table A.1). Property crime (from the most to the least prevalent in our sample) encompasses theft, fencing, aggravated vandalism, fraud, burglary, forgery, and economic crimes. Violent crime (similarly prioritized) covers simple violence (assault), severe or life threatening violence, threats, violence against or obstructing a public servant, failure to help or assist an individual in (life-threatening) danger, cohesion, and attempted murder or homicide. Other crime (in order of prevalence) includes possession of drugs, sale of drugs, possession of weapons/explosives, giving false testimony in courts, and sexual crimes (e.g., rape).

2.2 Data and Samples

We use three samples constructed from Danish full population register data: i) a sample of first time fathers, ii) a neighborhood sample, iii) a victim sample. The samples are constructed using information from seven registers; the birth, demographic, crime, income, education, occupational, and residential registers. Each register contains a unique individual identifier that allows us to merge them. Data with exact information on the date of crime is available from 1990 and onwards so we focus on children born between 1991 and 2004.[11]

2.2.1 Primary sample: The Fathers

We merge data from the birth register, which includes birth date and gestational length for all births in Denmark from 1973 onward, with the demographic register, which includes birth dates, unique identifiers of parents, and home address. We are thus able to identify each child's parents as well as the parents' date of birth. This enables us to determine whether a child is the father's first or subsequent child, the fathers' exact age at the time of childbirth, and whether the parents were living together before and after the birth. The birth date and gestational length also allows us to estimate the approximate time of conception.

We define our main sample of young fathers as all males who father their first child between 1991 and 2004 and were younger than 21 when the child was born. Crime peaks at around age 19 to 20 and has decreased by 50% by the late 20's (Figure 1), which suggests focusing on this age group. Furthermore, we also study a 5 year follow up period after childbirth, where the young fathers are still in age ranges with relatively high crime rates.

[11] Crime convictions, our main outcome, may take up to four years to process through courts/appeals. The period's upper bound is given by the most recent data: 2013=2004+5 years post-birth +4 years to process.

An important pre-requisite to our analysis is the ability to link the father to the child and its mother, made possible by the legal procedures in Denmark aimed at identifying the father for each child. In the Danish register data, a child's father is the individual given legal paternity. As default, if the mother is married or separated for less than six months, paternity is given to the husband unless the mother reports otherwise or the paternity is contested (see below). If the mother is not married at the time of the birth, she is asked to report who the father is. Once the mother and the reported father have both signed a "Care and Responsibility Declaration", paternity is formally recognized and cannot be withdrawn. If the father and/or mother do not sign a declaration within one month of the birth, the mother must inform the State Administration of likely fathers. Should she refuse to do so, she is notified of possible consequences (financial as well as those related to the child's well-being) of not conveying a father, and if withholding of information is suspected, a formal investigation is initiated. If for some reason the State Administration cannot resolve the case, it is brought to court where the mother and all possible fathers are obliged to appear, must testify to when they had intercourse, and can be subject to DNA testing.[12]

During our sample period (1991-2004) there were a total of 408,093 first time fathers, of whom 3,979 were aged 20 or below at childbirth (Stage 1). We restrict our sample to live-born children with information on both parents from birth and a minimum of

[12] Such legal recourse is rare: in 2014, only 1,803 paternity cases were brought to court, around 3 percent of total births. None were appealed to higher courts (see Statistics Denmark, http://www.dst.dk/pukora/epub/upload/17958/staa.pdf). In the full population of children born in Denmark between 1991 and 2004 (the cohorts we study), 1.85% of children have no recorded father. There is no difference in the mean share of boys in the group of children with a recorded vs. non-recorded father (0.51 for both). Among mothers aged 20 or under at childbirth, 4.12% have no assigned father, representing 10% of all cases of "no recorded father" in the full population. Again, the share of boys in the groups with and without assigned fathers is identical (the *p*-value of a test on equal shares is 0.496).

five subsequent years, resulting in 3,579 observations (Stage 2).[13] Focusing on those who can be matched to neighborhood information results in our main estimation sample of 2,803 first time fathers (Stage 3).[14] Table A2 reports the number of births, the share of boys, and t-tests for differences in share of boys by each stage of sample selection. The shares are almost identical at each stage (between 0.501 and 0.505) with no significant differences.

2.2.2 Neighborhood Sample: The Peers

The neighborhood sample consists of individuals living in the fathers' neighborhoods on January 1st of the year the child was born (i.e. before the child was born). We define neighborhoods as follows: We use groups of 431,000 geo-referenced hectare cells that divide Denmark's entire area into 9,400 small (2,296 larger) neighborhoods (Damm and Schultz-Nielsen, 2008), containing 150–600 (600–1,100) households, with 275–1,100 (1,100–2,500) individuals, respectively. The larger neighborhoods nest the smaller ones.[15] We combine the two neighborhood definitions to obtain neighborhoods homogeneous in magnitude, as the smallest neighborhoods comprise only a few housing blocks, while the larger neighborhoods may include many individuals who have no connection to the focal

[13] We lose observations (from the most to the least prevalent reason in our sample) due to individuals having just immigrated to Denmark and for whom we have no pre-birth characteristics, native and foreign born who emigrate after birth, loss of custody or child adoption, or infant death.

[14] Because our neighborhood classification is constructed in 2004 (see below), we are unable to match 441 fathers from earlier cohorts to neighborhoods. When two or more young fathers have their first child in the same neighborhood in the same year (which occurs in 154 neighborhoods for a total of 335 fathers), we exclude these. These exclusions result in a loss of 776 observations. We limit our results to the sample that can be matched uniquely to a neighborhood in a given year to ensure compatibility with the neighborhood analysis, but we report also results for father's crime for the full sample, which are very similar.

[15] The cell aggregation identifies compact clusters while maximizing homogeneity in type of housing and ownership, and number of inhabitants within each grid. The neighborhoods are constructed by maximizing an objective function of the following criteria in order of priority: inhabited by at least 150 and 600 households (small and large neighborhoods, respectively), unaltered across years, delineated by physical barriers, comprising a contiguous cluster of cells, compact, homogeneous in type of housing and ownership, relatively small, homogeneous in number of inhabitants (see Damm and Schultz-Nielsen, 2008, for further information).

individual. We link unique identifiers of home addresses within each neighborhood with the unique individual identifiers in the full population demographic register. Hence, we identify *all* individuals in each neighborhood in a given year, including each young father and his potential peers. We discard focal individuals and their family members from the neighborhood sample. We also remove the 154 neighborhoods in which more than one father from our main sample had his first child the same year (included in robustness checks). We define 'peers' as all males ± 3 years from the father's age who lived in the neighborhood the year the child is born. This resulting sample contains 101,132 males from 2,114 different neighborhoods, and each individual is linked to the crime registers. The age range has been chosen based on an analysis of age differences between offenders in crimes for which two individuals have been charged. We show the age-difference distribution in Figure A2. Alternatively, we define 'peers' as all males between 14 and 25 at the time of the child's birth. In both cases the match is as of January 1st of the year the child is born, no matter whether fathers or peers move out of the area after that date.[16]

Figure A3 shows the distributions of peer group sizes. Most neighborhoods include around 20-40 males ± 3 years of fathers' age and 30-60 males age 14-25 at the child's birth.[17] The tails contain very large neighborhoods where measures of spillover effects are likely diluted by the inclusion of irrelevant peers and very small neighborhoods where many relevant peers may be excluded. To enhance the homogeneity of neighborhood sizes

[16] Neighborhood samples are thus fixed irrespective of subsequent mobility in or out of neighborhoods. There are no child-gender differences in fathers' and peers' mobility away from neighborhoods after childbirth.
[17] The mean, median, and standard deviations for number of individuals in each of the two different peer definitions are as follows: Males plus/minus three years of fathers: mean 36, median 28, std. dev. 29. Males age 14-25: mean 67, median 50, std. dev. 55.

and to avoid potential confounding influence of outliers, we exclude the 5% largest and smallest neighborhoods from our main estimations resulting in a sample of 82,475 males in the age range ± 3 years of fathers' age. Including all neighborhoods except the largest 1% produces similar results, as we show below. [18] We also show results for peers of first-time fathers aged 21-25 (sample constructed as described for young fathers). As these fathers do not respond to the child's gender, we do not expect any response from their peers.

2.2.3 Victim sample

Since 2001, the Danish register data also contains information about individuals who report having been the victim of a crime. Matching victim information to neighborhoods in which a first child was born to a young father from 2001 to 2004 results in 702 different neighborhoods with a total of 717,358 individuals living in them. Because each reported crime is registered with a unique individual identifier for the victim and the reported date of the crime, we can match an address to each victim. We thereby identify the exact number of individuals within a given neighborhood who were victims of a crime and relate the date of the crime to the date at which a young male in that neighborhood fathered a child. Our victim sample includes *all* individuals who lived in the same neighborhood as the father as of January 1st of the year when the child was born, no matter whether they leave the area after childbirth. Again, we exclude the smallest and largest 5% of neighborhoods to avoid

[18] Percentiles of neighborhood size are defined based on the number of 14-25 year olds. Defining size by all inhabitants or peers age ± 3 years of the fathers yield very similar delimitations, as the correlation between percentiles based on 14-25 year olds and all inhabitants is 0.92 and between percentiles based on 14-25 year old and peers age ± 3 years of the fathers is 0.93.

any potential confounding influence of outliers, thereby arriving at a sample of 524,314 individuals. We also generate a victim sample for fathers aged 21-25.

2.3 Descriptive Evidence

2.3.1 Sample characteristics

Figure 2A shows the age distribution of the young fathers and corresponding mothers at the time of the fathers' firstborn child. Whereas our sample selection truncates the distribution of fathers at age 20, the age distribution of the mothers is quite symmetric around age 20, with a sizeable fraction being over 20 at childbirth.[19] The fathers studied here are far younger than the modal age of 29 revealed by our distribution plot of first time fathers in Denmark between 1991 and 2004 in Figure 2B.[20] This deviation from the norm is reflected in Table 1 which shows summary statistics for the main sample of fathers in the first column and differences in these characteristics across child gender in the second column. Column 3 presents the *p*-value for the null hypothesis that these characteristics are the same between fathers who father a boy vs. a girl. None of these background characteristics differ significantly by children's gender; something we come back to in Sections 3 and 4.

For comparison, the fourth column shows characteristics for a random sample of males from the full Danish population who were of the same age in the same year. This reveals stark differences in average characteristics to our sample of young fathers shown in column one. Young fathers have less schooling and are far more likely to be redshirted

[19] We find no significant differences in the effects of a child's gender on fathers' crime across mothers' age.
[20] There were no nationwide initiatives to young parents from 1991-2004, apart from the general services that all parents receive: pre-natal ultrasound screening, GP / mid-wife counseling, and post-natal home-nurse visits.

during school (from delayed school entry or by repeating a grade). The share of non-natives is more than threefold the share for equally aged males, they have lower wage income, and their fathers and mothers have lower employment rates, higher unemployment rates and fewer years of schooling.[21] All this suggest that individuals who father a child at a very young age are from disadvantaged backgrounds. Figure A4 illustrate that this deprived family background existed throughout the young fathers' childhood, with their parents' employment rates consistently below employment rates of average young males' parents, and with young fathers' parents being less likely to be married or cohabiting.

2.3.2 Crime and convictions

We define *crime* as any criminal act for which the individual is later convicted. Alternatively, we measure crime as charges. We measure victimization as a reported crime against a person or his/her property, no matter whether the offender was identified or not. Our precise information on date of birth and crime allows us to determine the exact time between a birth and a given crime. Using this, we construct variables for being convicted (charged) of a crime and the number of convictions (charges) for crimes committed within the first, second, third, fourth, and fifth year after childbirth.

Table 2 reports the fractions of individuals who committed any crime for which they were later convicted before the child was conceived, for young fathers, male family members, and other young males in the neighborhood (columns 1, 3, and 5, respectively). In columns 2, 4, and 6 we report the equivalent means for random samples of males from

[21] The 14.2% of young fathers with non-native background consist of 7.92% of Turkish, 1.50% of (Former) Yugoslavian, 0.82% of Pakistani, 0.68% of Lebanese or Palestinian, and 0.96% of European origin. The remaining 2.35%-points are of various non-western backgrounds.

the overall population matched by age and year to the young fathers (column 2), from the full population (column 4), and where we match young men in neighborhoods where the father lives at childbirth to young males from the overall population, by age and year (column 6). A comparison across columns shows that not only are the young fathers highly prone to commit crime (34% carry a conviction for a crime committed before the pregnancy compared to 12% of equally aged males in the same years), they also come from families whose other male members have a high conviction probability (30% vs. 16% for the overall Danish male population). [22] The crime conviction rate for other young men in the neighborhood who are aged 14-25 at childbirth are with 17% substantially below young fathers' rate, but roughly 5 percentage points (40%) higher than the average of 14-25 year olds with a similar age by year profile. Thus, young fathers live in neighborhoods with peers that are more crime prone than the average young male.

This suggests that young fathers are particularly predisposed to criminal activities, and that they come from crime prone and disadvantaged families. Further, peers in neighborhoods where the father lives when the child is born are more likely to carry convictions compared to similar youths in Denmark, but the young fathers themselves are among the most criminal individuals, even in these neighborhoods. Young fathers' pre-pregnancy crime convictions also predict post-birth crime (Table A3), and many young fathers commit crime after the birth of their first child (and continue to have higher crime rates than their peers, cf. the outcome means presented in Tables 3 and 5 below).

---

[22] Average crime rates in Denmark (Scandinavian countries) are almost on level with those in the US (pp. 207 in OECD, 2005 and http://www.oecdbetterlifeindex.org/topics/safety/), but with differences in specific crime types such as gun violence and homicides.

3. Empirical Approach and Identification of Child Gender Effects

In our empirical analysis, we proceed in three steps. First, we estimate the average effect of the birth of a boy vs. a girl on young fathers' crime. Then we analyze how this same event affects the crime of young males living in the fathers' immediate neighborhood when the child is born. Finally, we estimate the effects on victimization in these neighborhoods.

We measure crime $\mathrm{y_{it}}$ as either the probability that individual *i* has committed a crime for which he is convicted (charged) or the *number* of crimes for which he is convicted (charged) in year t after childbirth or accumulated from the birth until year *t*. We estimate regressions of the following form:

$$\mathrm{y}_{it}^{F} = \alpha + \beta^{\mathrm{F}}\mathrm{G_i} + \mathbf{X}_{i,-1}\boldsymbol{\gamma} + \mathrm{u_{it}}, \qquad (1)$$

where the dummy $\mathrm{G_i}$ for child gender equals 1 if the child is a boy and zero otherwise. β^{F} is the parameter of interest. It measures the average causal effect of child gender on crime outcomes.[23] The vector $\mathbf{X_{i,-1}}$ collects variables that represent individual-specific or family characteristics, measured at the time of the child's conception.[24] Given the exogeneity of child gender (i.e. that $\mathrm{E(u_{it}|G_{i0}) = Cov(G_{i0}, \mathbf{X_{i,-1}}) = 0}$), these variables do not affect the point estimates but only improve precision.

In the second step, we seek to identify spillovers from the effect that child gender has on fathers onto young males living in the neighborhood. Here, we focus on all males ± 3 years of the father's age, or alternatively all males age 14-25 at childbirth. We estimate:

---

[23] We report heteroskedastic-consistent standard errors for all regression results.
[24] The vector $\boldsymbol{X_{i,-1}}$ includes father's and mother's age, preconception cohabitation status, years of schooling, and income (if any), as well as indicators for crime convictions in the father's family before the child's conception.

$$y^{\mathrm{P}}_{\mathrm{jt,n(i)}} = a + \beta^{\mathrm{P}} \mathrm{G_i} + \mathrm{v_{jt}}, \qquad (2)$$

where $y^{\mathrm{P}}_{\mathrm{jt,n(i)}}$ measures convictions/charges of peer j, or whether peer j has been convicted/charged at least once, t years after the child's birth in neighborhood $n(i)$ where father i is living when the child is born. The parameter β^{P} is the difference in peers' crime between neighborhoods where the child is a boy and where it is a girl.

Importantly, the parameters β^{F} in (1) and β^{P} in (2) measure not only the direct effect that child gender has on fathers' crime and peers' crime via the fathers' responses, but also subsequent recursive effects through peers influencing each other, which may be more persistent than the direct effect itself. Hence, estimates are scaled up by a social multiplier that depends on the dynamics of social connections and criminal behavior in peer groups.[25] We will formalize these relationships in Section 5.1.

We run similar individual level regressions for the victim sample, with the dependent variable $y^{\mathrm{V}}_{\mathrm{jt,n(i)}}$ representing whether individual j living in neighborhood $n(i)$ at January 1st in the year the child was born was a victim of crime in year t after the child's birth. Finally, we investigate heterogeneity in fathers' response to child gender and in spillovers to peers by including interactions between child gender and pre-birth characteristics in equations (1) and (2), respectively.

[25] Glaeser et al. (2003) define social multipliers as a recursive series of spillovers between all individuals in a network. Alternatively, Dahl et al. (2014) analyze one-way spillovers. In both settings, multipliers depend on how individuals are linked and whether spillovers are one-way or recursive.

4. Results

4.1 Balancing tests

The key assumption for our identification strategy is that child gender is unrelated to preconception characteristics of the father. The 0.505 share of boys in our sample of 2,803 children is very similar to the 0.502 share of boys in the population of all 408,093 first born children born between 1991 and 2004 (*p*-value of 0.72), which is a first indication of no selective determination of fatherhood based on child gender in our sample (see Table A2). As a first balancing test of this assumption, we inspect differences in characteristics between fathers of boys vs. fathers of girls (Table 1, column 2) and *p*-values (column 3). We find no significant differences between characteristics of the fathers or their parents.

As an additional test, in Table A4 we first predict the father's probability of receiving a crime conviction in the first five post-birth years using different sets of preconception explanatory variables and then regress these predictions on child's gender. All estimated coefficients are insignificant and close to zero regardless of whether we only focus on individual characteristics of the father before the child is conceived or include characteristics of the father's parents and his neighborhood. Hence, child gender is not correlated with observable characteristics predicting future criminal behavior. We also regress child's gender directly on these same three different sets of covariates for both mothers and fathers (Table A5). We find no evidence suggesting that covariates are significantly related to child gender: *p*-values range between 0.37 and 0.77.

One further possible concern is selective abortions, which could induce a correlation between child's gender and father's criminal propensity. Our balancing tests above and the similarity between the share of boys in our sample and in the overall population suggest that this is not the case. Moreover, abortions motivated by gender are practically impossible in Denmark. Whatever the reason, abortion is only possible up until week 12 of the pregnancy, after which only abortions by medical indication are legal. We nevertheless test for whether selective abortion could be a confounding factor. Table A6 reports estimates for all relevant abortions in terms of gender selectivity. The results show that mothers' previous abortions are not significantly associated with their live-born children's gender.

While the results above illustrate that the gender of the child is exogenous in the population we consider, a further concern could be that the courts decide differently on a case depending on whether the individual is father to a son or a daughter. However, in cases where judges consult a summary of offenders' background, it is only done to assess the type of sanction/punishment the offender should receive (Johansen, 2012), but not the question of guilt, which is our main outcome. We nevertheless address this further by alternatively using *charges* rather than convictions as an outcome variable. Charges are levied at police level at the site of the crime and/or when the offender is apprehended, and cannot depend on the gender of an individual's child, because police in the field only have information of criminal records and not of children and marital status.[26]

4.2 The Effect of Child Gender on Father's Crime

In Figure 3 we provide a first visual analysis of the effect of child's gender on the father's crime conviction rate. The figure shows the accumulated number of crime convictions of

[26] We have also regressed the ratio of convictions to charges on the child's gender. That coefficient in year one after the child's birth is -0.001 (std. error 0.031).

young fathers from three years prior to their child's birth to five years after it, distinguishing between the fathers of boys (solid line) vs. girls (dashed line).

Prior to the child's conception, there are no differences between the average number of crime convictions for individuals who will later father a boy vs. a girl. After the child is born (indicated by the zero line), however, the two crime conviction rates diverge and the difference increases slightly over the next five years, with fathers of boys accumulating fewer crime convictions than fathers of girls. Sixty months after conception, fathers who had a boy have roughly 0.12 fewer crime convictions than fathers who had a girl.

We provide more detail in Panel A in Table 3, where we present estimates of the effect of child's gender on the *probability* of being convicted for a crime for each of the first five years after the child's birth.[27] We report yearly and accumulated effects measured from the date of childbirth. Panel B shows the estimated child gender effect for the *number* of crimes. The table's first column summarizes the effect of having a girl vs. a boy on crime in the year *before* estimated conception, which serves as a placebo test for unobservables affecting gender as well as crime propensities. As already suggested by Figure 3, these latter estimates are small in every specification and insignificant throughout.

For post-birth years, rows 1 and 2 in Panel A show a 2.5 to 3.3 percentage points reduction in the probability of being convicted of a crime in the first three years when the child is a boy rather than a girl. As 13.5% are convicted of a crime in the first year after the child's birth (see Table 3), this implies a 19% reduction in crime conviction probabilities

[27] All results are robust to inclusion of year-of-childbirth fixed effects. Results are also robust to excluding observations for specific years of birth (i.e. excluding data for children born in 1991, 1992,..., 2004).

for fathers of sons rather than daughters. The effect increases slightly in year two, decreases again in year three to 2.3 percentage points, and fades away in later years. The accumulated effect remains significant at the 1% level until three years after the child's birth, with an effect size of about 4.4 percentage points in year three.[28] From Panel B we see that the estimated effects on the number of crime convictions are larger and more persistent than for the probability of receiving a crime conviction. In the years after childbirth, fathers of boys receive on average 0.12-0.13 fewer crime convictions than fathers of girls.[29]

Table 4 presents further specifications and robustness checks. Again, the first column shows the placebo results obtained from regressions one year before conception. Rows 1 and 2 report estimates when using charge probabilities and counts as dependent variables. Charges are a noisier measure of crime behavior than convictions, but are unrelated to any potential bias in the judicial system towards fathers of boys vs. girls as mentioned above. Overall, results are similar to those in Table 3.

During the first post-birth year, convicted individuals spend an average of two weeks in prison, with the most prone to crime being the most incapacitated by imprisonment. In row 3, we proxy how large the gender effect would be in each post-birth year if incapacitation through imprisonment had not occurred by dividing the (accumulated) number of convictions by the fraction of the year that the individual is not incarcerated. The resulting estimates are slightly larger, albeit overall similar. Finally, in rows 4 and 5 we present results using the entire sample of young fathers, including those

[28] Because the table reports probabilities, the year effects do not sum up to the accumulated effects.

[29] In Table A7, we break overall crime down into crime types and find reductions for all crime types.

we cannot match to a neighborhood, and fathers from neighborhoods where we have two observations in the same year. Again, estimates are very similar to those of the main specification.

In Panel C of the table, we report estimates for mothers. Here, we cannot detect any response. Also, crime rates of mothers are lower than those of fathers, although still above those of comparable females drawn from the overall population.

In Panel D we report findings for fathers who were 21-25 years old at childbirth. The estimates show that these fathers do not respond to their child's gender. This could either be related to compositional effects, the fact that older fathers are beyond the peak age of crime, or simply because the behavioral responses we illustrate above are age related (we investigate this further in Section 5.1).[30] The group of very young fathers on whom we focus seems therefore well suited to study possible spillovers, due to their strong responses to child gender, their high criminal propensities, and disadvantaged background. This is illustrated in Figure 4 where we plot crime the first year after the birth of first child by fathers' age and child gender. While we see large differences for very young fathers, fathers' post-birth crime rates are exactly alike once age at first child is higher than 20.

To further investigate who the young fathers who adjust their criminal behavior according to their child's gender are, Table A9 shows the average 'complier characteristics' (see e.g., Almond and Doyle, 2011). These are computed by treating child gender as an

[30] Table A8 reports fractions of individuals with a crime conviction for fathers age 21-25 (crime committed before the child was conceived), their equal aged neighborhood peers, and a random sample of equally aged males. Crime conviction rates of fathers age 21-25 are much lower than those of very young fathers (see Table 2), and at par with equally aged neighborhood peers and equally aged males in the full population.

instrument for whether young fathers' receive a crime conviction after childbirth.[31] Table A9 shows that young fathers who respond to their child's gender by changing criminal behavior come from even more disadvantaged backgrounds than young fathers on average. They have lower wage income prior to childbirth, and are more likely to have non-native origin, grown up in low SES families, parents whose education do not exceed compulsory schooling, been redshirted in primary school, and a crime conviction before the conception of their first child.

Table A10 shows responses to child gender other than criminal behavior (and similar to those examined in studies such as Lundbergh and Rose, 2002, 2003, and Dahl and Moretti, 2008). Having a boy rather than a girl increases the probability of employment or education enrollment, and makes fathers who were previously not cohabiting with the mother more likely to move in with her. Also, having a boy reduces the probability of the father having another child in the year following the birth, it increases in the period between the first and next child, and, in couples not cohabiting at the time of the birth, it increases the likelihood that the father holds the custody over the child. All this points towards a more "responsible" conduct when the child is a boy and is indicative for a role model behavior towards sons, discouraging young fathers from engaging in criminal activity.

---

[31] Average complier characteristics are given by: $\frac{\pi_c+\pi_a}{\pi_c}[E(X|y^F=1,Z=0)-\frac{\pi_a}{\pi_c+\pi_a}E(X|y^F=1,Z=0)]$ where y^F is an indicator of fathers' crime post childbirth, Z is child gender (girl=1), π_a is the fraction of fathers of boys who commit crime, π_n is the fraction of fathers of girls who do not commit crime, and $\pi_c=1-\pi_a-\pi_n$ is the fraction of fathers who commit crime after childbirth if they have a girl but not if they have a boy.

4.3 The Effect of Child Gender on Crimes Committed by Others

We now turn to the question of whether young fathers' crime-related responses to the birth of a son or daughter spill over onto other young men living in the immediate neighborhood. To do so, we estimate equation (2) for males living in the father's immediate vicinity in the year of the child's birth and who are $\pm$ 3 years of the father's age. We run all regressions on the individual level and cluster standard errors by neighborhood.

Figure 5 illustrates the evolution of the average monthly number of crime convictions for peers who lived in the father's neighborhood at January 1st of the year when the child was born, from 24 months pre-birth up until 5 years post-birth, with the solid and dashed lines representing neighborhoods in which a boy or girl is born, respectively. Whereas no differences in average crime conviction rates are observable among peers in girl-child vs. boy-child neighborhoods *before* the child's birth, *after* the event, rates drop noticeably in boy-child neighborhoods. This gap opens in the first three years post-birth and remains roughly constant until the end of the observation period.

Table 5, which has a similar structure as Table 3, reports estimates for the number of convicted criminals in the neighborhood in Panel A, year-by-year and accumulated from childbirth. Panel B reports the estimates for the number of crime convictions accumulated from childbirth. The coefficient estimates measure the difference in convicted criminals and crime convictions in the respective year *per 10 peers* when a boy is born as compared to a girl. The estimates show that, in a group of 10 peers, the number of individuals in the neighborhood convicted for a crime drops by 0.044 in the first year after the child's birth if the focal father has a son rather than a daughter. In other words, in neighborhoods where the child is a boy rather than a girl, the average probability that a peer ±3 years of the father has committed a crime for which he is later convicted decreases from 6.29% to 5.85% in the first year after childbirth. This effect is persistent and accumulates to 0.087 fewer convicted offenders per 10 individuals by year five with quite precisely determined estimates. It combines the direct spillover effect from fathers to neighborhood peers and the multiplier effect through peers affecting each other. Panel B shows that the estimates for the *number* of convictions rather than for convicted criminals are larger and continue to increase from childbirth and onwards. Once crime is broken down by type (Table A11), effects are again observable for individuals convicted for both property and violent crimes.

Table 6 reports further specifications and robustness checks. Panel A reports the same specifications using charges rather than convictions as outcome. Overall, the patterns are similar to those in the previous table, with estimates for charges being slightly larger. The results reported so far implicitly weight neighborhoods by size, thus giving more weight to neighborhoods with a larger number of peers. Yet, it is not clear whether more weight should be given to larger neighborhoods, where a large number of possibly unconnected peers may dilute estimates of potential spillovers. Hence, in Panel B, we report the same specification as in Table 5, but we now assign equal weight to all neighborhoods, regardless of neighborhood size (row 2), and consider all neighborhoods, except for the 1% largest ones (row 3). Estimates are again very similar to those in Table 5. In Panel C of the Table, we report results for an alternative and broader definition of the peer group. Here we include all individuals who lived in the father's neighborhood at birth and were between the age of 14 and 25 at the time of childbirth. Despite this different definition, the overall pattern of estimates is very similar to that in the other specifications.

Estimates are slightly smaller, which may be due to the broader definition of the peer group. In the last panel of the table, panel D, we report results for peers of fathers who were age 21-25 at the birth of their first child. As we have illustrated above, older fathers do not respond to child gender in terms of their crime, and are far more similar to their peers in terms of family background and criminal behavior. Hence, we should not expect any change in peers' convictions for these fathers, which is exactly what the estimates in rows 7 and 8 show. Neither the number of convicted criminals in the neighborhood nor the number of crime convictions differs by child gender for this age group.[32]

In Table A12, Panel A, we investigate whether child's gender is related to peers' educational attainment or labor market outcomes, estimating similar regressions as for fathers, and displayed in Table A10. If child gender had an impact on other outcomes of peers than crime, then this could suggest that the spillovers are not behavioral spillovers from criminal behavior, but rather fathers' behavior more broadly or even peers' direct response to the child's gender. The results in Panel A reject this hypothesis: all estimates are close to zero and insignificant, pointing at criminal behavior itself as the major channel of spillovers.

4.4 Father's crime propensity and spillovers

We illustrate above that our sample of young fathers consists of young men who are particularly crime prone, with more than one in three having had a conviction before the child is conceived. However, not all fathers are potential criminals. Obviously, only fathers

[32] Panels B and C in Table A12 show results on labor market outcomes and education for young fathers' peers age 14-25 and for the peers of fathers age 21-25. Table A13 summarizes placebo estimates for different crime measures and different peer group definitions of older fathers. We find no significant child gender differences.

who commit crimes can respond to the child's gender, and only in those neighborhoods should we expect responses by peers. To investigate this further, we create a variable measuring an individual's pre-conception crime propensity, by constructing an index of "crime potential" that combines pre-conception information on the individual himself with that of the family and the immediate neighborhood, and normalize this index to range between 0 and 1.[33]

In Table 7, we provide estimates for fathers (Panel A) and peers (Panel B) where we distinguish between fathers (neighborhoods with fathers) with a normalized index smaller and larger than 0.6 to proxy low and high crime potential. The estimates show that the impact of son vs. daughter on fathers' crime convictions is far more pronounced for those fathers whose crime propensity is high. The estimates also show that it is exactly in those neighborhoods where fathers who have a high crime propensity live where peers respond as well, which re-enforces our hypothesis that the effect on peers works through fathers' crime response.

4.5 Crime Measured by Victimization Rates

We next turn to the effects on victimization. Our dependent variable is now whether an individual living in the father's neighborhood of residence at January 1st of the year the child is born reported being a victim of crime in any of the subsequent five years. Because

[33] We estimate the crime index by running a principle-factor model on pre-conception crime variables and subsequently rank the predicted factor values from 0 to 1. We estimate the factor model using a jackknife procedure excluding each father from the estimation that is used to create his predicted factor. The crime index is balanced by child gender (p=0.79 for a t-test of difference in means).

victimization data is only available from 2001 and onwards, we explore the relation between child's gender and victimization using only a subset of the years previously used.

Figure 6 gives a first visual impression of how the gender of the child affects victimization. In the two years before the child's birth, there is no difference in monthly victimization rates between neighborhoods with girls and boys. However, after the birth, the two lines diverge, with victimization rates being higher in neighborhoods with girls.

We investigate this further in Table 8, which displays the estimated effect of child's gender on yearly reported victimizations for all potential victims living in the neighborhood when the child was born. These estimates show a difference in reported victimizations in the post-birth years, which accumulate until year five. Specifically, if the focal father has a boy rather than a girl, there are 0.057 fewer victimizations per 10 individuals within the first five post-birth years. These findings therefore support our results that there are fewer crimes in neighborhoods where the young father's child is a boy rather than a girl.[34]

5. Interpretation and Implications

We show above that child's gender induces exogenous variation in young fathers' crime, which in turn creates spillovers to the crime of young fathers' peers and changes in victimization rates in their neighborhoods. These findings confirm behavioral spillovers in

[34] In Table A14 we present estimates by crime type. The effects are particularly pronounced for violent crimes, which is not surprising given that property crime in the victimization data does not cover crimes directed at commercial property (e.g., shoplifting). Hence, the magnitude of the estimates relative to mean victimization rates in Table 8 do not reflect the aggregate crime reduction but predominantly the reduction in violent crime, which constitutes approximately 15-20% of all crime convictions. In Table A13, Panel E, we report the same regressions for victimizations, but for the child gender effect of fathers who are between 21 and 25 years old at birth of their first child. As for the other outcomes for fathers age 21-25, we do not find any effects of child's gender on victimization.

criminal behavior and are in themselves intriguing. Yet, to further assess the economic and policy relevance of our results, a deeper inquiry into the underlying mechanisms is needed.

5.1 Spillovers and Crime Multipliers

To do so, we first interpret the estimates of child's gender on crime behavior of fathers and peers within a model structure. We provide a detailed derivation in the Appendix. Let the father and his $N-1$ potential peers in neighborhood g be indexed by $i=1,\dots,N$ and denote individual i's crime by y_i. The "best response" function for individual i is then:[35]

$$y_{ig} = \kappa + f_0\xi_{ig} + f_1 a_{ig} + \frac{\gamma}{P}\sum_{j=1}^{N} d_{ij,g}y_{jg} + \epsilon_{ig} \quad (3)$$

where crime y_i is a linear function of a constant κ, the crime of each of individual i's N-1 potential peers y_j and the events of having a child, and the child being a boy (switching on the binary variables ξ_i and a_i, respectively). The variable d_{ij} is a binary indicator equal to one if individual i and individual j are connected, and P is the number of peers known directly.[36] The parameter γ measures the *spillover* (complementarity) between individual $i's$ crime and that of other individuals j with whom i is connected.[37] Unobservable

---

[35] Equation (3) can be derived from an individual decision problem, constituting a unique Nash equilibrium under assumptions on preferences; see e.g. Blume et al. (2011) for a derivation.

[36] For simplicity we assume that everyone knows the same number of peers P. This is easily extended to individual sets of peers $P_i = \sum_j d_{ij}$. Similarly, variation in strength of ties could also be included by defining d_{ij} as a continuous variable between 0 and 1 instead of a binary indicator.

[37] Our estimates of social multipliers do not depend on the specification γ/P but the estimate of γ does. We use this specification because this mimics the results from Table 6, which show that effects are overall similar when we weight by neighborhood size or put equal weights to neighborhoods irrespective of size. This suggests that a 'fixed' fraction of behavior is determined by peers such that, for example, five peers are each twice as influential for one's behavior as 10 peers are. The γ/P specification does not, however, imply that spillovers are invariant across P because spillovers, all else equal, increase in the dimension of $\left(I-\frac{\gamma}{P}D\right)^{-1}$.

characteristics affecting crime are given by ϵ_i, which could include unobserved group effects or neighborhood characteristics leading to "correlated effects". Given the randomness of child's gender, ϵ_i is orthogonal to a_{ig}, so that correlated effects will not contaminate our estimates of behavioral spillovers. For the same reason, we omit here observable characteristics of the individual and his peers as factors that influence criminal behavior, with the latter giving rise to contextual effects, as these are likewise orthogonal to the child's gender and will not affect the estimated parameters and the multiplier.[38] The orthogonality of child's gender to any contextual and correlated effects is key to our identification strategy, allowing us to isolate endogenous from exogenous social effects and from correlated effects.

Equation (3) is a version of the Spatial Autoregressive model (see e.g., Bramoullé et al., 2009; Blume et al., 2011, 2015). Re-writing equation (3) using matrix notation and solving for crime, we obtain:

$$Y = \left(I - \frac{\gamma}{P}D\right)^{-1}[\kappa + f_0\Xi + f_1A + E] \quad (4)$$

where κ, Ξ, A and E are $N \times 1$ vectors and $\left(I - \frac{\gamma}{P}D\right)^{-1}$ is an $N \times N$ matrix. The Matrix D consists of elements d_{ij} and determines how peers affect each other. Equation (4) defines equilibrium crime in each neighborhood.[39]

[38] For completeness, we include them in the model derivation in the Appendix.

[39] In our setup, we think of spillovers as influences that can go back and forth between peers in a recursive manner. Hence, D is a symmetric matrix. Dahl et al. (2014), for example, consider within firm spillovers in paternity leave following the birth of the first child. Hence, there are no recursive spillovers to the focal individual in their case, and D simplifies to a matrix that contains zeros in the upper triangular.

Because the gender of the child is orthogonal to all neighborhood characteristics, the estimates of child's gender on a father's and his peers' criminal activity are given by $E(Y|a_1 = 1) - E(Y|a_1 = 0) = f_1 \left(I - \frac{\gamma}{P} D\right)^{-1} A$, where β^F and β^P are the first and the remaining elements of that vector. These are the estimates that we report in the tables above. The structural parameters f_1 (direct effect on fathers' crime) and γ (spillover parameter) can only be identified if we impose further assumptions about the social interactions in each neighborhood. We assume here that all N peers are connected, so that $P = N - 1$. The estimated reduced form effects for fathers and peers then become (see Appendix A for derivation):

$$\beta^F = f_1 \left(1 + \frac{\gamma^2}{(1-\gamma)(N-1+\gamma)}\right) \quad (5)$$

$$\beta^P = f_1 \frac{\gamma}{(1-\gamma)(N-1+\gamma)} \quad (6)$$

Equations (5) and (6) thus allow us to recover the spillover parameter γ and the child gender shock f_1 from estimates of β^F and β^P and the neighborhood size N, under the above assumptions about the matrix D. The social multiplier is then defined as:

$$SM = \frac{(N-1)\beta^P + \beta^F}{f_1} \quad (7)$$

Alternatively, we can compute a 'naïve' social multiplier:

$$\widehat{SM} = \frac{(N-1)\beta^P + \beta^F}{\beta^F} \quad (8)$$

The expression in (8) is precisely the multiplier in Glaeser et al. (2003). The 'naïve' social multiplier is attenuated if $\beta^F > f_1$. Only in designs excluding recursive spillovers, as Dahl et al. (2014), are 'actual' and 'naïve' multipliers the same.

Table 9 shows the estimates of γ, f_1 and $\widehat{SM}$. The estimate for γ lies between 0.814 and 0.895. Furthermore, the implied values of f_1 are between -0.092 and -0.114. Hence, comparing these estimates with those in the first row of the table (which restates the estimates of β^F from Table 3) shows that recursive spillovers between peers and fathers enhance fathers' responses by at least 10-20%. From the table's last row we see that the naïve social multiplier ranges between 4.8 and 7.7. Thus, social interactions increase the total effects of the initial shock substantially and the multipliers increase as time passes. This 'snowball effect' from the initial shock is in line with Dahl et al. (2014), who find that their effects are solely driven by subsequent spillovers between peers six years after an initial shock to paternity leave.

Moreover, equations (7) and (8) illustrate the relationship between, on the one hand, spillovers and social multipliers from a shock to a focal individual and, on the other hand, an IV framework. In our specific setting child gender can be thought of as an instrument for crime, young fathers' responses (Tables 3 and 4) are first stage estimates, the response of peers (Tables 5 and 6) are reduced form estimates between the outcome and instrument, and the balancing tests (Tables A2, A4, A5, and A6) and the absence of any other peer responses to child gender (Table A12) are tests of the exclusion restriction.

5.2 Potential Benefits of Reducing Young Offenders' Crime

The resources that a social planner devotes to lower crime ultimately rest on comparison of the costs associated with these, and the benefits through crime reductions, including those induced by social multipliers that we establish above. One way to quantify such benefits in monetary terms is to use estimates of *individuals' willingness to pay to eliminate one crime*, as computed by Cohen (2009). We weight Cohen's costs across crime-types by the pattern observed in our sample (see Table A.1) to estimate the average costs per crime. The results are summarized in Figure 7A. The average cost per crime committed by a focal individual is approximately \$18,000, and social multipliers increase these by almost \$87,000 within the first two years. As spillovers continue to ripple during the subsequent years, the cost of one initial crime is magnified through the multiplier to approximately \$140,000 in year 5. In Figure 7A we further use the estimates from Table 9 to separate the costs by their source for years 2-5 after childbirth.[40] The figure shows that the spillovers continue to increase as time progresses. By year 5, they constitute about 87% of costs associated with crime.

Thus, the potential benefits of reducing crime committed by individuals such as the young fathers in our sample are far larger than what the primary effects suggest. We next illustrate the potential cost-effectiveness of crime prevention programs that target particularly high crime individuals at an early stage. We use our estimates as proxies for the benefits of eliminating crime in groups with characteristics that are readily available to

[40] We monetize costs in year t of social multipliers $C(\widehat{SM}_t)$ as $\widehat{SM}_t * \$17{,}949$. From the results in Table 9, we separate these by: Initial shock f_1; Spillovers back to father $\beta_t^F - f_1$; spillovers between peers $\widehat{SM}_t - \beta_t^F - f_1$

policy makers and authorities.[41] As illustrated by equations (7) and (8), the social multipliers estimated in this paper are in essence LATEs. Generalizing our estimates to other young males therefore implies the assumption that spillover effects are homogenous for young males, with heterogeneity only arising from differences in crime given by observable characteristics (i.e. that spillovers are constant across the entire range of unobserved characteristics that affect a focal individual's crime).[42] With this in mind, Figure 7B shows the estimated benefits of eliminating crime for young men with different background information. The figure shows substantial benefits from directed crime prevention according to particular backgrounds, with the largest potential benefits from targeting males with violent criminals in their nearest family or males who have committed crime at a very young age. This illustrates the large potential gains of such policies over and above the primary effects that are achieved by eliminating spillovers effects.

6. Discussion and Conclusion

This paper uses a novel identification strategy to provide new evidence on behavioral (endogenous) social effects in crime. The strategy we pursue in this paper exogenously varies the crime behavior of one focal individual, where variation is induced by the gender

---

[41] We estimate potential benefits for group $x = 1$ as: $E(crime|x = 1) * C(\widehat{SM}_5)$

[42] This is a strong assumption, which we cannot verify. We can, however, investigate whether we can reject it within the area of support between our two treatment points "boy" and "girl". By treating child gender as instrument Z, crime conviction of young fathers after childbirth as treatment y^F, and number of convicted peers in year 5 after childbirth as outcome y^P, we test whether spillover effects differ between the margins of unobserved characteristics that affect fathers' crime at two treatment points "boy" and "girl":

$$H_0: \Delta_0 = \Delta_1, \text{ where } \Delta_j = E(y^P|y^F = j, Z = 1) - E(y^P|y^F = j, Z = 0), \text{ for } j = \{0,1\}$$

against $H_1: \Delta_0 \neq \Delta_1$ (see Brinch et al., 2017). The p-value is 0.290. Hence, we cannot reject the null hypothesis of equal spillover effects at our two points of variation.

of his first child, and measures the effect this has on other group members. Based on this design, we present strong evidence for peers responding to changes in one focal individual's criminal activity. By illustrating that child's gender-induced reduction in criminal activity likewise leads to a reduction in victimization rates, we further corroborate the findings on spillovers of crime to peers in the neighborhood. Overall, our findings not only add support to the existence of spillovers in criminal behavior, but our design allows us to conclude further that these spillovers are due to behavioral (*endogenous*) social interactions.

Our findings have important implications for the optimal approaches to crime prevention, as the cost – benefit considerations of such policies ranging from 'kingpin strategies' against organized crime to the promotion of positive role models for adolescents all depend on such interactions and the existence and magnitude of social multipliers. By using our estimates to recover the parameters of a structural model of crime interaction, we illustrate that spillovers in crime increase not only the effects of an exogenous shock to a focal individual's crime (through feedback from his peers), but they also affect peers and generate crime multipliers that continue to increase even after the primary impact of the initial shock has dissipated. We illustrate that the benefits from programs and policies that reduce crime at an early stage of a young person's life, targeted at individuals with easily observable individual and circumstantial characteristics, are far larger than suggested by the primary effects alone.

References

Almond, D., and Doyle, J.J. (2011). "After midnight: A regression discontinuity design in length of postpartum hospital stays". *American Economic Journal: Economic Policy*, 3(3), 1-34.

Ballester, C., Calvo-Armengol, A., and Zenou, Y. (2006). "Who's who in networks. Wanted: The key-player." *Econometrica,* 74(5), 1403–1417.

Ballester, C., Calvo-Armengol, A., and Zenou, Y. (2010). "Delinquent networks." *Journal of the European Economic Association,* 8(1), 34-61.

Bayer, P., Hjalmarsson, R., and Pozen, D. (2009). "Building criminal capital behind bars: Peer effects in juvenile corrections." *The Quarterly Journal of Economics*, 124(1), 105-147.

Bennedsen, M., Nielsen, K. M., Perez-Gonzalez F., and Wolfenzon, D. (2007). "Inside the family firm: The role of families in succession decisions and performance" *Quarterly Journal of Economics*, 122(2), 647-691.

Berg, M. T., Stewart, E. A., Schreck, C- J., and Simons, R. L. (2012). "The victim-offender overlap in context: Examining the role of neighborhood street culture." *Criminology*, 50(2), 1–31.

Billings, S. B., Deming, D. J., and Ross, S. L. (2016). "Partners in crime: Schools, neighborhoods, and the formation of criminal networks." NBER Working Paper No. 21962, National Bureau of Economic Research, Cambridge, MA.

Blume, L. E., Brock, W. A., Durlauf, S. N., Ioannides, Y. (2011). "Identification of social interactions". In Handbook of Social Economics, Edited by J. Benhabib, A. Bisin, and M. Jackson, 853-964. Amsterdam: North-Holland.

Blume, L. E., Brock, W. A., Durlauf, S. N., Jayaraman, R. (2015). "Linear social interaction models". *Journal of Political Economy*, 132(2), 444-496.

Bramuollé, Y., Djebbari, H., and Fortin, B. (2009). "Identification of peer effects through social networks." *Journal of Econometrics*, 150(1), 41-55.

Clark, R.V. and Cornish, D. B. (1985). "Modeling offenders' decisions: A framework for research and policy." *Crime and Justice* 6, 147–185.

Carrell, S. E. and Hoekstra, M. L. (2010) "Externalities in the classroom: How children exposed to domestic violence affect everyone's kids." *American Economic Journal: Applied Economics*, 2(1), 211–228.

Case, A. C. and Katz, L. F. (1991). “The company you keep: The effects of family and neighborhood on disadvantaged youths.” NBER Working Paper No. 3705, National Bureau of Economic Research, Cambridge, MA.

Dahl, G. B, Løken, K. V., and Mogstad, M. (2014) “Peer effects in program participation” *American Economic Review*, 104(7), 2049-2074.

Dahl, G. B. and Moretti, E. (2008). “The demand for sons” *Review of Economic Studies*, 75(4), 1085–1120.

Damm, A. P. and Dustmann, C. (2014). “Does growing up in a high crime neighborhood affect youth criminal behavior?” *American Economic Review*, 104(6), 1806–1832.

Damm, A. P. and Schultz-Nielsen, M. L. (2008). “Danish neighborhoods: Construction and relevance for measurement of residential segregation.” *National Økonomisk Tidsskrift*, 3, 241–262.

Deming, D. J. (2011). “Better school, less crime?” *Quarterly Journal of Economics*, 126(4), 2063–2115.

Drago, F. and Galbiati, R. (2012). “Indirect effects of a policy altering criminal behavior: Evidence from the Italian prison experiment”. *American Economic Journal: Applied Economics*, 4(2), 199-218.

Elango, S. Garcia, J. L., Heckman, J. J., Hojman, A. (2015). “Early Childhood Education.” in: Economics of Means-Tested Transfer Programs in the United States, volume 2, pages 235-297 National Bureau of Economic Research, Inc.

Glaeser, E. L., Sacerdote, B. I., and Scheinkman, J. A. (1996). “Crime and social interactions.” *The Quarterly Journal of Economics*, 111(2), 507-548

Glaeser, E. L., Sacerdote, B. I., and Scheinkman, J. A. (2003). “The social multiplier.” *Journal of the European Economic Association*. 1(2-3), 345-353.

Gottfredson, M. and Hirschi, T. (1990). “A general theory of crime.” Stanford: Stanford University Press

Heckman, J. J., Moon, S. H., Pinto, R., Savelyev, P. A., Yavitz, A. (2010). “The rate of return to the High/Scope Perry Preschool Program.” *Journal of Public Economics*. 94(1-2), 114-128

Heckman, J. J., (1979). “Sample selection bias as a specification error.” *Econometrica*, 47(1), 153-161.

Heckman, J. J., and Robb, R., (1986). “Alternative methods for solving the problem of selection bias in evaluating the impact of treatments on outcomes.” In *Drawing Inferences from Self-Selected Samples*, Edited by H. Wainer, 63-113. New York: Springer.

Hirschi, T. (1969). “Causes of Delinquency.” Berkeley: University of California Press.

Hirschi, T. and Gottfredson, M. (1983). “Age and the explanation for crime.” *American Journal of Sociology*, 89(3), 552–584.

Jensen, G. F. and Brownfield, D. (1986). “Gender, lifestyles, and victimization: Beyond routine activity.” *Violence and Victims*, 1(2), 85–99.

Johansen, L. V. (2012). “Vidensprocesser om den sigtedes person”, PhD Thesis, University of Copenhagen, Faculty of Law.

Kremer, M. and Levy, D. (2008). “Peer effects and alcohol use among college students.” *Journal of Economic Perspectives*, 22(3), 189–206.

Kyvsgaard, B. (2003). *The criminal career: The Danish longitudinal study*. Cambridge: Cambridge University Press.

Laub, J. H. and Sampson, R. J. (2001). “Understanding of desistance from crime.” Crime and Justice, 28, 1–69.

Lindquist, M. and Zenou, Y. (2014). “Key-players in co-offending networks.” IZA Discussion Paper No. 812, Bonn, Germany.

Ludwig, J. and Kling, J. R. (2007). “Is crime contagious?” *Journal of Law and Economics*, 50, 491–518.

Lundberg, S. and Rose, E. (2002). “The effects of sons and daughters on men’s labor supply and wages.” *Review of Economics and Statistics*, 84(2), 251–268.

Lundberg, S. and Rose, E. (2003). “Child gender and the transition to marriage.” *Demography*, 40(2), 333–349.

Mammen, K. (2008). “The Effects of Children’s Gender on Living Arrangements and Child Support.” *The American Economic Review, Papers and Proceedings*, 98(2), 408-412.

Manski, C. F. (1993). “Identification of endogenous social effects: The reflection problem.” Review of Economic Studies, 60(3), 531-542.

Manski, C. F. (2000). “Economic analysis of social interactions.” *Journal of Economic Perspectives*, 14(3), 115-136.

Maurin, E., and Moschion, J. (2009). “The Social Multiplier and Labor Market Participation of Mothers.” *American Economic Journal: Applied Economics*, 1(1), 251-272.

Morgan, S. P., Lye, D. N., and Condran, G. A. (1988). “Sons, daughters and the risk of marital disruption.” *American Journal of Sociology*, 94(1), 110–129.

OECD (2005). "OECD Factbook 2005, economic environmental and social statistics." OECD publications, Paris.

Olson, L. (1983). *Costs of children*. Lexington, MA: Heath and Company.

Oswald, A. J. and Powdthavee, N. (2010) "Daughters and left-wing voting", *The Review of Economics and Statistics*, 92(2), 213-227.

Papachristos, A. V. (2009). "Murder by structure: Dominance relations and the social structure of gang homicide." *American Journal of Sociology*, 11581), 74-128.

Piquero, A. R., Farrington D. P., and Blumstein, A. (2007). "Key issues in criminal career research: New analyses of the Cambridge Study in Delinquent Development." Cambridge: Cambridge University Press.

Sacerdote, B. (2001). "Peer effects with random assignment: Results for Dartmouth roommates." *The Quarterly Journal of Economics*, 116(2), 681–704.

Sampson, R. J. and Laub, J. H. (1992). "Crime and deviance in the life course." *Annual Review of Sociology*, 18, 63–84.

Schreck, C. J. (1999). "Criminal victimization and low self-control: An extension and test of a general theory of crime", *Justice Quarterly*, 16(3), 633-654.

Schreck, C. J., Fisher, B. S., and Mille, J. M. (2004). "The social context of violent victimization: A study of the delinquent peer effect." *Justice Quarterly*, 2(1), 23–47.

Statistics Denmark, Kriminalitet 2005 [Criminality 2005].

Short, J. F., Jr. and Strodtbeck, F. L. (1965). "Group processes and gang delinquency." Chicago: University of Chicago Press.

Thrasher, F. M. (1927). "The gang: A study of 1,313 gangs in Chicago." Chicago: University of Chicago Press.

Uggen. C. (2000). "Work as a turning point in the life course of criminals: A duration model of age, employment, and recidivism." *American Sociological Review*, 65, 529–546.

Warner, R. L. (1991) "Does the sex of your child matter? Support for feminism among women and men in the United States and Canada", *Journal of Marriage and Family*, 53(4), 1051-1056.

Warner, R. L., and Steel, B. S. (1999) "Child rearing as a mechanism for social change: The relationship of child gender to parents' commitment to gender equity", *Gender and Society*, 13(4), 503-517.

Washington, E. (2008) "Female Socialization: How Daughters Affect Their Legislator Fathers' Voting on Women's Issues," *American Economic Review*, 98(1): 311-332.

Appendix A – Model of crime (for online publication)

In this Appendix we describe in more detail the model of spillovers in crime outlined in Section 5 of the paper. Denote the father and his $N-1$ potential peers by $i=1,\ldots,N$. The "best response" function for individual i is given by

$$y_i = \kappa + f_0\xi_i + f_1 a_i + \delta_0 x_i + \frac{\gamma}{P}\sum_{j=1}^{N} d_{ij}y_j + \frac{\delta_1}{P}\sum_{j=1}^{N} d_{ij}x_j + \epsilon_i \quad \text{(A.1)}$$

Crime of individual i, y_i, is a linear function of a constant κ, the events of having a child ξ_i and the child being a boy a_i, own observable characteristics x_i, spillover effects from the criminal behavior of each of individual i's N-1 potential peers y_j and his peers' characteristics x_j. The variable d_{ij} is a binary indicator equal to one if individual i is connected to individual j.[43] While each neighborhood consists of N-1 potential peers, some of these may not be directly connected to each other. We define P as the number of peers known directly.[44] Unobservable characteristics affecting crime are given by ϵ_i, which could include unobserved group effects leading to "correlated effects". The parameter γ measures *spillovers*, the degree of complementarity between individual $i's$ crime and that of other individuals j with whom i is connected.[45] We can re-write equation (A.1) using matrix notation:

[43] This is a version of the Spatial Autoregressive (SAR) model as e.g. in Bramoullé, Djebbari, and Fortin (2009) and Blume et al. (2011). Equation (A.1) can be derived from an individual decision problem, and constitutes a unique Nash equilibrium under certain assumptions on preferences; see Blume et al. (2011) for a derivation.

[44] For simplicity we assume that everyone knows a given number of peers P. This is easily extended to individual set of peers $P_i = \sum_j d_{ij}$. Similarly, variation in strength of ties could also be included by defining d_{ij} as a continuous variable between 0 and 1 instead of a binary indicator.

[45] We use a linear specification of γ (or $\frac{\gamma}{P}$), but that could be generalized to $f(\gamma, P)$.

$$Y = \kappa + f_0 \Xi + f_1 A + \frac{\gamma}{P} DY + X\delta_0 + DX\frac{\delta_1}{P} + E \qquad \text{(A.2)}$$

where Y is an $N \times 1$ vector and Ξ and A are $N \times 1$ vectors. In the following, we have ordered the observations such that the young father is the first element. Thus, the first element of Ξ equals one and the remaining zero. In similar vein, the first element of A defines child gender taking either the value zero or one, while the remaining elements are zero. Finally, X is $N \times K$ matrix of individual characteristics. Thus, crime is given by

$$Y = \left(I - \frac{\gamma}{P} D\right)^{-1} [\kappa\iota + f_0 \Xi + f_1 A\, X\delta_0 + DX\frac{\delta_1}{P} + E] \quad \text{(A.3)}$$

In order to have a well-defined solution for Y we need $det\left(I - \frac{\gamma}{P} D\right) > 0$. In our empirical specification, we estimate effects for fathers and peers separately, using variation across neighborhoods g in the gender of the child. As A (capturing variation in child gender) is orthogonal to observed characteristics in X of both the individual and his peers (exogenous effects) and all other (non-observed) neighborhood characteristics in E (correlated effects), the estimates β^F and β^P of child's gender on a father's and his peers' criminal activity are given by $E(Y|a_1 = 1) - E(Y|a_1 = 0) = f_1 \left(I - \frac{\gamma}{P} D\right)^{-1} A$, given fathers have a boy. Because only the first element in A is equal to 1 (when fathers have a boy) and the remaining equal to zero, the reduced form parameter for young fathers in Tables 3 and 4 equals:

$$\beta^F = f_1 \frac{C_{11}}{det\left(I - \frac{\gamma}{P} D\right)} \qquad \text{(A.4)}$$

and the corresponding reduced form parameter for the peers equals the average spillovers across the $N - 1$ potential peers:

$$\beta^P = f_1 \frac{1}{N-1} \frac{\sum_{i=2}^{N} C_{i1}}{det\left(I-\frac{\gamma}{P}D\right)} \qquad (A.5)$$

where C_{i1} is the absolute value[46] of the i[th] row and 1[st] column of the adjugate matrix of $\left(I-\frac{\gamma}{P}D\right)$.

A.1 Recovering the structural parameters

The two structural parameters f_1 (the direct, immediate effect of child's gender on father's crime propensity) and γ (the spillover effect) are only identified from the two reduced form estimates of the effects of child's gender on fathers' and peers' crime subject to the assumptions we make about the social interactions in each neighborhood captured by the matrix D. We assume here that all N peers are connected. Thus, the number of known peers becomes $P = N - 1$ and the matrix $\frac{\gamma}{P}D$ will have a main diagonal of 0's and $-\gamma/(N-1)$ in all other cells. For the matrix $I - \frac{\gamma}{P}D$ it follows that $\det\left(I-\frac{\gamma}{P}D\right) = [1-(N-1)\frac{\gamma}{P}](1+\frac{\gamma}{P})^{N-1}$. Furthermore, C_{11} will be equal to the same expression, only with one dimension less: $\mathrm{C}_{11} = [1-(N-2)\frac{\gamma}{P}](1+\frac{\gamma}{P})^{N-2}$. By dividing the latter by the former as in Equation (4) and noting that $P = N - 1$, we obtain:

$$\beta^F = f_1 \frac{1-(N-2)\gamma/P}{\left(1-(N-1)\frac{\gamma}{P}\right)\left(1+\frac{\gamma}{P}\right)}$$

$$= f_1\left(1+\frac{\gamma^2}{(1-\gamma)(N-1+\gamma)}\right) \qquad (A.6)$$

[46] Note that the adjugate matrix takes the form +,-,+,-,+,-…

This expression is what Glaeser, et al. (2003) label *the individual level regression* (as opposed to an aggregate level regression where crime is only observed at group level). Next, we make use of Laplace's expansion: $\det(M) = \sum_{i=1}^{N} m_{ij} C_{ij}$. From Equations (A.4) and (A.5) we get that:

$$\det\left(I - \frac{\gamma}{P} D\right) = C_{11} - \frac{\gamma}{P} \sum_{i=2}^{N} C_{i1}$$

$$= \frac{\beta^F}{f_1} \det\left(I - \frac{\gamma}{P} D\right) - (N-1) \frac{\beta^P \det\left(I - \frac{\gamma}{P} D\right)}{f_1} \frac{\gamma}{P}$$

$$\Rightarrow \quad \beta^F = f_1 + \gamma \beta^P \qquad (A.7)$$

Hence, for a given γ we can now recover the size of the initial child gender shock. By inserting the effects for fathers β^F from Equation (A.6), we obtain:

$$\beta^P = f_1 \frac{\gamma / P}{\left(1 - (N-1)\frac{\gamma}{P}\right)\left(1 + \frac{\gamma}{P}\right)}$$

$$= f_1 \frac{\gamma}{(1-\gamma)(N-1+\gamma)} \qquad (A.8)$$

Now divide β^P from Equation (A.7) by β^F in Equation (A.6):

$$\frac{\beta^P}{\beta^F} = \frac{\gamma/(N-1)}{1 - \gamma(N-2)/(N-1)}$$

$$\Rightarrow \gamma = \frac{(N-1)\beta^P}{(N-2)\beta^P + \beta^F} \qquad (A.9)$$

This allows us to recover γ using the neighborhood size, and the estimated effects for fathers β^F and peers β^P. These estimates of the spillover parameter γ and the size of the child gender shock f_1 rest on assumptions about a particular network structure. The social multiplier can, however, be identified with reasonable accuracy without imposing any further assumptions on D and how spillover intensity γ is specified.

A.2 Social Multipliers

As we study the derived spillovers from a change to one individual's behavior and not relative to a behavioral change of all individuals in a peer group directly, we define this as the aggregate spillover effects from the initial shock f_1. With $N-1$ peers and recursive spillovers back to the focal individual, the multiplier becomes:

$$SM = \frac{(N-1)\beta^P + \beta^F}{f_1} \quad (A.10)$$

Inserting Equations (A.4) and (A.5) into equation (A.10) yields:

$$SM = \frac{1}{f_1}\left[(N-1)f_1 \frac{1}{N-1} \frac{\sum_{i=2}^{N} C_{i1}}{det\left(I - \frac{\gamma}{P}D\right)} + f_1 \frac{C_{11}}{det\left(I - \frac{\gamma}{P}D\right)}\right]$$

$$= \frac{\sum_{i=1}^{N} C_{i1}}{det\left(I - \frac{\gamma}{P}D\right)} \quad (A.11)$$

This equation states that the social multiplier equals the sum of the first column in the inverse of the network matrix $\left(I - \frac{\gamma}{P}D\right)$. Note that the social multiplier does not depend on the size of the initial shock, as the scaling parameter f_1 is netted out when the social multiplier is written in full in (A.11). Yet, we still face the problem that connections within the neighborhood and the size of the initial shock f_1 – thus all of the terms in (A.11) – are not directly observed. Using instead what we actually do observe, we can estimate a 'naïve' Wald-like statistic with the effect for focal individuals β^F instead of f_1:

$$\widehat{SM} = \frac{(N-1)\beta^P + \beta^F}{\beta^F} = \frac{\sum_{i=1}^{N} C_{i1}}{C_{11}} = \frac{N-1+\gamma}{(1-\gamma)(N-1)+\gamma} \qquad (A.12)$$

This is the social multiplier reported by Glaeser et al. (2003). While closely related to the 'actual' social multiplier in Equation (A.10), the 'naïve' social multiplier in Equation (A.12) differs in many instances. To measure the bias we consider the percentage deviation between the 'actual' and the 'naïve' social multiplier:

$$\frac{\widehat{SM}}{SM} = \frac{f_1}{\beta^F} \qquad (A.13)$$

Thus, the bias is given by the degree to which total effects for fathers β^F exceed the initial shock f_1 due to spillovers back and forth between peers and the father. By inserting the definition of β^F from Equation (A.4) we get that $f_1/\beta^F = det\left(I - \frac{\gamma}{P}D\right)/C_{11}$. As $C_{11} > det\left(I - \frac{\gamma}{P}D\right)$, the 'naïve' social multiplier will be biased towards zero, for $0 < \gamma < 1$. The 'naïve' Wald social multiplier will, furthermore, converge to the actual social multiplier as neighborhood size N and number of known peers P increase while the bias will increase in spillover intensity γ. Also, the naïve social multiplier will equal the actual one in cases with no recursive spillovers. Here, the matrix D becomes a lower triangular matrix with $C_{11} = det\left(I - \frac{\gamma}{P}D\right) = 1$. This is, however, a special case which applies only to settings as e.g., Dahl et al. (2014), who consider within-firm spillovers in paternity leave following the birth of the first child.

As a next step, we assess the magnitude of the bias of our best guess social multiplier. Figure A5 shows simulated biases (the relative differences between the 'actual' and 'naïve' social multiplier) as defined in Equation (A.13) for different neighborhood sizes and values of γ. From the figure it is evident that the bias will quickly diminish as neighborhood size (and/or number of peers) increase. Using a spillover parameter as large as implied in our estimation of around 0.8 would result in a 10% bias with a neighborhood of 30 peers, which is the mean number of peers ± 3 years in our sample, and 20% in a neighborhood of 10 peers (or a larger neighborhood but with fewer connections). Thus, the estimated naïve Wald social multiplier in our empirical analysis is likely downward biased by about 10-20%.

A.3 Relation to other studies

In a recent paper, Drago and Galbiati (2012) discuss their findings in relation to endogenous effects and social multipliers. They analyze variation in the effects of a collective pardon in Italy on crime rates after release across the average clemency of fellow inmates. Clemency was given conditional on not recidivating, thereby increasing incentives to remain law-abiding for offenders who were pardoned large proportions of their sentences. The regression estimate of individual recidivism on average clemency of fellow inmates is interpreted as behavioral (endogenous) spillovers from peers due to variation in their incentive not to reoffend. However, conditional on sentence length, clemency and time served are perfectly collinear: for a sentence length of *a* days where *b* days are served in prison, the clemency equals *a-b*. Therefore, the effects of average clemency of peers cannot be separated from the effects of time that peers have spent in prison together. Numerous studies find that inmates make connections in prison, e.g. Bayer et al. (2009) (indeed this is the same mechanism Drago and Galbiati focus on). Therefore, variation in peers' clemency, even when quasi-random, is identical to variation in time that peers served in prison and thus associated with the connections made there. Hence, the study conflates variation in D with behavioral spillovers.

Similarly Billings et al. (2016) use plausibly exogenous variation in school catchment areas and find that individuals who have more schoolmates living in their immediate vicinity are arrested more often. The variation in connections (how many youths from a given neighborhood who attends school together) corresponds to changing the matrix defining connections D and does not isolate behavioral (endogenous) spillovers.

A.4 A Simple Numerical Example

Consider a neighborhood with 6 peers where all are connected: $P = N - 1 = 5$. Let $\gamma = 0.1$; $f_1 = 0.5$. The matrices D, $-\frac{\gamma}{P}D$, and the total effects $f_1\left(I - \frac{\gamma}{P}D\right)^{-1} A$ are:

$$D = \begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

$$I - \frac{\gamma}{P}D = \begin{pmatrix} 0 & -0.02 & -0.02 & -0.02 & -0.02 & -0.02 \\ -0.02 & 0 & -0.02 & -0.02 & -0.02 & -0.02 \\ -0.02 & -0.02 & 0 & -0.02 & -0.02 & -0.02 \\ -0.02 & -0.02 & -0.02 & 0 & -0.02 & -0.02 \\ -0.02 & -0.02 & -0.02 & -0.02 & 0 & -0.02 \\ -0.02 & -0.02 & -0.02 & -0.02 & -0.02 & 0 \end{pmatrix}$$

$$f_1\left(I - \frac{\gamma}{P}D\right)^{-1} A = 0.5\left(I - \frac{\gamma}{P}D\right)^{-1} \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 0.501089 \\ 0.010893 \\ 0.010893 \\ 0.010893 \\ 0.010893 \\ 0.010893 \end{pmatrix}$$

This implies that $\beta^F = 0.501089$ and $\beta^F = 0.010893$. Next, we will show that we arrive at the same results using Equations (A.6)-(A.9). First, $\det\left(I - \frac{\gamma}{P}D\right) = [1-\gamma]\left(1 + \frac{\gamma}{N-1}\right)^{N-1}$. Inserting the values of N and γ gives $\det\left(I - \frac{\gamma}{P}D\right) = [1-0.1]\left(1 + \frac{0.1}{6-1}\right)^{6-1} = 0.993673$.

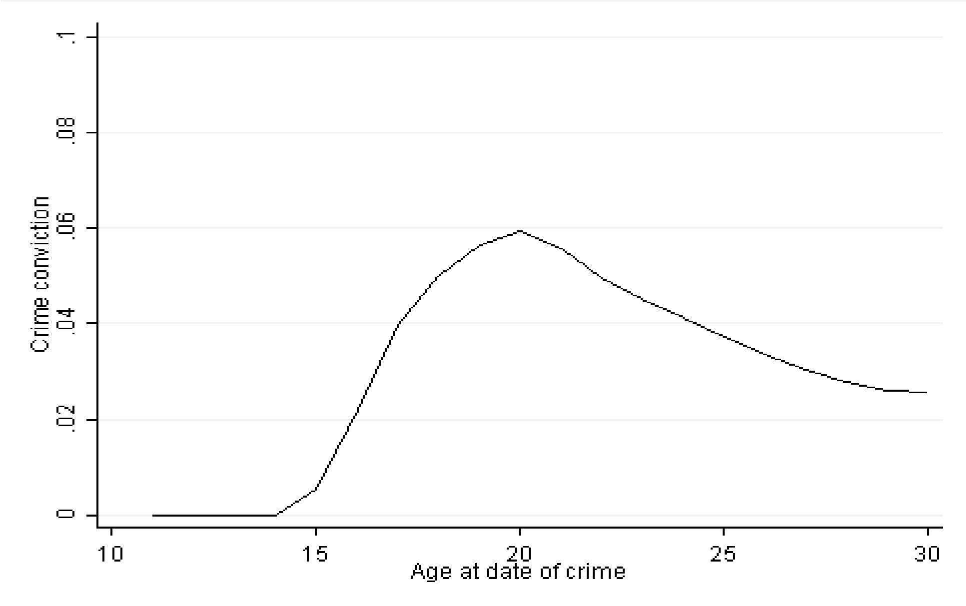
Further, as $[1-\gamma]\left(1 + \frac{\gamma}{N-2}\right)^{N-2} = 0.497919$, then: $\beta^F = \frac{0.497919}{0.993673} = 0.501089$. By inserting $\beta^F = 0.501089$, $\beta^P = 0.010893$ and $N = 6$ into Equation (A.9) we get:

$$\gamma = \frac{(6-1) * 0.010893}{(6-2) * 0.010893 + 0.501089} = 0.1$$

Finally, following Equation (A.7) we get that: $f_1 = 0.501089 - 0.1 * 0.010893 = 0.5$

Figures and Tables from the Main Text

Figure 1: Probability of crime conviction by age



Note: The figure shows probability of crime conviction for the full population of males in Denmark in 2003, by age at date of the crime; excluding traffic crimes.
Source: Own calculations based on data from Statistics Denmark.

Figure 2: Histogram of parents' age at childbirth

Figure 2.A: Father's and mother's age at childbirth, main sample

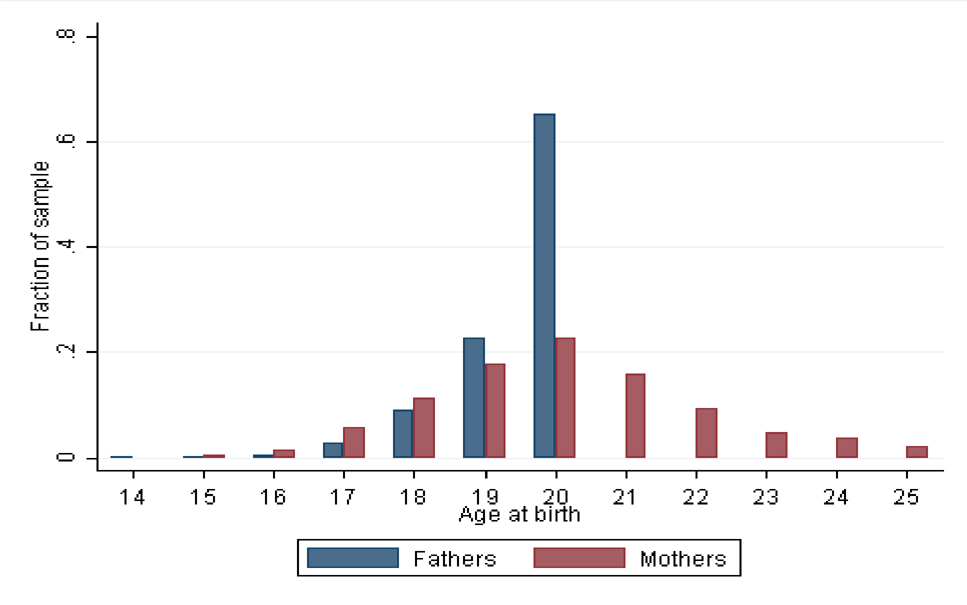
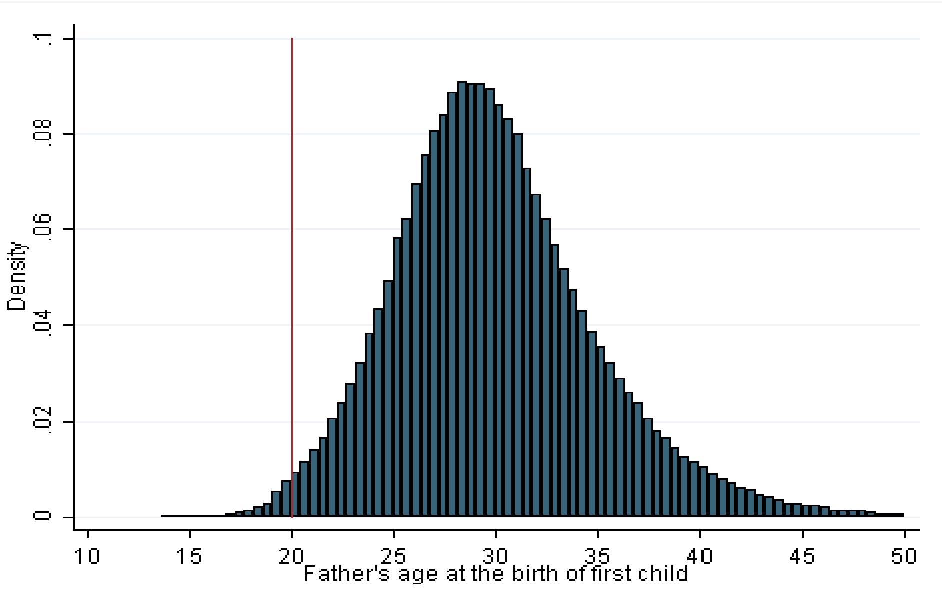


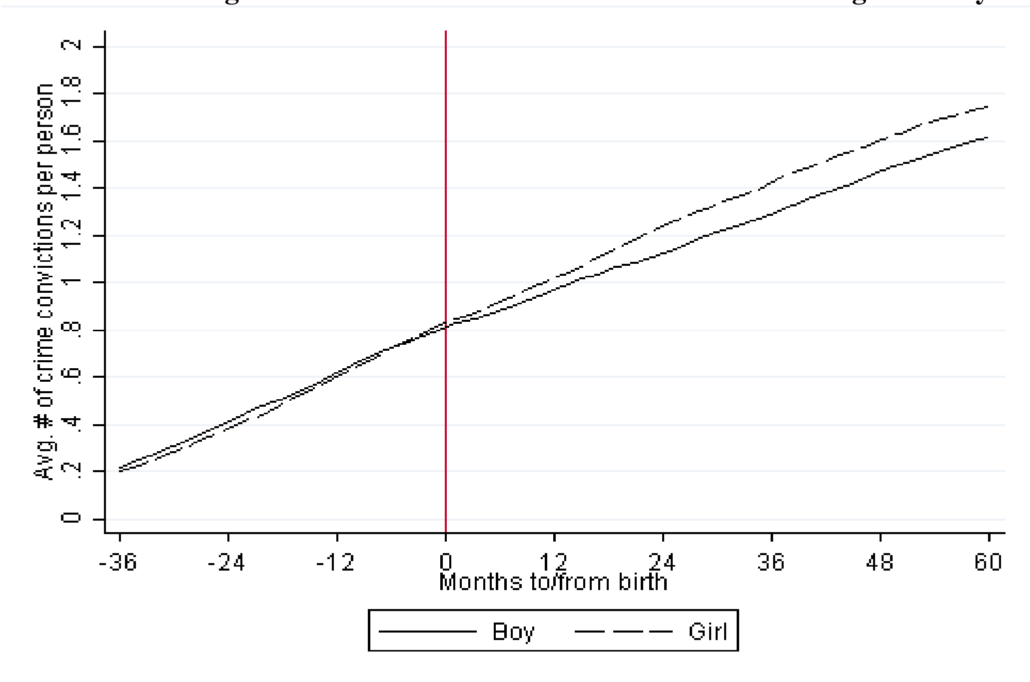
Figure 2.B: Full population denisty of age at child irth for all first time fathers, 1991-2004



Note: Figure A shows a histogram of age at childbirth for main sample of fathers and a histogram of age at childbirth for the mothers (of the fathers' first child). Figure B shows histogram of age at first child for full population of fathers from year 1991-2004. The vertical line marks the age cutoff we use in our sample defintion.

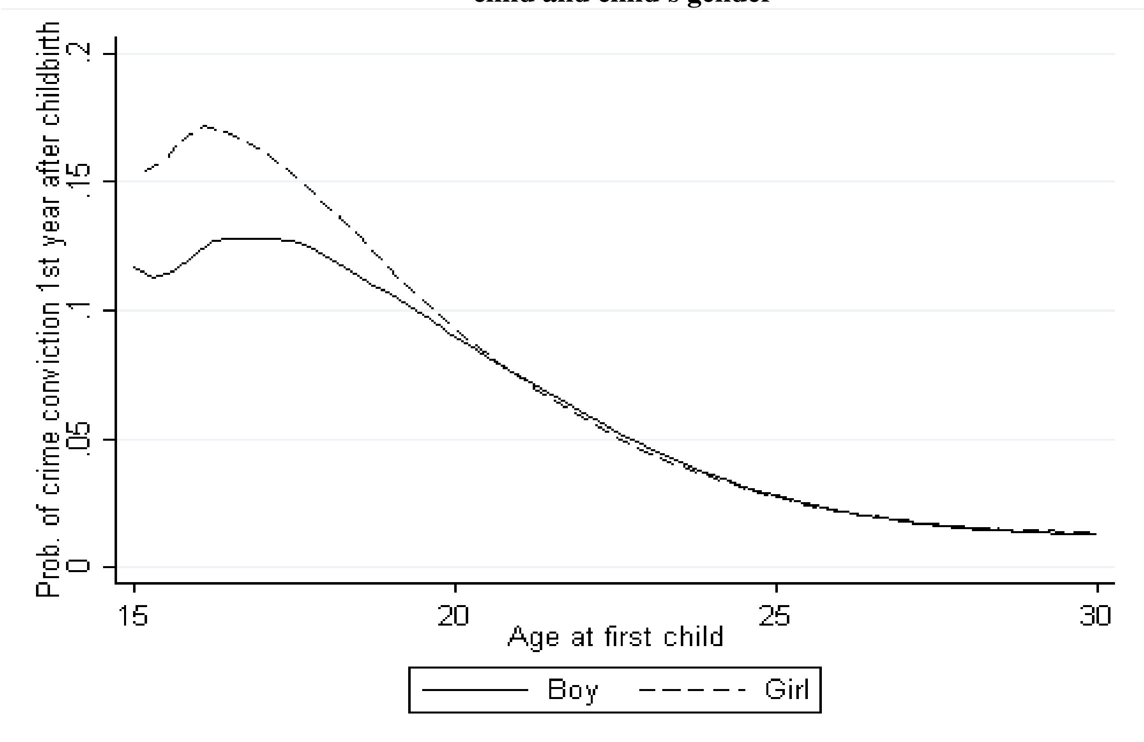
Source: Own calculations based on data from Statistics Denmark.

Figure 3: Number of crime convictions and birth of girl vs. boy



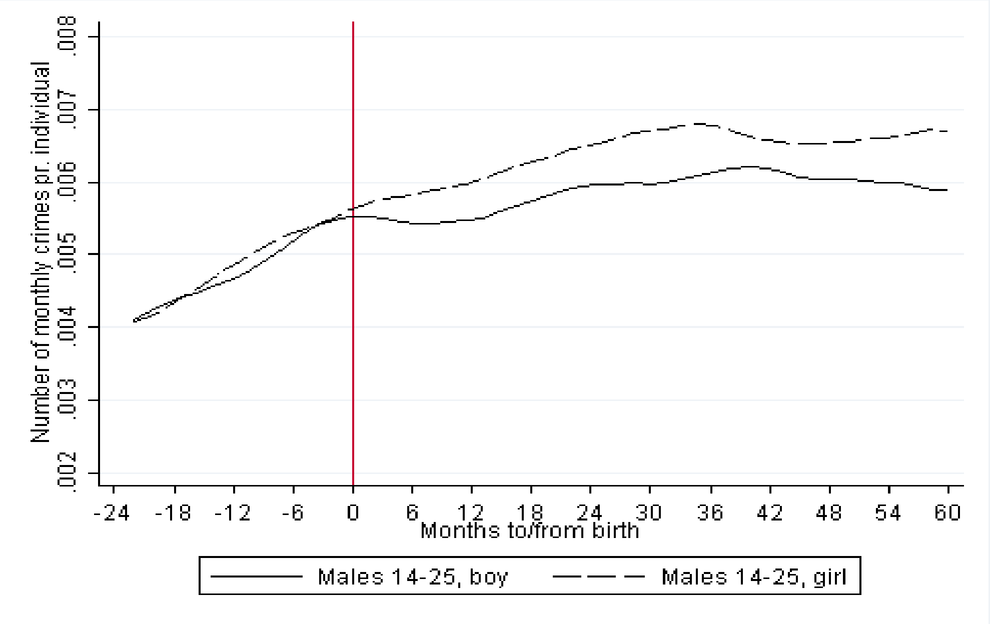
Note: The figure shows accumulated number of crimes per person around the time of childbirth (time 0) by gender of child, for the main sample of first time fathers aged 20 or below at time of childbirth.
Source: Own calculations based on data from Statistics Denmark.

Figure 4: Fraction of fathers with a crime conviction first year after first child's birth, by age at first child and child's gender



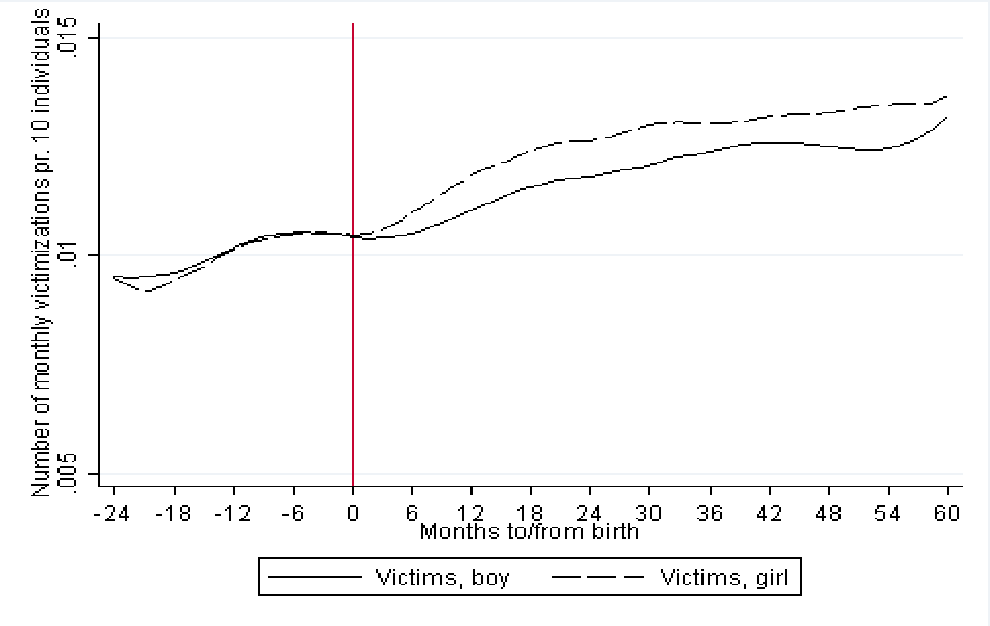
Note: The figure shows the fraction of fathers with a crime conviction for a crime committed the first year after childbirth by child gender across age at the birth of first child.
Source: Own calculations based on data from Statistics Denmark.

Figure 5: Number of crime convictions, neighborhood peers, birth of girl vs. boy



Note: The figure shows monthly number of crimes by males age 14-25 at time of childbirth per male person in main sample of father's neighborhood before and after birth (time 0), by gender of child.
Source: Own calculations based on data from Statistics Denmark.

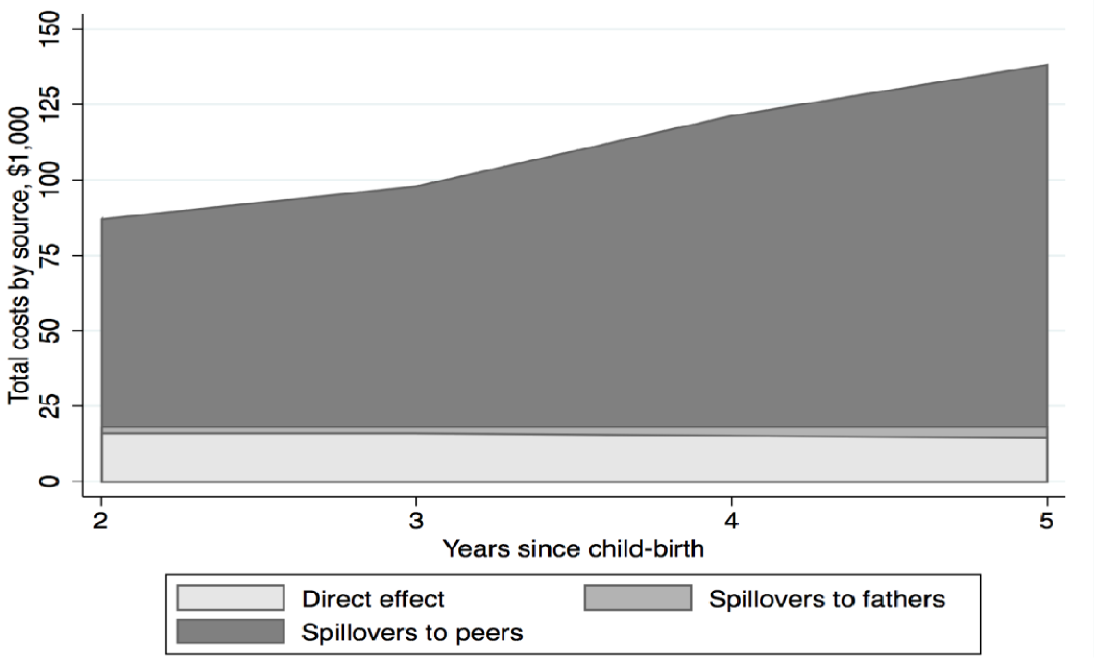
Figure 6: Number of victimization/10 individuals, birth of girl vs. boy



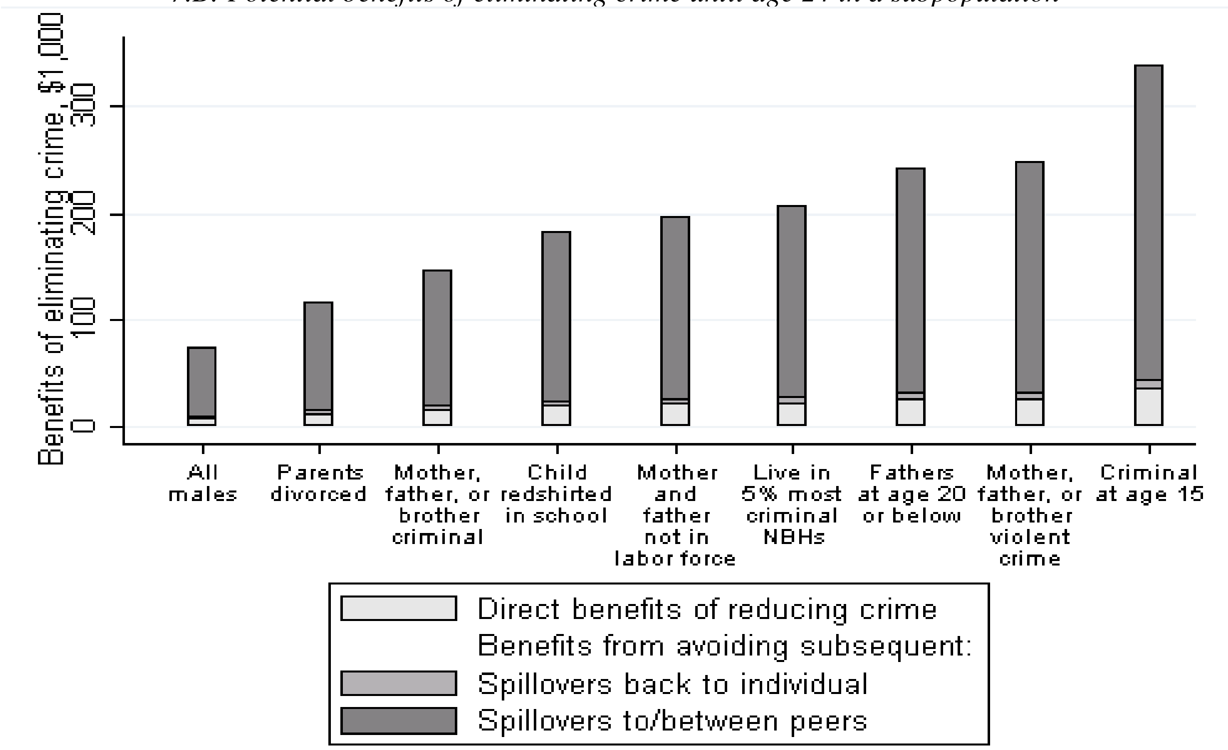
Note: The figure shows monthly number of victimizations per 10 individuals for peers in the focal individuals' neighborhoods before and after birth (time 0), by gender of child.
Source: Own calculations based on data from Statistics Denmark.

Figure 7: Monetizing spillover effects; costs of crime and benefits of crime prevention

7.A: Estimated costs generated by one crime, separated by the source of the costs



7.B: Potential benefits of eliminating crime until age 24 in a subpopulation



Note: Figure A shows the estimated costs of one crime committed by young fathers using the estimated social multipliers and crime costs, separated by which mechanism that generates the costs; the crime itself, spillovers to and between peers, and spillovers back to the fathers. Figure B shows the potential benefits of eliminating crime in a given subpopulation until they turn 24 using the estimated social multiplier and crime costs. The estimates are separated by the mechanism that generates them: crime of the targeted individuals, spillovers to and between peers, and spillovers back to the targeted individuals. The costs per crime are estimated using 'average willingness to pay for for a crime reduction' (Cohen, 2009). We weight the individual costs for each specific type using offences shares from Table A.1 to estimate the average costs per crime observed in the data ($17,949).
Source: Own calculations based on data from Statistics Denmark.

Table 1: Summary statistics of main sample

	1) Sample	2) Boy/girl difference	3) P-value of boy/girl difference	4) Random sample, age/ year weight as main
Gender of child	0.505	-	-	-
	(0.500)			
Father's wage income (1,000 2010USD)	14.533	-0.440	0.313	19.774
	(11.544)	(0.436)		(13.018)
Father was redshirted in primary school	0.246	-0.001	0.970	0.118
	(0.431)	(0.016)		(0.323)
Father is non-native (immigrant/descendant)	0.142	0.015	0.254	0.040
	(0.349)	(0.013)		(0.194)
Father's parents are married or cohabitting	0.578	-0.020	0.176	0.750
	(0.494)	(0.015)		(0.433)
Father's parents household wage income (1,000 2010USD)	59.464	-2.002	0.150	78.427
	(36.844)	(1.392)		(47.100)
Father of father's years of schooling	10.556	-0.071	0.254	12.099
	(2.824)	(0.107)		(3.139)
Father of father's is employed	0.687	0.007	0.664	0.851
	(0.431)	(0.016)		(0.356)
Father of father's is unemployed	0.109	0.004	0.688	0.058
	(0.289)	(0.011)		(0.234)
Mother of father's years of schooling	9.826	0.118	0.187	11.544
	(2.373)	(0.090)		(2.976)
Mother of father's is employed	0.602	0.003	0.883	0.800
	(0.466)	(0.018)		(0.400)
Mother of father's is unemployed	0.134	-0.003	0.838	0.067
	(0.325)	(0.012)		(0.250)
Number of observations	2,803			30,360

Note: Column 1 shows summary statistics for the main sample of fathers and their parents. Column 2 shows mean differences of the variables by gender of child and column 3 shows p-values from t-tests for differences of the means. Column 4 show the equivalent measures for a sample drawn from the full Danish population with same age and year weights as the sample of first time fathers. Standard deviations appear below the sample means in coloumns 1 and 4, and standard errors appear below mean differences in column 2.

*: $p<0.10$; **: $p<0.05$; ***: $p<0.01$
Source: Own calculations based on data from Statistics Denmark.

Table 2: Probability of crime conviction before child conception

Prior to pregnancy	1) Main sample of fathers	2) R.S. of male population matched to fathers	3) Male family members	4) R.S. of full male population 15-60	5) Young males in neighborhood	6) R.S. matched to young males in neighborhoods
Crime	0.339	0.124	0.303	0.158	0.173	0.119
	(0.473)	(0.329)	(0.460)	(0.365)	(0.783)	(0.234)
Property crime	0.287	0.098	0.228	0.108	0.126	0.091
	(0.452)	(0.297)	(0.419)	(0.311)	(0.607)	(0.288)
Violent crime	0.065	0.019	0.076	0.028	0.016	0.021
	(0.247)	(0.136)	-0.265	(0.166)	(0.150)	(0.143)
Number of observations	2,803	30,360	3,797	1,691,931	152,660	132,414

Note: The table shows the fraction of convicted offenders for the main sample of fathers, their male family members, and young males in the main sample's neighborhood in columns 1, 3, and 5, respectively. The random sample in column 2 has been drawn from the full Danish population with same age and year weights as the main sample. The sample in column 4 is a random draw from the full male population of 15-60 years olds from 1991 to 2004 with the same year distribution as the main sample of fathers. The sample in column 6 consists of young males in a random sample of neighborhoods where the young males in the random sample have an age-year distribution equal to young males in the main sample's neighborhoods. Standard deviations appear in parentheses below means.
Source: Own calculations based on data from Statistics Denmark.

Table 3: Probability of crime conviction, boy vs. girl

Time relative to childbirth		Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
A) Probability of crime conviction							
	Yearly						
	β^F	-0.009	-0.025**	-0.033**	-0.023*	0.013	-0.003
		(0.012)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
	Mean		0.135	0.145	0.134	0.130	0.115
	Accumulated from childbirth						
	β^F	-0.009	-0.025**	-0.040***	-0.044***	-0.023	-0.017
		(0.012)	(0.013)	(0.015)	(0.016)	(0.017)	(0.017)
	Mean		0.135	0.222	0.275	0.313	0.337
B) Number of crime convictions							
	Accumulated from childbirth						
	β^F	-0.005	-0.030	-0.102***	-0.130***	-0.122**	-0.121*
		(0.017)	(0.021)	(0.034)	(0.046)	(0.059)	(0.069)
	Mean		0.185	0.384	0.570	0.757	0.910
Observations		2,803	2,803	2,803	2,803	2,803	2,803

Note: The table shows results from OLS regression of probability of crime conviction (Panel A) and number of crime convictions (Panel B) in the years before/after birth on gender of first child (boy=1). Having a girl is the reference category, i.e. the table shows the estimated change from having a boy instead of a girl. Standard errors appear in parentheses below coefficients. 'Mean' refers to the mean of the dependent variable in the estimation sample.

OLS regression conditional on: crime before year -1 father's age, mother's age, married/cohabiting, father enrolled in education, fathers' income, mother enrolled in education, mother's income, crime in nearest family (all measured before conception), and year of childbirth fixed effects.

*: p<0.10; **: p<0.05; ***: p<0.01

Source: Own calculations based on data from Statistics Denmark.

Table 4: Alternative crime outcomes and robustness checks, crime of fathers, boy vs. girl

Time relative to childbirth	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
Panel A: Fathers matched to neighborhoods (main sample)						
1) Probability of charge (0/1)	-0.008	-0.027**	-0.028*	-0.031*	-0.020	-0.012
	(0.013)	(0.013)	(0.016)	(0.017)	(0.017)	(0.017)
2) # Charges as count variable	-0.014	-0.043*	-0.119***	-0.141**	-0.143*	-0.143
	(0.018)	(0.025)	(0.042)	(0.058)	(0.074)	(0.088)
3) # Crime convictions/time not in prison	-0.006	-0.050**	-0.135***	-0.179***	-0.178**	-0.180*
	(0.019)	(0.025)	(0.044)	(0.059)	(0.079)	(0.100)
Panel B: Fathers, incl. those we cannot match to neighborhoods						
4) Probability of crime conviction (0/1)	-0.005	-0.020*	-0.026*	-0.024	-0.011	-0.006
	(0.011)	(0.011)	(0.014)	(0.015)	(0.015)	(0.016)
5) # Crime convictions as count variable	-0.001	-0.022	-0.083***	-0.098**	-0.079	-0.072
	(0.015)	(0.019)	(0.031)	(0.043)	(0.055)	(0.064)
Panel C: Mothers						
6) Probability of crime conviction, Mothers	0.001	-0.006	-0.008	0.001	-0.009	0.002
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Panel D: Fathers 21-25						
7) Probability of crime conviction, Fathers 21-25	-0.002	0.001	0.004	0.004	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)

Note: The table shows results from OLS regression of crime outcomes in year before conception and accumulated for the first 5 years from childbirth on gender of first child (boy=1). Having a girl is the reference category, i.e. the table shows the estimated change from having a boy instead of a girl. Standard errors appear in parentheses below coefficients. OLS regression conditional on: crime before year -1, father's age, mother's age, married/cohabiting, father enrolled in education, fathers' income, mother enrolled in education, mother's income, crime in nearest family (all measured before conception), and year of childbirth fixed effects.

Panel A: Fathers in the main sample, i.e. fathers aged 20 or below whom we can uniquely match to a neighborhood. Observations: 2,803.

Panel B: Fathers aged 20 or below disregarding neighborhood match. Data includes sample from Panel A + fathers whom we cannot link to a neighborhood and neighborhoods with multiple young fathers having children within the same year. Observations: 3,549

In 3) Crime convictions divided by time not spent in prison, i.e. 1 crime in a year where 6 months were spent in prison is equals to 2 crimes without any time in prison.

*: p<0.10; **: p<0.05; ***: p<0.01

Source: Own calculations based on data from Statistics Denmark.

Table 5: Convicted criminals, per 10 males in the neighborhood, boy vs. girl

Time relative to childbirth		Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
A) Convicted criminals							
Yearly							
	β^P	-0.009	-0.044*	-0.047**	-0.037*	-0.029	-0.019
		(0.020)	(0.023)	(0.022)	(0.022)	(0.020)	(0.019)
	Mean	0.477	0.607	0.593	0.566	0.516	0.482
Accumulated from childbirth							
	β^P	-0.009	-0.044*	-0.063**	-0.077**	-0.092**	-0.087**
		(0.020)	(0.023)	(0.031)	(0.036)	(0.040)	(0.042)
	Mean	0.477	0.607	0.993	1.265	1.466	1.627
B) Number of crime convictions							
Accumulated from childbirth							
	β^P	-0.005	-0.073**	-0.125**	-0.185**	-0.224**	-0.259*
		(0.029)	(0.034)	(0.062)	(0.088)	(0.111)	(0.134)
	Mean	0.612	0.801	1.596	2.356	3.048	3.697
	Observations	82,475	82,475	82,475	82,475	82,475	82,475

Note: The table shows results from OLS regression of convicted criminals per 10 males +- 3 years of father's age in neighborhood the years before/after birth on gender of first child (boy=1), using neighborhoods within the 5th-95th percentiles of neighborhood sizes. Regressions include year of childbirth fixed effects. Standard errors appear in parentheses below coefficients and are clustered by level of neighborhood. 'Mean' refers to the mean of dependenct variable in the estimation sample. Estimation is performed on level of individuals, thus weighted by number of males +- 3 years of father's age in each neighborhood. Having a girl is reference category, i.e. the table shows the estimated change from the focal individual having a boy instead of a girl.
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark.

Table 6: Alternative crime outcomes and robustness checks, per 10 males in the neighborhood, boy vs. girl

Time relative to childbirth	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
A: Males in neighborhoods, +/- 3 years of father's age						
1) # Charges as count variable	-0.016	-0.080**	-0.149**	-0.217**	-0.273**	-0.290**
	(0.022)	(0.035)	(0.062)	(0.095)	(0.119)	(0.142)
B: Males in neighborhoods, +/- 3 years of father's age, all neighborhoods weighted equally						
2) Convicted criminals, 5-95 percentiles neighborhood size	-0.008	-0.044*	-0.062*	-0.075**	-0.089**	-0.083*
	(0.020)	(0.023)	(0.032)	(0.037)	(0.040)	(0.042)
3) Convicted criminals, all but 1% largest neighborhoods	-0.015	-0.046**	-0.070**	-0.086**	-0.094**	-0.087**
	(0.020)	(0.023)	(0.032)	(0.037)	(0.041)	(0.043)
C: Males in neighborhoods age 14-25 at childbirth						
4) Convicted criminals	-0.013	-0.026	-0.043*	-0.060**	-0.064*	-0.068*
	(0.015)	(0.018)	(0.026)	(0.030)	(0.034)	(0.036)
5) # Crime convictions as count variable	-0.024	-0.046*	-0.082*	-0.134*	-0.158*	-0.192*
	(0.021)	(0.026)	(0.049)	(0.071)	(0.091)	(0.110)
6) # Charges as count variable	-0.018	-0.056**	-0.097*	-0.158**	-0.186*	-0.230*
	(0.015)	(0.027)	(0.050)	(0.077)	(0.098)	(0.119)
D: Placebo test: Males in neighborhoods where fathers were age 21-25 at childbirth						
7) Convicted criminals	0.014	-0.004	-0.001	0.006	0.008	-0.005
	(0.009)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
8) # Crime convictions as count variable	0.014	0.003	0.005	0.009	0.018	0.011
	(0.014)	(0.016)	(0.030)	(0.043)	(0.055)	(0.066)

Note: The table shows results from OLS regression of crime outcomes per 10 males in neighborhood in year before conception and accumulated for the first 5 years from childbirth on gender of first child (boy=1). Standard errors appear in parentheses below coefficients and are clustered by level of neighborhood. Estimation is performed on level of individuals.

Panel A: Peers whose age is within +-3 year range of father's age, defined by exact dates of birth. Weighted by neighborhood size. Observations: 82,475.

Panel B: Assigning equal weights to all neighborhoods disregarding the number of males +- 3 years of father's age in each neighborhood.

In 2) Neighborhoods within 5th-95th percentiles of neighborhood size, observations 82,475. In 3) until the 99th percentiles. Observations: 94,688.

Panel C: Neighborhoods within 5th-95th percentiles of neighborhood sizes. Estimation weighted by neighborhood size. Observations: 152,660.

Panel D: Peers age 14-25 in neighborhoods of fathers age 21-25 at time of first child. Neighborhoods sizes in 5th-95th percentiles. Weighted by size.

*: p<0.10; **: p<0.05; ***: p<0.01

Source: Own calculations based on data from Statistics Denmark.

Table 7: Accumulated convicted criminals by pre-conception crime propensity

Time relative to childbirth	Year 1	Year 2	Year 3	Year 4	Year 5
Panel A: Fathers					
*Boy * (1-**1** [Crime Index > 0.6])*	-0.002	-0.018	-0.022	-0.005	0.003
	(0.016)	(0.019)	(0.020)	(0.021)	(0.021)
*Boy * **1** [Crime Index > 0.6]*	-0.058***	-0.071***	-0.076***	-0.051**	-0.049*
	(0.020)	(0.024)	(0.025)	(0.026)	(0.026)
Observations	2,803	2,803	2,803	2,803	2,803
Panel B: Peers					
*Boy * (1-**1** [Crime Index > 0.6])*	0.020	0.001	-0.007	-0.031	-0.036
	(0.028)	(0.038)	(0.044)	(0.049)	(0.051)
*Boy * **1** [Crime Index > 0.6]*	-0.088**	-0.098**	-0.114**	-0.117**	-0.098
	(0.034)	(0.046)	(0.052)	(0.057)	(0.060)
Observations	82,475	82,475	82,475	82,475	82,475

Note: The table shows results from OLS regression of accumulated convicted criminals the years after birth of first child where child gender is interacted with fathers' crime propensity. Panel A shows results for fathers and Panel B shows results for peers (males +-3 years of father's age) in the fathers' neighborhoods. The model is fully saturated such that child gender has been interacted with 1[Crime Index>0.6] as well as (1-1[Crime Index>0.6]), while we condition on both 1[Crime Index>0.6] and (1-1[Crime Index>0.6]). Thus, coefficients for 'Boy*1[Crime Index>0.6]' show the additional response to boy vs girl for fathers with high crime propensity and their peers. Standard errors appear in parentheses below coefficients. Regressions include year of childbirth fixed effects.
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark.

Table 8: Number of crime victimizations per 10 individuals, boy vs. girl

Time relative to childbirth	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
<u>*Yearly*</u>						
β^V	0.006	-0.003	-0.017**	-0.013*	-0.008	-0.017**
	(0.006)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Mean	0.107	0.080	0.091	0.096	0.100	0.102
<u>*Accumulated from childbirth*</u>						
β^V	0.006	-0.003	-0.020	-0.032*	-0.040*	-0.057**
	(0.006)	(0.008)	(0.013)	(0.017)	(0.022)	(0.027)
Mean	0.107	0.080	0.171	0.266	0.365	0.467
Observations	524,314	524,314	524,314	524,314	524,314	524,314

Note: The table shows results from OLS regression of probability of victimization per 10 individuals in neighborhood the years before/after birth on gender of first child (boy=1). I.e. the table shows the estimated change from focal individuals having a boy instead of a girl. Standard errors appear in parentheses below coefficients and are clustered by level of the father in the main sample. 'Mean' refers to the mean of dependenct variable in the estimatation sample. Estimation is performed on level of each individual, thus weighted by number of individuals in each neighborhood. Estimation sample only includes neighborhoods within the 5th-95th percentile of neighborhood sizes.
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark.

Table 9: Estimates of model parameters and Social Multipliers using estimated effect of child gender on young fathers' and their peers' number of crimes

Outcome used: Accumulated crime until		year 2	year 3	year 4	year 5
βf, from Table 3, Panel B		-0.102	-0.130	-0.122	-0.121
βp, from Table 5, Panel B		-0.125	-0.185	-0.224	-0.259
Spillover parameter γ =	$\frac{(N-1)\beta^P}{(N-2)\beta^P+\beta^F}$	0.814	0.838	0.876	0.895
Initial child gender shock f_1 =	$\beta^F - \gamma\beta^P$	-0.092	-0.114	-0.102	-0.098
Naïve Social multiplier =	$\frac{(N-1)\beta^P+\beta^F}{\beta^F}$	4.835	5.453	6.745	7.698
Mean observations per neighborhood, N		32.29	32.29	32.29	32.29

Note: The table shows in the first two rows estimated effects from Table 3 and Table 5 of having a boy relative to having a girl on accumulated number of crime convictions 2, 3, 4, and 5 years after child birth corresponding to βf and βp in the model. Table 5 reports estimates per 10 peers should thus be divided by 10 before inserted into the equations as βp. The third and fourth rows show the implied spillover parameter (γ) and shock from boy vs. girl to father (f_1) assuming that all peers in each neighborhood are connected. The fifth row shows the 'naïve' Wald social multiplier (which does not rest on the aforementioned assumption). Number of observations are average number of peers in each neighborhood after dropping the 5% largest and 5% smallest neighborhoods.
Source: Own calculations based on data from Statistics Denmark.

Appendix Figures and Tables

Figure A1: Crime age curves for Denmark and the U.S.

Figure A1.A: Crime in 1995

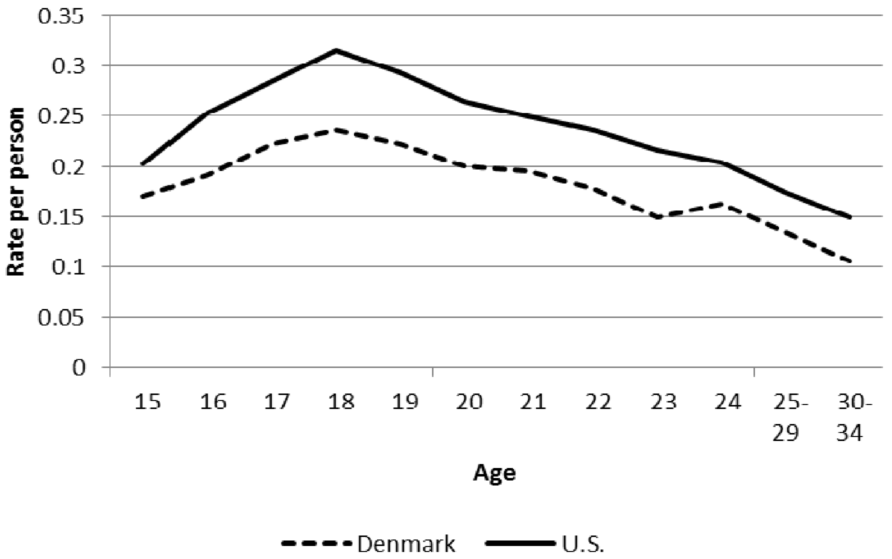


Figure A1.B: Crime in 2000

Note: The figures show aggregated number of non-traffic arrests for the U.S. and charges for Denmark per male at a given age in 1995 and 2000.
US source: US Bureau of Justice Statistics:
http://www.bjs.gov/index.cfm?ty=datool&surl=/arrests/index.cfm#
Denmark source: Own calculations based on data from Statistics Denmark.

Figure A2: Ages of offenders at time of crime, when multiple offenders are involved in a crime

Figure A2.A: Distribution of age of crime when multiple offenders are involved

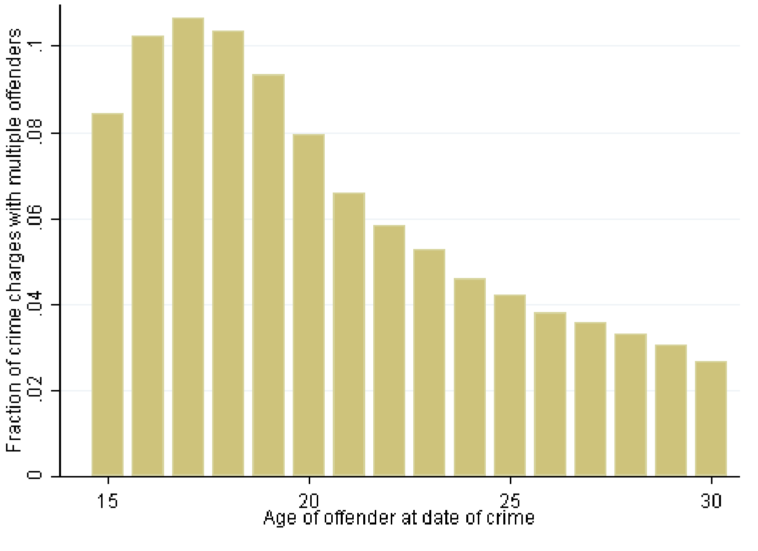
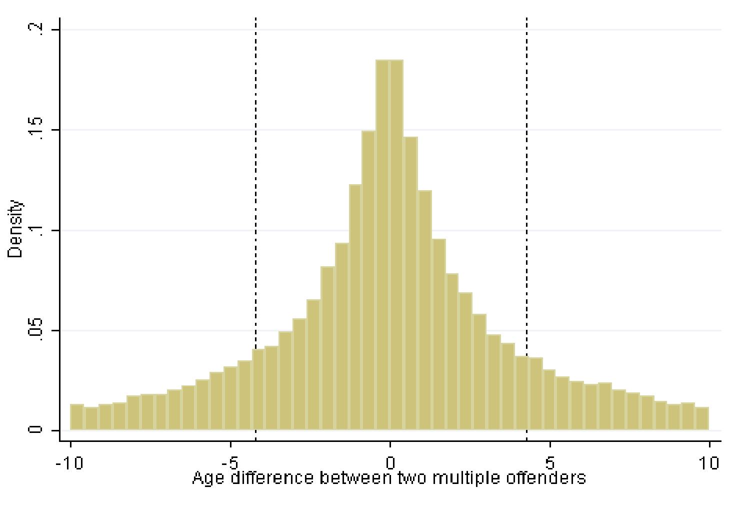


Figure A2.B: Distribution of age differences between two multiple offenders



Note: Figure A shows density of age at time of crime for offenders of crimes committed between 1991 and 2004, in which two or more offenders have been charged for the same crime. Figure B shows density of age difference between offenders of crimes committed between 1991 and 2004, in which two offenders have been charged for the same crime. The vertical lines show one standard deviation from the mean of 0.

Denmark source: Own calculations based on data from Statistics Denmark.

Figure A3: Distribution of neighborhood sizes

Figure A3.A: Males in neighborhoods age +-3 years of father

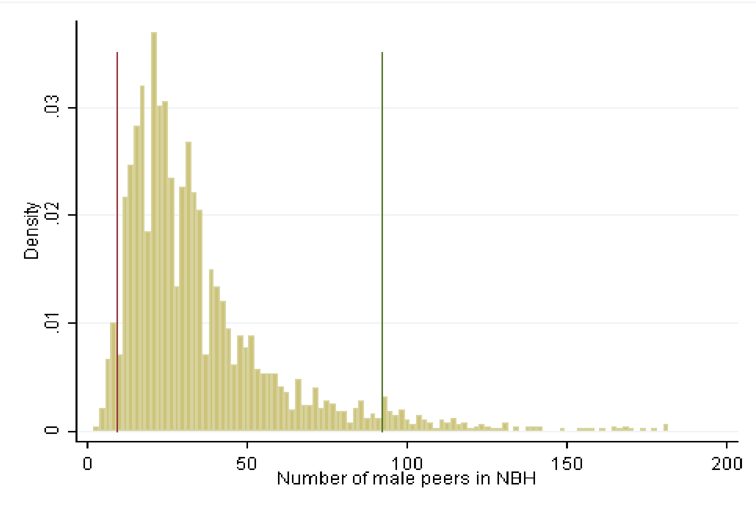
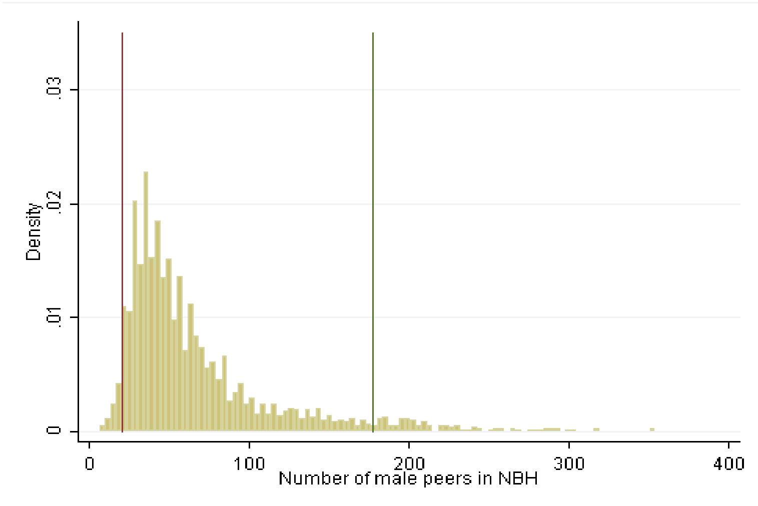


Figure A3.B Males in neighborhoods, age 14-25 at childbirth



Note: Figure A shows histogram of number of males in each neighborhood who are minimum 3*365 days younger and maximum 3*365 days older than the father. The left vertical line marks the 5th percentile of neighborhood sizes and the right marks the 95th percentile. Figure B shows histogram of number of males age 14-25 at time of childbirth in neighborhoods. The left vertical line marks the 5th percentile of neighborhood sizes and the right marks the 95th percentile.
Both figures have been censored at the top 1 percentile for illustrative purposes.
Source: Own calculations based on data from Statistics Denmark.

Figure A4: Descriptives of main sample and random sample's parents

Figure A4.A: Father is in employment

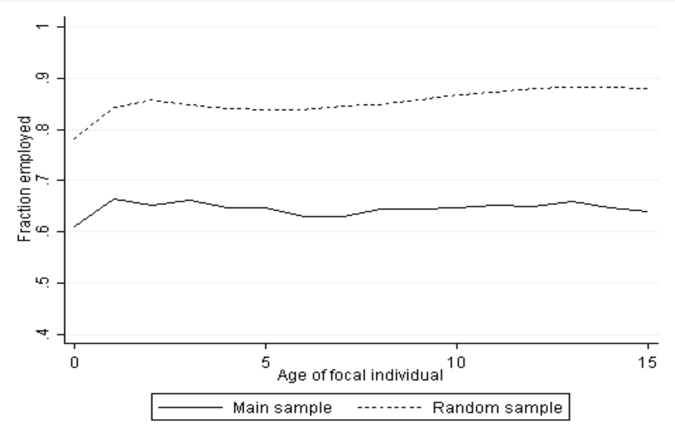


Figure A4.B: Mother is in employment

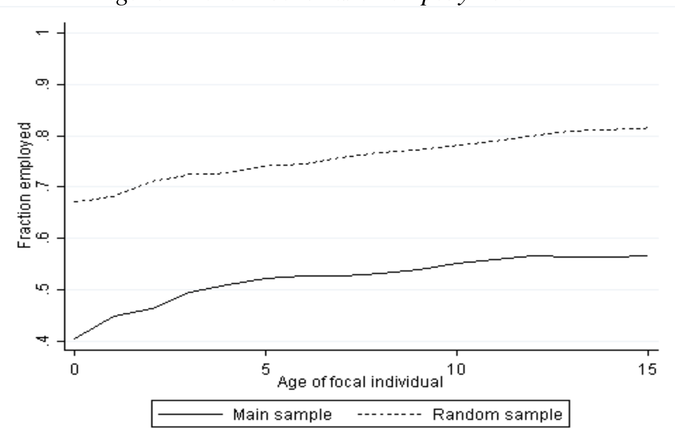
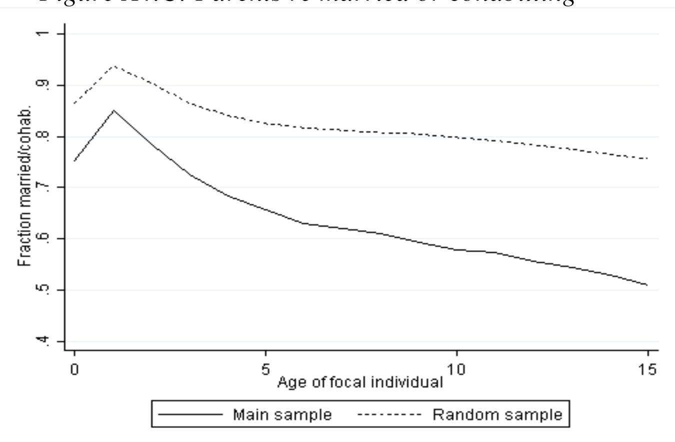
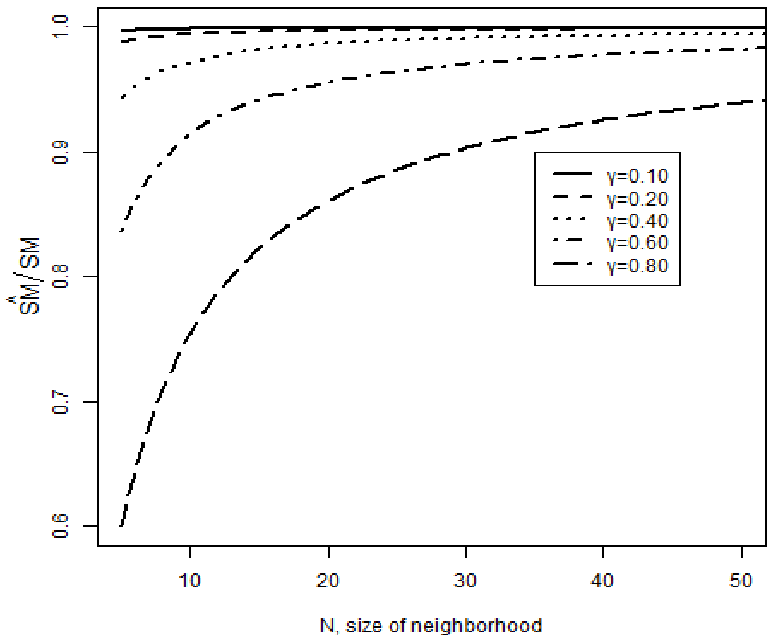


Figure A4.C: Parents re married or cohabitting



Note: The figures show average characteristics of the parents to the main sample and a random weighted sample with same age/year distribution as the main sample from age 0 to age 15. Figure A shows employment rates of the samples' fathers, Figure B shows employment rates of the samples' mothers, and Figure C shows the fraction of parents who are married or cohabiting.
Source: Own calculations based on data from Statistics Denmark.

Figure A5: Simulated bias between naïve social multiplier and actual social multiplier



Note: The figure shows difference between actual social multiplier as defined in Equation (8) (and (A.11) in the Appendix) and naïve social multiplier as defined in Equation (9) (and (A.13) in the Appendix) simulated using varying neighborhood sizes N and spillover parameters γ. For simplicity, the number of known peers P is set to N-1.

Table A1: Crime categorization: Crime categories in Danish Law and categorization of crime in our study

	Definitions			*Fraction convicted*	
Criminal Code	*Main categories of crime*	*Subcategories of crime*	*Our category*	*Prior to pregn.*	*Year 1 postbirth*
Penal Code:					
	1. All sexual crimes	*Incest*	Other crime	0.004	0.001
		Rape	Other crime	-	-
		Pedophilia	Other crime	0.002	-
		Voyerism, flashing, palpation	Other crime	0.001	-
		Other sexual violations	Other crime	0.000	0.016
	2. Violent crimes	*Violence against public servant*	Violence	0.008	0.002
		Disturbance of public peace	Violence	-	-
		Murder, manslaughter	Violence	-	-
		Simple violence	Violence	0.049	0.016
		Major violence	Violence	0.009	0.006
		Threats	Violence	0.004	0.004
		Other violent assualts	Violence	0.002	0.001
	3. Property crimes	*Fraud*	Property crime	0.021	0.009
		Arson	Property crime	0.001	0.001
		Theft	Property crime	0.197	0.038
		Burglary	Property crime	0.088	0.019
		Robbery	Property crime	0.017	0.004
		Vandalism	Property crime	0.042	0.007
		Other property crime	Property crime	0.036	0.009
	4. Other crimes against the penal code	*Crime against/as public servant*	Other crime	0.002	0.001
		Drug smuggling or sales	Other crime	0.001	0.001
		Obstruction of justice	Other crime	0.005	0.001
		Restrain orders	Other crime	-	-
		Other crimes, penal code	Other crime	0.002	0.001
Other Acts:					
	Violation of Traffic Act	*Accidents and speeding*	Other crime	0.012	0.013
		Traffic accidents w. alcohol	Other crime	0.174	0.073
	Violation of Drug Act	*Possession and/or drug sales*	Other crime	0.035	0.021
	Violation of Weapons/Arms Act	*Explosives, firearms, knives*	Other crime	0.033	0.011
	Smuggling, construction, health, social fraud, other special acts		Other crime	0.021	0.016

Note: The table shows crime categories in Danish Law, by Criminal code and by their categorization in the paper (property crime, violent crime, other crime). The two right columns show the fraction of the main sample of fathers that has committed each type of crime before the (mother's) pregancy and after the child's birth.
Source: www.retsinformation.dk and own calculations based on data from Statistics Denmark.

Table A2: Balancing tests, number of births and share of boys, by stages of sample selection

	Stage 1	Stage 2	Stage 3	Stage 4
Number of births	408,093	3,979	3,579	2,803
Share of boys	0.502	0.501	0.503	0.505

P-value for difference in share of boys

	Stage 1	Stage 2	Stage 3	Stage 4
Stage 1				
Stage 2	0.96			
Stage 3	0.45	0.89		
Stage 4	0.72	0.76	0.86	

Note: The table shows average share of boys by stages of sample selection.
Stage 1) all first born children in Denmark 1991-2004.
Stage 2) all first born children were the father was age 20 or below at childbirth.
Stage 3) the full data for which we identify fathers and mothers before and after childbirth.
Stage 4) the sample for which we also identify neighborhoods and where there was no more than one childbirth to a father age 20 or below in a given year.
Source: Own calculations based on data from Statistics Denmark.

Table A3: Crime convictions before and first 5 years after childbirth

	After birth					
Before pregnancy	0	1	2	3	4 or more	Total
0	1,480	237	75	31	31	1,854
	0.798	*0.128*	*0.040*	*0.017*	*0.017*	*0.833*
1	263	84	56	29	46	478
	0.550	*0.176*	*0.117*	*0.061*	*0.096*	*0.219*
2	73	39	26	28	45	211
	0.346	*0.185*	*0.123*	*0.133*	*0.213*	*0.101*
3	16	24	17	20	23	100
	0.160	*0.240*	*0.170*	*0.200*	*0.230*	*0.047*
4 or more	25	16	25	20	74	160
	0.156	*0.100*	*0.156*	*0.125*	*0.463*	*0.076*
Total	1,857	400	199	128	219	2,803

Note: The table shows transition matrix of crime convictions for crimes committed before pregnancy and crime convictions for crimes committed the first 5 years after childbirth (by date of crime, not date of conviction) for the main sample of fathers. Crime convictions have been top-coded at 4 crimes.
Source: Own calculations based on data from Statistics Denmark.

Table A4: Balancing tests, predicted crime conviction from pre-birth covariates

Difference girl/boy			
Year 1	0.001	0.002	0.002
	(0.005)	(0.005)	(0.005)
Year 2	0.001	0.002	0.002
	(0.005)	(0.005)	(0.005)
Year 3	0.001	0.001	0.000
	(0.005)	(0.005)	(0.005)
Year 4	0.000	0.001	0.001
	(0.005)	(0.005)	(0.005)
Year 5	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)
Observations	2,803	2,803	2,803
Father covariates	X	X	X
His parents' covariates		X	X
Neighborhood covariates			X

Note: The table shows t-tests of linear predictions of crime conviction in the first 5 years after childbirth by gender of child. Post birth crime is predicted from pre-birth covariates. Father pre-birth covariates includes: married to mother, years of schooling, redshirted, immigrant or descendant, income, employment, crimes. Parents' covariates: married, income and years schooling father and mother. Neighborhood covariates: Mean of the abovementioned variables for males in the neighborhood of the same age.

*: p<0.10; **: p<0.05; ***: p<0.01

Source: Own calculations based on data from Statistics Denmark.

Table A5: Balancing tests, pre-birth covariates of fathers, mothers, their parents, and neighborhoods

	Fathers			**Mothers**		
	Own covariates	Own and parental covariates	Own, parental, and NBH	Own covariates	Own and parental covariates	Own, parental, and NBH
Obs	2,803	2,803	2,803	2,803	2,803	2,709
R-squared	0.005	0.007	0.008	0.005	0.007	0.009
P(F)	0.54	0.54	0.77	0.37	0.44	0.67

Note: The table shows regression of gender of child (boy 0/1) on i) focal individual's characteristics, ii) focal individual's and his parents' characteristics, and iii) focal individual's, his parents', and mean characteristics of neighborhood. Focal individual pre-birth covariates: married to mother, years schooling, redshirted, immigrant or descendant, income, employment, crimes. Parents' covariates: married, income and years schooling father, income and years schooling mother. Neighborhood covariates: Mean of the abovementioned for equal aged males in the neighborhood.

*: p<0.10; **: p<0.05; ***: p<0.01

Source: Own calculations based on data from Statistics Denmark.

Table A6: Balancing tests, probability of abortion previous to childbirth, boy vs. girl

	Any abortion	*Planned abortion*	*Spontaneous abortion*
Gender=boy	-0.011	0.009	-0.005
	(0.009)	(0.008)	(0.005)
Observations	2,791	2,791	2,791

Note: The table shows probability of mother having had an abortion before the childbirth in question regressed on gender (boy=1) of life-born child in question. Having a girl the is reference catergory, i.e. the table shows the estimated difference from having a boy instead of a girl.
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark

Table A7: Probability of crime conviction by crime type, boy vs. girl, by crime type

Time relative to childbirth		Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
A) Violent crime	*Yearly*						
	β^F	0.004	0.005	-0.013*	-0.003	-0.001	-0.001
		(0.005)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
	Mean		0.029	0.034	0.026	0.026	0.025
	Accumulated from childbirth						
	β^F		0.005	-0.002	0.000	0.002	-0.003
			(0.006)	(0.009)	(0.010)	(0.011)	(0.012)
	Mean		0.029	0.057	0.076	0.093	0.110
B) Property crime	*Yearly*						
	β^F	-0.001	-0.017*	-0.027**	-0.010	0.007	-0.004
		(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)
	Mean		0.077	0.088	0.072	0.072	0.059
	Accumulated from childbirth						
	β^F		-0.017*	-0.033**	-0.037***	-0.027*	-0.023
			(0.010)	(0.013)	(0.014)	(0.015)	(0.015)
	Mean		0.077	0.144	0.182	0.213	0.230
C) Other crime	*Yearly*						
	β^F	-0.007	-0.011	-0.008	-0.011	0.008	0.004
		(0.006)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
	Mean		0.050	0.047	0.054	0.050	0.045
	Accumulated from childbirth						
	β^F		-0.011	-0.019*	-0.023*	-0.014	-0.010
			(0.008)	(0.011)	(0.012)	(0.013)	(0.014)
	Mean		0.050	0.088	0.122	0.151	0.170
Observations		2,803	2,803	2,803	2,803	2,803	2,803

Note: The table shows results from OLS regression on probability of crime conviction the years before/after birth on gender of first child (boy=1). Having a girl is the reference category, i.e. the table shows the estimated change from having a boy instead of a girl. Standard errors appear in parentheses below coefficients. 'Mean' refers to the mean of the dependent variable for the estimation sample. OLS regression conditional on: crime before year -1 father's age, mother's age, married/cohabiting, father enrolled in education, fathers' income, mother enrolled in education, mother's income, crime in nearest family (all measured before conception), and year of childbirth fixed effects.
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark.

Table A8: Conviction probabilities of fathers age 21-25, a random sample of 21-25 year old males, and males living in the same neighborhood as 21-25 year old fathers

	Fathers age 21-25	Random full population sample with same age/year profile as fathers age 21-25	Equal aged males in neighborhoods of fathers age 21-25
Crime	0.194	0.185	0.179
	(0.396)	(0.388)	(0.383)
Property crime	0.136	0.144	0.125
	(0.343)	(0.351)	(0.330)
Violent crime	0.044	0.034	0.017
	(0.207)	(0.181)	(0.130)
Observations	48,759	31,211	412,678

Note: The table shows pre-pregnancy crime rates for the sample of fathers age 21-25, for a random sample of males age 21-25, and for equal aged neighborhood peers to the sample of fathers age 21-25. Standard deviations appear below the sample means.
Source: Own calculations based on data from Statistics Denmark.

Table A9: Average characteristics of 'compliers', treating child gender as instrument for young fathers' crime

Variable	*Compliers' mean characteristics*	*Mean of all fathers in main sample*
Father's characteristics		
Father's wage income (1,000 2010USD)	1.327	14.533
Father was redshirted in primary school	0.513	0.246
Father is non-native (immigrant/descendant)	0.328	0.142
Father's pre-conception criminal history		
Father has pre-conception crime conviction	0.643	0.339
Father has pre-conception property crime conviction	0.395	0.287
Father has pre-conception violent crime conviction	0.182	0.065
Father's number of pre-conception crime convictions	0.824	0.750
Fathers pre-conception crime convictions with co-offenders	0.373	0.250
Parents' characteristics		
Father's parents are married or cohabitting	0.500	0.578
Father's parents household wage income (1,000 2010USD)	45.054	59.464
Father of father's years of schooling	9.498	10.556
Mother of father's years of schooling	9.748	9.826
Fathers' father has crime conviction	0.496	0.234
Neighborhood peers' characteristics		
Pre-conception crime conviction (males +-3 years)	0.109	0.086
Pre-conception property crime conviction (males +-3 years)	0.093	0.066
Pre-conception violent crime conviction (males age +-3 years)	0.013	0.007
Pre-conception crime conviction (males age 14-25)	0.260	0.173
Pre-conception property crime conviction (males age 14-25)	0.163	0.126
Pre-conception violent crime conviction (males age 14-25)	0.030	0.016

Note: The table analyzes observable acharacteristics of the young fathers who respond to child gender treating gender as IV: Z, young fathers' accumulated crime until year 3 after childbirth as treatment: D.
It shows average characteristics of those first time fathers who commit crime within the first three years from childbirth, because they had a girl instead of a boy. We estimate this as e.g., shown in Almond and Doyle (2011). The table also shows the corresponding averages for young fathers and their parents (shown in Table 1, column 1), additional covariates detailing fathers' pre-conception criminal history, and average pre-conception crime of peers in fathers' neighborhoods (shown in Table 2, column 5).
Source: Own calculations based on data from Statistics Denmark.

Table A10: Other responses by young fathers, boy vs. girl

	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
Prob. of employment or education enrollment, in each year[A]	0.005	0.028*	0.029*	0.035**	0.027	0.015
	(0.013)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)
Prob. of employment or education enrollment, accumulated[A]	0.005	0.028*	0.029**	0.031**	0.030**	0.027**
	(0.013)	(0.017)	(0.014)	(0.012)	(0.012)	(0.011)
Prob. of father cohabiting with mother[B]		0.027	0.043*	0.012	-0.011	-0.012
		(0.023)	(0.022)	(0.022)	(0.021)	(0.021)
Prob. of father and mother having subsequent children 0/1[C]		-0.010**	0.006	0.001	-0.035**	0.016
		(0.005)	(0.017)	(0.018)	(0.016)	(0.014)
Days until next child, measured until 8 years after birth (2nd stage tobit)[A]		87.732*				
		(49.896)				
Prob. of father only parent who lives with child (hold custody)[D]		0.014*	0.039*	-0.017	-0.031	-0.013
		(0.008)	(0.022)	(0.022)	(0.024)	(0.024)

Note: The table shows estimates of child's gender on other outcomes than crime for main sample of fathers. Having a girl is the reference category, i.e. the table shows the estimated change from having a boy instead of a girl. Regressions include year of childbirth fixed effects. Standard errors appear in parentheses below coefficients.
A: Full sample (2,803 observations); B: Mother and father not cohabiting before birth (1,964 observations); C: Mother and father cohabiting at time of birth (1,778 observations); D: Mother and father not cohabiting at time of birth (1,025 observations).
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark.

Table A11: Probability of crime conviction per 10 males in the neighborhood, boy vs. girl, by crime type

Time relative to childbirth		Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
Violent crime	*Yearly*						
	β^P	-0.002	-0.023	-0.040**	-0.014	-0.021	-0.017
		(0.017)	(0.017)	(0.016)	(0.015)	(0.013)	(0.012)
	Mean	0.063	0.101	0.108	0.103	0.095	0.090
	Accumulated from childbirth						
	β^P	-0.002	-0.023	-0.049**	-0.043	-0.054*	-0.052*
		(0.017)	(0.017)	(0.023)	(0.027)	(0.030)	(0.032)
	Mean	0.063	0.101	0.198	0.280	0.346	0.405
Property crime	*Yearly*						
	β^P	-0.003	-0.021***	-0.013*	-0.018**	-0.014**	-0.007
		(0.006)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
	Mean	0.350	0.382	0.347	0.301	0.261	0.228
	Accumulated from childbirth						
	β^P	-0.003	-0.021***	-0.031***	-0.045***	-0.059***	-0.064***
		(0.006)	(0.008)	(0.011)	(0.014)	(0.016)	(0.017)
	Mean	0.350	0.382	0.628	0.794	0.917	1.011
Other crime	*Yearly*						
	β^P	-0.004	-0.011	0.006	-0.015	0.004	-0.001
		(0.008)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
	Mean	0.111	0.200	0.218	0.234	0.229	0.232
	Accumulated from childbirth						
	β^P	-0.004	-0.011	-0.009	-0.022	-0.021	-0.019
		(0.008)	(0.012)	(0.017)	(0.021)	(0.024)	(0.027)
	Mean	0.111	0.200	0.383	0.548	0.691	0.829
Observations		82,475	82,475	82,475	82,475	82,475	82,475

Note: The table shows results from OLS regression on convicted criminals (by crime type) per 10 males +- 3 years of father's age in the neighborhood in the years before/after birth on gender of first child (boy=1), using neighborhoods within the 5th-95th percentiles of neighborhood sizes. Regressions include year of childbirth fixed effects. Standard errors appear in parentheses below coefficients and are clustered by level of neighborhood. 'Mean' refers to the mean of dependenct variable in the estimation sample. Estimation is performed on level of individuals, thus weighted by number of males +- 3 years of father's age in each neighborhood. Having a girl is the reference category, i.e. the table shows the estimated change from the focal individual having a boy instead of a girl.
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark.

Table A12: Peers' probability of employment, unemployment, and education enrollment, boy vs. girl

Time relative to childbirth	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
A: Males in neighborhoods +- 3 years of father's age						
Employment	0.009	0.008	0.005	-0.000	0.001	-0.001
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Unemployment	-0.003	-0.001	-0.001	0.001	-0.001	0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Education enrollment	-0.001	0.001	0.003	-0.000	0.005	0.006
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Employment or education enrollment	0.003	0.006	0.006	-0.001	0.002	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
B: Peers age 14-25 in neighborhoods of fathers at childbirth						
Employment	0.008	0.005	0.003	0.002	0.003	0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Unemployment	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Education enrollment	-0.002	0.002	0.004	0.002	0.004	0.005
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Employment or education enrollment	0.003	0.006*	0.005	0.002	0.004	0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
C: Placebo test: Males in neighborhoods where fathers were age 21-25 at childbirth						
Employment	-0.001	-0.001	-0.001	-0.001	-0.002	-0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment	0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education enrollment	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employment or education enrollment	-0.001	-0.001	-0.002	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Note: The table shows results from OLS regression on labor and education outcomes the years before/after birth on gender of first child (boy=1). Having a girl is the reference category, i.e. the table shows the estimated change from focal individuals (fathers) having a boy instead of a girl. Standard errors appear in parentheses below coefficients and are clustered by level of neighborhood. Estimation is performed on level of individuals, thus weighted by number of peers in each neighborhood.

Panel A: Peers in neighborhoods of fathers at time of first child whose age is within +-3 year range of father's age. Observations: 82,475.

Panel B: Peers age 14-25 in neighborhoods of fathers at time of first child. Observations: 152,660.

Panel C: Peers age 14-25 in neighborhoods of fathers age 21-25 at time of first child. Neighborhoods sizes in 5th-95th percentiles.

*: p<0.10; **: p<0.05; ***: p<0.01

Source: Own calculations based on data from Statistics Denmark.

Table A13: Placebo tests - Accumulated crime of young fathers' peers age 25-35 at childbirth, fathers age 21-25 at childbirth, peers of fathers age 21-25 at childbirth, and accumulated victimization rates in the neighborhoods of fathers age 21-25 at childbirth, boy vs. girl

	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
A) Per 10 male peers age 25-35 at time of childbirth						
Convicted criminals	-0.003	-0.008	-0.005	-0.009	-0.008	-0.014
	(0.015)	(0.013)	(0.018)	(0.021)	(0.024)	(0.026)
# Crime convictions as count variable	0.004	-0.010	-0.003	-0.015	-0.010	-0.017
	(0.023)	(0.020)	(0.037)	(0.051)	(0.064)	(0.077)
B) Fathers with first child at age 21-25a t time of childbirth						
Convicted criminals	-0.002	0.001	0.004	0.004	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
# Crime convictions as count variable	-0.002	0.002	0.008	0.006	0.009	0.012
	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)	(0.010)
C) Per 10 male peers of fathers in Panel B), peers age 14-25 at time of childbirth						
Convicted criminals	0.014	-0.004	-0.001	0.006	0.008	-0.005
	(0.009)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
# Crime convictions as count variable	0.014	0.003	0.005	0.009	0.018	0.011
	(0.014)	(0.016)	(0.030)	(0.043)	(0.055)	(0.066)
D) Per 10 male peers of fathers from Panel B), peers' age +-3 years of father						
Convicted criminals	0.016	0.004	-0.007	-0.009	-0.005	-0.007
	(0.013)	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)
# Crime convictions as count variable	0.014	0.014	0.011	0.002	-0.004	-0.015
	(0.018)	(0.017)	(0.029)	(0.040)	(0.050)	(0.059)
E) Victims, Per 10 peers of all ages in neighborhoods of fathers in Panel B)						
Probability of victimization	-0.002	-0.002	0.005	-0.001	0.001	0.003
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
# Victimizations as count variable	-0.003	-0.002	0.004	0.006	0.006	0.009
	(0.004)	(0.005)	(0.008)	(0.011)	(0.013)	(0.016)

Note: The table shows placebo test using samples where we should see no effect of child gender. Results from OLS regression of child's gender on crime outcomes, with standard errors in parentheses below coefficients.

A) Peers age 25-35 in the neighborhoods of the main sample (fathers with first child at age 20 or below).

B) Fathers with first child at age 21-25

C) Males age 14-25 at time of childbirth, in neighborhood of fathers with first child at age 21-25

D) Males with age +-3 years of fathers with first child at age 21-25

E) Victimization rates for all peers in neighborhoods of father with first child at age 21-25.

In all results, crime and victimization rates are measured as accumulated from childbirth and onwards.

In C), D), E): regression estimated using the 5th-95th percentiles of neighborhood sizes. Estimations are performed at individual level, and thus weighted by neighborhood size.

*: p<0.10; **: p<0.05; ***: p<0.01

Source: Own calculations based on data from Statistics Denmark.

Table A14: Number of crime victimizations per 10 individuals by crime type, boy vs. girl, by crime type

Time relative to childbirth		Year -1	Year 1	Year 2	Year 3	Year 4	Year 5
Property crime	Yearly	0.006	0.003	-0.007*	-0.003	-0.003	-0.012***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
	Accumulated	0.006	0.003	-0.004	-0.007	-0.011	-0.023
		(0.004)	(0.004)	(0.007)	(0.010)	(0.013)	(0.016)
Violent crime	Yearly	0.001	-0.006	-0.009**	-0.009**	-0.006	-0.005
		(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
	Accumulated	0.001	-0.006	-0.015**	-0.024***	-0.029***	-0.034**
		(0.002)	(0.004)	(0.006)	(0.009)	(0.011)	(0.013)
Other crime	Yearly	0.000	-0.001	-0.002**	-0.000	-0.000	-0.003**
		(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
	Accumulated	0.000	-0.001	-0.004	-0.004	-0.004	-0.007*
		(0.000)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Observations		524,314	524,314	524,314	524,314	524,314	524,314

Note: The table shows results from OLS regression on probability of crime victimization per 10 individuals (at time of childbirth) in the neighborhood in the years before/after birth on gender of first child (boy=1). Having a girl is reference category, i.e. the table shows the estimated change from focal individuals having a boy instead of a girl. Standard errors appear in parentheses below coefficients and are clustered by level of the father in the main sample. Estimation is performed on level of each individual, thus weighted by number of individuals in each neighborhood. Sample is censored such that only neighborhoods within the 5th-95th percentile of neighborhood sizes are used.
*: p<0.10; **: p<0.05; ***: p<0.01
Source: Own calculations based on data from Statistics Denmark.