Life-cycle Bias and Intergenerational Associations in Crime

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Abstract

In this paper, we develop a novel methodology based on the generalized error-in-variable (GEiV) model to account for the so-called life-cycle bias. We estimate the life-cycle bias directly from a representative cohort and then correct the estimates for intergenerational crime associations that are based on short-run proxies. We estimate the intergenerational elasticities between fathers and sons to be around 0.7 for the likelihood of crimes and 0.5 for the number of crimes. The estimated elasticities are stable across ages, birth cohorts, types of crimes, and either criminal charges or criminal convictions are used. The intergenerational elasticities between fathers and children appear to be stronger than those between mothers and children. We recommend this methodology to be applied to intergenerational association estimation for outcomes with a strong life cycle.

1. Introduction

Nearly all estimates for intergenerational association rely on short-run proxies because datasets that cover lifetime outcomes for both parents' and children's generations are generally unavailable. When the outcomes exhibit a strong age profile, such as earnings, consumptions, or crimes, the intergenerational association estimates can be extremely sensitive to the ages in which the outcomes are observed. The so-called life-cycle bias is the main source of bias in estimating intergenerational associations in outcomes with a strong life cycle. However, no solution has been developed to systematically address this well-known issue.

Crime appears to run within families. The intergenerational crime association is crucial to understand the evolution of criminal behaviors in a society as a substantial proportion of the population have committed crimes. Around a quarter to one third of adult population have criminal records in countries such New Zealand, Sweden, and the U.S. (Frisell, Lichtenstein, and Långström 2011; Hjalmarsson and Lindquist 2012; Vallas et al. 2015). The intergenerational transmission of criminal behaviors has been well documented since the inception of criminology research.[1] Nearly a century later, both the quality and quantity of the datasets available today are beyond the imagination of researchers of the previous generations. However, the methodology for estimating intergenerational crime transmission has not advanced as much as the available data. There is only a small number of studies on the intergenerational association in crime. In economics, both the economics of crime literature and the intergenerational mobility literature largely ignore the intergenerational relationship in criminal behaviors.[2] In criminology, research generally does not account for the life-cycle nature of criminal behaviors and their implications in estimations.

The coefficient of interest is the intergenerational association between a parent's and a child's *lifetime* criminal behaviors. As representative crime data covering two generations are not widely available, many studies rely on non-representative samples from a single city (e.g.,

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[1] Dugdale's (1877) and Goddard's (1912) ethnographic studies on the Jukes and the Kallikak family were the earliest studies identifying intergenerational continuity in criminal and delinquent behaviors within a family. Glueck and Glueck's (1930, 1934) pioneer criminology research documented that among a sample of boys sent to a reformatory from the Boston area, 66 percent had a father who had been arrested and 45 percent also had a mother who had been arrested. Nevertheless, the literature on intergenerational transmission in crime were relatively small and only started to grow since late twentieth century. In addition to the lack of longitudinal data that cover two generations, after the Second World War, many criminologists were reluctant to have research agenda that may suggest biological and genetical causes of crime (Besemer et al. 2017; van de Weijer, Megan Bears, and Besemer 2017).

[2] Except for the earlier work by Williams and Sickles (2002) and Duncan et al. (2005), the only economics studies on intergenerational crime associations are those by Hjalmarsson and Lindquist (2010, 2012, 2013). Another related but conceptually different economics literature utilizes exogenous variations such as randomization of judges to causally estimate the intergenerational effects of incarceration (Bhuller et al. 2018; Bhuller et al. 2022; Dobbie et al. 2018).

Stockholm Metropolitan Study, Christchurch Health and Development Study) or sometimes from high-risk and criminal populations (e.g., Transfive Study, Cambridge Study in Delinquent Development).[3] However, a homogenous sample can introduce substantial bias into the intergenerational estimates (Solon 1999). More importantly, almost no available dataset is long enough to cover the entire life cycle of two generations beginning from their young ages when most crimes are committed.[4] As criminal behaviors exhibit an extremely strong life-cycle pattern, short-run crime measures can be a very poor proxy for long-run criminal behaviors. The measurement error in the short-run proxy varies by age and thus is nonclassical. The so-called life-cycle bias can cause either amplification or attenuation bias in the estimates for intergenerational association depending on the ages in which the crimes are measured. While the life-cycle bias is well understood in the intergenerational income literature, the criminology literature is not aware of the econometric problem and often resorts to underlying causal channels to explain the difference in the estimates. A recent meta-analysis by Besemer et al. (2017) document that the existing estimates for intergenerational crime associations are often greater with younger cohorts, when crimes are measured at teenage years and as young adults, and also when parents' crimes are measured before children's crimes happen. The effects of exposure to parental criminal behaviors on children waning off over time are often cited as the reason but the life-cycle bias is completely ignored by criminologists (Besemer et al. 2017; Van de Rakt et al. 2010; van de Weijer, Megan Bears, and Besemer 2017).

Nearly all studies focus on the extensive margin and estimate intergenerational crime associations in odd ratios probably because arrests, charges, and convictions are count variables with many zeros. The focus on the extensive margin implicitly assumes a lifetime measure even though the criminology literature does not explicitly recognize the long-run nature of intergenerational association. Intergenerational crime associations in odd ratios are straightforward to interpret. However, unlike the intergenerational elasticity that represents percentage changes relative to the means, an odd ratio represents the levels and are not directly comparable across sexes or cohorts without standardization. For example, because the mother-

[33] For a list of datasets that have been used to estimate intergenerational crime association, see the literature reviews by Besemer et al. (2017), Wildeman (2020), and Eichelsheim and Weijer (2018)

[4] Even in Sweden where perhaps the best quality data are available, studies only have complete information on criminal behaviors over the life cycle of one generation. Frisell, Lichtenstein, and Långström (2011) and Kendler et al. (2015) use the Swedish Crime Register that includes convictions from 1973. As these studies do not restrict the cohorts of the offspring, the parents of older cohorts were in their teens and 20s before 1973, and thus the data do not have complete criminal history for parents. Hjalmarsson and Lindquist (2012) uses the Stockholm Metropolitan Study that contains convictions for fathers before 1953, the birth years of the cohort member in that study. However, the information on fathers' convictions does not appear to be complete as their numbers of convictions (or the likelihoods of convictions) are less than the half of the numbers of the sons.

child odd ratios are almost always greater than the father-child odd ratios, a somewhat misplaced consensus in the criminology literature is that mothers play a more direct role than fathers in the intergenerational crime transmission (Aaltonen and Mikkonen 2018; Besemer et al. 2017; Jahanshahi, McVie, and Murray 2021; van de Weijer, Megan Bears, and Besemer 2017; van Gaalen and Besjes 2018). However, for mothers to commit any crime, it represents a much greater deviation from their average likelihood to commit a crime than for fathers to commit any crime. Therefore, larger mother-child odd ratios do not necessarily imply a stronger intergenerational transmission from mothers. Only a small number of studies account for the intensive margin and estimate the intergenerational association in the number of crimes. However, the number of crimes has the same problem for cross-group comparison and is even more susceptible to the life-cycle bias than the likelihood of crime.

In this paper, we develop a novel methodology based on the generalized-error-in-variable (GEiV) model to correct the life-cycle bias (Haider and Solon 2006). Let β be the linear projection of children's lifetime outcomes y_i on parents' lifetime outcomes x_i and β_{ts} be the linear projection of children's age t outcomes y_{it} on parents' age s outcomes x_{is}. The GEiV model gives a relationship between the true intergenerational association β and the short-run association β_{ts}: $\beta = \frac{\beta_{ts}}{\lambda_t \theta_s}$, where λ_t is the linear projection of children's age t outcomes y_{it} on their lifetime outcomes y_i, and θ_s is the linear projection of the parents' lifetime outcome x_i on parents' age s outcome x_{is}. In practice, the GEiV model does not seem to be useful because we would estimate the intergenerational association β directly if we had lifetime data to estimate the life-cycle bias λ_t and θ_s. In fact, in the intergenerational income literature, no study tries to estimate the life-cycle bias in their own datasets.[5] The standard approach implicitly assumes that the earnings life-cycle is homogenous across countries and choose earnings measured at the prime working age around 30–35 based on the findings from Sweden and the U.S. (Böhlmark and Lindquist 2006; Haider and Solon 2006). However, even when the short-run outcomes are measured around 30–35, the short-run estimates for intergenerational association can still be substantially biased (Nybom and Stuhler 2016, 2017).

Our empirical strategy is to choose a representative cohort with the most complete life cycle during the sample period and to estimate the life-cycle bias λ_t and θ_s. Based on the age range with smaller life-cycle bias, we select corresponding cohorts and estimate the intergenerational association using their short-run outcomes. Then, we rescale the short-run

[5] One exception was Chen, Ostrovsky, and Piraino (2017) who estimate the life-cycle bias in earnings to be minimized around 40 years old in Canada but they do not conduct any correction.

intergenerational association estimate β_{ts} by the life-cycle bias estimates of λ_t and θ_s to recover the intergenerational association in lifetime outcomes β. Moreover, to address the issue that we cannot take logarithm on crimes due to large amounts of zeros, we derive estimators for the mean level of crimes of both generations as well as estimators for the intergenerational elasticity for the likelihood of commit a crime and the number of crimes. Nybom and Stuhler (2016, 2017) show that rescaling the short-run intergenerational estimates can effectively reduce the life-cycle bias. However, to the best of our knowledge, this is the first paper to adopt this kind of novel GEiV correction.

To estimate the intergenerational associations in crime, we use the New Zealand Integrated Data Infrastructure (IDI) that contains linked administrative records. We link the birth registry to the court of justice records that include all criminal charges and convictions from 1992 to 2019 to generate criminal records for both children and parents. First, we estimate the life-cycle bias at each age between 17 to 44 years old using the 1975 cohort. 17 is the legal age that a person can be tried as an adult in New Zealand. Most people would have committed their first crimes and most of their lifetime crimes before 45.[6] This age range covers a nearly complete life cycle of criminal behaviors for both the extensive and intensive margins. Second, we use the 1998 cohort of first-born children to estimate the intergenerational crime association. The 1998 cohort were the first cohort with fully digitalized birth records and thus have most complete linkages with other datasets in the IDI. The 1998 cohort were 17–21 years old in the most recent sample period, and the average age of their parents was around 24 in the earliest sample period. The sample period covers the peak of the children's life cycle as well as the majority of the parents' life cycle. Notice that, given a fixed sample period, parents' age ranges are determined by the choice of children's birth cohort. As a robustness check, we also estimate the intergenerational associations in crime using the 1990 cohort.

Our estimates from the 1975 cohort show that both λ_t and θ_s monotonically decrease with age for the extensive margin. Therefore, the life-cycle bias in the likelihood of crimes is smallest around 18–20 years old. This is very intuitive because the probability to misclassify a person's lifetime status is lower when he is young and with a higher likelihood to commit a crime. However, the estimates for both λ_t and θ_s are always below one and therefore the combined life-cycle bias is still large even during young ages. For the intensive margin, λ_t is monotonically decreasing with age. It is greater than one in 18–20 years old and close to one

[6] In the IDI court data, only 10% of the total criminal charges are laid against people who are older than 44 years old.

around the ages of late 20s. In contrast, θ_s is monotonically increase with age and always below one. Therefore, while the life-cycle bias in the left-hand side is an amplification bias around younger ages, the combined life-cycle bias is still likely an attenuation bias. Based on the estimates for λ_t and θ_s, the 1998 cohort and their parents have small life-cycle bias. The life-cycle bias is likely greater for the 1990 cohort because the average age of their parents was older and in their 30s during the earliest sample period.

The GEiV corrected estimates for the 1998 cohort suggest that the sons whose fathers have at least one criminal charge are 28 percentage points more likely to have at least one criminal charge than those without. Also, on average, one additional criminal charge laid against fathers is associated with 0.14 more criminal charges laid against sons. More importantly, the GEiV corrected estimates for the intergenerational elasticities between fathers and sons are around 0.75 for the likelihood of criminal charges and 0.50 for the number of criminal charges. For the 1990 cohort, the GEiV corrected estimates are roughly twice greater than those of the 1998 cohort but the elasticity estimates remain similar. This is because the 1998 cohort has much less criminal charges than the 1990 cohort. The estimated intergenerational elasticities are around 0.70 for the likelihood of criminal charges and 0.40 for the number of criminal charges. The estimates are nearly identical for the intensive margin, regardless of whether the numbers of crimes are measured in 17–21 years old or 25–29 years old. For the extensive margin, however, the likelihood of criminal charges in 25–29 years old generates larger estimates than 17–21 years old. In general, our GEiV correction performs very well when the life-cycle bias is small to medium sizes. The intergenerational association estimates are stable across ages and different numbers of years of averages for both parents and children. With large life-cycle bias, however, the intergenerational association estimates are overcorrected and upward biased.

For other parent-child relationships, the intergenerational transmission in crime is stronger from fathers to children compared to from mothers to children. The father-daughter associations appear to be the strongest, but the estimates also have largest standard errors among the four parent-child dyads. The estimated intergenerational elasticities between fathers and daughters are around 1.0 for the extensive margin and 0.60–0.85 for the intensive margin. The intergenerational elasticities between mothers and daughters are around 0.30–0.50 for the extensive margin and 0.30–0.40 for the intensive margin. The intergenerational elasticities between mothers and sons are the weakest and only around 0.15–0.30. The intergenerational elasticities appear to be very homogenous across different types of crimes. We find no evidence that the intergenerational association in violent crime is stronger than non-violent crimes.[7] All of the estimates based on criminal convictions are very similar to those based on the criminal charges. In addition, we standardize the criminal charges to mean zero and standard deviation one and estimate intergenerational correlation coefficients. The GEiV corrected correlation coefficients in criminal charges are also very stable and around 0.30–0.50 but somewhat smaller than the intergenerational elasticities. Overall, the estimates indicate a strong intergenerational association in crime between fathers and children that is stable across ages, birth cohorts, types of crimes, and either criminal charges or criminal convictions are used.

Our paper contributes to the literature in several important ways. First, we propose a novel methodology that corrects life-cycle bias in the estimates for intergenerational association using short-run proxies. In addition to the standard case for continuous outcome variables, we derive a GEiV corrected estimator for binary outcome variables as well as an alternative estimator for the intergenerational elasticity that can accounts for zeros. Our methodology can be applied to any outcomes with strong life-cycle patterns such as income and consumption and can account for the extensive margin. Second, our findings provide plausible estimates for the intergenerational crime associations. In fact, we are the first to directly correct the life-cycle bias in the intergenerational association estimates not only in the criminology literature but also the economics literature. Third, we provide the first set of estimates for life-cycle bias for criminal behaviors. As the life cycle of criminal behaviors is likely very homogenous across countries, our estimates for λ_t and θ_s can inform the magnitudes of life-cycle bias in the estimates for intergenerational crime association in other countries.

2. Generalized Error-in-Variable (GEiV) Model

2.1. GEiV Model on the Intensive Margin

Our goal is to estimate the intergenerational association in the following model:

$$y_i = \alpha + \beta x_i + u_i, \tag{1}$$

where y_i is the lifetime outcome for child i, x_i is the lifetime outcome for child i's parent, and u_i is the idiosyncratic error term that is orthogonal to x_i, i.e., $\mathrm{Cov}(x_i, u_i) = 0$. The coefficient of interest, β, is the linear projection of children's lifetime outcome on parents' lifetime outcome; and α is the intercept term. If lifetime outcomes x_i and y_i are available, an ordinary

[7] Some criminology studies suggest a stronger intergenerational association in violent crime because of the genetic origin of violent behaviors (Farrington, Ttofi, and Crago 2017; Van de Weijer, Bijleveld, and Blokland 2014).

least squares (OLS) regression of y_i on x_i gives a consistent estimate of β. However, lifetime outcomes are unavailable in nearly all datasets, and most studies rely on short-run proxies. Consider the following model based on short-run proxies:

$$y_{it} = \alpha_{ts} + \beta_{ts} x_{is} + u_{it}, \tag{2}$$

where y_{it} is child *i*'s outcome at age *t*, x_{is} is child *i*'s parent's outcome at age *s*, u_{it} is orthogonal to x_{is}, β_{ts} is the linear projection of children's age *t* outcomes on parents' age *s* outcomes, and α_{ts} is the associated intercept term. An OLS regression of y_{it} on x_{is} does not give a consistent estimate of β but only β_{ts} that varies with age *t* and *s*. In most applications, due to the lengths of datasets, the short-run proxies y_{it} and x_{is} are not measured at the same age and thus $t \neq s$. In practice, children's and parents' ages and their squared are also included as covariates in equation (2). In this paper, as we use a single cohort for children, we only include parents' age and age squared.

We consider a generalized errors-in-variables (GEiV) model from the following "forward" regressions:

$$y_{it} = \alpha_t^y + \lambda_t y_i + e_{it}; \tag{3}$$

$$x_{is} = \alpha_s^x + \lambda_s x_i + \varepsilon_{is}\,. \tag{4}$$

In equations (3) and (4), we assume that both children and parents follow the same life cycle pattern and thus have the same slope λ_t at each age *t* but the levels can be different: $\alpha_t^y \neq \alpha_t^x$. Haider and Solon (2006) assume that e_{it} and ε_{is} are classical measurement error:

$$\mathrm{Cov}(y_i, e_{it}) = \mathrm{Cov}(x_i, \varepsilon_{is}) = \mathrm{Cov}(y_i, \varepsilon_{is}) = \mathrm{Cov}(x_i, e_{it}) = \mathrm{Cov}(\varepsilon_{is}, e_{it}) = 0. \tag{5}$$

Under the assumption in (5), equations (2), (3), and (4) together imply:

$$\beta_{ts} = \frac{\mathrm{Cov}(y_{it}, x_{is})}{Var(x_{is})} = \frac{\lambda_t\lambda_s \mathrm{Cov}(y_i, x_i) + \lambda_t \mathrm{Cov}(y_i, \varepsilon_{is}) + \lambda_s \mathrm{Cov}(x_i, e_{it}) + \mathrm{Cov}(\varepsilon_{is}, e_{it})}{\lambda_s^2 Var(x_i) + Var(\varepsilon_{is}) + 2\lambda_s \mathrm{Cov}(x_i, \varepsilon_{is})}$$

$$= \frac{\lambda_t\lambda_s \mathrm{Cov}(y_i, x_i)}{\lambda_s^2 \mathrm{Var}(x_i) + \mathrm{Var}(\varepsilon_{is})} = \lambda_t \frac{\lambda_s \mathrm{Var}(x_i)}{\lambda_s^2 \mathrm{Var}(x_i) + \mathrm{Var}(\varepsilon_{is})} \frac{\mathrm{Cov}(y_i, x_i)}{\mathrm{Var}(x_i)} \equiv \lambda_t \theta_s \beta. \tag{6}$$

Rewrite $x_i = -\frac{1}{\lambda_s}\alpha_s^x + \frac{1}{\lambda_s} x_{is} - \frac{1}{\lambda_s}\varepsilon_{is}$, and note that $\mathrm{Cov}(x_{is}, \varepsilon_{is}) = \mathrm{Var}(\varepsilon_{is}) \neq 0$, then:

$$\frac{\mathrm{Cov}(x_i, x_{is})}{\mathrm{Var}(x_{is})} = \frac{1}{\lambda_s}\left[\frac{\mathrm{Var}(x_{is}) - \mathrm{Cov}(x_{is}, \varepsilon_{is})}{\mathrm{Var}(x_{is})}\right] = \frac{1}{\lambda_s}\left[\frac{\lambda_s^2 \mathrm{Var}(x_i) + \mathrm{Var}(\varepsilon_{is}) - \mathrm{Var}(\varepsilon_{is})}{\lambda_s^2 \mathrm{Var}(x_i) + \mathrm{Var}(\varepsilon_{is})}\right]$$

$$= \frac{\lambda_s \mathrm{Var}(x_i)}{\lambda_s^2 \mathrm{Var}(x_i) + \mathrm{Var}(\varepsilon_{is})} = \theta_s. \tag{7}$$

Therefore, θ_s is a linear projection of x_i on x_{is} and can be consistently estimated from a "reverse" regression of equation (4):

$$x_i = \delta_s^x + \theta_s x_{is} + v_{is}, \tag{8}$$

where $\mathrm{Cov}(x_i, v_{is}) = 0$ by construction and thus $v_{is} \neq \varepsilon_{is}$.

2.2. GEiV Model on the Extensive Margin

Now, we consider the extensive margin where the outcomes y_i, x_i and y_{it}, x_{it} are binary variables. A well-known econometric property is that measurement error cannot be classical in a binary random variable and must be negatively correlated with the true value, i.e., $\text{Cov}(y_i, e_{it}) < 0$ and $\text{Cov}(x_i, \varepsilon_{is}) < 0$. Fortunately, the relationship between β and β_{ts} in equation (6) holds for binary outcomes. If we maintain the assumption that $\text{Cov}(y_i, \varepsilon_{is}) = \text{Cov}(x_i, e_{it}) = \text{Cov}(\varepsilon_{is}, e_{it}) = 0$, then:

$$\beta_{ts} = \frac{\text{Cov}(y_{it}, x_{is})}{\text{Var}(x_{is})} = \frac{\lambda_t \lambda_s \text{Cov}(y_i, x_i)}{\lambda_s^2 \text{Var}(x_i) + \text{Var}(\varepsilon_{is}) + 2\lambda_s \text{Cov}(x_i, \varepsilon_{is})} \equiv \lambda_t \theta_s \beta. \tag{9}$$

An interesting but often ignored implication is that the denominator in equation (9) is closer to $\text{Var}(x_i)$ than equation (6) because λ_s is positive and x_i and ε_{is} are negatively correlated. Therefore, the OLS estimates for the extensive margin are less biased than the intensive margin. This is likely the reason as to why the intergenerational crime association estimates in the literature for the extensive margin are less sensitive than those for the intensive margin. To show that $\theta_s = \frac{\lambda_s \text{Var}(x_i)}{\lambda_s^2 \text{Var}(x_i) + \text{Var}(\varepsilon_{is}) + 2\lambda_s \text{Cov}(x_i, \varepsilon_{is})}$ is the linear projection of x_i on x_{is}, we write $x_i = \frac{1}{\lambda_s} x_{is} - \frac{1}{\lambda_s} \varepsilon_{is}$:

$$\frac{\text{Cov}(x_i, x_{is})}{\text{Var}(x_{is})} = \frac{1}{\lambda_s}\left[\frac{\text{Var}(x_{is}) - \text{Cov}(x_{is}, \varepsilon_{is})}{\text{Var}(x_{is})}\right] = \frac{1}{\lambda_s}\left[\frac{\lambda_s^2 \text{Var}(x_i) + \text{Var}(\varepsilon_{is}) + 2\lambda_s \text{Cov}(x_i, \varepsilon_{is}) - 2\lambda_s \text{Cov}(x_i, \varepsilon_{is}) - \text{Var}(\varepsilon_{is})}{\lambda_s^2 \text{Var}(x_i) + \text{Var}(\varepsilon_{is}) + 2\lambda_s \text{Cov}(x_i, \varepsilon_{is})}\right]$$

$$= \frac{\lambda_s \text{Var}(x_i)}{\lambda_s^2 \text{Var}(x_i) + \text{Var}(\varepsilon_{is}) + 2\lambda_s \text{Cov}(x_i, \varepsilon_{is})} = \theta_s. \tag{10}$$

Therefore, θ_s can be consistently estimated from the same reverse regression in equation (8).

Before we turn to the estimation of the GEiV model, we note that while the measurement error can be nonclassical, the derivation of both equations (6) and (9) requires parents' and children's life cycles to be uncorrelated, i.e., $\text{Cov}(y_i, \varepsilon_{is}) = \text{Cov}(x_i, e_{it}) = \text{Cov}(\varepsilon_{is}, e_{it}) = 0$. This assumption could be untrue when there is strong heterogeneity in life cycle (Böhlmark and Lindquist 2006; Nybom and Stuhler 2016). For example, children with high level of education probably have parents with high levels of education, and their earnings profile can be steeper than people with lower education as they enter the labor market later but earn more. The GEiV model can greatly reduce life-cycle bias but unlikely to completely eliminate the bias as λ_t and θ_s ignore such heterogeneity (Nybom and Stuhler 2016).

Equation (6) and (9) offer an important econometric insight, but λ_t and θ_s cannot be estimated in the data as lifetime outcomes x_i and y_i are not available. (Otherwise, we can simply regress y_i on outcomes x_i to obtain β.) In the income literature, nearly all researchers make an implicit assumption that the income life cycles in their datasets are similar to those in

Sweden and U.S. and use the findings from Haider and Solon (2006) and Böhlmark and Lindquist (2006) to justify selecting samples around 30–35 years old. Not only is this a strong assumption but Nybom and Stuhler (2016) also show that significant bias still remains even when this assumption is true. We note that while most datasets cannot cover two generations, many datasets are long enough to estimate one or nearly one life cycle for a cohort. Our estimation strategy is to use a representative cohort to estimate λ_t and θ_s and then applies these estimates to recover the true intergenerational association β.

2.3. Estimation of the GEiV Model and Elasticity

Assume a representative cohort whose life cycle follows the same slopes as those of parents and children. Both the forward and reverse regressions for this cohort are given by:

$$z_{it} = \alpha_t^z + \lambda_t^z z_i + \eta_{it} = \alpha_t^z + \lambda_t z_i + \eta_{it}. \tag{11}$$

$$z_i = \delta_t^z + \theta_s^z z_{it} + \omega_{it} = \delta_t^z + \theta_t z_{is} + \omega_{it}, \tag{12}$$

where $\mathrm{Cov}(z_i, \eta_{it}) = \mathrm{Cov}(z_{is}, \omega_{is}) = 0$ by construction. Equations (11) and (12) assume the life-cycle bias the same across cohorts. Thus, the representative cohort, parents' cohort, and children's cohort have the same λ_t and θ_t at each age *t*. Under (11) and (12), a feasible estimator for the intergenerational association β is given by:

$$\hat{\beta} = \frac{\hat{\beta}_{ts}}{\hat{\lambda}_t^z \hat{\theta}_s^z}, \tag{13}$$

where $\hat{\lambda}_t^z$ and $\hat{\theta}_s^z$ are the OLS estimates from equations (11) and (12) at children's age *t* and parents' age *s*.

In the current context, due to a large number of zeros, we cannot take logarithm on the outcome variables to obtain an elasticity from (13). Our goal is to estimate an intergenerational elasticity defined as the following:

$$\beta \frac{\mathrm{E}(x_i)}{\mathrm{E}(y_i)} = \frac{\beta_{ts}}{\lambda_t \theta_s} \frac{\mathrm{E}(x_i)}{\mathrm{E}(y_i)}. \tag{14}$$

where $\mathrm{E}(x_i)$ and $\mathrm{E}(y_i)$ are the means of lifetime outcomes. We cannot directly estimate the intergenerational elasticity in (14) even with estimates for λ_t and θ_s because $\mathrm{E}(x_i)$ and $\mathrm{E}(y_i)$ are not observed in the data. Note that equation (11) assumes the same λ_t as equations (3) and (4) but allows the intercepts to be different: $\alpha_t^z \neq \alpha_t^x \neq \alpha_t^y$. To estimate α_s^x and α_t^y, we make an additional assumption:

$$\alpha_s^x = \rho^x \alpha_s^z \text{ and } \alpha_t^y = \rho^y \alpha_t^z, \tag{15}$$

where ρ^x and ρ^y are assumed to be constant and not depending on the age *t* or *s*. Also, we can write $\mathrm{E}(z_i)$ as a function of α_k^z and λ_k:

$$\mathrm{E}(z_i) = \frac{\sum_{k=1}^{T} \mathrm{E}(z_{ik})}{T} = \frac{\sum_{k=1}^{T} [\alpha_k^z + \lambda_k \, \mathrm{E}(z_i)]}{T} = \frac{\sum_{k=1}^{T} \alpha_k^z}{T} + \frac{\mathrm{E}(z_i) \sum_{k=1}^{T} \lambda_k}{T} \Rightarrow \mathrm{E}(z_i) = \frac{\sum_{k=1}^{T} \alpha_k^z}{T - \sum_{k=1}^{T} \lambda_k}. \quad (16)$$

Equations (15) and (16) imply:

$$\mathrm{E}(x_i) = \frac{\sum_{k=1}^{T} \alpha_k^x}{T - \sum_{k=1}^{T} \lambda_k} = \frac{\rho^x \sum_{k=1}^{T} \alpha_k^z}{T - \sum_{k=1}^{T} \lambda_k} = \rho^x \mathrm{E}(z_i); \quad (17)$$

$$\mathrm{E}(y_i) = \frac{\sum_{k=1}^{T} \alpha_k^y}{T - \sum_{k=1}^{T} \lambda_k} = \frac{\rho^y \sum_{k=1}^{T} \alpha_k^z}{T - \sum_{k=1}^{T} \lambda_k} = \rho^y \, \mathrm{E}(z_i); \quad (18)$$

Therefore, ρ^x and ρ^y can be written as functions of short-run outcomes:

$$\mathrm{E}(x_{is}) = \alpha_s^x + \lambda_s \mathrm{E}(x_i) = \rho^x \alpha_s^z + \lambda_s \rho^x \mathrm{E}(z_i) = \rho^x \mathrm{E}(z_{it}) \Rightarrow \rho^x = \frac{\mathrm{E}(x_{is})}{\mathrm{E}(z_{is})}; \quad (19)$$

$$\mathrm{E}(y_{it}) = \alpha_t^y + \lambda_t \mathrm{E}(y_i) = \rho^y \alpha_t^z + \lambda_t \rho^y \mathrm{E}(z_i) = \rho^y \mathrm{E}(z_{it}) \Rightarrow \rho^y = \frac{\mathrm{E}(y_{it})}{\mathrm{E}(z_{it})}. \quad (20)$$

Equations (19) and (20) give an estimable expression for $\mathrm{E}(x_i)$ and $\mathrm{E}(y_i)$:

$$\mathrm{E}(x_i) = \frac{[\mathrm{E}(x_{is}) - \alpha_s^x]}{\lambda_s} = \frac{[\mathrm{E}(x_{is}) - \rho^x \alpha_s^z]}{\lambda_s} = \frac{\left[\mathrm{E}(x_{is}) - \frac{\mathrm{E}(x_{is})}{\mathrm{E}(z_{is})} \alpha_s^z\right]}{\lambda_s}; \quad (21)$$

$$\mathrm{E}(y_i) = \frac{[\mathrm{E}(y_{it}) - \alpha_t^y]}{\lambda_t} = \frac{[\mathrm{E}(y_{it}) - \rho^y \alpha_t^z]}{\lambda_t} = \frac{\left[\mathrm{E}(y_{it}) - \frac{\mathrm{E}(y_{it})}{\mathrm{E}(z_{it})} \alpha_t^z\right]}{\lambda_t}. \quad (22)$$

Let $\overline{x}_{is}$ and $\overline{y}_{it}$ be the sample averages of parents' and children's outcomes in age *s* and *t*, and $\overline{z}_{is}$ and $\overline{z}_{it}$ be the sample averages of the representative cohort's outcomes in age *s* and *t*. Then, a feasible estimator for the intergenerational elasticity $\beta \frac{\mathrm{E}(x_i)}{\mathrm{E}(y_i)}$ is:

$$\frac{\hat{\beta}_{ts}}{\hat{\lambda}_t^z \hat{\theta}_s^z} \frac{\left[\overline{x}_{is} - \frac{\overline{x}_{is}}{\overline{z}_{is}} \hat{\alpha}_s^z\right]}{\hat{\lambda}_s^z} \frac{\hat{\lambda}_t^z}{\left[\overline{y}_{it} - \frac{\overline{y}_{it}}{\overline{z}_{it}} \hat{\alpha}_t^z\right]} = \frac{\hat{\beta}_{ts}}{\hat{\lambda}_s^z \hat{\theta}_s^z} \frac{\left[\overline{x}_{is} - \frac{\overline{x}_{is}}{\overline{z}_{is}} \hat{\alpha}_s^z\right]}{\left[\overline{y}_{it} - \frac{\overline{y}_{it}}{\overline{z}_{it}} \hat{\alpha}_t^z\right]}. \quad (23)$$

For the extensive margin, the intercept term α_t^z in the forward regression (11) represents the likelihood to misclassify someone without any lifetime crime and therefore is zero.[8] Therefore, the intergeneration elasticity estimator can be further simplified:

$$\frac{\hat{\beta}_{ts}}{\hat{\lambda}_s^z \hat{\theta}_s^z} \frac{\left[\overline{x}_{is} - \frac{\overline{x}_{is}}{\overline{z}_{is}} \cdot 0\right]}{\left[\overline{y}_{it} - \frac{\overline{y}_{it}}{\overline{z}_{it}} \cdot 0\right]} = \frac{\hat{\beta}_{ts}}{\hat{\lambda}_s^z \hat{\theta}_s^z} \frac{\overline{x}_{is}}{\overline{y}_{it}}. \quad (24)$$

In this paper, we estimate equations (2) with parents age and age squared as covariates to obtain $\hat{\beta}_{ts}$ for the 1998 or 1990 cohort, estimate equations (11) and (12) to obtain $\hat{\lambda}_s^z$ and $\hat{\theta}_s^z$ from the 1975 cohort, and scale $\hat{\beta}_{ts}$ by $\hat{\lambda}_s^z$ and $\hat{\theta}_s^z$. To calculate the standard error for

[8] There is no intercept term in the forward regression (11): $\alpha_t^z = \mathrm{E}(z_{it}|z_i = 0) = \mathrm{P}(z_{it} = 1|z_i = 0) = 0$, and $\lambda_t = \mathrm{E}(z_{it}|z_i = 1) - \mathrm{E}(z_{it}|z_i = 0) = \mathrm{P}(z_{it} = 1|z_i = 1)$. In contrast, the intercept term exists in the reverse regression (12) and represents the likelihood to misclassify the lifetime status for someone without a short-run crime: $\delta_t^z = \mathrm{E}(z_i|z_{it} = 0) = \mathrm{P}((z_i = 1|z_{it} = 0)$ and $\theta_t = \mathrm{E}(z_i|z_{it} = 1) - \mathrm{E}(z_i|z_{it} = 0) = 1 - \mathrm{P}(z_i = 1|z_{it} = 0) = \mathrm{P}(z_i = 0|z_{it} = 0)$.

$\frac{\hat{\beta}_{ts}}{\hat{\lambda}_t\hat{\theta}_s}$, we apply the delta method and take the cross-regression covariance structure of $\hat{\beta}_{ts}$, $\hat{\lambda}_t$, and $\hat{\theta}_s$ into account. Similarly, for the estimated elasticities in (23) and (24), the standard errors are obtained by the delta method and accounts for the cross-regression covariance structure of $\hat{\beta}_{ts}$, $\hat{\lambda}_t$, $\hat{\theta}_s$ as well as $\overline{x}_{is}, \overline{y}_{it}, \overline{z}_{is}, \overline{z}_{it}$. These sample means are estimated from regressing the outcomes on an intercept term. We implement the delta method in Stata using the "*suest*" (seemingly unrelated estimation) command to obtain heteroskedasticity-robust standard errors.

3. Integrated Data Infrastructure (IDI) and Sample Construction

Data for this study are accessed through the IDI maintained by the Statistics New Zealand. The IDI houses nationally comprehensive data on all individuals from linked government administrative records. In this paper, we link the national court records to the birth records to create parent-child pairs.

The court records are provided by the Ministry of Justice and available from 1992–2019. The court records contain all criminal charges and their outcomes such as conviction status and sentences. The court records include the dates of the offense, the dates of charges laid, the dates of the first and the last hearings, and the dates of outcomes. Because the criminal justice system can sometimes take years from the charges laid to conviction or discharge, we use the date of the offense to determine the age for both criminal charges and convictions. For example, a person may commit a crime at age 18, be charged at age 19, and be convicted at age 20. We code both criminal charge and conviction to be age 18 because they are related to an offense committed at age 18. We consider all criminal charges as well as criminal charges of three categories: violent, property, and other crimes. The Australian and New Zealand Standard Offence Classification (ANZSOC) defines violent crimes as "crimes against people": homicide, assault, sexual assault, robbery (including extortion), dangerous and negligent acts (including driving under influence), and abduction. Property crimes are those defined as "crimes against properties" in the ANZSOC: burglary, theft, fraud, property damage (including environmental pollution). We also create a category of other crimes that includes the rest of the offenses in the ANZSOC: illicit drug, weapons and explosives, public order, offenses against justice, traffic and vehicles, and miscellaneous offenses. We focus on criminal charges as our measure for crimes and use criminal convictions for robustness checks. In New Zealand, a person can be tried as adult at age 17. (The adult age has been raised to 18 years old since July 2019.) Therefore, with 28 years of criminal records, we can observe a nearly complete life cycle of the 1975 cohort's criminal behaviors from 17 to 44 years old.

The birth records in the IDI are provided by the Department of Internal Affairs (DIA). The birth records go back to 1848 but earlier records are generally not linked to other records. Almost all birth records before 1970 cannot be linked to their parents. In 1998, the DIA moved to digital storage of paper records, and birth records are fully digitalized since then. We focus on the 1998 cohort as our main sample of children as they are the first cohort that can be completely linked to their parents. DIA birth records from 1990 are retrospectively digitalized in recent years and most parent-children can be linked. Therefore, the 1990 cohort is the oldest cohort that we can estimate intergenerational association in the IDI data.

We restrict both the 1998 and 1990 cohorts to be first-born children and require both parents were born in New Zealand so that they can be linked from the birth records. There were around 57,000 births in 1998; 70% of them were first born children, and 59% had both parents born in New Zealand. The 1990 cohort had around 61,000 births with a similar proportion of first-born children, and 57% of them have both parents born in New Zealand that can be linked. We drop a small number of people born in 1990 and 1998 who had died by 2019. We also drop people if one of their parents had died before they were born. The final sample sizes for both the 1990 and 1998 cohorts are about 22,000.

In Table 1, we report the descriptive statistics for the 1998 and 1990 cohorts in the upper panel and for their parents in the lower panel. The criminal charges are measured in 17–21 years old so the data are drawn from 2015–2019 for the 1998 cohort and from 2007–2011 for the 1990 cohort. 16% of the sons and 5% of the daughters born in 1998 cohort had at least one criminal charge when they were 17–21 years old. Sons have on average 0.14 charges per year (equivalent to $0.144 \times 5 \div 0.161 = 4.5$ charges for people with at least one charge in 17–21 years old); roughly a quarter of the charges are for violent crimes, a quarter of the charges are for property crimes, and half of the charges are for other crimes. The numbers of charges for daughters are only around one third of the sons but the composition of violent and property crimes is similar. The levels of criminal charges are much higher for the 1990 cohort and around two to three times larger than those of the 1998 cohort. 37% of sons and 16% of daughters born in 1990 have at least one criminal charges during 17–21 years old. On average, sons and daughters have 0.42 and 0.10 criminal charges per year, respectively. The proportions of violent and property crimes account for 40% of the total criminal charges, and other crimes account for 60% of the charges.

In the lower panel, we report the five-year averages of criminal charges from 1992–1996 for the parents. For the 1998 cohort, on average, their fathers are 24–28 years old and their mothers are 22–26 years old in 1992–1996. 27% of the fathers and 8% of the mothers have at least on criminal charges. The fathers and mothers on average have 0.28 and 0.05 criminal charges per year. The average fathers and average mothers of the 1990 cohorts are 31–35 years old and 29–33 years old in 1992–1996. Likely because the parents of the 1990 cohort are older, their criminal charges are a bit lower than those of the 1998 cohort's parents. For the 1990 cohort, 23% of the fathers and 7% of the mothers have at least one criminal charges. The fathers and mothers on average have 0.22 and 0.05 criminal charges per year. The proportions of crimes for the parents are roughly comparable to those of the children. Overall, Table 1 shows that there are substantial age differences as well as cohort differences in terms of the likelihood and numbers of crimes.[9] Therefore, when using short-run proxies for lifetime outcomes, correcting the life-cycle bias and accounting for the age difference in the propensity to commit crimes is crucial. It is also important to measure the intergenerational associations in terms of elasticities to account for cohort differences in the level of crimes.

4. Estimates of Life-Cycle Bias

In this section, we present the life cycle of criminal charges from 17 to 44 years old and then estimate λ_t and θ_t using the 1975 cohort. (Appendix Table A1 shows the descriptive statistics for the 1975 cohort.)

Figure 1 shows the life cycle of criminal charges of all crimes for the extensive margin in the upper panel and for the intensive margin in the lower panel. In the upper pane, the likelihood to have at least one criminal charge is highest at age 19 for both males and females but males exhibit a much strong age profile than females. At age 19, 14% males and 3% females have at least one criminal charges against them. At age 44, only 2% males and 1% females have any criminal charges. In the lower panel, we calculate the proportions of the number of charges in each age relative to the total number of charges over ages 17–44. Interestingly, while females commit much less crime than males, their life cycle is extremely similar to males' life cycle for the intensive margin. For both males and females, the proportion peaks at age 19 and decreases with age. Therefore, people are most likely to commit a crime and commit the largest numbers of crimes at age 19 but commit less and less crimes as they grow older. (Appendix Figure A1 shows separately the life cycles for violent, property, and other crimes.)

[9] Notice that we cannot distinguish cohort effects and secular trends because cohorts are collinear with calendar years. The lower numbers of charges for the 1998 cohort could be due to that the criminal justice system becomes more lenient. However, the proportions of charges that are convicted remain around 70% for both cohorts and thus the change in the criminal justice system is unlikely the main factor.

Figure 2 shows the estimates for life-cycle bias in the likelihood of criminal charges for all crimes where the ages are measured as five-year moving averages: 17–21, 18–22, …, 40–44. The upper panel shows the estimates of λ_t from equation (11), where $\lambda_t = \mathrm{P}(z_{it} = 1|z_i = 1)$ represents the probability that the short-run proxy correctly reflects the lifetime status of having at least one criminal charge. The estimates of λ_t are largest when people are around their late teens and decrease with age. This is very intuitive. Because people are most likely to commit crimes during young ages, the likelihoods of charges observed in younger ages are more consistent with the lifetime status than those in older ages. The estimates of λ_t among males are larger than those among females but the estimates converge after age 30. Nevertheless, the estimates of λ_t are maximized at around 0.75 for males and 0.50 for females and well below one throughout the life cycle for both genders, suggesting substantial life-cycle bias. Even in the best-case scenario that no life-cycle bias from parents, and children's crimes are observed from their late teens, the uncorrected estimates for the intergenerational associations in the likelihood of crimes will be underestimated by 25% for males and by 50% for females. The lower panel shows the estimates for θ_s from equation (12), where $\theta_t = \mathrm{P}(z_i = 0|z_{it} = 0)$. Like λ_t, θ_t represents the probability that the short-run proxy is consistent with the lifetime status and are always below one. The estimates of θ_t are largest around late teens and decrease with age. Interestingly, the estimates of θ_t among females are very flat and always greater than those among males. One possible explanation is that females' criminal behaviors only exhibit a weak age gradient and thus their $\mathrm{Var}(\varepsilon_{it})$ is smaller and more stable over the life cycle. The estimates of θ_t are 0.60–0.75 for males and 0.8 for females. Therefore, the life-cycle bias from the parents alone can cause 20% to 40% drop in the intergenerational association estimates for the likelihood of crimes.

Figure 3 shows the estimates for life-cycle bias in the number of criminal charges for all crimes. The upper panel shows the estimates for λ_t from equation (11). Unlike that the life-cycle bias in incomes are generally attenuation bias, in the upper panel, the estimates for λ_t indicate strong amplification bias and are around 1.5 during the late teens to early 20s. Suppose no life-cycle bias from the parents, the estimates for intergenerational crime associations using criminal charges observed in late teens can be overestimated by about 50%. The estimates of λ_t for males are decreasing with age and around one in late 20s. The estimates of λ_t for females fluctuate quite a bit; they are also close to one in late 20s but generally greater than one before age 35. In the lower panel, the θ_t are below one throughout the life cycle and gradually increasing with age for both genders but the θ_t for males are greater than those for females. As most θ_t are around 0.50–0.60, the intergenerational association estimates can be underestimated by 40–50% due to the life-cycle bias from the parents alone. However, if the observations are drawn around the late teens to early 20s, the amplification bias from λ_t and the attenuation bias from θ_t can be largely cancelled out. Appendix Figures A2 and A3 show the estimates for λ_t and θ_t separately for violent, property, and other crimes, and they are generally very similar to Figures 2 and 3.

Both Figures 2 and 3 suggest that crimes measured in younger ages generally have smaller life-cycle bias. However, even we can select a sample that minimizes the life-cycle bias for both children and parents, the uncorrected estimates for the intergenerational crime association are still substantially biased. In the next section, we will compare the GEiV corrected estimates with uncorrected estimates from different ages. Before we turn to the next section, we note that λ_t and θ_t also depend on how many years of observations used for the short-run proxies. For both the extensive and intensive margins, the right-hand-side measurement error θ_t is always increasing when the short-run proxies using more years of observation. Intuitively, using more data can reduce attenuation bias by averaging out the measurement error in the explanatory variable. For the extensive margin, the left-hand-side measurement error λ_t is monotonically increasing with the number of years used in the short-run proxy. The probability to correctly infer the lifetime status goes up when more years are observed. However, it is not the case for the intensive margin, and the left-hand-side measurement error λ_t does not necessarily increase with more data. The next section will present the estimates for λ_t and θ_t based on criminal charges of one year, five years, ten years, and twenty years.

5. Estimates of Intergenerational Crime Associations

5.1. Estimates of Intergenerational Elasticities

Table 2 presents the estimates for intergenerational associations in criminal charges of all crimes between fathers and sons of the 1998 cohort. The sons' criminal charges are measured in 17–21 years old (2015–2019), and the estimates of λ_{17-21} from males of the 1975 cohort are reported in column (1). The fathers' criminal charges are measured in five years in 1992–1996 (average ages 24–28), ten years in 1992–2001 (average ages 24–33), and twenty years in 1992–2011 (average ages 24–43). The estimates for θ_{24-28}, θ_{24-33}, θ_{24-43} from the males of the 1975 cohort are reported in column (2). Column (3) shows the uncorrected estimates while column (4) shows the GEiV corrected estimates. Column (5) shows the estimates for intergenerational elasticities.

In the upper panel of Table 2, we estimate the intergenerational associations in the likelihood of criminal charges. The uncorrected estimates $\hat{\beta}_{ts}$ are around 0.13–0.14 and slightly increasing with more years of averages used for fathers. However, the estimates for λ_t and θ_s indicate these uncorrected estimates are likely downward biased by about 50% (1 – 0.70 × 0.68 = 0.52). The GEiV corrected estimates $\frac{\hat{\beta}_{ts}}{\hat{\lambda}_t\hat{\theta}_s}$ are 0.27–0.28, suggesting that on average, sons with criminal fathers are 27-percentage-point more likely to have at least one criminal charge than those without criminal fathers. If we translate these estimates into odd ratios based on the sample mean (0.16) reported in Table 1, they are around 2.7 (0.27 ÷ 0.16 + 1 = 2.7). The GEiV corrected intergenerational crime elasticities on the extensive margin are around 0.75 and very robust to the number of years of averages used for fathers. Relative to the sample means, a 10% increase in the lifetime likelihood of any criminal charges for fathers is associated with a 7–8% increase in the lifetime likelihood of any criminal charges for sons.

In the lower panel of Table 2, we estimate the intergenerational associations in the number of criminal charges. The uncorrected estimate $\hat{\beta}_{ts}$ using five-year average of fathers' crimes is 0.13. However, when fathers' crimes are measured in ten-years and twenty years, the uncorrected estimates increase to 0.17 and 0.22, respectively. As the estimate of λ_t is 1.58 and the estimates of θ_s are close to 1, the uncorrected estimates using ten-year and twenty-year averages can be upward biased up to 60%. In contrast, the uncorrected estimate using five-year average of fathers have little bias as the multiplication of λ_t and θ_s largely cancel out the life-cycle bias. The GEiV corrected estimates $\frac{\hat{\beta}_{ts}}{\hat{\lambda}_t\hat{\theta}_s}$ are around 0.13–0.14 and very robust to the number of years of averages used for fathers. On average, one additional criminal charge laid against fathers in their lifetime is associated with 0.13 more criminal charges laid against sons in their lifetime. The estimated intergenerational crime elasticities on the intensive margin are around 0.50, suggesting that a 10% deviation from the mean of fathers' lifetime criminal charges on average is associated with a 5% deviation from the mean of sons' lifetime criminal charges.

To further investigate the role of life-cycle bias and the performance of our GEiV correction, in Table 3, we continue to use five-year averages for fathers' crimes but use single years for sons' crimes to estimate the intergenerational crime associations for the 1998 cohort. In the upper panel, for the likelihood of criminal charges, the estimates for λ_t are very small and around 0.17–0.31, and the estimate for θ_s is 0.68. The life-cycle bias in the extensive margin is very large when we use single years of data to proxy the lifetime status even during the peak of the crime life cycle. The uncorrected intergenerational association estimates $\hat{\beta}_{ts}$ are severely downward biased by more than 80% and only around 0.05–0.07. The GEiV corrected estimates are around 0.28–0.43, and the GEiV corrected elasticities are around 0.87–1.20. Compared to Table 2, the GEiV corrected estimates in Table 3 are overestimated by at least 20% especially for the elasticity estimates. The GEiV correction seems to overcorrect the estimates when the life-cycle bias is of large magnitudes. In the lower panel, for the number of criminal charges, the estimates for λ_t are around 1.60 and similar to Table 2. With an estimate for θ_s of around 0.6, the estimates of λ_t and θ_s together imply only a small life-cycle bias in the intensive margin. Indeed, in the lower panel, both the uncorrected estimates $\hat{\beta}_{ts}$ and the corrected estimates $\frac{\hat{\beta}_{ts}}{\hat{\lambda}_t\hat{\theta}_s}$ are around 0.13–0.15 and very similar. The GEiV corrected estimated elasticities are around 0.50 and very robust across ages for the sons.

Overall, Tables 2 and 3 suggest that our GEiV correction method performs very well especially for the intensive margin. While the uncorrected estimates are generally sensitive to the life cycle bias, the GEiV corrected estimates and estimated elasticities are very stable and do not substantially change with different ages or the numbers of years of aggregation. Our findings suggest that the GEiV correction is very effective for reducing the life-cycle bias of small to medium sizes. However, the GEiV correction tends to overscale the estimates and causes upward bias when the life-cycle bias is an attenuation bias and of large sizes.

In Table 4, we estimate the intergenerational crime associations and elasticities in each dyad of parent-child relationships as well as for each type of crimes among the 1998 cohort. Sons and daughters are 17–21 years old with five-year averages of criminal charges from 2015–2019.[10] The criminal charges of fathers and mothers are five-year averages from 1992–1996, and the average ages of fathers and mothers are 24–28 and 22–26, respectively. To correct the life-cycle bias from daughters (sons), we use the estimates of λ_t from females (males) of the 1975 cohort. To correct the life-cycle bias from mothers (fathers), we use the estimates of θ_s from females (males) of the 1975 cohort. The upper panel shows the extensive margin, and the lower panel shows the intensive margin.

Several patterns are observed in Table 4. First, somewhat surprisingly, the intergenerational associations are very homogenous across types of crimes. We do not observe

[10] The sample sizes are different in the four types of family relationships because we only keep the first-born children, and a person may be the first-born child only to a father but not the mother or vice versa.

stronger intergenerational associations in violent crime like some research suggests. (See Footnote 7.) Second, based on the elasticities, the intergenerational crime association is strongest among the father-daughter dyads, followed by the father-son dyads, the mother-daughter dyads, and the association among mother-son dyads is the weakest. For the extensive margin, the father-son intergenerational elasticities are 0.52–0.75, the father-daughter elasticities are 0.72–1.22, the mother-daughter elasticities are 0.16–0.54, and the mother-son elasticities are 0.09–0.30. For the intensive margin, the father-son intergenerational elasticities are 0.40–0.59, the father-daughter elasticities are 0.65–0.91, the mother-daughter elasticities are 0.27–0.43, and the mother-son elasticities are 0.11–0.22. Therefore, in terms of intergenerational transmission of criminal behaviors, fathers appear to play a more important role than mothers.

Notice that it is crucial to compare groups based on the elasticities, as point estimates can be misleading for comparison across groups. For example, in the lower panel of Table 4, the point estimates seem to suggest that the mother-son associations are more than twice stronger than the father-son associations. However, because mothers commit much fewer crimes than fathers, one additional criminal charge represents a much greater percentage deviation from mothers' average level of criminal behaviors than from fathers' average level. Appendix Tables A2 and A3 report the estimates for the GEiV corrected intergenerational crime associations and elasticities using ten-year and twenty-year averages for the parents. The results are quantitatively similar to those reported in Table 4.

Table 5 presents the estimates for intergenerational associations in criminal charges of all crimes between fathers and sons of the 1990 cohort. This cohort allows us to measure the children's criminal charges in older ages. However, as their parents are also older, we cannot use twenty-year averages for the parents because the average age of these parents would be outside 17–44 years old that we have estimates for λ_t and θ_s. The sons' criminal charges are measured in either 17–21 years old (2007–2011) or 25–29 years old (2015–2019), and the estimates of λ_{17-21} and λ_{25-29} from the 1975 cohort are reported in column (1). The fathers' criminal charges are measured in five years in 1992–1996 (average ages 31–35) and ten years in 1992–2001 (average ages 31–40). The estimates for θ_{31-35} and θ_{31-40} from the 1975 cohort are reported in column (2). Column (3) shows the uncorrected estimates while columns (4) and (5) show the GEiV corrected estimates and estimated intergenerational elasticities.

In the upper panel, for the likelihood of criminal charges, the GEiV correction works well when the sons' crimes are measured in 17–21 years old. Both the uncorrected estimates

$\hat{\beta}_{ts}$ and the corrected estimates $\frac{\hat{\beta}_{ts}}{\hat{\lambda}_t \hat{\theta}_s}$ of the 1990 cohort are about twice greater than those of the 1998 cohort. However, larger point estimates do not necessarily imply a stronger intergenerational association because the 1990 cohort are more likely to commit crimes than the 1998 cohort. Our GEiV methodology successfully accounts for the level differences across cohorts when the life-cycle bias is of medium size. The GEiV corrected estimates for the intergenerational elasticity between fathers and sons of the 1990 cohort are 0.68–0.73 and very similar to those of the 1998 cohort. On average, a 10% deviation from the mean of fathers' lifetime likelihood of criminal charges is associated with approximately a 7% deviation from the mean of sons' lifetime likelihood of criminal charges. However, as the previous tables suggest, the GEiV correction tends to overcorrect life-cycle bias of large magnitudes. When the likelihood of criminal charges is observed in 25–29 years old, the GEiV corrected estimates for the intergenerational elasticity are above one and appear to be substantially upward biased. In contrast, in the lower panel, for the number of criminal charges, the GEiV corrected estimates are very robust and nearly identical regardless of the ages and years of averages of both fathers and sons. Like the extensive margin, the point estimates for the intensive margin of the 1990 cohort are also about twice greater than those of the 1998 cohort. The estimated elasticities are around 0.36–0.38 and suggest that a 10% increase in the lifetime criminal charges of the fathers is associated with an approximately 4% increase in the lifetime criminal charges of the sons. The intergenerational elasticities among the 1990 cohort appear to be slightly smaller than those among the 1998 cohort but the differences are not statistically significant.

Table 6 shows the GEiV corrected estimates and estimated elasticities among the 1990 cohort for all four parent-child dyads and for each type of crimes. Sons and daughters are 17–21 years old with five-year averages of criminal charges from 2007–2011. The criminal charges of fathers and mothers are five-year averages from 1992–1996, and the average ages of fathers and mothers are 31–35 and 29–33, respectively. In Table 6, for both the extensive and intensive margins, the intergenerational crime associations between fathers and children are stronger than those between mothers and children, and there is no strong heterogeneity across types of crimes. We observe similar intergenerational crime elasticities for the 1990 and 1998 cohorts. In the upper panel, the GEiV corrected intergenerational elasticities of the likelihood of criminal charges for the 1990 cohort are almost identical to the 1998 cohort, despite that the point estimates are about twice greater than those in Table 4. In the lower panel, the point estimates among the 1990 cohort are also twice greater than the 1998 cohort, while the intergenerational elasticities of the number of criminal charges among the 1990 cohort are slightly smaller. The estimates for the intergenerational elasticities for the 1998 and 1990 cohorts are not statistically different as nearly all of their 95% confidence intervals are overlapped. In Appendix Table A4, we use ten-year average of criminal charges for parents. In Appendix Table A5, we use ten-year average of criminal charges for both children and parents where sons and daughters are 17–26 years old with ten-year averages of criminal charges from 2007–2016. The estimates in Appendix Tables A4 and A5 are quantitatively similar to those in Table 6 but with smaller standard errors.

In Table 7, we conduct a robustness check and estimate the intergenerational elasticities of criminal convictions. Sons and daughters are 17–21 years old with five-year averages of criminal convictions from 2015–2019 for the 1998 cohort and from 2007–2011 for the 1990 cohort. The criminal convictions of fathers and mothers are five-year averages from 1992–1996, and the average ages of fathers and mothers are 24–28 and 22–26 for the 1998 cohort and 31–35 and 29–33 for the 1990 cohort. The results based on criminal convictions in Table 7 are very similar to those based on criminal charges in Tables 4 and 6. Appendix Table A6 shows the estimated elasticities using 10-year average of criminal convictions for parents from 1992–2001 for both the 1990 and 1998 cohorts. Overall, our GEiV corrected estimates indicate strong intergenerational crime associations especially between fathers and children. Once the life-cycle bias is corrected, the intergenerational elasticities of crimes are quantitatively similar across ages, birth cohorts, types of crimes, and either criminal charges or convictions are used.

5.2. Estimates of Intergenerational Correlation Coefficients

In this section, we standardize both parents' and children's criminal charges to mean zero and standard deviation one and estimate the intergenerational correlation coefficients. We estimate λ_t and θ_t from the 1975 cohort where $\lambda_t = \theta_t$ by construction due to standardization. Figure 4 shows the estimates of λ_t from 17–21 to 40–44 years old by gender. In the upper panel, the figure for the extensive margin is very similar to Figure 2. The estimates of λ_t peak around 0.75 in the late teens and decrease with age. They are smaller than one throughout the life cycle, indicating substantial attenuation bias. In the lower panel, the figure for the intensive margin exhibits a much weaker life cycle compared to Figure 3. The estimates of λ_t are maximized around 0.80 in early 20s and only slowly decreasing with age. In contrast to Figure 3 where an amplification bias exists during young ages, the estimates of λ_t in Figure 4 are always below one and indicate attenuation bias throughout the life cycle. The lower panel of Figure 4 is consistent with the finding from the income literature that correlation coefficients are less sensitive to life-cycle bias but underestimated throughout the life cycle (Nybom and Stuhler 2017). Appendix Figure A4 shows the estimates of λ_t for violent, property, and other crimes for both the extensive and intensive margins.

In Table 8, we apply the GEiV correction to the intergenerational correlation coefficients for criminal charges of all crimes between fathers and sons of the 1998 cohort. In the upper panel, for the extensive margin, the uncorrected estimates for the correlation coefficients between fathers and sons are around 0.16–0.19 and not sensitive to the number of years of averages used for fathers. However, the estimates of λ_t and θ_s suggest that the uncorrected correlation coefficients are underestimated by at least 50% (1 – 0.75 × 0.69 = 0.48). The GEiV corrected estimates for the intergenerational correlation coefficients between fathers and sons' likelihoods of criminal charges are around 0.37–0.39. In the lower panel, for the intensive margin, the uncorrected correlation coefficients between fathers and sons are around 0.20–0.24. While both the estimates of λ_t and θ_s are large and close to one, their multiplication still suggest that the estimates are downward biased by at least 20% (1 – 0.81 × 0.94 = 0.21). The GEiV corrected correlation coefficients between fathers' and sons' criminal charges are around 0.30–0.32.

In Table 9, we estimate the intergenerational correlation coefficients for criminal charges of all crimes between fathers and sons of the 1990 cohort. In upper panel, for the extensive margin, the uncorrected estimates are around 0.19–0.22 and very robust to both the age of sons and the number of years of averages used for fathers. However, the estimates of λ_t and θ_s suggest substantial attenuation bias in the uncorrected correlation coefficients. The GEiV corrected estimates for the correlation coefficients are around 0.53–0.60 when the sons' likelihood criminal charges are observed in 17–21 years old. The GEiV corrected estimates for the correlation coefficients are implausibly large and close to one when the sons' likelihood of criminal charges are observed in 25–29 years old. Like Table 5, the GEiV correction seems to overcorrect the estimates when the life-cycle bias is of large magnitudes. In contrast, in the lower panel, the GEiV correction perform well with the intensive margin. For the number of criminal charges in the lower panel, the uncorrected correlation coefficients are around 0.18–0.23. The GEiV corrected correlation coefficients are around 0.29–0.35 and very robust to both the age of sons and the number of years of averages used for fathers. Overall, consistent with the intergenerational elasticities, the intergenerational correlation coefficients are also similar across the 1990 and 1998 cohorts.

In Table 10, for both the 1998 and 1990 cohorts, we estimate the intergenerational correlation coefficients among all four parent-child dyads and for each type of crimes. Sons and daughters are 17–21 years old with five-year averages of standardized criminal charges from 2015–2019 for the 1998 cohort and from 2007–2011 for the 1990 cohort. The criminal charges of fathers and mothers are ten-year averages from 1992–2001, and the average ages of fathers and mothers are 24–33 and 22–31 for the 1998 cohort and 31–40 and 29–38 for the 1990 cohort. Since the life-cycle bias in the correlation coefficients is always an attenuation bias, we focus on ten-year averages for parents that have smaller life-cycle bias. The findings in Table 10 are consistent with those in the previous tables such as Table 7. First, like elasticities, we do not find strong heterogeneity across different types of crimes for the intergenerational correlation coefficients. The estimates for violent crimes appear to be somewhat smaller but they are not statistically different from property and other crimes. Second, also similar to elasticities, the father-child correlation coefficients are slightly greater than the mother-child correlation coefficients. However, the differences in the estimated correlation coefficients across the four parents-child dyads are smaller than those of elasticities, and almost none of them are statistically significant. Finally, there is little difference between the 1998 and the 1990 cohorts. The differences across cohorts in the correlation coefficient are also smaller than those in the elasticities.

Notice that the intergenerational elasticity accounts and reflects the changes in distributions across generations while the correlation coefficient forces the same dispersion across generations due to standardization. Therefore, the difference between the two measures of intergenerational association reflects the change in the dispersion of the data from the parents' generation to the children's generation:

$$\text{Correlation coefficient} \times \frac{SD(y)}{E(y)} \Big/ \frac{SD(x)}{E(x)} = \text{elasticity.}$$

One interesting observation is that the difference between the correlation coefficient and the elasticity is greater among the 1998 cohort than among the 1990 cohort. The greater difference between the two measures among the 1998 cohort suggest that the distributions of criminal behaviors likely become more disperse among the children than among their parents. In other words, for the 1998 cohort, crimes are likely more concentrated among a smaller group of people relative to their parents. In contrast, for the 1990 cohort, there is little difference across elasticity and correlation coefficients, suggesting that the distributions of criminal behaviors likely remain stable across the two generations. Therefore, while the intergenerational associations are similar across cohorts, the distribution of criminal behaviors seems to become more unequal among the 1998 cohort than the 1990 cohort.

6. Conclusion

In this paper, we build upon the GEiV models and develop a novel methodology to correct the life-cycle bias in the estimates for intergenerational associations. Nearly all available datasets are not long enough to cover lifetime outcomes of two generations, and therefore researchers rely on short-run proxies to estimate the intergenerational associations. When the outcome variables exhibit a strong life cycle, the estimates are often sensitive to the ages in which the short-run proxies are observed. While the issue is well known in the intergenerational mobility literature, no formal solution has been developed to solve the problem of life-cycle bias. Almost all studies simply rely on the finding from Haider and Solon (2006) and choose their samples around ages 30–35 hoping to minimize the life cycle bias in their own contexts. Not only strong assumptions are imposed but substantial life-cycle bias may remain even when the assumptions are true. We note that many datasets are long enough to cover almost the entire life cycle of one cohort. Therefore, we estimate the life-cycle bias at each age from a representative cohort and then correct the intergenerational association estimates by the estimates of the life-cycle bias. We develop GEiV estimators for both the extensive and intensive margins as well as estimators for elasticity. Our methodology can correct the life-cycle bias in the estimates of intergenerational associations for any outcome variables with strong age profiles.

We apply the GEiV correction to estimate the intergenerational crime associations in New Zealand. We first estimate the life-cycle bias using the 1975 cohort in 17–44 years old. We then estimate the intergenerational associations in criminal charges and convictions using the 1998 and 1990 cohorts and apply the GEiV correction based on the life-cycle bias estimates from the 1975 cohort. The GEiV corrected estimates for the intergenerational crime associations are robust to the ages of the children, the average ages of parents, the number of years of averages, and whether crime is measured in charges or convictions. The intergenerational elasticities of crime between fathers and son are around 0.70 for the extensive margin and around 0.50 for the intensive margins. The intergenerational correlation coefficients between fathers' and sons' crimes are approximately 0.40 for both margins. The intergeneration crime associations are homogenous across violent, property, and other crimes and remain stable across cohorts. We also find that father-child associations are greater than mother-child associations, suggesting that the fathers play a more direct role in the intergenerational transmission of criminal behaviors. Our findings show that the GEiV correction performs very well. The GEiV corrected point estimates and estimated elasticities are very stable when the life-cycle bias is estimated to be of small to medium magnitudes. However, when the life-cycle bias is of large magnitudes, the GEiV correction tends to overcorrect and introduces substantial upward bias into the estimates.

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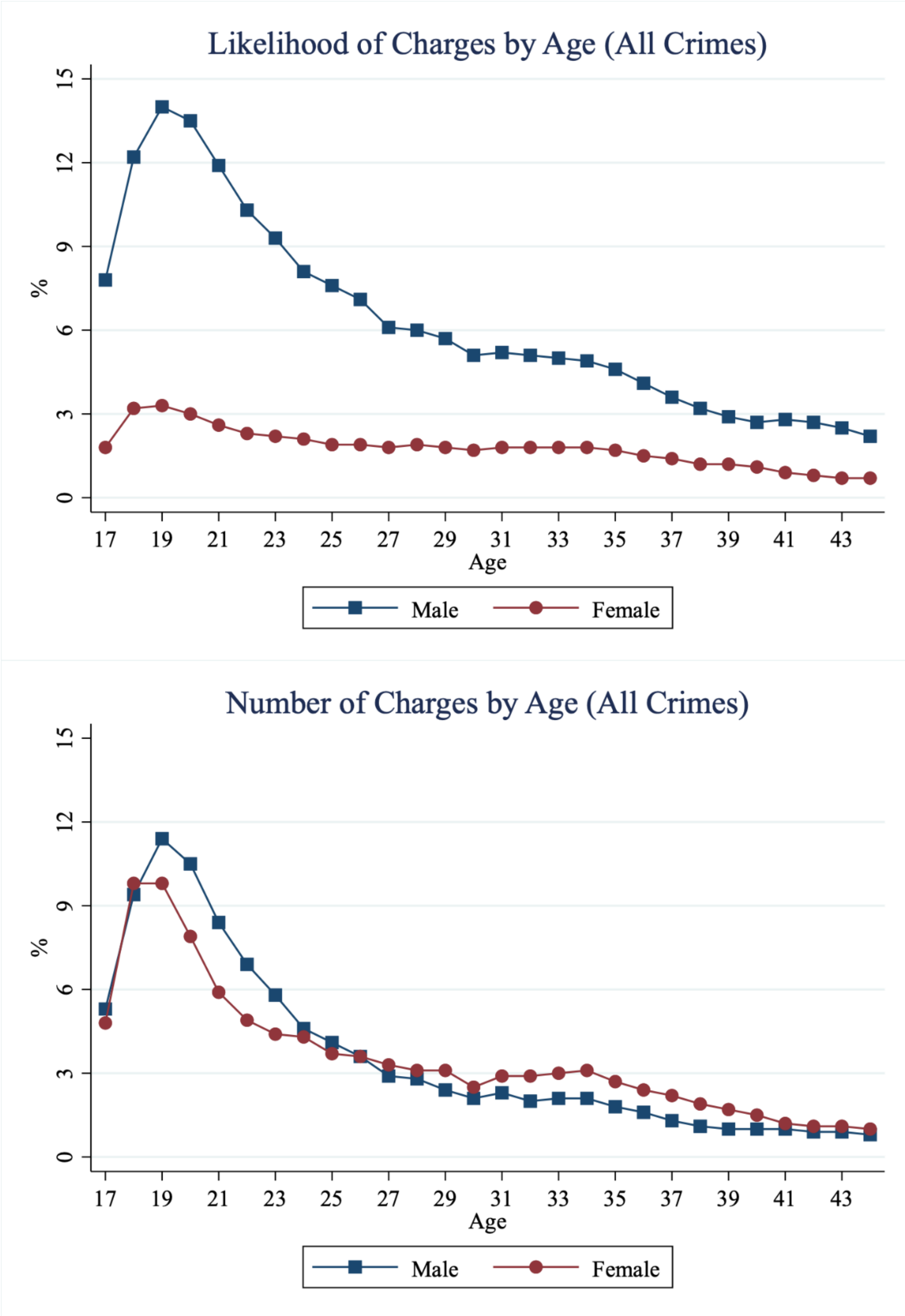


Figure 1: Criminal Charges of All Crimes by Age on the Extensive Margin (upper) and Intensive Margin (lower) for the 1975 Cohort

Note: The upper panel shows the proportion of the 1975 cohort with at least one criminal charges in each age. The lower panel shows the number of criminal charges in each age as a proportion of the total criminal charges over age 17–44 among the 1975 cohort with at least one criminal charges.

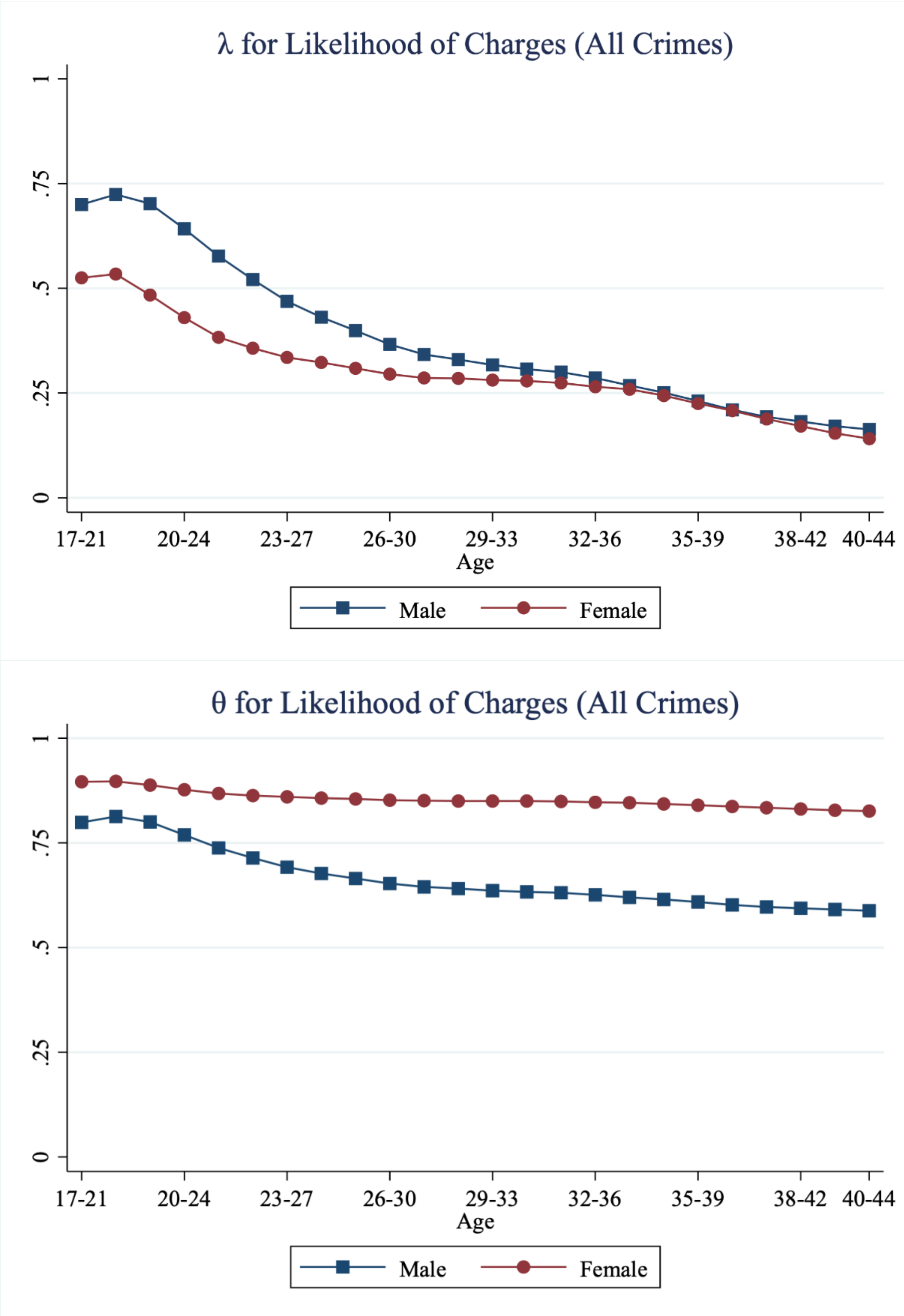


Figure 2: Estimates of λ_t and θ_t by Age (5-Year Moving Average) for the Likelihood of Criminal Charges of All Crimes among the 1975 Cohort

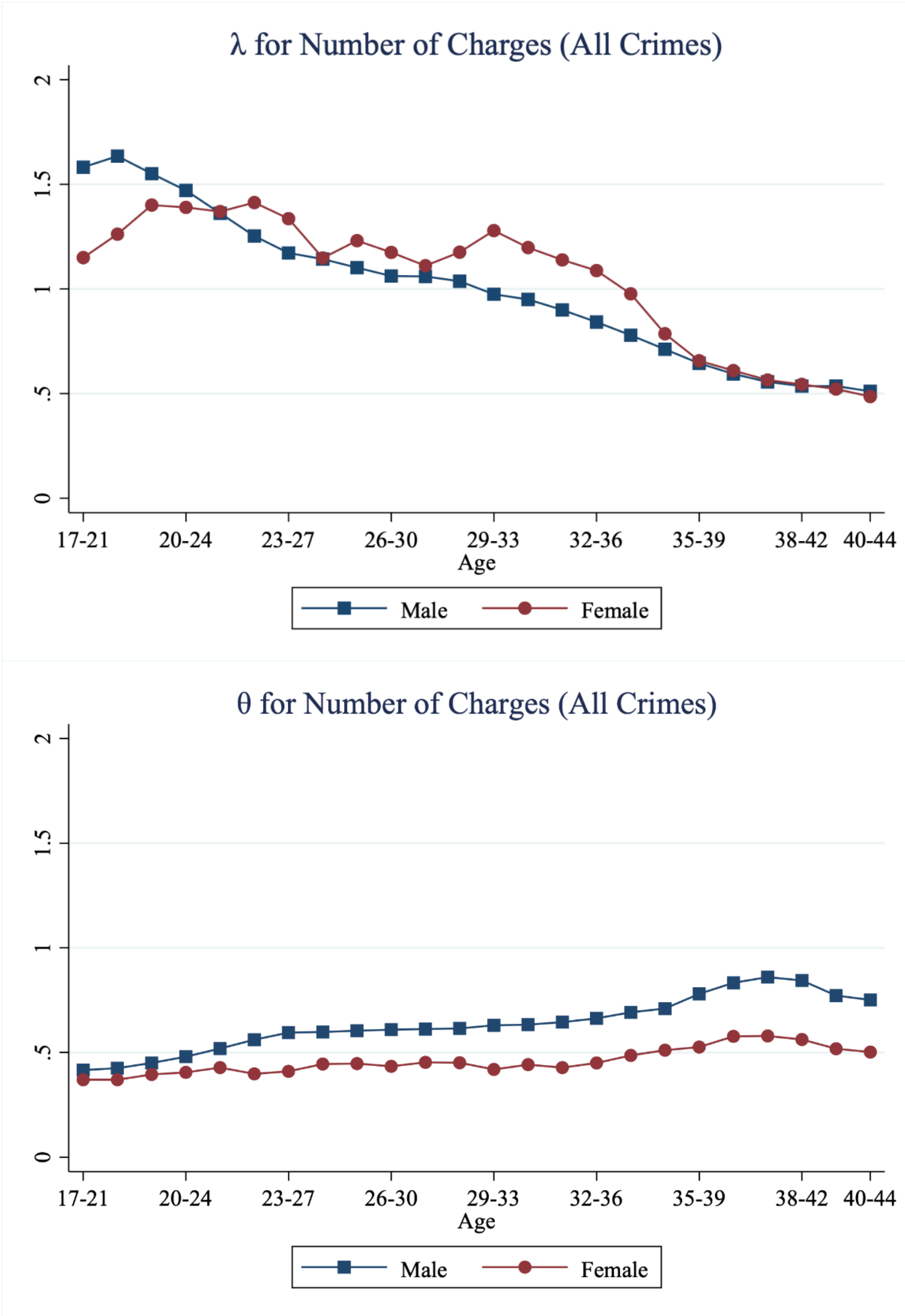


Figure 3: Estimates of λ_t and θ_t by Age (5-Year Moving Average) for the Number of Criminal Charges of All Crimes among the 1975 Cohort

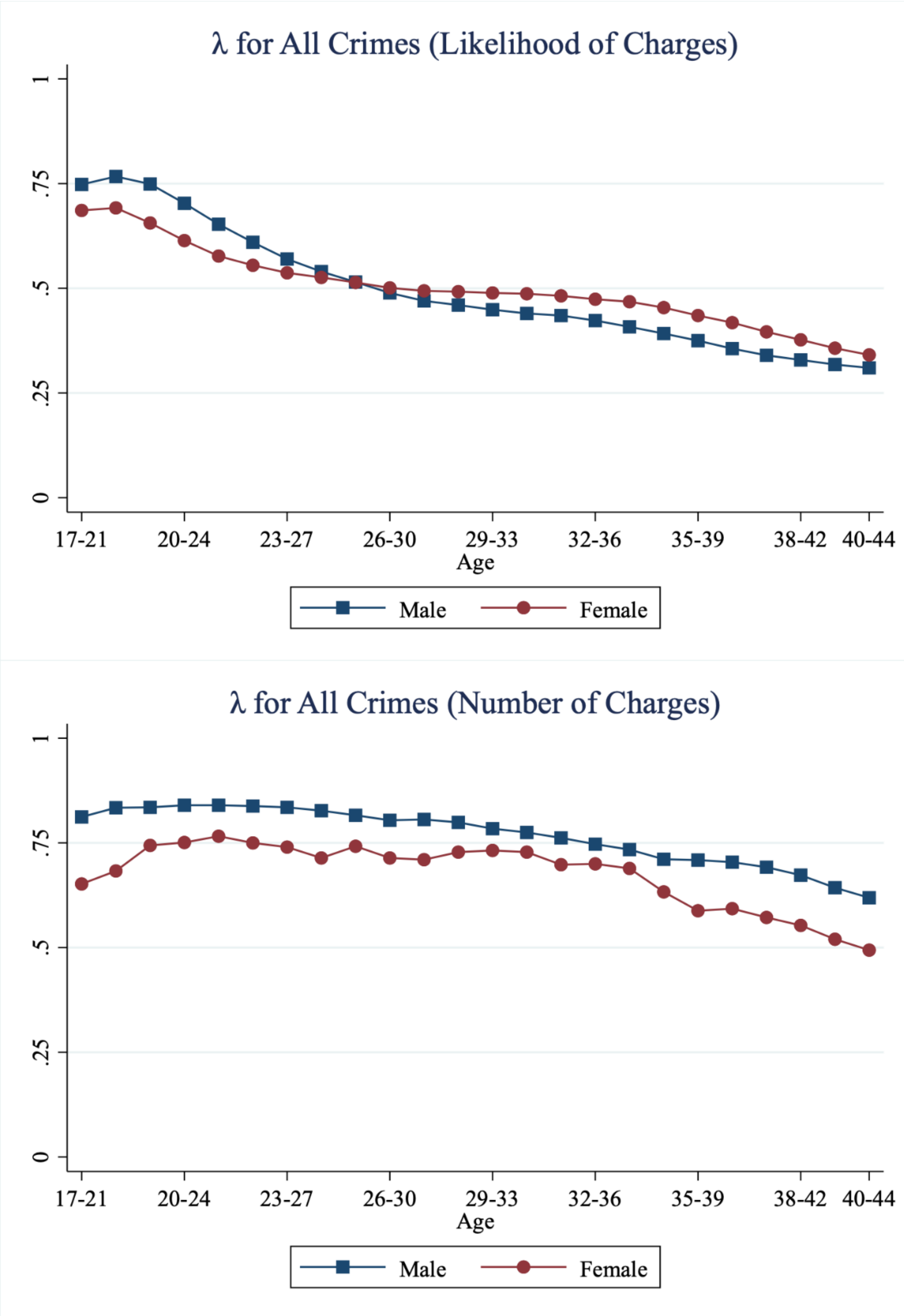


Figure 4: Estimates of λ_t by Age (5-Year Moving Average) for the Standardized Likelihood (left) and Number (right) of Criminal Charges of All Crimes among the 1975 Cohort

Note: The likelihood and number of criminal charges are standardized to mean zero and standard deviation one. Therefore, $\lambda_t = \theta_t$ and represents correlation coefficients between changes in age t and lifetime charges.

Table 1: Descriptive Statistics (5-Year Average)

	1998 Cohort (2015-2019)		1990 Cohort (2007-2011)	
(17-21 Years Old)	Sons	Daughters	Sons	Daughters
Likelihood of Charges	0.161	0.054	0.368	0.156
	(0.368)	(0.227)	(0.482)	(0.363)
Likelihood of Violent Charges	0.089	0.024	0.190	0.052
	(0.284)	(0.153)	(0.393)	(0.222)
Likelihood of Property Charges	0.053	0.018	0.148	0.055
	(0.223)	(0.132)	(0.355)	(0.229)
Likelihood of Other Charges	0.119	0.040	0.297	0.116
	(0.324)	(0.196)	(0.457)	(0.320)
Number of Charges	0.144	0.041	0.419	0.099
	(0.612)	(0.315)	(1.130)	(0.414)
Violent Crime Charges	0.036	0.007	0.078	0.016
	(0.166)	(0.059)	(0.235)	(0.086)
Property Crime Charges	0.037	0.012	0.100	0.025
	(0.255)	(0.147)	(0.437)	(0.176)
Other Crime Charges	0.071	0.022	0.240	0.059
	(0.302)	(0.170)	(0.640)	(0.254)
	1998 Cohort		1990 Cohort	
(Years 1992-1996)	Father (24-28)	Mother (22-26)	Father (31-35)	Mother (29-33)
Likelihood of Charges	0.267	0.084	0.228	0.074
	(0.443)	(0.277)	(0.419)	(0.262)
Likelihood of Violent Charges	0.131	0.028	0.111	0.022
	(0.338)	(0.164)	(0.314)	(0.145)
Likelihood of Property Charges	0.107	0.039	0.074	0.033
	(0.309)	(0.194)	(0.262)	(0.179)
Likelihood of Other Charge	0.204	0.048	0.175	0.047
	(0.403)	(0.213)	(0.380)	(0.211)
Number of Charges	0.281	0.054	0.222	0.050
	(0.926)	(0.348)	(0.808)	(0.376)
Violent Charges	0.049	0.007	0.043	0.006
	(0.174)	(0.054)	(0.171)	(0.053)
Property Charges	0.087	0.025	0.054	0.022
	(0.461)	(0.246)	(0.403)	(0.286)
Other Charges	0.144	0.022	0.125	0.022
	(0.482)	(0.147)	(0.446)	(0.141)
Observations	10,641	10,392	10,956	10,767

Table 2: Intergenerational Associations in Criminal Charges between Fathers and Sons for the 1998 Cohort

Age of Average Fathers	(1) $\hat{\lambda}_t$	(2) $\hat{\theta}_s$	(3) $\hat{\beta}_{ts}$	(4) $\hat{\beta}_{ts} / \hat{\lambda}_t \hat{\theta}_s$	(5) *Elasticity*
Likelihood of Criminal Charges for All Crimes (Age of Sons 17–21)					
Age 24–28	0.700***	0.677***	0.132***	0.279***	0.752***
(1992–1996)	(0.004)	(0.003)	(0.009)	(0.020)	(0.054)
Age 24–33	0.700***	0.724***	0.140***	0.277***	0.789***
(1992–2001)	(0.004)	(0.003)	(0.009)	(0.017)	(0.048)
Age 24–43	0.700***	0.764***	0.142***	0.265***	0.764***
(1992–2011)	(0.004)	(0.003)	(0.008)	(0.015)	(0.042)
Number of Criminal Charges for All Crimes (Ages of Sons 17–21)					
Age 24–28	1.582***	0.598***	0.132***	0.140***	0.482***
(1992–1996)	(0.040)	(0.017)	(0.018)	(0.020)	(0.063)
Age 24–33	1.582***	0.769***	0.174***	0.143***	0.543***
(1992–2001)	(0.040)	(0.012)	(0.022)	(0.019)	(0.062)
Age 24–43	1.582***	1.047***	0.216***	0.130***	0.536***
(1992–2011)	(0.040)	(0.012)	(0.026)	(0.017)	(0.060)
Observations			10,641		

Note: Sons are 17–21 years old with five-year averages of criminal charges from 2015–2019. Standard errors are in parentheses. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Intergenerational Associations in Criminal Charges between Fathers and Sons for the 1998 Cohort (Single Years of Ages for Sons)

	(1)	(2)	(3)	(4)	(5)
Age of Sons	$\hat{\lambda}_t$	$\hat{\theta}_s$	$\hat{\beta}_{ts}$	$\hat{\beta}_{ts} / \hat{\lambda}_t \hat{\theta}_s$	*Elasticity*
	Likelihood of Criminal Charges (Average Age of Fathers 24–29)				
Age 21	0.260***	0.677***	0.049***	0.277***	0.887***
	(0.004)	(0.003)	(0.006)	(0.034)	(0.105)
Age 20	0.296***	0.677***	0.057***	0.285***	0.868***
	(0.004)	(0.003)	(0.007)	(0.033)	(0.096)
Age 19	0.308***	0.677***	0.072***	0.344***	0.974***
	(0.004)	(0.003)	(0.007)	(0.033)	(0.089)
Age 18	0.269***	0.677***	0.066***	0.360***	0.983***
	(0.004)	(0.003)	(0.007)	(0.037)	(0.094)
Age 17	0.172***	0.677***	0.049***	0.425***	1.198***
	(0.003)	(0.003)	(0.005)	(0.048)	(0.122)
	Number of Criminal Charges (Average Age of Fathers 24–29)				
Age 21	1.547***	0.598***	0.137***	0.147***	0.547***
	(0.067)	(0.017)	(0.028)	(0.031)	(0.105)
Age 20	1.761***	0.598***	0.128***	0.121***	0.444***
	(0.071)	(0.017)	(0.022)	(0.022)	(0.075)
Age 19	1.643***	0.598***	0.125***	0.127***	0.441***
	(0.068)	(0.017)	(0.024)	(0.026)	(0.084)
Age 18	1.729***	0.598***	0.139***	0.135***	0.462***
	(0.074)	(0.017)	(0.023)	(0.023)	(0.074)
Age 17	1.230***	0.598***	0.132***	0.180***	0.526***
	(0.068)	(0.017)	(0.027)	(0.038)	(0.097)
Observations			10,641		

Note: The criminal charges of fathers are five-year averages from 1992–1996 and the average ages of fathers are 24–28. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Intergenerational Associations in Criminal Charges for the 1998 Cohort

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*
Likelihood of Criminal Charges (Age of Children17–21)								
All Crimes	0.279***	0.752***	0.211***	1.261***	0.226***	0.219***	0.215***	0.471***
	(0.020)	(0.054)	(0.019)	(0.101)	(0.028)	(0.028)	(0.029)	(0.063)
Violent	0.183***	0.516***	0.100***	0.718***	0.134***	0.094***	0.097**	0.161**
	(0.023)	(0.066)	(0.021)	(0.143)	(0.043)	(0.031)	(0.041)	(0.069)
Property	0.164***	0.742***	0.120***	1.216***	0.205***	0.304***	0.141***	0.543***
	(0.019)	(0.086)	(0.018)	(0.164)	(0.032)	(0.050)	(0.030)	(0.111)
Other	0.282***	0.689***	0.197***	0.978***	0.275***	0.190***	0.227***	0.358***
	(0.021)	(0.051)	(0.021)	(0.094)	(0.038)	(0.028)	(0.040)	(0.063)
Number of Criminal Charges (Age of Children 17–21)								
All Crimes	0.140***	0.482***	0.083***	0.804***	0.373***	0.206***	0.217***	0.363***
	(0.020)	(0.063)	(0.020)	(0.166)	(0.121)	(0.063)	(0.068)	(0.102)
Violent	0.163***	0.396***	0.086***	0.907***	0.313**	0.107**	0.275**	0.417**
	(0.032)	(0.073)	(0.021)	(0.197)	(0.143)	(0.048)	(0.113)	(0.174)
Property	0.098***	0.590***	0.054**	0.761**	0.178*	0.221**	0.141*	0.430**
	(0.022)	(0.116)	(0.025)	(0.332)	(0.098)	(0.111)	(0.075)	(0.217)
Other	0.149***	0.439***	0.090***	0.648***	0.355***	0.139***	0.240**	0.266***
	(0.021)	(0.057)	(0.022)	(0.138)	(0.083)	(0.032)	(0.094)	(0.093)
Observations	10,641		10,392		10,278		10,122	

Note: Sons and daughters are 17–21 years old with five-year averages of criminal charges from 2015–2019. The criminal charges of fathers and mothers are five-year averages from 1992–199, and the average ages of fathers and mothers are 24–28 and 22–26, respectively. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Intergenerational Associations in Criminal Charges of All Crimes between Fathers and Sons for the 1990 Cohort

Age of Average Fathers	(1) $\hat{\lambda}_t$	(2) $\hat{\theta}_s$	(3) $\hat{\beta}_{ts}$	(4) $\hat{\beta}_{ts} / \hat{\lambda}_t \hat{\theta}_s$	(5) *Elasticity*
Likelihood of Criminal Charges for All Crimes (Age of Sons 17–21)					
Age 31–35	0.700***	0.631***	0.223***	0.506***	0.729***
(1992–1996)	(0.004)	(0.003)	(0.012)	(0.027)	(0.043)
Age 31–40	0.700***	0.658***	0.208***	0.453***	0.676***
(1992–2001)	(0.004)	(0.003)	(0.011)	(0.024)	(0.038)
Likelihood of Criminal Charges for All Crimes (Age of Sons 25–29)					
Age 31–35	0.399***	0.631***	0.185***	0.737***	1.451***
(1992–1996)	(0.004)	(0.003)	(0.011)	(0.043)	(0.085)
Age 31–40	0.399***	0.658***	0.171***	0.653***	1.332***
(1992–2001)	(0.004)	(0.003)	(0.009)	(0.036)	(0.072)
Number of Criminal Charges for All Crimes (Age of Sons 17–21)					
Age 31–35	1.582***	0.645***	0.302***	0.296***	0.376***
(1992–1996)	(0.040)	(0.023)	(0.040)	(0.041)	(0.047)
Age 31–40	1.582***	0.917***	0.395***	0.272***	0.376***
(1992–2001)	(0.040)	(0.024)	(0.044)	(0.032)	(0.040)
Number of Criminal Charges for All Crimes (Age of Sons 25–29)					
Age 31–35	1.102***	0.645***	0.162***	0.228***	0.372***
(1992–1996)	(0.030)	(0.023)	(0.023)	(0.034)	(0.049)
Age 31–40	1.102***	0.917***	0.207***	0.205***	0.364***
(1992–2001)	(0.030)	(0.024)	(0.026)	(0.027)	(0.043)
Observations			10,956		

Note: Sons are 17–21 and 25–29 years old with five-year averages of criminal charges from 2007–2011 and 2015–2019, respectively. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Intergenerational Associations in Criminal Charges for the 1990 Cohort

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*
Likelihood of Criminal Charges (Age of Children 17–21)								
All Crimes	0.506***	0.729***	0.431***	1.110***	0.382***	0.186***	0.360***	0.334***
	(0.027)	(0.043)	(0.031)	(0.080)	(0.031)	(0.017)	(0.039)	(0.038)
Violent	0.369***	0.507***	0.218***	0.796***	0.329***	0.098***	0.214***	0.173***
	(0.033)	(0.047)	(0.031)	(0.110)	(0.061)	(0.020)	(0.061)	(0.051)
Property	0.394***	0.739***	0.217***	0.844***	0.284***	0.204***	0.221***	0.329***
	(0.031)	(0.066)	(0.030)	(0.119)	(0.040)	(0.031)	(0.042)	(0.065)
Other	0.505***	0.606***	0.419***	0.924***	0.476***	0.155***	0.430***	0.278***
	(0.030)	(0.038)	(0.035)	(0.075)	(0.042)	(0.016)	(0.055)	(0.037)
Number of Criminal Charges (Age of Children 17–21)								
All Crimes	0.296***	0.376***	0.139***	0.601***	0.592***	0.129***	0.311***	0.254***
	(0.041)	(0.047)	(0.030)	(0.117)	(0.183)	(0.035)	(0.089)	(0.062)
Violent	0.404***	0.444***	0.113***	0.589***	0.805**	0.109**	0.217**	0.133***
	(0.063)	(0.064)	(0.038)	(0.191)	(0.352)	(0.044)	(0.088)	(0.051)
Property	0.117***	0.269***	0.096*	0.632**	0.114*	0.062*	0.144*	0.248**
	(0.039)	(0.080)	(0.050)	(0.301)	(0.068)	(0.033)	(0.076)	(0.111)
Other	0.378***	0.380***	0.172***	0.552***	1.155***	0.166***	0.443***	0.223***
	(0.050)	(0.045)	(0.032)	(0.091)	(0.191)	(0.028)	(0.094)	(0.044)
Observations	10,956		10,767		10,683		10,605	

Note: Sons and daughters are 17–21 years old with five-year averages of criminal charges from 2007–2011. The criminal charges of fathers and mothers are five-year averages from 1992–1996, and the average ages of fathers and mothers are 31–35 and 29–33, respectively. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Intergenerational Elasticities of Criminal Convictions for the 1998 and 1990 Cohorts

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort
Likelihood of Criminal Convictions (Age of Children 17–21)								
All Crimes	0.633***	0.738***	1.044***	1.049***	0.185***	0.176***	0.378***	0.281***
	(0.051)	(0.042)	(0.100)	(0.081)	(0.028)	(0.018)	(0.063)	(0.040)
Violent	0.465***	0.512***	0.888***	1.051***	0.059*	0.114***	0.127	0.182**
	(0.072)	(0.052)	(0.184)	(0.151)	(0.031)	(0.024)	(0.078)	(0.071)
Property	0.481***	0.670***	0.849***	0.720***	0.240***	0.190***	0.543***	0.295***
	(0.076)	(0.065)	(0.152)	(0.124)	(0.051)	(0.032)	(0.129)	(0.070)
Other	0.611***	0.563***	0.871***	0.804***	0.160***	0.151***	0.282***	0.230***
	(0.048)	(0.036)	(0.092)	(0.071)	(0.027)	(0.016)	(0.062)	(0.037)
Number of Criminal Convictions (Age of Children 17–21)								
All Crimes	0.390***	0.370***	0.668***	0.573***	0.156***	0.095***	0.269***	0.182***
	(0.058)	(0.048)	(0.155)	(0.116)	(0.058)	(0.029)	(0.092)	(0.049)
Violent	0.393***	0.501***	0.915***	0.797***	0.064	0.086**	0.161*	0.160**
	(0.078)	(0.071)	(0.206)	(0.218)	(0.045)	(0.040)	(0.096)	(0.072)
Property	0.376***	0.303***	0.490**	0.743**	0.122	0.047*	0.344*	0.166**
	(0.102)	(0.099)	(0.238)	(0.358)	(0.080)	(0.028)	(0.198)	(0.084)
Other	0.369***	0.331***	0.554***	0.479***	0.116***	0.150***	0.176**	0.169***
	(0.051)	(0.037)	(0.135)	(0.083)	(0.029)	(0.027)	(0.072)	(0.039)
Observations	10,641	10,956	10,392	10,767	10,278	10,683	10,122	10,605

Note: Sons and daughters are 17–21 years old with five-year averages of criminal convictions from 2015–2019 for the 1998 cohort and from 2007–2011 for the 1990 cohort. The criminal convictions of fathers and mothers are five-year averages from 1992–1996, and the average ages of fathers and mothers are 24–28 and 22–26 for the 1998 cohort and 31–35 and 29–33 for the 1990 cohort. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Intergenerational Correlation Coefficients in Criminal Charges between Fathers and Sons for the 1998 Cohort

Age of Average Fathers	(1) $\hat{\lambda}_t$	(2) $\hat{\theta}_s$	(3) $\hat{\beta}_{ts}$	(4) $\hat{\beta}_{ts} / \hat{\lambda}_t \hat{\theta}_s$
Likelihood of Criminal Charges for All Crimes (Age of Sons 17–21)				
Age 24–28	0.748***	0.540***	0.159***	0.394***
(1992–1996)	(0.004)	(0.002)	(0.011)	(0.028)
Age 24–33	0.748***	0.628***	0.183***	0.389***
(1992–2001)	(0.004)	(0.003)	(0.011)	(0.024)
Age 24–43	0.748***	0.694***	0.190***	0.366***
(1992–2011)	(0.004)	(0.003)	(0.011)	(0.021)
Number of Criminal Charges for All Crimes (Ages of Sons 17–21)				
Age 24–28	0.812***	0.827***	0.200***	0.298***
(1992–1996)	(0.020)	(0.024)	(0.028)	(0.043)
Age 24–33	0.812***	0.902***	0.237***	0.323***
(1992–2001)	(0.020)	(0.015)	(0.030)	(0.042)
Age 24–43	0.812***	0.939***	0.239***	0.314***
(1992–2011)	(0.020)	(0.011)	(0.029)	(0.040)
Observations		10,641		

Note: Sons are 17–21 years old with five-year averages of criminal charges from 2015–2019. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Intergenerational Correlation Coefficients in Criminal Charges of All Crimes between Fathers and Sons for the 1990 Cohort

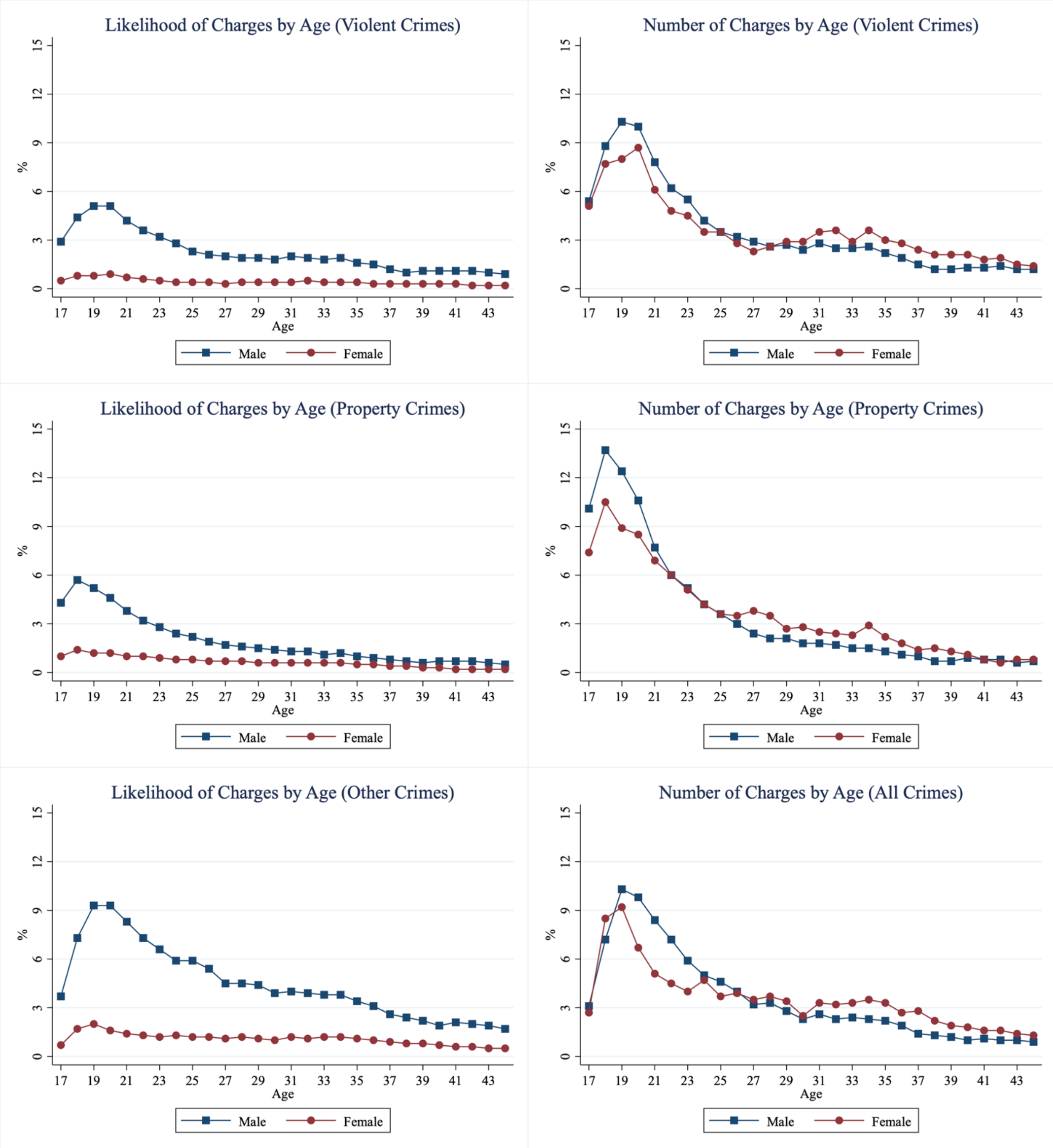
	(1)	(2)	(3)	(4)
Age of Average Fathers	$\hat{\lambda}_t$	$\hat{\theta}_s$	$\hat{\beta}_{ts}$	$\hat{\beta}_{ts}/\hat{\lambda}_t\hat{\theta}_s$
Likelihood of Criminal Charges for All Crimes (Age of Sons 17–21)				
Age 31–35	0.748***	0.435***	0.194***	0.597***
(1992–1996)	(0.004)	(0.002)	(0.010)	(0.032)
Age 31–40	0.748***	0.498***	0.197***	0.530***
(1992–2001)	(0.004)	(0.002)	(0.010)	(0.028)
Likelihood of Criminal Charges for All Crimes (Age of Sons 25–29)				
Age 31–35	0.515***	0.435***	0.216***	0.962***
(1992–1996)	(0.006)	(0.002)	(0.012)	(0.056)
Age 31–40	0.515***	0.498***	0.217***	0.845***
(1992–2001)	(0.006)	(0.002)	(0.012)	(0.047)
Number of Criminal Charges for All Crimes (Ages of Sons 17–21)				
Age 31–35	0.812***	0.762***	0.216***	0.350***
(1992–1996)	(0.020)	(0.027)	(0.028)	(0.049)
Age 31–40	0.812***	0.828***	0.233***	0.346***
(1992–2001)	(0.020)	(0.022)	(0.026)	(0.041)
Number of Criminal Charges for All Crimes (Ages of Sons 25-29)				
Age 31–35	0.816***	0.762***	0.182***	0.294***
(1992–1996)	(0.022)	(0.027)	(0.026)	(0.044)
Age 31–40	0.816***	0.828***	0.192***	0.285***
(1992–2001)	(0.022)	(0.022)	(0.024)	(0.038)
Observations		10,956		

Note: Sons are 17–21 and 25–29 years old with five-year averages of criminal charges from 2007–2011 and 2015–2019, respectively. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.

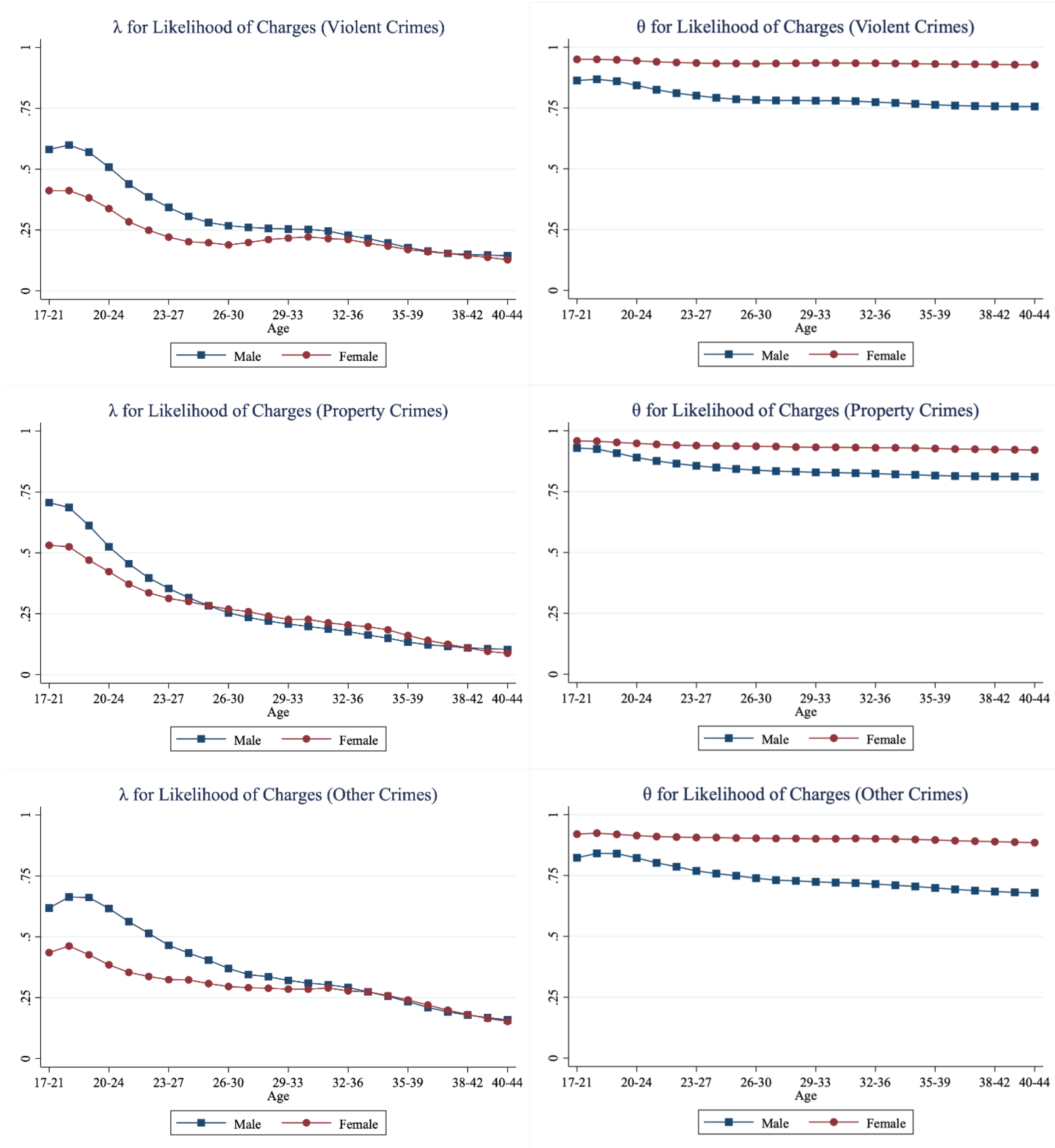
Table 10: Intergenerational Correlation Coefficients in Criminal Charges for the 1998 and 1990 Cohorts

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort
Likelihood of Charges (Age of Children 17–21)								
All Crimes	0.389***	0.530***	0.339***	0.499***	0.282***	0.310***	0.310***	0.327***
	(0.024)	(0.028)	(0.029)	(0.034)	(0.025)	(0.023)	(0.033)	(0.031)
Violent	0.275***	0.390***	0.246***	0.321***	0.172***	0.186***	0.179***	0.180***
	(0.029)	(0.032)	(0.039)	(0.042)	(0.032)	(0.029)	(0.046)	(0.042)
Property	0.325***	0.482***	0.334***	0.361***	0.244***	0.246***	0.240***	0.273***
	(0.032)	(0.036)	(0.043)	(0.046)	(0.032)	(0.029)	(0.045)	(0.042)
Other	0.386***	0.517***	0.325***	0.505***	0.297***	0.302***	0.299***	0.355***
	(0.025)	(0.028)	(0.031)	(0.037)	(0.028)	(0.024)	(0.040)	(0.036)
Number of Charges (Age of Children 17–21)								
All Crimes	0.323***	0.346***	0.321***	0.413***	0.245***	0.263***	0.190***	0.347***
	(0.042)	(0.041)	(0.069)	(0.086)	(0.051)	(0.046)	(0.057)	(0.078)
Violent	0.236***	0.303***	0.239***	0.307***	0.194***	0.177***	0.252***	0.153***
	(0.039)	(0.058)	(0.057)	(0.095)	(0.059)	(0.056)	(0.086)	(0.048)
Property	0.298***	0.250***	0.270**	0.360**	0.176**	0.152***	0.164**	0.257**
	(0.069)	(0.068)	(0.113)	(0.182)	(0.070)	(0.050)	(0.079)	(0.115)
Other	0.318***	0.344***	0.278***	0.367***	0.238***	0.295***	0.157***	0.310***
	(0.037)	(0.038)	(0.060)	(0.060)	(0.046)	(0.050)	(0.056)	(0.057)
Observations	10,641	10,956	10,392	10,767	10,278	10,683	10,122	10,605

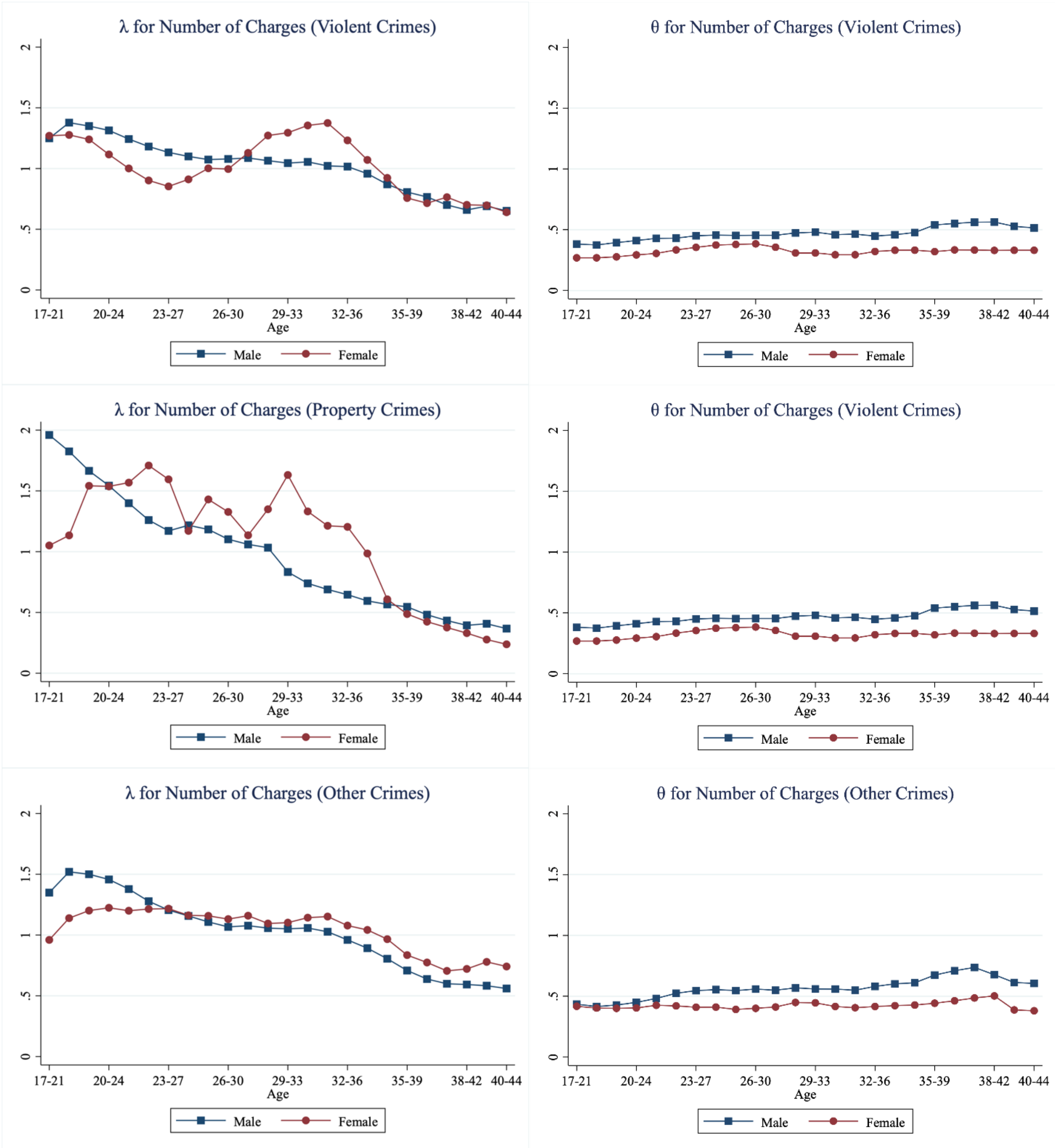
Note: Sons and daughters are 17–21 years old with five-year averages of criminal charges from 2015–2019 for the 1998 cohort and from 2007–2011 for the 1990 cohort. The criminal charges of fathers and mothers are ten-year averages from 1992–2001, and the average ages of fathers and mothers are 24–33 and 22–31 for the 1998 cohort and 31–40 and 29–38 for the 1990 cohort. Standard errors are in parentheses, and those for scaled estimates and elasticities are based on the delta method and account for the covariance structure across regressions. *** p<0.01, ** p<0.05, * p<0.1.



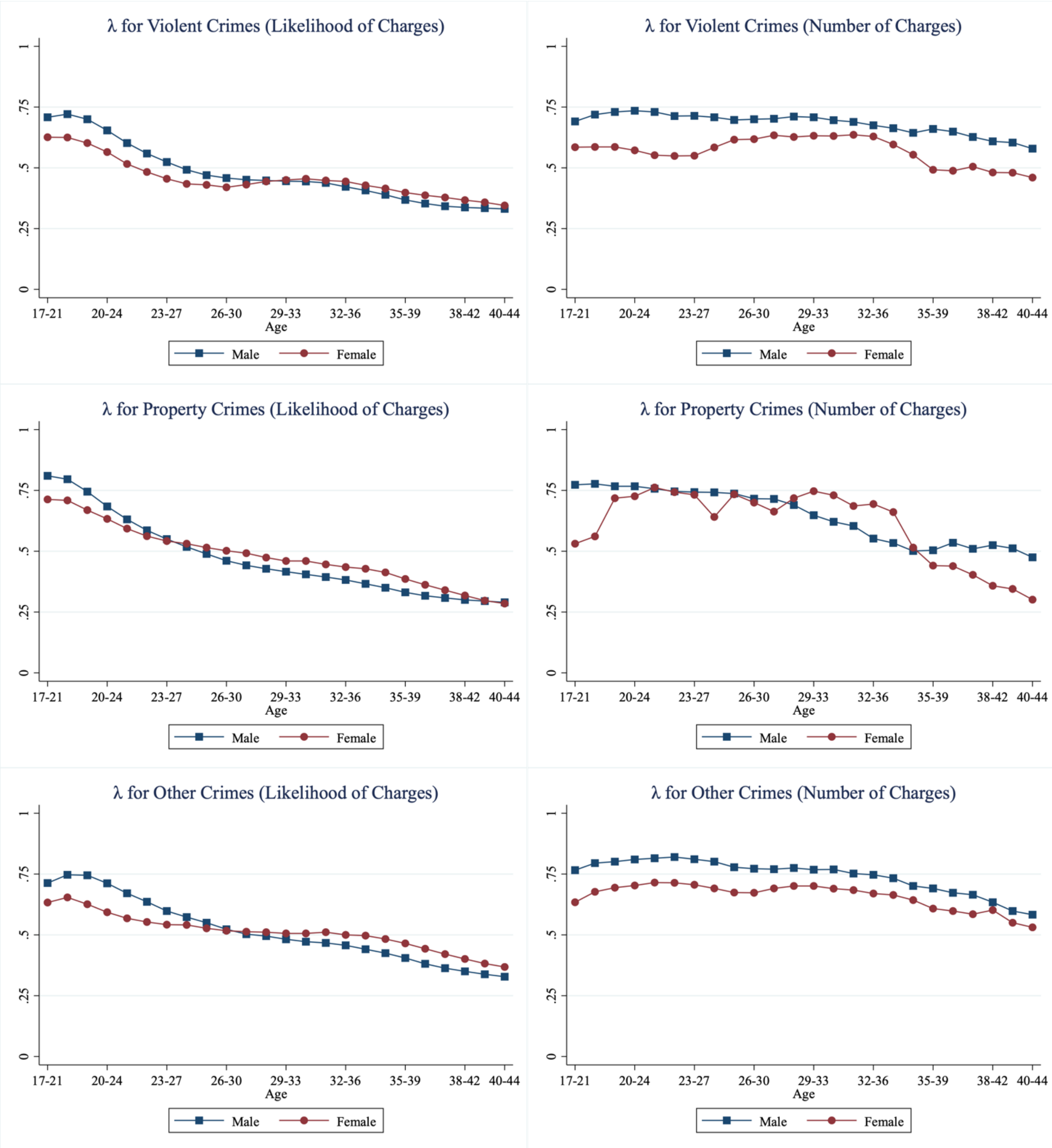
Appendix Figure A1: Criminal Charges for Violent (upper), Property (middle), and Other Crimes (lower) by Age on the Extensive Margin (left) and Intensive Margin (right) for the 1975 Cohort.



Appendix Figure A2: Estimates of λ_t and θ_t by Age (5-Year Moving Average) for the Likelihood of Criminal Charges of Violent (upper), Property (middle), and Other Crimes (lower) among the 1975 Cohort



Appendix Figure A3: Estimates of λ_t and θ_t by Age (5-Year Moving Average) for the Number of Criminal Charges of Violent (upper), Property (middle), and Other Crimes (lower) among the 1975 Cohort



Appendix Figure A4: Estimates of λ_t by Age (5-Year Moving Average) for the Standardized Likelihood (left) and Number (right) of Criminal Charges of Violent (upper), Property (middle), and Other Crimes (lower) among the 1975 Cohort

Appendix Table A1: Descriptive Statistics for the 1975 Cohort

	Male	Female
Likelihood of Charges	0.456	0.197
	(0.498)	(0.398)
Likelihood of Violent Charges	0.274	0.082
	(0.446)	(0.274)
Likelihood of Property Charges	0.206	0.086
	(0.405)	(0.280)
Likelihood of Other Charges	0.360	0.133
	(0.480)	(0.339)
Number of Charges	0.169	0.038
	(0.541)	(0.197)
Violent Charges	0.033	0.005
	(0.102)	(0.027)
Property Charges	0.044	0.014
	(0.206)	(0.116)
Other Charges	0.093	0.018
	(0.299)	(0.095)
Observations	27,669	26,967

Appendix Table A2: Intergenerational Associations in Criminal Charges for the 1998 Cohort (20-year Averages for Parents)

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*
Likelihood of Charges (Age of Children 17–21)								
All Crimes	0.265***	0.764***	0.155***	0.989***	0.241***	0.293***	0.178***	0.490***
	(0.015)	(0.042)	(0.013)	(0.074)	(0.018)	(0.022)	(0.017)	(0.044)
Violent	0.183***	0.537***	0.097***	0.729***	0.206***	0.158***	0.116***	0.232***
	(0.016)	(0.046)	(0.014)	(0.094)	(0.027)	(0.021)	(0.024)	(0.047)
Property	0.152***	0.764***	0.105***	1.155***	0.183***	0.354***	0.111***	0.515***
	(0.014)	(0.066)	(0.013)	(0.116)	(0.020)	(0.038)	(0.018)	(0.075)
Other	0.244***	0.671***	0.147***	0.844***	0.264***	0.249***	0.209***	0.429***
	(0.015)	(0.039)	(0.014)	(0.069)	(0.022)	(0.021)	(0.023)	(0.043)
Number of Charges (Age of Children 17–21)								
All Crimes	0.130***	0.536***	0.074***	0.842***	0.453***	0.320***	0.183***	0.398***
	(0.017)	(0.060)	(0.016)	(0.148)	(0.078)	(0.052)	(0.048)	(0.090)
Violent	0.182***	0.506***	0.049***	0.609***	0.637***	0.234***	0.159***	0.277***
	(0.025)	(0.064)	(0.012)	(0.132)	(0.181)	(0.065)	(0.058)	(0.094)
Property	0.089***	0.572***	0.066**	0.961***	0.231***	0.336***	0.121**	0.460**
	(0.021)	(0.117)	(0.027)	(0.358)	(0.073)	(0.100)	(0.058)	(0.202)
Other	0.134***	0.511***	0.079***	0.721***	0.436***	0.254***	0.224***	0.354***
	(0.016)	(0.055)	(0.016)	(0.123)	(0.066)	(0.037)	(0.057)	(0.076)
Observations	10,641		10,392		10,278		10,122	

Note: Sons and daughters are 17–21 years old with five-year averages of criminal charges from 2015–2019. The criminal charges of fathers and mothers are twenty-year averages from 1992–2011, and the average ages of fathers and mothers are 24–43 and 22–41, respectively. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A3: Intergenerational Associations in Criminal Charges for the 1998 Cohort (10-year Averages for Parents)

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*
Likelihood of Charges (Age of Children 17–21)								
All Crimes	0.277***	0.789***	0.182***	1.142***	0.246***	0.282***	0.205***	0.510***
	(0.017)	(0.048)	(0.015)	(0.086)	(0.022)	(0.026)	(0.022)	(0.053)
Violent	0.176***	0.508***	0.107***	0.784***	0.185***	0.138***	0.133***	0.245***
	(0.019)	(0.053)	(0.017)	(0.113)	(0.035)	(0.027)	(0.034)	(0.062)
Property	0.159***	0.796***	0.114***	1.252***	0.183***	0.321***	0.119***	0.511***
	(0.016)	(0.075)	(0.015)	(0.137)	(0.024)	(0.042)	(0.022)	(0.088)
Other	0.266***	0.711***	0.171***	0.955***	0.296***	0.255***	0.226***	0.409***
	(0.017)	(0.044)	(0.016)	(0.079)	(0.028)	(0.025)	(0.030)	(0.053)
Number of Charges (Age of Children 17–21)								
All Crimes	0.143***	0.543***	0.079***	0.834***	0.398***	0.251***	0.172***	0.313***
	(0.019)	(0.062)	(0.017)	(0.154)	(0.083)	(0.049)	(0.051)	(0.083)
Violent	0.177***	0.458***	0.054***	0.620***	0.621***	0.220***	0.220***	0.343***
	(0.030)	(0.071)	(0.013)	(0.129)	(0.190)	(0.066)	(0.075)	(0.114)
Property	0.099***	0.632***	0.066**	0.971***	0.170**	0.229***	0.133**	0.431**
	(0.023)	(0.126)	(0.028)	(0.369)	(0.068)	(0.084)	(0.064)	(0.193)
Other	0.153***	0.517***	0.086***	0.698***	0.438***	0.216***	0.167***	0.214***
	(0.018)	(0.054)	(0.018)	(0.131)	(0.084)	(0.038)	(0.059)	(0.067)
Observations	10,641		10,392		10,278		10,122	

Note: Sons and daughters are 17–21 years old with five-year averages of criminal charges from 2015–2019. The criminal charges of fathers and mothers are ten-year averages from 1992–2001, and the average ages of fathers and mothers are 24–33 and 22–31, respectively. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A4: Intergenerational Association in Criminal Charges for the 1990 Cohort (10-year Average for Parents)

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*
Likelihood of Charges (Age of Sons and Daughters 17–21)								
All Crimes	0.453***	0.676***	0.394***	1.028***	0.355***	0.177***	0.336***	0.311***
	(0.024)	(0.038)	(0.027)	(0.068)	(0.026)	(0.014)	(0.032)	(0.031)
Violent	0.331***	0.475***	0.192***	0.716***	0.300***	0.089***	0.203***	0.157***
	(0.027)	(0.040)	(0.025)	(0.089)	(0.047)	(0.015)	(0.047)	(0.037)
Property	0.355***	0.690***	0.200***	0.785***	0.280***	0.192***	0.230***	0.329***
	(0.026)	(0.056)	(0.025)	(0.099)	(0.033)	(0.025)	(0.035)	(0.052)
Other	0.462***	0.589***	0.400***	0.914***	0.422***	0.148***	0.429***	0.282***
	(0.025)	(0.034)	(0.029)	(0.064)	(0.033)	(0.013)	(0.043)	(0.029)
Number of Charges (Age of Sons and Daughters 17–21)								
All Crimes	0.272***	0.376***	0.130***	0.607***	0.706***	0.153***	0.344***	0.274***
	(0.032)	(0.040)	(0.027)	(0.114)	(0.125)	(0.025)	(0.077)	(0.053)
Violent	0.295***	0.353***	0.109***	0.584***	0.894***	0.117***	0.293***	0.167***
	(0.056)	(0.061)	(0.034)	(0.172)	(0.285)	(0.035)	(0.093)	(0.049)
Property	0.128***	0.302***	0.082**	0.587**	0.194***	0.101***	0.153**	0.264***
	(0.035)	(0.075)	(0.041)	(0.275)	(0.064)	(0.033)	(0.068)	(0.102)
Other	0.336***	0.377***	0.167***	0.585***	1.158***	0.173***	0.520***	0.259***
	(0.037)	(0.037)	(0.028)	(0.086)	(0.195)	(0.029)	(0.096)	(0.043)
Observations	10,956		10,767		10,683		10,605	

Note: Sons and daughters are 17–21 years old with ten-year averages of criminal charges from 2007–2011. The criminal charges of fathers and mothers are ten-year averages from 1992–2001, and the average ages of fathers and mothers are 31–40 and 29–38, respectively. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A5: Intergenerational Association in Criminal Charges for the 1990 Cohort
(10-year Average for Both Children and Parents)

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*	$\hat{\beta}/\hat{\lambda}\hat{\theta}$	*Elasticity*
Likelihood of Charges (Age of Sons and Daughters 17–21)								
All Crimes	0.384***	0.645***	0.327***	0.995***	0.288***	0.162***	0.289***	0.310***
	(0.019)	(0.035)	(0.020)	(0.061)	(0.020)	(0.013)	(0.024)	(0.027)
Violent	0.283***	0.446***	0.154***	0.644***	0.242***	0.079***	0.169***	0.146***
	(0.021)	(0.035)	(0.018)	(0.075)	(0.035)	(0.012)	(0.035)	(0.031)
Property	0.313***	0.656***	0.165***	0.767***	0.256***	0.188***	0.185***	0.314***
	(0.022)	(0.051)	(0.019)	(0.089)	(0.027)	(0.022)	(0.026)	(0.047)
Other	0.382***	0.575***	0.332***	0.934***	0.317***	0.132***	0.355***	0.286***
	(0.019)	(0.031)	(0.021)	(0.057)	(0.024)	(0.011)	(0.030)	(0.026)
Number of Charges (Age of Sons and Daughters 17–21)								
All Crimes	0.244***	0.386***	0.096***	0.525***	0.626***	0.156***	0.274***	0.254***
	(0.027)	(0.038)	(0.015)	(0.074)	(0.094)	(0.022)	(0.057)	(0.047)
Violent	0.267***	0.355***	0.081***	0.503***	0.764***	0.112***	0.229***	0.150***
	(0.045)	(0.054)	(0.024)	(0.144)	(0.244)	(0.033)	(0.066)	(0.040)
Property	0.105***	0.265***	0.052***	0.409***	0.143***	0.080***	0.094**	0.180**
	(0.028)	(0.065)	(0.018)	(0.130)	(0.045)	(0.024)	(0.041)	(0.072)
Other	0.287***	0.395***	0.131***	0.571***	0.954***	0.175***	0.458***	0.281***
	(0.030)	(0.038)	(0.019)	(0.071)	(0.154)	(0.028)	(0.078)	(0.044)
Observations	10,956		10,767		10,683		10,605	

Note: Sons and daughters are 17–26 years old with ten-year averages of criminal charges from 2007–2016. The criminal charges of fathers and mothers are ten-year averages from 1992–2001, and the average ages of fathers and mothers are 31–40 and 29–38, respectively. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A6: Intergenerational Elasticities of Criminal Convictions for the 1998 and 1990 Cohorts (10-year Average for Parents)

	Father-Son		Father-Daughter		Mother-Son		Mother-Daughter	
	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort	1998 Cohort	1990 Cohort
	Likelihood of Charges (Age of Children 17–21)							
All Crimes	0.720***	0.683***	1.023***	0.988***	0.252***	0.179***	0.436***	0.259***
	(0.046)	(0.037)	(0.084)	(0.067)	(0.026)	(0.015)	(0.055)	(0.032)
Violent	0.498***	0.490***	0.871***	1.006***	0.117***	0.101***	0.171**	0.161***
	(0.060)	(0.045)	(0.143)	(0.122)	(0.030)	(0.018)	(0.072)	(0.052)
Property	0.656***	0.610***	1.029***	0.702***	0.271***	0.174***	0.450***	0.312***
	(0.069)	(0.055)	(0.129)	(0.104)	(0.043)	(0.025)	(0.095)	(0.056)
Other	0.668***	0.546***	0.859***	0.795***	0.230***	0.151***	0.341***	0.236***
	(0.042)	(0.032)	(0.077)	(0.060)	(0.025)	(0.013)	(0.053)	(0.029)
	Number of Charges (Age of Children 17–21)							
All Crimes	0.500***	0.377***	0.745***	0.594***	0.195***	0.128***	0.230***	0.212***
	(0.063)	(0.041)	(0.145)	(0.116)	(0.046)	(0.024)	(0.073)	(0.044)
Violent	0.491***	0.438***	0.672***	0.755***	0.201***	0.100***	0.179**	0.136***
	(0.085)	(0.067)	(0.147)	(0.201)	(0.063)	(0.034)	(0.080)	(0.053)
Property	0.530***	0.312***	0.709**	0.714**	0.148**	0.084***	0.310*	0.187**
	(0.129)	(0.085)	(0.278)	(0.334)	(0.071)	(0.032)	(0.166)	(0.076)
Other	0.466***	0.353***	0.618***	0.519***	0.179***	0.153***	0.165***	0.210***
	(0.050)	(0.034)	(0.125)	(0.085)	(0.030)	(0.027)	(0.060)	(0.040)
Observations	10,641	10,956	10,392	10,767	10,278	10,683	10,122	10,605

Note: Sons and daughters are 17–21 years old with five-year averages of criminal convictions from 2015–2019 for the 1998 cohort and from 2007–2011 for the 1990 cohort. The criminal convictions of fathers and mothers are ten-year averages from 1992–2001, and the average ages of fathers and mothers are 24–33 and 22–31 for the 1998 cohort and 31–40 and 29–38 for the 1990 cohort. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.