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ORIGINAL ARTICLE

From Childhood System Contact to Adult Criminal Conviction: Investigating Intersectional Inequalities using Queensland Administrative Data

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Abstract

It is well known that youth justice contact is associated with criminal conviction in adulthood. What is less well understood is whether 'cross-over' children, who have contact with both child welfare and youth justice systems, experience relatively worse outcomes and, if so, whether these outcomes vary by important demographic factors, such as sex and race. Criminal careers scholars have examined patterns of adult convictions for different groups, but attempts to understand intersectional variation in these outcomes have been constrained by limitations of standard statistical analysis. Using administrative data from the Queensland Cross-sector Research Collaboration, we adopt a flexible regression model specification to explore the cumulative effects of both child welfare and youth justice contact on adult conviction trajectories, and how these associations vary by sex and Indigenous status. We find clear evidence across all demographic groups that contact with both justice and welfare systems in childhood is associated with increased likelihood and severity of conviction trajectories in adulthood. The *cumulative effect* of cross-over status results in greater equity of negative outcomes across groups, although the conviction profile is worst for Indigenous men. Evidence of an *additional* inequality is present only for non-Indigenous women, who have the lowest likelihood of conviction overall. We conclude that while cross-over children are at elevated risk of conviction in adulthood, the nature and seriousness of their conviction pathways is conditional on pre-existing intersectional inequalities. The model specification used is a promising method by which to explore the existence of such inequalities.

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Introduction

There is substantial evidence to show that people who experience youth justice contact[1] are far more likely than others to receive criminal convictions in adulthood (McAra et al., 2010; Craig et al., 2020). Research also shows that children who have contact with both youth justice and child welfare services—so-called cross-over children—are at increased risk of penetrating most deeply into the justice system (Bromwich, 2019; Herz et al., 2010; Kolivoski et al., 2017) and may be more likely to have persistent adult criminal careers (Baidawi & Sheehan, 2019; Baidawi, 2020). Developmental and Life-Course (DLC) criminology has long sought to distinguish between different types of offenders based on the duration and volume of their offending, particularly between persistent or chronic offenders and short-term offenders, as well as understanding childhood factors associated with these adult offending patterns. So determining the individual and combined impacts of different forms of early system contact on adult criminal convictions appears to be a fruitful area of exploration. In addition, there is strong evidence from DLC criminology that the relationship between childhood experiences and adult criminal careers differs by both sex and race/ethnicity[2] (Broidy et al., 2015), which indicates a need to assess whether any such cross-over effect is universal or highlights intersectional inequalities for boys and girls from different racial backgrounds.

Unfortunately, examining such complex relationships between different forms of early system contact in childhood and adult conviction outcomes, for males and females, from different racial/ethnic backgrounds poses a set of analytical challenges that are difficult to incorporate into standard statistical methods. Therefore, this paper addresses the problem by applying a flexible regression model specification to explore the cumulative effects of child welfare and youth justice system contact on adult conviction trajectories, and whether there is intersectional variation in these associations by sex and race/ethnicity. Using a novel dataset of linked administrative data from Queensland, Australia, our aim is to examine how cross-over status in childhood and demographic profile impact both individually and cumulatively on inequalities of criminal conviction outcome in adulthood. This study has important implications for the development of methods and theory within DLC criminology and for the development of policies to prevent negative outcomes for children involved in formal systems of intervention.

[1] In this paper, we use the term 'contact' to refer to any known referral to or involvement with Child Welfare and/or Youth Justice. This is an inclusive term that makes no assumption about the degree or nature of actual intervention through programs and/or initiatives.

[2] On terminology: throughout this paper we refer to 'sex' as opposed to 'gender'. As discussed in the data section, our analysis uses registered sex at birth as an indicator, and so we remain consistent with the Australian Bureau of Statistics (2020) terminology. In regards Indigenous status, when discussing the existing literature in general terms (including international literature), we use 'race/ethnicity', but recognize that the usage and history of this terminology are complex and not settled (Gardiner-Garden, 2003; Watt & Kowal, 2019), and so we use 'Indigenous status' when referring to our own analysis. We discuss the limitations of our Indigenous status measure in the *Data* section.

Literature Review

One of the most common issues researched by DLC criminologists is the heterogeneity of adult 'criminal careers'. Emerging from a series of debates in the 1980s (Blumstein et al., 1986; Hirschi & Gottfredson, 1983), and particularly prominent following Moffitt's (1993) dual taxonomy theory of offending, a large theoretical and methodological literature has developed describing the substantial *variation* in adult criminal careers (Nagin & Land, 1993; Nagin & Tremblay, 2005; Skardhamar, 2010). It is now common for DLC criminologists to summarise heterogeneous conviction patterns as sets of discrete trajectories with distinctive shapes, which distinguish between people with short-term and long-term conviction trajectories of various types, with the particulars of these trajectories defined empirically from the observed patterns in a given dataset.[3] Central questions for DLC researchers and for policy makers are: what drives variation within adult criminal careers? And to what extent is this variation influenced by factors that occur in childhood?

There is also a well-established body of literature examining childhood factors associated with criminal conviction in adulthood (see Farrington et al. 2012). Many scholars have identified juvenile justice system contact as a risk factor for later criminal conviction (e.g. McAra et al., 2010; Craig et al., 2020). However, research also shows that 'cross-over children'—those who have contact with both child welfare and youth justice systems—are an especially vulnerable group (Herz et al., 2010; Kolivoski et al., 2017), and at particular risk of later contact with the adult justice system (Bromwich, 2019; Baidawi, 2020). Of specific relevance to this paper, Baidawi and Sheehan (2019, p. 12) note that 'children with a "life-course persistent" offending profile may be over-represented among cross-over children compared to the overall cohort of youth offenders'. This hypothesized *cumulative* negative association between having both child welfare *and* youth justice contact is in line with international evidence that a high proportion of people with convictions or experience of imprisonment in adulthood have been 'looked after' or known to social care or justice services earlier in life (Carr & McAlister, 2016; Staines, 2016; Yang et al., 2021). However, it is unclear to what extent there is a particularly unequal relationship between cross-over status and different types of adult conviction trajectories, especially persistent adult conviction trajectories, over and above the association between contact with either youth justice or child welfare in isolation.

To further complicate this picture, any investigation of the impact of formal system contact on children's outcomes in adulthood must be contextually specific. In particular, it is vital that life-course studies examine the independent and intersectional impacts of sex and race/ethnicity on such systemic processes, especially in contexts where these factors form such a prominent role in justice inequalities

[3] This is common practice, although McGee et al. (2020) argue for simpler measures of particular offending trajectories—for example, considering the 20% of offenders with the longest criminal career durations in a given sample as 'persistent offenders'—rather than model-based estimates.

(Broidy et al., 2015; Bell, 2013; Herz et al., 2010; Jones et al., 2021), especially for cross-over children (Bromwich, 2019; Kolivoski et al., 2017). This is consistent with intersectional theories which recognise that peoples' experiences, including offending patterns, are shaped by a whole set of underlying systems of oppression and inequality associated with multiple factors, including their sex or their race/ethnicity (Bell, 2013; Lorenz & Hayes, 2020). Since the influence of factors such as sex and race/ethnicity cannot be disentangled, if we explore these facets independently, we risk masking important intragroup differences (Lorenz & Hayes, 2020). An emerging body of research has demonstrated the value of exploring intersectional distinctions in offending patterns (Broidy et al., 2015; Bell, 2013), experiences of child maltreatment (Jones et al., 2021), relationships between child maltreatment and youth offending (Baidawi et al., 2021; Goodkind et al., 2013; Kolivoski, 2022), and the relationship between childhood experiences and adult violent or antisocial behaviour (Augustyn & Jackson, 2020; Jones et al., 2021). However, this area of research is still in its infancy, and there is much still to be learned, not least how best to identify and measure such intersectional effects.

In the Australian context, the over-representation of Indigenous[4] people in the criminal justice system is of significant concern (Papalia et al., 2019), with stark inequalities between Indigenous people and other Australians. Of course, these inequalities in justice system involvement are set against the backdrop of former and current systemic injustices experienced by Indigenous people in Australia and must be interpreted in this context (Cunneen, 2006; Cunneen & Tauri, 2019). Taking Queensland as an example, 2018/19 justice statistics show that people from Indigenous backgrounds (Aboriginal and/or Torres Strait Islanders) accounted for 17.1% of all convicted adult court appearances, despite making up only 4% of the population (Queensland Treasury, 2020). Australian statistics also show a clear over-representation of Indigenous children in the care system (Tilbury, 2009). For example, in the year ending June 2019, 23.5% of children referred for child protection decision-making and 34.8% of notifications requiring investigation concerned Indigenous children. Indigenous children are also highly over-represented amongst children subject to 'ongoing intervention' such as a child protection order (43.0%) or living away from home (43.2%) (Queensland Government, 2020). In 2017/2018, Indigenous young people aged 10–17 were 17 times more likely than non-Indigenous children to be under youth justice supervision and 32 times more likely to be subject to detention (Australian Institute of Health & Welfare, 2019b).

Importantly, these inequalities between Indigenous status and both contact with child welfare and youth justice services are not uniformly distributed by sex. Indigenous males are most over-represented in the justice system, while non-Indigenous females are most under-represented (e.g., AIHW, 2020), whereas in the child protection system, Indigenous females are most over-represented and non-Indigenous males most under-represented, although intersectional differences

[4] In this article, we respectfully refer to Aboriginal and Torres Strait Islander Peoples as Indigenous Australians or Indigenous people.

are far less salient than those observed for justice system contact (e.g., AIHW, 2019a). This underlines Broidy et al. (2015, p. 145) assertion that 'developmental and life course models need to highlight not just the… age-graded risk and protective factors at play, but also the ways in which gender and race/ethnicity condition these processes both independently and jointly'. In understanding the cumulative relationship between formal childhood system contact and adult conviction outcomes, we must also examine how these effects vary by sex and race. There is, then, not only a gap in our understanding of the cumulative relationship between youth justice system contact, child welfare system contact and adult conviction trajectories, but also of how these effects vary by sex and Indigenous status. However, analysing how the cumulative effects of childhood system contact are associated with adult convictions, and how these associations vary by sex and race/ethnicity, raise two practical challenges.

The first challenge is finding a suitable data source. Linked administrative data holds great promise for DLC criminology in understanding the relationships between childhood experiences and adult outcomes (Stewart et al., 2015), and particularly as it relates to cross-over status, which by definition is related to contact with care and justice systems in childhood. Administrative data also reflects the experiences of women and Indigenous people, who are not included in all self-reported longitudinal studies (Stewart et al., 2015). Given our interest in understanding how the association between cross-over status and adult offending may vary by sex and race, this makes administrative data the most suitable type of data source. However, interpreting the results of studies using administrative data is complicated. Contact with child welfare and youth justice systems are not random, arising in response to adverse conditions in children's lives and being associated with risk factors also related to adult offending, such as childhood poverty (Bywaters et al., 2016). There is also evidence to suggest that formal interventions in childhood intended to support children in difficult circumstances can themselves act as a 'risk factor' in respect of later criminal justice outcomes. In the Edinburgh Study of Youth Transitions and Crime, McAra et al. (2010) found that the key factors differentiating between chronic and desisting conviction pathways between age 9 to 22 were school exclusion, adversarial police contact and youth justice intervention by age 12. Importantly, they found that differences in levels of self-reported offending did not account for these differences in conviction trajectories. McAra et al. concluded that early system contact may itself be iatrogenic, either by causing behavioural or emotional problems or creating a labelling effect by which people are repeatedly caught up by formal systems. As such, associations between childhood circumstances (as measured through early system contact) and subsequent offending reflect a complex mix of people's actions and social and justice system responses to their actions (McAra et al., 2005). Whilst administrative data provide the most suitable resource for exploring the potentially complex interactions between cross-over status, sex, race and adult convictions, results must be interpreted carefully. We return to this issue in the *Methods* section.

The second challenge is fitting a statistical model able to incorporate the complex interactions[5] between sex, Indigenous status, child welfare and youth justice contact, and adult conviction patterns. Modelling these relationships is difficult using standard regression specifications due to the twin problems of multiple testing and the 'curse of dimensionality' (Bell et al., 2019). In the context of models with complex interactions, as is the case here, multiple testing could lead to finding statistically significant interaction effects between the independent variables due to the large number of comparisons undertaken. The 'curse of dimensionality' could manifest in parameter estimates for rare combinations of variables becoming unreliable because sample sizes shrink as more interactions are included in the model (Bell et al., 2019). This would make estimates of interactions terms 'noisier' and potentially more likely to be significant. This is not a problem specific to criminology, and Jones et al. (2016; see also Bell et al., 2019; Evans et al., 2018) propose a solution to this problem which has been used in health research to find complex interactions between socio-demographic characteristics and health outcomes (e.g. Holman et al., 2020). We describe the model in more detail in the *Methods* section below, but it is worth briefly reflecting on the type of analysis this kind of approach requires. Lesley McCall (2005) describes the necessary complexity of studies which focus on describing inequalities between multiple characteristics simultaneously, which inevitably leads to an analysis structured by comparisons across multiple dimensions with the aim of understanding how advantage and disadvantage affect *all* groups. It is only by embracing this complexity, by fitting models which can uncover these interactions, and presenting comparisons across all of the multiple groups can we achieve what Broidy et al. (2015) describe in understanding how sex *and* race, separately and jointly, condition the effects of cross-over status on adult outcomes.

Aims and Research Questions

The aim of this paper is to examine whether there are differences by sex and Indigenous status in the associations between childhood contact with welfare and youth justice systems and patterns of criminal conviction in adulthood. The study is conducted in an Australian context, using data from a linked longitudinal administrative dataset known as the Queensland Cross-sector Research Collaboration (QCRC). The analysis presented here sets out to answer three research questions:

[5] What we have termed here as 'interactions'—the cross-product terms between sex, Indigenous status and childhood system contact—may be more precisely considered an effect measure modification (VanderWeele 2009) rather than an interaction per se. We use the term 'interaction' in this paper as this is consistent with the terminology used in the methodological literature describing the methods we have used (e.g. Bell et al., 2019; Jones et al., 2016), as well as in criminology more generally (e.g. MacQueen, 2016). We thank the reviewers for pointing out this distinction.

1. To what extent do adult criminal conviction trajectories vary by sex and Indigenous status?
2. Are there cumulative effects of childhood system contact across groups (defined by sex and Indigenous status) on adult criminal conviction trajectories?
3. Is there evidence of additional inequality in the impact of cross-over status in childhood on adult criminal convictions?

Methodology

Data

The QCRC dataset is held in the Social Analytics Lab at Griffith University in Brisbane, Australia. It contains linked administrative data from a range of health, child welfare and protection, youth justice and adult criminal justice systems for three cohorts, born in 1983, 1984 and 1990.[6] To give a suitable length of follow-up in which to investigate adult conviction trajectories, this paper used only the 1983/1984 birth cohorts. The resulting population included 83,371 individuals, followed to age 29. Focusing on these cohorts means that people included in our analysis were in contact with child welfare between 1983/1984 and 2001/2002, and with youth justice between around 1993/1994 to around 2000/2001 (see below for discussion of how these variables are measured). So, whilst we can estimate the cumulative associations between cross-over status and adult outcomes, there are likely to be differences between practice during this period and current practice which must be accounted for when interpreting our results. This is a limitation of the study, but an inevitable consequence of studying long-term effects of early system contact on outcomes in adulthood.

The QCRC dataset does not contain Queensland Census data; however, births data were provided by the Queensland Registry of Births, Deaths, and Marriages (Qld BDM) in the Department of Justice and Attorney-General (DJAG). These data were used to exclude all individuals in the 1983/1984 cohort who were *not* born in Queensland. This minimised the risk of inflating estimates of late onset conviction trajectories as a result of people migrating into Queensland as adults. It was not possible to identify outward migration of the cohort (because QCRC only contains criminal justice data from Queensland) so there will be some over-estimate of non-convictions in adulthood that cannot be avoided. Sex registered at birth and Indigenous status were also drawn from these data. Descriptive information about the variables used in this analysis is detailed below and in Table 1.

Dependent variable: Adult criminal conviction

The dependent variable for this study, adult criminal convictions for individuals born in Queensland in 1983/84, was based on court data provided by the DJAG.

[6] For further description of the QCRC, see Stewart et al. (2015, 2020).

Table 1 Description of dependent and independent variables

Variable	Level	All individuals in the dataset		Individuals convicted in adulthood	
		Number	Percent	Number	Percent
Sex	Female	40,416	48	3,576	9
	Male	42,946	52	11,793	28
Indigenous status	Indigenous	4,821	6	2,978	62
	Non-indigenous	78,541	94	12,391	16
Child Welfare/Youth Justice	None	71,232	85	9,115	13
	Child welfare only	2,048	2	583	28
	Youth justice only	8,528	10	4,472	52
	Both	1,554	2	1,199	77
Total		83,371	100	16,802	20

Percentages in the 'Individuals in the dataset' column sum to 100 within variables. Percentages in the 'Individuals convicted in adulthood' column show prevalence of conviction within group and so do not sum to 100

This included adult court finalisation data for offences that people were found or pled guilty to, with the exception of *minor* motor vehicle offences (which are typically dealt with by on-the-spot infringement notices issued under the Traffic Act) and breaches of justice order offences (which largely involve technical breaches of administrative orders rather than offences). At the time, individuals could be dealt with by the adult justice system from age 17; however, only criminal convictions from age 18 onwards were included in this analysis. This is consistent with widely adopted legal, social and human rights definitions of adulthood (Thompson et al., 2014). This clearly separates the timing of our childhood and adulthood data periods and removes ambiguity that could arise from children aged 16 and 17 being involved with both youth justice and adult justice concurrently. At the time of extraction, adult conviction data were available up to age 29 inclusive. Table 1 shows that 20% of the population had at least one criminal conviction, with 13% (n = 10,897) having two or more convictions, 7% (n = 5,745) having five or more, 4% (n = 3,246) with ten or more and less than 1% (n = 523) having 50 or more.

Independent variables

The independent variables for this study were the two demographic variables (sex and Indigenous status) and five measures of childhood system contact based on child protection or welfare data and policing or youth justice data. We grouped these measures of system contact into two binary variables to indicate whether each individual had had any contact with child welfare systems and/or youth justice systems.

Registered Sex at Birth Sex at the time of birth was extracted from the Queensland BDM registration data held in QCRC. There were very few (less than 10) cases where information on sex was missing, so these were excluded from the analysis.

The population of this study was reasonably evenly split between males (52%) and females (48%), although the prevalence of conviction in adulthood was three times higher for males (28%) than for females (9%).

Indigenous Australian Status Data on Aboriginal or Torres Strait Islander status (Indigenous status) are not always routinely recorded; therefore, linked administrative datasets from across the QCRC were interrogated to identify whether each individual had ever been recorded as an Indigenous Australian. This coding method is consistent with the national best practice guidelines for data linkage activities relating to Aboriginal and Torres Strait Islander People (Australian Institute of Health and Welfare and Australian Bureau of Statistics, 2012) and helps to take account of under-identification in administrative datasets. Walter and Andersen (2013) are critical of the umbrella term Indigenous status as this obscures the rich diversity of ethnic groups in Australia (there are more than 500 Aboriginal and Torres Strait Islander nations in Australia as a whole). However, the use of this umbrella term is unavoidable for our analysis as the datasets did not provide any further detail. The population for this study was predominantly non-Indigenous, with only 6% being from an Aboriginal or Torres Strait Islander background.[7] However, the prevalence of conviction in adulthood was almost four times greater for Indigenous people (62%) than non-Indigenous people (16%).

Child Welfare Contact This variable combined information on child maltreatment and whether a child was placed in out-of-home care. These data were obtained from the Department of Communities, Child Safety and Disability Services[8] (DCCSDS). This included data on children with at least one substantiated episode of abuse (emotional, physical, and sexual) or neglect based on reports from a Child Protection Officer (CPO). Cases are considered substantiated where, after investigation, the CPO is satisfied that there is 'reasonable cause to believe that the child has been harmed or is at risk of harm' (Department of Families[9] 2002, p. 21). Unsubstantiated cases were excluded from the analysis. The DCCSDS also provided data on any periods of 'out of home care' placements. These are regarded as a measure of last resort to protect a child's safety and well-being. We combined information about these child welfare contacts into a binary variable representing any contact (1) or no contact (0). This is a simplified measure of child welfare contact; however, given the

[7] The proportion of individuals who identify as Indigenous Australian in our study is somewhat higher than estimates attained through snapshot census data (4.6% of all Queenslanders) due to methodological differences (e.g., cross-sectional versus longitudinal measurement and differences in both reporting mechanisms and errors in under/over-estimation across these methodologies; see ABS, 2018 and AIHW 2012 for further information). While census estimations are known to undercount the Indigenous Australian population and are advised to be used with caution (ABS, 2018), an ever-never counting strategy also has the potential to over-assign Indigenous status. Our counting rules follow national best practice guidelines and attempt to rectify recognised issues with under-reporting in administrative dataset (AIHW, 2012), particularly with longitudinal designs that use historical data (ABS, 2018). Our estimates are consistent with expected rates based on research using similar definitions and methodologies (e.g. Stewart et al., 2020).

[8] Now called the Department of Children, Youth Justice and Multicultural Affairs.

complexity of the current analysis and the novelty of our model specification, this was preferred. Under Queensland child protection legislation, any individual under the age of 18 is defined as a child; therefore, these data span from birth to age 17. Only 4% of the population had child welfare experience.

Youth Justice Contact Data were collected on whether an individual had been formally processed for offending between the age of 10 and 16, including formal police diversion. This included details of formal police cautions, youth justice conferences, and Children's Court finalisations resulting in a guilty outcome. We combined information about these youth justice contacts into a binary variable representing any contact (1) or no contact (0). These data were provided by the Queensland Police Service (formal police cautions and youth justice conferences) and the Department of Youth Justice (Children's Court outcomes). Diversion of juveniles from formal court processes is promoted in Queensland (*Youth Justice Act 1992),* and police cautions are the most frequently adopted formal response to youth offending (Little & Allard, 2011). Until 2018, individuals in Queensland transitioned to the adult justice system at age 17 (*Youth Justice Act 1992)*. Consequently, data on youth justice contact only goes up to age 16 for the 1983/1984 QCRC cohort. Around 12% of the population had some form of youth justice contact.

Cross-Over Status We define 'cross-over children' as any individual who had contact with both the youth justice *and* child welfare systems. Table 1 shows that only 2% (n = 1,554) of individuals in the dataset were cross-over children; however, 77% of them had been convicted in adulthood. This compared with 52% for those with youth justice contact only, and 28% for those with child welfare contact only. In contrast, only 13% of those with no system contact in childhood were convicted in adulthood.

Table 2 shows the distribution of childhood system contact by sex and Indigenous status. Around 14% of Indigenous men and 11% of Indigenous women were cross-over children, whilst the equivalent figures for non-Indigenous men and women

Table 2 Prevalence of childhood system contact by sex and Indigenous status

Indigenous status	Sex	Childhood system contact % *(n)*				
		None	Child welfare	Youth justice	Both	***Total***
Indigenous	Male	42 (1,089)	4 (111)	41 (1,065)	14 (357)	*100 (2,622)*
	Female	59 (1,293)	10 (215)	20 (441)	11 (250)	*100 (2,199)*
Non-Indigenous	Male	85 (34,158)	2 (637)	12 (4,932)	1 (597)	*100 (40,324)*
	Female	91 (34,692)	3 (1,085)	5 (2,090)	1 (350)	*100 (38,217)*

Percentages are rounded to nearest integer so may not sum to 100 were around 1%. Moreover, child welfare and, especially, youth justice contact were significantly more prevalent amongst Indigenous males and females than their non-Indigenous counterparts. This information, in combination with the adult conviction prevalence data shown in Table 1, exposes extreme inequalities between the four demographic groups and provides grounds to explore the potential existence of a cumulative effect of childhood system contact on adult criminal convictions. In this analysis, we focus on the conditional relationships between childhood system contact and adult conviction trajectories—that is, what happens to children who have different types of contact, rather than how frequent these forms of contact are—but these disparities in the prevalence of cross-over status, as well as the other system contacts, are necessary to put the conditional relationships in context.

Research Design: Exploratory Analysis

We adopt an exploratory analytical approach, describing how the cumulative associations between child welfare contact, youth justice contact and adult conviction trajectories vary by sex and Indigenous status. We do not claim to estimate the direct *causal effects* of childhood system contact on adult convictions. Instead, we focus on understanding the cumulative associations between two types of system contact in childhood and conviction outcomes in adulthood. Moreover, our focus is primarily on any inequalities in the way that relationships between childhood system contact and adult conviction trajectories vary by sex and Indigenous status. We cannot determine whether differences in adult conviction outcomes are *caused* by these types of childhood system contact, as distinct from the circumstances which led to this system contact or any other differences between the groups we analyse, but we can describe how such outcomes vary according to different levels of childhood system contact and by sex and Indigenous status. It is possible, indeed likely, that any observed relationships are influenced by a range of other factors, but this does not interfere with our analytical focus on *describing* whether cumulative effects of childhood system contact on adult conviction trajectories can be observed in administrative data and how they vary by sex and Indigenous status. This is an important point that we shall return to later.

Analytical Strategy

To analyse sex/Indigenous status variation in the cumulative effects of childhood system contact on adult conviction trajectories, we adopt a three-stage modelling approach, as described below. It is notable that this approach has not previously been used in DLC research to examine aspects of inequality in criminal careers outcomes.

Stage One: Describing adult conviction trajectories using Latent class growth curves

We use Latent Class Growth Curves (LCGC; Nagin & Land, 1993; Nagin & Tremblay, 2005) to summarise the QCRC cohort members' heterogeneous adult conviction trajectories into a small number of discrete groups. This method has been widely adopted as a way to model conviction trajectories. Groups produced by this method must be interpreted with care, as identifying distinct trajectories of convictions does not necessarily imply that members of different trajectories have different causes for their conviction patterns (Skardhamar, 2010). Trajectories were modelled using the count of criminal convictions in a given year of age as the dependent variable, with counts capped at 10 convictions per year.[9] We used a zero-inflated Poisson model to account for over-dispersion and fit our LCGC model with linear and quadratic terms for age of conviction.[10] As the entropy of the fitted model was higher than 0.8, the person's most-likely class assignment estimated by the model was used as the dependent variable for analysis at Stage Two. This high entropy value indicates a high level of separation between classes, and so it is appropriate to use most likely class as an indicator for further analysis (Clark and Muthén, 2009). As this most-likely class method may underestimate the uncertainty in our results, we display 99% confidence intervals as opposed to 95% confidence intervals (Clark and Muthén, 2009).

Stage Two: Multilevel multinomial logistic regression

Once latent conviction classes were identified, we used Bayesian multinomial logistic regression to understand the relationships between membership of the different conviction trajectories and contact with child welfare and youth justice, as well as sex and Indigenous status.

The method outlined by Jones et al. (2016) works as follows: the main effects of all independent variables are included in the model, as well as explicit interactions between sex and Indigenous status, and youth justice and child welfare contact. We also include an 'intersectional' random effect incorporating every unique *combination* of the independent variables found in the dataset (Bell et al., 2019). This random-effect models interactions between *all* the independent variables—that is, between sex, Indigenous status, child welfare contact and youth justice contact—and so allows the model to estimate whether there is an additional effect of a specific type of early system contact on adult conviction trajectory for each combination of sex and Indigenous status. By modelling these complex interactions, referred to in the literature as 'strata', as a random effect they are subject to 'regularisation' where estimates for the interactions are 'shrunk' towards zero when there are little data to support them, but are preserved when there are sufficient data to estimate them robustly (Bell et al., 2019). As a result, the model specification is both flexible enough to find the kind of complex varying effects that are set by our research

[9] This capping affected 2,411 (0.24%) of the 1,000,452 person-years (83,371 people each with 12 years observed). Capping was necessary for the model to converge; the model would not converge with the data uncapped.

[10] Technically a LCGC is defined with no within-trajectory variance. As a robustness check, we also modelled the data allowing within-group variance (a Growth Mixture Model). Results between the two models were similar, but the LCGC allowed distinctions between people with the same shape of trajectory but different levels of convictions (i.e. high-rate and medium-rate). As these distinctions are substantively interesting we decided to focus on the LCGC.

questions when there is enough data to identify them, but conservative enough to pull extreme estimates for very small strata towards those implied by the main effects of our independent variables. This lets us identify whether the cumulative effects of child welfare contact and youth justice contact vary by sex and Indigenous status if the signal in the data is strong enough to warrant this extra model complexity. If there is not a strong enough signal in the data, the model will shrink the estimates of these interactions towards zero.

The fit of this model specification was compared to a standard 'main effects' model without this interaction parameter to assess whether the additional complexity of the model was justified by an increase in accuracy model fit (see 13 section below). As is recommended, we used a Bayesian model specification fitted using the *brms* R package (Bürkner, 2017). Model fit was assessed using the recommended ELPD-LOO measure (Vehtari, 2017)[11]—this measure allows us to assess whether the additional complexity of the intersectional model is justified. As is recommended, we present the differences between the ELPD-LOO for the best-fitting model and each other model specification, alongside the standard errors of these differences. Vehtari (2017) suggests a rule of thumb that a difference in model fit greater than five times the standard error of the difference model fit suggests a meaningful improvement in fit.

Stage Three: Model interpretation through post-fit estimation

After model fitting and checking,[12] the parameter estimates were converted into estimated probabilities of conviction trajectory membership (Gelman & Pardoe, 2007). This aids in interpretation of the model results as raw parameters from multinomial regression models are notoriously hard to interpret (McElreath, 2020).[13] While we could look at the parameter estimates for particular combinations of sex, Indigenous status and child welfare and youth justice system contact to assess if there are additional effects of cross-over status, these estimates are conditional on all the other model parameters and are difficult to interpret in isolation. Therefore, we calculated the trajectory class probabilities separately for Indigenous men, Indigenous women, non-Indigenous men and non-Indigenous women based on whether they had: no childhood system contact; child welfare contact only; youth justice contact only; or contact with both systems. By comparing the estimated class probabilities for non-Indigenous and Indigenous men and women across the four combinations of childhood system contact, we can identify the overall *cumulative effects* of early system contact and identify how these vary by sex and Indigenous status.

A desirable property of presenting results as estimated trajectory probabilities, rather than the parameters from a multinomial logistic regression model, is that the probabilities of class membership are more straightforward to understand. However,

[11] Bell and colleagues (2019) suggest fitting this model using Bayesian rather than frequentist estimation.

[12] We include model checking information in Appendix Three.

[13] The raw parameter estimates are presented in Appendix Four.

a limitation associated with presenting our results with estimated probabilities is that this captures both the cumulative effects of our independent variables due to our 'intersectional' random effect, but also the cumulative effects of the independent variables induced by transforming the parameters estimated on the log-odds scale to probabilities through the inverse-logit function. This transformation from log-odds to probabilities itself introduces 'mathematical' rather than 'subject-matter relevant' interactions between our independent variables (Harrell, 2020). So, to highlight the *additional* effect of our 'intersectional' random effect—that is, the how the effects of child welfare and youth justice contact on adult conviction vary by sex and Indigenous status—we compare the estimated probabilities from our intersectional model to those from the main-effects only model. The difference in these estimated probabilities show the specific additional contributions of the intersectional random effect, and, for children with both types of childhood contact, the difference in estimated trajectory probabilities between the results of these two model specifications will show the additional effect of cross-over status on adult conviction trajectories. We calculate the difference in the estimated trajectory probabilities between the two model specifications, creating confidence intervals for these differences using draws from the models' posteriors. These intervals are only indicative as to whether the models' estimates are similar, and should not be read as strict hypothesis tests of no difference.

Results

LCGC Model Fit and Descriptives: Number of People by Conviction Trajectory and Sex/Indigenous Status

After fitting a series of LCGC models with one through to seven classes, we chose a five-class trajectory solution based on a combination of model fit statistics and substantive interpretability (see Appendix for details of model fit and discussion of alternative solutions). Figure 1 shows the trajectories for the five classes, where the solid lines are the estimated number of convictions per year from the fitted model. The model estimated that the majority (86.93%) of individuals were most likely to have a trajectory with little or no probability of being convicted between age 18 and 29[14] (the 'No/Low Class'). The model also estimated two small classes of individuals with a low probability of conviction at age 18: one with a declining trajectory which approached zero probability of conviction by age 29 (the 'Low/Declining Class', 6.48%) and one with an increasing trajectory which indicated a moderate probability of conviction by age 29 (the 'Low/Increasing Class', 3.27%). The model also estimated two very small classes with a high probability of conviction at age 18: one with a trajectory which fell to a low probability of conviction by age 29 (the 'High/Declining Class', 1.69%) and one with a mostly stable trajectory which

[14] Note that the prevalence of conviction in the dataset was around 20% and yet only around 13% of people in the dataset were classified into convictions trajectories on the basis of most likely class. Indeed, the No/Low convictions class includes all people in the dataset with exactly one conviction, as well as those with no convictions.

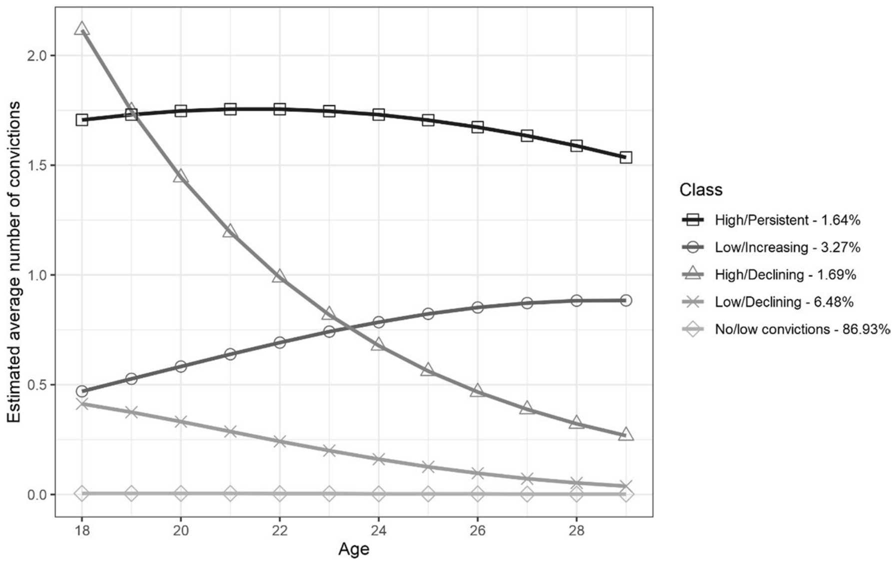

Fig. 1 Estimated Trajectories of Criminal Conviction for Five LCGC Classes

demonstrated a consistently high probability of conviction between the ages of 18 and 29 (the 'High/Persistent class', 1.64%).[15] These classes are similar to LCGC solutions identified in previous criminal career analyses, including trajectories estimated from previously linked administrative data for the 1983/1984 Queensland cohorts (for example, Broidy et al. 2015). The model's entropy—a measure of how distinctly people can be placed into the latent classes—was 0.877, indicating a high degree of separation between the five classes.

Estimated Adult Conviction Trajectories by Sex and Indigenous Status

Addressing our first research question, we find substantial differences in the membership of the five adult conviction classes between men and women from Indigenous and non-Indigenous backgrounds. Figure 2 shows the proportion of each sex and Indigenous status group by their most likely class membership based on the latent class model. The first thing to note is that the majority of people in each demographic group, with the exception of Indigenous men, was assigned to the No/Low class. The proportion of Indigenous men in the No/Low class was low at around 35%, and they were considerably over-represented in the remaining four conviction classes relative to the other demographic groups, particularly in the two high-level conviction groups. There is a clear ordering of conviction class membership by sex

[15] We refer to this group as High/Persistent, but bear in mind that persistent offending between 18 to 29 does not necessarily imply persistence after this point (Laub and Sampson, 2006).

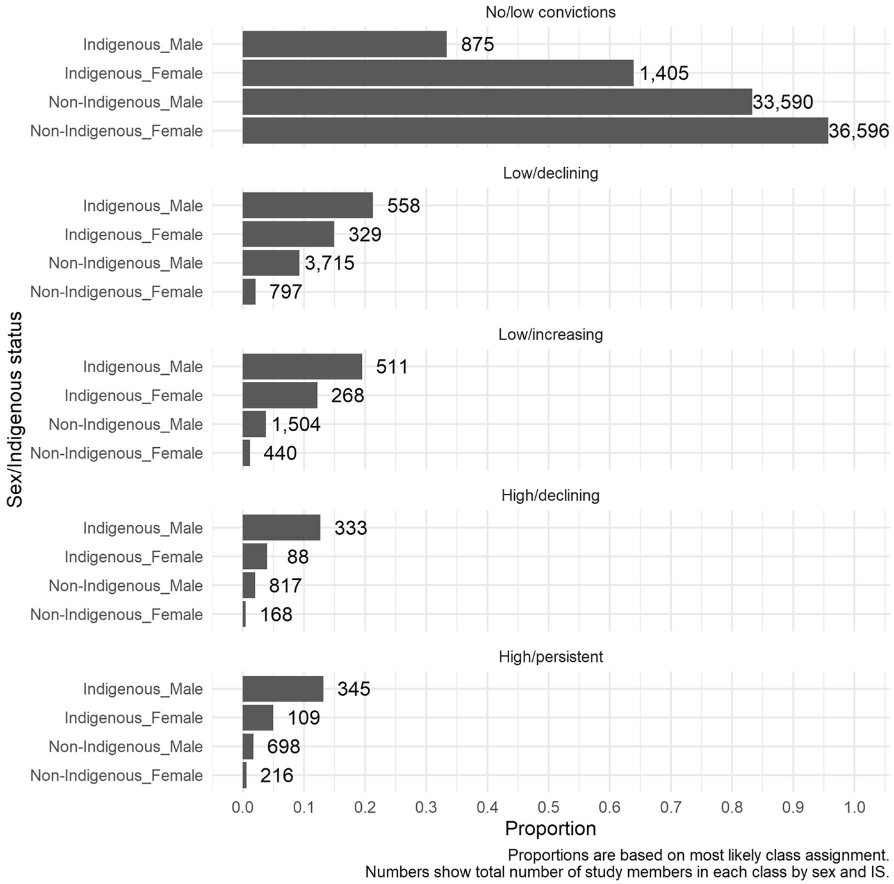

Fig. 2 Membership of LCGC Trajectories by Sex and Indigenous Status

and Indigenous status, with Indigenous men having the highest proportion in the four substantive conviction classes, followed by Indigenous women, then by non-Indigenous men and, finally, non-Indigenous women, with this ordering reversed for the No/Low convictions class. So, even before considering the effect of system contact, there were already substantial baseline differences in the adult conviction trajectories by sex and Indigenous status.

Estimated adult conviction trajectories by sex, Indigenous status and childhood system contact: model comparison

Table 3 shows the model fit of our series of regression models, building from an intercept-only model to our full 'intersectional' model. The table shows the difference in ELPD-LOO between the best-fitting model and the other models. As the improvement in model fit between the intersectional model and the fixed-effects model is greater than five times the standard error of this difference, this suggests

Table 3 Regression model fit

Model specification	Independent variables	ELPD-LOO difference	SE of difference
Intersectional	Sex, Indigenous status and their interaction, child welfare, youth justice, stratum random effect	0	0
Fixed effects	Sex, Indigenous status and their interaction, child welfare, youth justice	-58.1	11.4
Sex and Indigenous Status only	Sex, Indigenous status and their interaction	-3211.2	88.9
Intercept only	*N/A*	-7706	130

that the intersectional model fit the dataset substantially better than the simpler models. Therefore, there are strong statistical grounds to prefer this more complex model to one which assumes that the associations between multiple childhood system contact and adult conviction trajectories are the same across all sex/Indigenous status groups.

To understand why the intersectional model fits the data better than the fixed-effects model, Table 4 shows the number and proportion of people in each conviction trajectory based on their sex, Indigenous status and combination of childhood system contact, as well as the proportion of people in each conviction trajectory estimated from the fixed effect and 'intersectional' models. We also present the random effects visually in Fig. 3, and we hold substantive discussion of the results until then.

Table 4 shows that the random-effects model's estimates are consistently closer to the observed proportions than the fixed-effect model estimates that is, for all 78 parameters[16] the confidence intervals for random-effect estimates included the observed proportion in the raw data. In contrast, 22 of the 78 confidence intervals for the proportions calculated using the fixed-effects model did not include the observed proportions. This is unsurprising—the random-effect model has an extra parameter for each stratum, allowing the estimates to adjust for every combination of sex, Indigenous status and childhood system contact. However, these results are helpful in showing *where* the differences between the two models are. The fixed-effects model does a good job of reconstructing the proportions of non-Indigenous men in the different conviction trajectories, with every parameter including the raw values—but worse for non-Indigenous women and Indigenous women and men. This may be due to the larger number of non-Indigenous men convicted, meaning that the fixed-effects model is able to recover these parameters—but does not have the flexibility to identify the interactions between sex, Indigenous status and childhood system contact which are identified in the random-effects model.

[16] We do not include two parameters where the observed number of people in that trajectory was fewer than 10.

Table 4 Number and proportions of people in adult conviction trajectories by sex, Indigenous status and childhood system contact

Indigenous status and sex	Childhood system contact	Adult conviction trajectory	N	Proportion (99% CIs)		
				Raw	Fixed-effect estimates	Random-effect estimates
Indigenous Female	No childhood contact	N/L	995	0.77	**0.81 (0.79, 0.83)**	0.78 (0.76, 0.81)
		LD	160	0.13	**0.10 (0.09, 0.12)**	0.12 (0.10, 0.15)
		LI	90	0.07	0.06 (0.05, 0.07)	0.07 (0.05, 0.08)
		HD	25	0.02	0.01 (0.01, 0.02)	0.01 (0.01, 0.02)
		HP	20	0.02	0.01 (0.01, 0.02)	0.01 (0.01, 0.02)
	Youth justice contact only	N/L	210	0.48	**0.41 (0.38, 0.45)**	0.46 (0.41, 0.51)
		LD	95	0.21	0.23 (0.20, 0.26)	0.21 (0.17, 0.26)
		LI	75	0.17	**0.21 (0.18, 0.24)**	0.18 (0.14, 0.22)
		HD	30	0.07	0.07 (0.05, 0.09)	0.07 (0.05, 0.10)
		HP	30	0.07	0.08 (0.06, 0.10)	0.08 (0.06, 0.10)
	Child welfare contact only	N/L	130	0.60	0.60 (0.56, 0.64)	0.60 (0.53, 0.67)
		LD	30	0.14	**0.17 (0.15, 0.20)**	0.14 (0.09, 0.21)
		LI	40	0.20	**0.14 (0.11, 0.16)**	0.18 (0.13, 0.24)
		HD	< = 10	-	0.04 (0.03, 0.05)	0.03 (0.01, 0.05)
		HP	10	0.05	0.05 (0.04, 0.07)	0.04 (0.03, 0.07)
	Both types of contact	N/L	70	0.27	**0.18 (0.15, 0.20)**	0.24 (0.19, 0.29)
		LD	45	0.17	**0.23 (0.19, 0.26)**	0.18 (0.13, 0.24)
		LI	60	0.25	0.30 (0.25, 0.35)	0.26 (0.20, 0.33)
		HD	30	0.12	0.12 (0.09, 0.15)	0.12 (0.08, 0.16)
		HP	50	0.19	0.18 (0.14, 0.23)	0.20 (0.15, 0.25)

Table 4 (continued)

Indigenous status and sex	Childhood system contact	Adult conviction trajectory	N	Proportion (99% CIs)		
				Raw	Fixed-effect estimates	Random-effect estimates
Non-Indigenous Female	No childhood contact	N/L	33,745	0.97	0.97 (0.97, 0.97)	0.97 (0.97, 0.97)
		LD	495	0.01	**0.02 (0.02, 0.02)**	0.01 (0.01, 0.02)
		LI	250	0.01	0.01 (0.01, 0.01)	0.01 (0.01, 0.01)
		HD	95	0.00	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
		HP	110	0.00	0.00 (0.00, 0.00)	0.00 (0.00, 0.00)
	Youth justice contact only	N/L	1,710	0.82	0.84 (0.82, 0.85)	0.82 (0.80, 0.84)
		LD	170	0.08	**0.06 (0.06, 0.07)**	0.08 (0.07, 0.10)
		LI	105	0.05	0.05 (0.04, 0.06)	0.05 (0.04, 0.06)
		HD	45	0.02	0.02 (0.02, 0.03)	0.02 (0.02, 0.03)
		HP	60	0.03	0.03 (0.02, 0.04)	0.03 (0.02, 0.04)
	Child welfare contact only	N/L	955	0.88	**0.92 (0.90, 0.92)**	0.89 (0.86, 0.91)
		LD	70	0.06	**0.04 (0.03, 0.04)**	0.06 (0.05, 0.08)
		LI	30	0.03	0.02 (0.02, 0.03)	0.03 (0.02, 0.04)
		HD	10	0.01	0.01 (0.01, 0.01)	0.01 (0.01, 0.01)
		HP	15	0.01	0.01 (0.01, 0.02)	0.01 (0.01, 0.02)
	Both types of contact	N/L	185	0.52	**0.61 (0.57, 0.64)**	0.55 (0.49, 0.60)
		LD	65	0.19	**0.11 (0.09, 0.12)**	0.17 (0.13, 0.23)
		LI	55	0.15	**0.12 (0.10, 0.14)**	0.14 (0.10, 0.19)
		HD	15	0.05	0.06 (0.05, 0.08)	0.05 (0.03, 0.07)
		HP	35	0.09	0.11 (0.09, 0.14)	0.09 (0.07, 0.12)

Table 4 (continued)

Indigenous status and sex	Childhood system contact	Adult conviction trajectory	N	Proportion (99% CIs)		
				Raw	Fixed-effect estimates	Random-effect estimates
Indigenous Male	No childhood contact	N/L	590	0.54	**0.59 (0.55, 0.61)**	0.55 (0.52, 0.59)
		LD	240	0.22	**0.19 (0.17, 0.21)**	0.22 (0.19, 0.25)
		LI	150	0.14	**0.12 (0.10, 0.13)**	0.14 (0.11, 0.16)
		HD	60	0.06	0.06 (0.05, 0.07)	0.05 (0.04, 0.07)
		HP	45	0.04	0.05 (0.04, 0.06)	0.04 (0.03, 0.05)
	Youth justice contact only	N/L	210	0.20	**0.17 (0.15, 0.19)**	0.19 (0.17, 0.22)
		LD	240	0.23	0.24 (0.22, 0.27)	0.23 (0.20, 0.26)
		LI	260	0.24	0.25 (0.22, 0.28)	0.24 (0.21, 0.28)
		HD	190	0.18	0.17 (0.15, 0.20)	0.17 (0.15, 0.20)
		HP	165	0.16	0.16 (0.14, 0.19)	0.16 (0.14, 0.19)
	Child welfare contact only	N/L	45	0.41	**0.31 (0.27, 0.35)**	0.35 (0.27, 0.42)
		LD	20	0.20	0.23 (0.20, 0.26)	0.20 (0.13, 0.30)
		LI	25	0.22	0.21 (0.17, 0.24)	0.22 (0.15, 0.31)
		HD	< = 10	-	0.12 (0.09, 0.14)	0.10 (0.06, 0.15)
		HP	10	0.11	0.14 (0.11, 0.17)	0.12 (0.08, 0.17)
	Both types of contact	N/L	30	0.08	**0.06 (0.05, 0.07)**	0.08 (0.06, 0.10)
		LD	55	0.16	0.18 (0.16, 0.21)	0.16 (0.11, 0.21)
		LI	75	0.22	**0.27 (0.23, 0.31)**	0.23 (0.17, 0.28)
		HD	75	0.21	0.21 (0.17, 0.25)	0.22 (0.17, 0.27)
		HP	120	0.33	0.29 (0.25, 0.33)	0.32 (0.27, 0.37)

Table 4 (continued)

Indigenous status and sex	Childhood system contact	Adult conviction trajectory	N	Proportion (99% CIs)		
				Raw	Fixed-effect estimates	Random-effect estimates
Non-Indigenous Male	No childhood contact	N/L	30,210	0.88	0.88 (0.88, 0.89)	0.88 (0.88, 0.89)
		LD	2515	0.07	0.07 (0.07, 0.08)	0.07 (0.07, 0.08)
		LI	775	0.02	0.02 (0.02, 0.03)	0.02 (0.02, 0.02)
		HD	370	0.01	0.01 (0.01, 0.01)	0.01 (0.01, 0.01)
		HP	290	0.01	0.01 (0.01, 0.01)	0.01 (0.01, 0.01)
	Youth justice contact only	N/L	2,725	0.55	0.56 (0.54, 0.57)	0.55 (0.54, 0.57)
		LD	1,000	0.20	0.20 (0.19, 0.21)	0.20 (0.19, 0.22)
		LI	575	0.12	0.11 (0.10, 0.12)	0.12 (0.11, 0.13)
		HD	335	0.07	0.07 (0.06, 0.08)	0.07 (0.06, 0.08)
		HP	300	0.06	0.06 (0.05, 0.07)	0.06 (0.05, 0.07)
	Child welfare contact only	N/L	475	0.75	0.73 (0.70, 0.75)	0.74 (0.70, 0.78)
		LD	75	0.12	0.14 (0.12, 0.15)	0.12 (0.09, 0.15)
		LI	45	0.07	0.06 (0.05, 0.08)	0.07 (0.05, 0.09)
		HD	25	0.04	0.03 (0.03, 0.04)	0.03 (0.02, 0.05)
		HP	15	0.02	0.04 (0.03, 0.04)	0.03 (0.02, 0.04)
	Both types of contact	N/L	180	0.30	0.29 (0.26, 0.31)	0.31 (0.27, 0.35)
		LD	125	0.21	0.24 (0.21, 0.26)	0.21 (0.17, 0.25)
		LI	110	0.18	0.18 (0.16, 0.21)	0.18 (0.15, 0.22)
		HD	85	0.14	0.13 (0.11, 0.16)	0.14 (0.11, 0.17)
		HP	95	0.16	0.16 (0.14, 0.19)	0.16 (0.13, 0.19)

N/L = No/Low Convictions, LD = Low Declining, LI = Low Increasing, HD = High Declining, HP = High Persistent. N is rounded to the nearest five, and numbers smaller than 10 are not presented. Point estimates of proportions from the fixed-effects and random-effects models are the median values, with 99% CIs calculated as the 0.5th and 99.5th percentiles. We use 99% CIs as discussed in Sect. 4.1. Estimates in bold indicate where the raw probabilities fall outside the modelled 99% confidence intervals

Estimated adult conviction trajectories by sex, Indigenous status and childhood system contact: intersectional model results

As discussed in the Methods section, we do not present the raw parameters from the model in our main analysis, but instead we use the best-fitting, 'intersectional' model to calculate the probabilities of being in each of the five conviction trajectories estimated by the LCGC. These estimated probabilities are visualised in Fig. 3, which is divided into rows that represent each demographic group and columns that represent each type of early system contact. Within each cell is an estimated probability of class membership (displayed on the *x*-axis) for each of the five criminal conviction trajectories (named on the *y*-axis). Thus, Fig. 3 shows the estimated probability of being in each conviction class for each combination of sex and Indigenous status, taking account of the type of system contact experienced in childhood. This addresses our second research question about the cumulative effects of different types of system contact on conviction outcomes for the four groups.

On the right of each cell we show the difference in estimated probability of class membership for a person with a given type of system contact compared to the estimated probability for a person with the same characteristics who did not have that system contact (that is, the difference between the figures in the left-most column and each other column; hence, the values in the left-most column are all zero, as this shows the difference between this column and itself). We have arranged the plot so that the combinations of childhood factors are ordered by the size of their effect on each adult conviction trajectory. This runs from no childhood system contact on the left-most column, to child welfare contact only, then youth justice contact only, ending with cross-over status on the right-most column.

The cells in the far left column show the estimated probability of being in each conviction trajectory for each sex/Indigenous status group, for those who had no experience of any type of early system contact. The bottom cell shows that for non-Indigenous women who had no childhood contact the median estimated probability of being in the No/Low conviction trajectory was extremely high, at 0.97. Comparing this across the demographic groups in the column, it is apparent that for Indigenous women this probability was much lower, at 0.78. Consequently, Indigenous women with no experience of early system contact had a higher probability of being in any of the conviction trajectories in adulthood—especially the Low/Declining and Low/Increasing classes—than Non-Indigenous women. Similarly, the median estimated probability of being in the No/Low conviction trajectory was higher for Non-Indigenous men (0.88) than for Indigenous men (0.55), whereas the probability of being in all four of the other conviction trajectory classes was higher for Indigenous men than for Non-Indigenous men. Indigenous women were also more likely than non-Indigenous men to be in the other four trajectory classes.

Because the probabilities of being in each conviction trajectory must sum to one within each cell, we can analyse the results within each 'cell' as a unit. Taking these results as a whole, the four demographic groups have very different baselines (with no system contact in childhood), but much more similar end points (when they have experienced both types of childhood system contact). We can clearly see cumulative effects for those with both types of childhood system contact on the most severe adult conviction trajectories. As shown in Fig. 2, Indigenous men have the highest probability of being in each conviction class and the lowest probability of being in the No/Low convictions class, followed by Indigenous women, then non-Indigenous men and finally non-Indigenous women. The pattern of class probabilities changes in a broadly similar way for all four demographic groups, such that both types of childhood system contact are associated with worse conviction outcomes (i.e. the model probabilities move away from the No/Low conviction trajectory towards the High/Persistent trajectory). This creates an increasingly even spread of probabilities across each of the five classes with different combinations of system contact for every sex/Indigenous status group. In other words, having both child welfare and youth justice system contact in childhood was associated with a worse criminal conviction outcome in adulthood for all four demographic groups.

Despite the overall similarities in our results by demographic group, there are some distinct differences between the four sex/Indigenous status groups in the patterning of convictions according to different types of childhood system contact. For example, the likelihood of an Indigenous man being in the Low/Declining conviction class gets progressively *lower* as the cumulative effect of childhood system contact is considered, which we can see reading Fig. 3 from left to right. In contrast, the likelihood of a non-Indigenous woman being in the Low/Declining class *increases* with more childhood system contact, and there are also more marginal increases in these estimated probabilities for non-Indigenous men and Indigenous women. This shows us that, whilst in broad terms the cumulative effect of system contact is associated with increasingly serious conviction trajectories for all demographic groups, these trends play out differently across the groups because the baseline probabilities (i.e. the estimated probability of conviction with no childhood system contact) vary so substantially by sex and Indigenous status. All sex/Indigenous status groups with cross-over contact shift towards more serious conviction trajectories, but the end results of this shift depend on where the group's estimated trajectory probabilities started (i.e. the estimated probabilities with no childhood system contact).

Next, we address research question three about whether cross-over status in childhood adds an additional layer of inequality for any group in terms of adult conviction outcomes. Figure 4 shows the differences in estimated probability between our best-fitting 'intersectional' model and the equivalent model without the 'intersectional' random effect (the estimates from the two models can be seen in Table 4). The figure is laid out in the same way as Fig. 3, with each sex/Indigenous status combination on a separate row, each combination of childhood system contact in a column and each conviction trajectory arranged within the cells. Differences are calculated so that values higher than zero show estimates that are higher in the standard model than the intersectional model—and because the intersectional model has better fit, we consider positive values to be 'too high' and negative values 'too low'. We interpret 'statistically significant' differences (where the 99% intervals for the difference in estimates do not include zero) between the estimates from the two models as providing evidence for an additional penalty of cross-over status if the intersectional model shows a higher value for the No/Low trajectory or a lower value for any of the conviction trajectories. Statistically significant differences are shown in black, and we are particularly interested in the right-most column, which shows the additional difference in the estimated association between cross-over status and adult conviction trajectory from the intersectional model. As discussed in Sect. 2.3.3, these significance tests are at best illustrative, but serve to show the amount of uncertainty in the differences between the models' estimates.

Figure 4 shows that non-Indigenous women experienced the largest additional effect of cross-over status. The standard model overestimates the probability of being in the No/Low trajectory by around 0.07 and underestimates the probability of being in the Low/Declining trajectory by around the same amount, which means that the standard model is too optimistic in its estimated probabilities. From Fig. 3, we see that the estimated probability of being in the Low/Declining trajectory for non-Indigenous cross-over women is only 0.17, so to underestimate this amount by 0.07 is a substantial error. Figure 4 estimates for the Low/Declining class for non-Indigenous women show that the standard model underestimates the probabilities for both child welfare and youth justice contact, although only the child welfare figure is statistically significant at the 99% level. In contrast, the probability for no childhood system contact is slightly over-estimated. We do not see any statistically significant results for the other conviction trajectories for the other groups, suggesting that the differences between the two models' estimates are less clear for these comparisons.

Taking these results together, we can conclude that cross-over status is associated with an additional increase in the estimated probability of being in the Low/Declining conviction trajectory for non-Indigenous women, but this is the only sex/Indigenous status group to show evidence of any additional inequality in the impact of multiple childhood system contact on adult conviction trajectory over-and-above the effects of child welfare contact and youth justice in isolation.

Discussion

In this paper, we apply a flexible analytical approach to a large Australian administrative dataset to examine inequalities in adult criminal conviction outcomes based on differential childhood system contact for people from different demographic backgrounds. Our results show that the *cumulative effects* of having both youth justice and child welfare contact are associated with an increase in the likelihood of conviction, and the severity of conviction trajectories, for all groups; however, variation in conviction outcomes is still conditional on underlying intersectional differences by sex and Indigenous status, with Indigenous men having the most serious adult conviction outcomes overall. We find evidence of *additional inequality*, in terms having more serious adult conviction trajectories than would be expected over and above the cumulative effects of cross-over status, only for non-Indigenous females who were at lowest risk of conviction, and only for the least serious

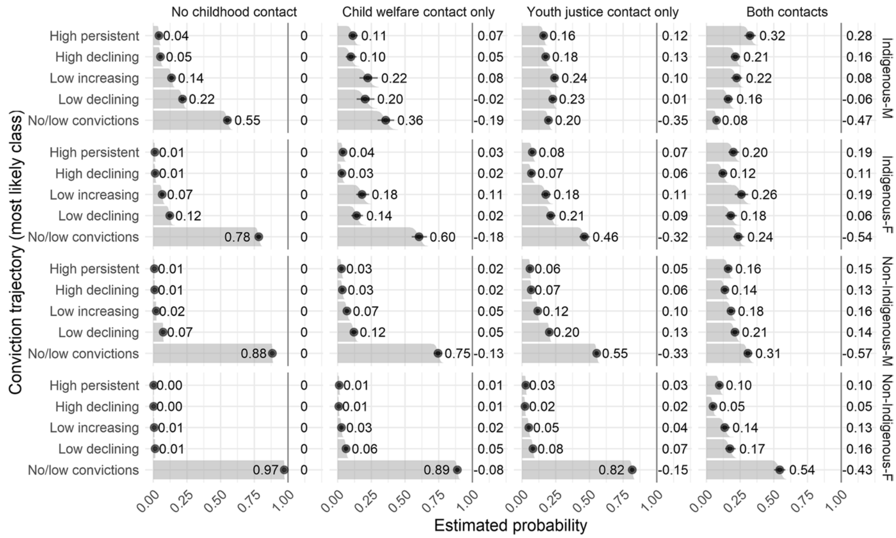

Fig. 3 Estimated Adult Conviction Trajectory Probabilities by Sex, Indigenous Status and Childhood System Contact

conviction trajectory. We now discuss these results by addressing our three research questions.

Our first research question asked whether adult criminal conviction trajectories varied by sex and Indigenous status and, as expected, we found that this was the case. Simple descriptive analysis showed that the prevalence of criminal conviction varied by sex, Indigenous status and cross-over status; however, our modelling approach provided a detailed exploration of the interrelationships and relative strength of these factors across five discrete conviction trajectories. Specifically, compared to the other demographic groups, Indigenous men were far less likely to be assigned to the No/Low conviction class and far more likely to be assigned to one of four conviction trajectories that varied according to level and trend. Non-Indigenous women were least likely to be assigned to any criminal conviction class, while Indigenous women and non-Indigenous men fell in between. There were, therefore, baseline differences in the pattern of criminal convictions according to sex and Indigenous status that were strongly associated with the outcomes of those with different types of early system contact.

Our results here are similar to the sex/Indigenous status differences in conviction trajectories identified by Broidy et al., 2015 using the same Australian cohorts, although they also reflect the 'social ordering' of offenders typically seen in US justice system data, where Black men are often over-represented and white women under-represented (Daly & Tonry, 1997; Steffensmeier et al., 2017). The analysis confirms the importance of Indigenous status and sex in differentiating between conviction trajectories, with Indigenous men being particularly over-represented in the more serious conviction trajectories, where our findings diverge somewhat from Broidy et al. (2015) is in relation to the low rate trajectories. While they found more evidence of low-level conviction amongst non-Indigenous males compared to Indigenous males, we found that low-level conviction was consistently more prevalent amongst Indigenous men and women than non-Indigenous men. This may be explained by different modelling approaches, stemming from the different substantive foci of our analyses, and also by the fact that additional data were made available in the QCRC since Broidy et al. (2015) conducted their analysis.[17] This highlights the point that any trajectories produced by LCGC are conditional on both data and model specification (Skardhamar, 2010).

Our second research question asked whether there were cumulative effects of childhood system contact across groups (defined by sex and Indigenous status) on adult criminal conviction trajectories. We also found this to be the case. The pattern of membership of the conviction classes varied considerably according to the extent of contact with formal childhood systems, and the probability of more serious conviction trajectories tended to be highest amongst Indigenous men and lowest amongst non-Indigenous women. Notably, therefore, the overall effect of these early types of system contact did not appear to be 'as bad' for the conviction outcomes of non-Indigenous women as they were for the other groups, and especially for Indigenous men. These overall results agree with Baidawi and Sheehan's (2019, p. 12) assessment that 'children with a "life-course persistent" offending profile may be over-represented among cross-over children compared to the overall cohort of youth offenders'—and we find this to be particularly true for Indigenous men.

A somewhat counterintuitive implication of our findings is that the cumulative associations between early system contact and adult conviction trajectories lead to more parity in conviction outcomes by sex and Indigenous status, despite the stronger associations seen between system contact and adult conviction trajectories for Indigenous men and their 'worse' baseline estimates. At first sight, this seems to contradict our conclusion that early system contact was most strongly associated with adult convictions for Indigenous men compared to the other groups—how then could the model estimate more similar outcomes by sex and Indigenous status in the presence of multiple risk factors? This seeming contradiction is because the 'baseline' probabilities of the adult conviction trajectories are so markedly low for non-Indigenous women, and to a lesser extent non-Indigenous men, with no childhood system contact. In comparison, the probabilities of different adult conviction trajectories for Indigenous men, and to a lesser extent Indigenous women, with no childhood system contact are much more evenly spread across the five trajectories, if still skewed towards the No/Low conviction trajectory. The effect of childhood system

[17] Specifically, Broidy et al. (2015) model youth offending and adult conviction data together, meaning that their findings about gendered processes of adolescence in the early teenage years do not map directly onto the adult conviction trajectories estimated in this study. We were also able to incorporate newer data QCRC into our analysis, which will affect the estimated trajectories: Broidy et al. also model trajectories to age 25, whilst our analysis goes up to age 29, and model trajectories only for people with a conviction, whereas the addition of BDM data to QCRC allowed us to focus on birth cohorts, thus minimizing potential bias in our regression model from inward migration to Queensland leading to missing data on childhood system contact. However, this also meant that the large number of one-off offenders captured in Broidy et al.'s low-rate trajectories are combined with non-offenders in ours.

contact in the model is to pull estimates for non-Indigenous women away from an extremely high probability of no or low convictions and towards evenness across trajectories. For Indigenous men, probabilities are pushed towards more serious conviction trajectories with multiple childhood system contact, but still remain quite evenly spread. The upshot is that members of all four sex/Indigenous status groups who have both types of childhood system contact are more similar in their estimated adult conviction outcomes than members of the same groups who have no childhood system contact, even though groups with the 'worst' baselines also have the largest estimated effects of early system contact. Put simply, as the outcomes for each group get worse, the intersectional differences become less pronounced, so *cross-over status is associated with greater equity of negative outcomes across all groups*.

Third, we asked whether there was evidence of additional inequality in the impact of being a cross-over child on adult criminal convictions and found that this was true for only one of our demographic groups. Despite the finding that childhood system contact had the smallest association with non-Indigenous women's adult conviction trajectories, it was only for this group that we found evidence of *additional inequality* in terms of a cross-over effect, and then only in terms of an increase in the Low/Declining trajectory. For other groups, the cumulative increase in the probability of more severe adult conviction trajectories after contact with both youth justice and child welfare were in line with what we would expect if the effects of these two types of system contact were independent of each other. One possible explanation for this observation is that non-Indigenous women in contact with both child welfare and youth justice have, on average, worse circumstances for other factors we have not measured than non-Indigenous women in contact with either child welfare or youth justice (but not both). For this explanation to hold, this would have to be true only for non-Indigenous women, and not non-Indigenous men, as we did not see strong evidence of an additional cross-over effect for non-Indigenous men. Another possible explanation is that there is a particularly strong effect of labelling through contact with both systems for non-Indigenous women, although given the purely quantitative focus of our study this possibility is speculative and would need further investigation.

Despite this additional cross-over effect, we should not lose sight of the fact that non-Indigenous women had the lowest estimated probability of being in any conviction trajectory, under any combination of childhood system contact. It may be that we could observe this additional association with cross-over status and the Low/Declining conviction trajectory because non-Indigenous women have a lower risk of conviction in general. Mathematically, this is reflected in our model because their intercept (when they have no contact with any system) is very low, in the part of the distribution where converting log-odds to probabilities has an outsized effect. It may also be that these results are sensitive to our data and model specification, a point to which we return in the *Limitations* section below. So whilst we did find that children with multiple childhood system contact were more likely to exhibit 'life-course persistent' adult conviction trajectories, as Baidawi and Sheehan (2019) proposed, with the possible exception of non-Indigenous women, this may not reflect *additional inequality* as a result of their cross-over status. Rather, it was consistent with an

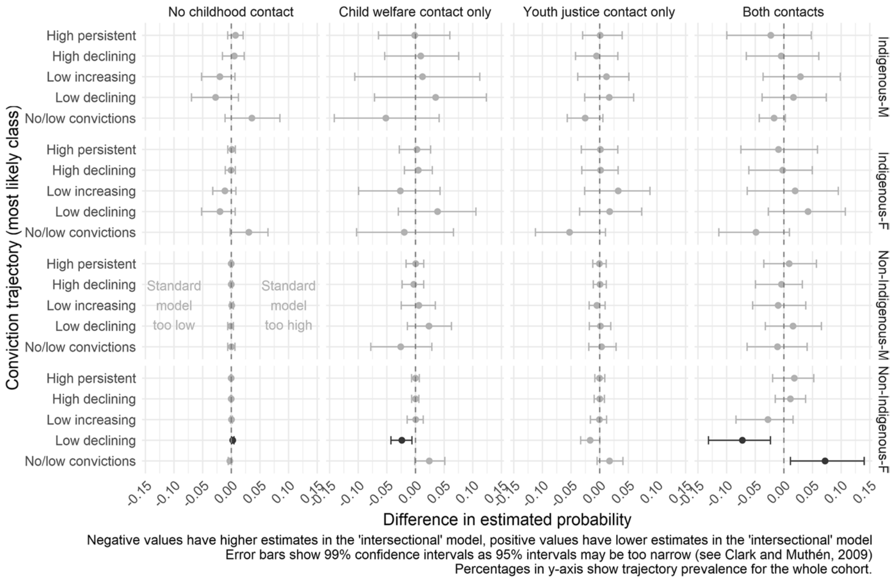

Fig. 4 Comparison of Conviction Trajectory Estimates from 'Intersectional' Random-Effect Model and Fixed-Effect Model

independent and additive association between child welfare contact and adult convictions, and youth justice contact and adult convictions. These findings highlight the importance of properly measuring, and the dangers of 'over claiming', system inequality effects at the expense of ignoring underlying intersectional differences.

It is worth noting that our results show substantial variation in adult conviction trajectories *within* sex and Indigenous status groups for people with identical observable characteristics, as well as *between* our four demographic groups. Displaying estimated trajectory probabilities for all classes, as in Fig. 3, shows that even though cross-over children may have an increased probability of being in the High/Persistent conviction trajectory, not all cross-over children will actually follow this conviction trajectory. Indeed, the model estimates that there would be some people with both types of childhood system contact in the No/Low conviction trajectory. Being able to see the range of outcomes for people with the same characteristics is a strength of our approach, helping us to avoid the 'erasure' of such differences. Even though we see a strong association between Indigenous status, sex and membership of the High/Persistent conviction trajectory (see Appendix 4), it would be wrong to assume that all Indigenous men with multiple childhood system contact end up with High/Persistent adult conviction trajectories—our model estimates that almost half of Indigenous men would *not* end up with a high-rate, persistent adult conviction trajectory even with this substantial childhood adversity.

Revealing both similarity and variation of outcomes within and between groups is important, as it reminds us to push back against essentialising assumptions about sex, Indigenous status and conviction. The constraints imposed on individuals by intersectionality are derived from a whole host of power structures and systems of oppression (Collins, 2000), so it would be unwise to conclude from this study that the differences we observe in conviction outcomes are simply the result of discriminatory practices within youth justice, child welfare, or adult criminal justice systems. However, our findings do highlight that where you end up is contingent on your starting point. For groups that were already subject to intersectional inequalities (such as Indigenous males), the addition of further 'risk factors' could only increase the probability of negative conviction outcomes by so much, whereas the baseline for less disadvantaged groups (such as non-Indigenous females) was far lower and, therefore, offered the largest scope to increase. As a consequence, the additional inequality of being a cross-over child was only apparent amongst this latter group. Yet an irony of our findings is that cross-over status is associated with both greater equity of negative outcomes across all groups, as well as substantial variation in outcomes within groups. This suggests that extreme care is needed in the application and interpretation of statistical models to examine the complex interactions between systemic and intersectional inequalities. Nevertheless, there is scope to widen the lens of intersectional theory to more fully explore the relative impact of state-based institutions across different constituent groups, and the methods we have adopted in this paper offer a promising approach with which to do so.

Limitations

In this paper, we have intentionally focused on the conditional relationships between childhood system contact and adult conviction trajectories—that is, what the typical outcomes are across sex/Indigenous status and different levels of childhood system contact. When relating our results back to the population as a whole, and in particular to the sharp inequalities between Indigenous and non-Indigenous Australians in adult justice system involvement, we need to recognise that some of our comparisons (including our estimated 'baselines') are more typical for some sex/Indigenous status groups than others. In our dataset, around 90% of non-Indigenous women had no childhood system contact at all, whilst the same was true for only around 42% of non-Indigenous men. This means that our 'baseline' condition of no childhood system contact is much more reflective of the experience of non-Indigenous women than it is of Indigenous men. This situation is even more acute when trying to estimate the associations between rare combinations of childhood system contact and adult conviction trajectories—for example, in the observed data there are around ten non-Indigenous women with child welfare and youth justice contact who were classified into the Low/Declining trajectory, from a population of roughly 38,000 non-Indigenous women overall. Whilst our novel model specification is particularly designed to handle this sparsity (Bell et al., 2019) and so our regression analyses account for these imbalances, this is not just an issue of statistical modelling—it reflects existing inequalities between Indigenous/non-Indigenous men/women in Queensland. This imbalance in the prevalence of child welfare and youth justice contact across demographic groups is one of the reasons why we see that in every convictions class there was a higher proportion of Indigenous men and Indigenous women, compared to non-Indigenous men and non-Indigenous women (Fig. 1).

We did not set out to explain criminal convictions in adulthood, and there will be many important factors that we have not accounted for in our model. Therefore, our results have to be interpreted carefully; quantitative research can often adopt non-Indigenous people as an unacknowledged norm, and then frame Indigenous status 'failure' against this norm as an assumed deficit of Indigenous people (Walter and Andersen, 2013). This approach obscures how non-Indigenous people in Australia (and elsewhere) have benefitted from historical inequalities and colonialism. This is another important factor to consider when interpreting the differences in our model's estimated baseline probabilities between Indigenous men and women and non-Indigenous men and women. We should not assume that these differences relate to 'deficits' amongst Indigenous people in individual or familial factors associated with offending risk, such as self-control, parenting practices; they likely reflect a complex set of factors, including the effects of poverty, policing, and the legacy of colonialism (Broidy et al., 2015; Walter and Andersen, 2013). In addition, these analyses are based only on administrative data, which does not include all child maltreatment or offending, and the actions of one or more formal systems in collecting these data may be subject to racial and gender biases (Malvaso et al., 2017).

In our regression analysis, we have focused on the estimated most likely class trajectory from our LCGC as the outcome. This introduces an amount of measurement error in the results. Given the LCGC's high entropy, Clark and Muthén (2009) indicate that this most-likely class approach performs better than possible alternatives, as a result there is some additional uncertainty that is not captured in our confidence intervals. We have adopted Clarke and Muthén's suggestion of using a more conservative interval (99%) rather than the standard 95% intervals, mitigating against this problem. However, as a robustness check, we re-ran our analysis using probability-weighting rather than most-likely class; an alternative approach discussed by Clark and Muthén (2009) but to which most-likely class regression is preferred. The results of these two methods were substantively the same, but for probability-weighted regression we did not find 'statistically significant' differences between the fixed-effects and random-effects models for any strata at the 0.01 level (or the more typical 0.05 level). Whilst our analytical approach is in line with best-practice and the probability-weighting method is not recommended by Clark and Muthén (2009), the fact that the particularly pronounced cumulative effect of cross-over status for non-Indigenous women were not as pronounced using an alternative method emphasises that our results should be seen as exploratory and provisional, and indicate the need for further research in this area.

Conclusions and Policy Implications

This study of a large cohort of people born in Queensland in 1983/84 found that having both welfare and justice system contact in childhood were associated with worse conviction outcomes in adulthood, regardless of sex and Indigenous status. As a consequence, there was *increasing equity of negative outcomes* across demographic groups amongst those with cross-over status; however, intersectional differences persisted, with Indigenous males having the worst conviction outcomes overall. *Additional inequality* of cross-over status was evident only amongst non-Indigenous females and then only at the lowest end of the conviction scale. While this analysis was exploratory, the findings are consistent with other research that shows the detrimental effects of experiencing multiple forms of system contact; however, differences in the nature and seriousness of conviction trajectories in adulthood are still conditional upon intersectional inequalities that exist at the point of entry into these children's systems.

From a policy perspective, our results are in line with McAra et al. (2010) emphasis on the importance of diversion from formal systems of care. However, context and demography are essential factors that must sit at the heart of any policy response (e.g. Department of Communities, Child Safety and Disability Services, 2017). This is demonstrably apparent within the Australian context, where official statistics show such a high degree of inequality amongst Indigenous youths, and especially boys, in the likelihood of being involved in formal systems of both care and justice. The fact that we found no evidence of heightened inequality amongst cross-over boys, or people from Indigenous backgrounds, does not diminish the critical policy importance supporting these groups; on the contrary, it likely reflects the fact that their risk of conviction in adulthood was already higher than non-Indigenous women. For DLC criminologists, our results support Broidy et al. (2015) call to investigate how sex and race/ethnicity shape the development of criminal careers, both separately and jointly. Our results also demonstrate that the modelling approach we adopted could be used to explore variation and inequality in a range of outcomes of interest to DLC scholars. We hope that our paper encourages others to adopt these or similar methods.

Appendix One: Latent class growth curves

A five-class latent-class growth curve model provided the best summary of the data, based on interpretability, theoretical expectations about criminal career trajectories and statistical fit. Figure 5 shows the aBIC, AIC and BIC fit for models with one through seven classes. These measures continued to decline with increasing numbers of classes, indicating that on statistical grounds we could justify a seven-class solution (and eight-class model did not converge to a stable solution). Likelihood ratio tests (Lo et al., 2001) also indicated that seven-class models were preferred to six-class models, and six to five. However, visual analysis of the shape of the trajectories suggested that the additional sixth class—which divided the increasing trajectory into low-rate and high-rate increasing trajectories—did not substantively add to the conclusions from the five-class model, and so we favour the simpler five-class model on grounds of interpretability. The five-class model is preferred to the four-class model as the five-class model identified the substantively interpretable Low/Increasing group which was not present in the four-class model.

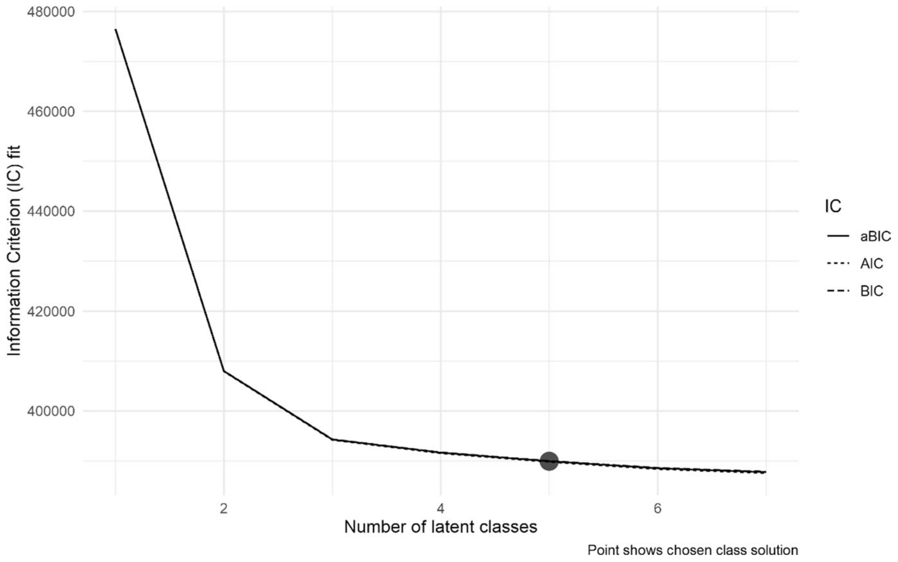

Fig. 5 Model Fit for Different Numbers of Latent Convictions Classes

Appendix Two: Details of Model Fitting

Latent class conviction trajectories were estimated in Mplus 8.2 (Muthén & Muthén 2017). We fit the regression models in the Stan Bayesian modelling platform (Carpenter et al., 2017) via the R package brms (Bürkner, 2017). This allowed the flexibility to fit the required regression model with a multinomial outcome and random effect. As recommended by Gabry et al. (2019), we adopted weakly informative priors for the model parameters. Priors for intercepts were defined as Normally distributed with mean -1 and standard deviation 4, and set priors for the standard deviation of the random effects as Exponential with a rate parameter of 2 as recommended by McElreath (2019:411). These priors help the model to estimate efficiently by avoiding implausible values of parameters on the log-odds scale. We tested other priors which gave identical results.

Appendix Three: Regression Model Checking

Diagnostic checks of the model showed that Rhat was close to 1 for all parameters, suggesting that the model's input Markov chains had converged appropriately (Betancourt, 2017). None of the model parameters have an effective sample size less than 10% of the total sample size, and parameters have a Monte Carlo standard error greater than 10% of the posterior standard deviation, and Pareto K diagnostics showed no overly influential values.

Figure 6 shows the close correspondence between the proportion of each conviction trajectory in the data (shown by the vertical bar) and those estimated by the model. These checks are recommended by Gabry et al. (2019) and indicate no serious model mis-specification as the fitted model accurately recovers the class proportions present in the data.

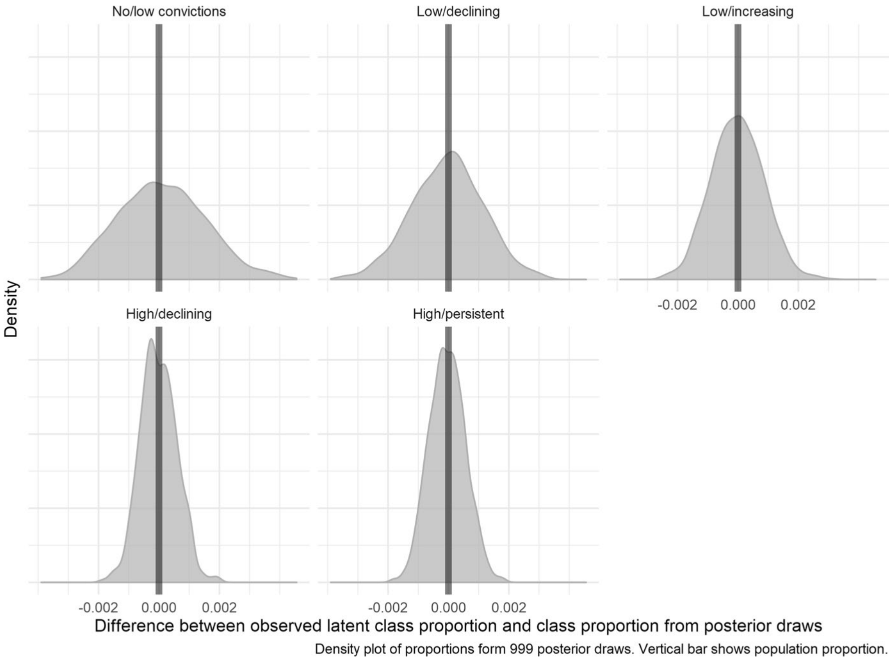

Fig. 6 Posterior predictive checks

Appendix Four: Regression Model Parameters

Table 5 Regression model parameter estimates. As defined in Table Three, models are (in order) Intercept only, Sex and IS only, Fixed effects, Fixed effects (interaction), Intersectional, Intersectional (extra interaction). Model fit is listed in Table 3. Estimates for random effects in Models 5 and 6 are listed in Table 6

Parameter	Conviction trajectory	Estimate (standard error)					
		Regression model					
		1	2	3	4	5	6
Intercept	Low declining	-2.60, (0.01)	-1.45, (0.06)	-2.06, (0.07)	-2.07, (0.06)	-2.15, (0.22)	-2.14, (0.25)
	Low increasing	-3.28, (0.02)	-1.66, (0.07)	-2.67, (0.08)	-2.69, (0.08)	-2.60, (0.19)	-2.64, (0.21)
	High declining	-3.94, (0.03)	-2.78, (0.11)	-4.04, (0.12)	-4.04, (0.13)	-4.08, (0.16)	-4.07, (0.17)
	High persistent	-3.97, (0.03)	-2.55, (0.10)	-4.10, (0.12)	-4.07, (0.12)	-4.17, (0.14)	-4.14, (0.14)
Sex	Low declining		1.00, (0.08)	0.94, (0.09)	0.94, (0.08)	0.95, (0.27)	0.94, (0.29)
	Low increasing		1.12, (0.09)	1.06, (0.09)	1.06, (0.10)	0.99, (0.22)	1.00, (0.23)
	High declining		1.81, (0.13)	1.73, (0.14)	1.74, (0.14)	1.70, (0.18)	1.71, (0.19)
	High persistent		1.63, (0.12)	1.61, (0.13)	1.61, (0.13)	1.58, (0.15)	1.59, (0.15)
Indigenous status	Low declining		-2.38, (0.07)	-1.99, (0.07)	-1.99, (0.07)	-1.49, (0.26)	-1.49, (0.28)
	Low increasing		-2.76, (0.08)	-2.15, (0.09)	-2.15, (0.09)	-1.99, (0.22)	-1.99, (0.23)
	High declining		-2.60, (0.13)	-1.88, (0.14)	-1.88, (0.14)	-1.77, (0.18)	-1.76, (0.19)
	High persistent		-2.58, (0.12)	-1.71, (0.13)	-1.71, (0.13)	-1.58, (0.14)	-1.58, (0.15)
Sex: Indigenous status	Low declining		0.62, (0.09)	0.62, (0.09)	0.62, (0.09)	0.21, (0.36)	0.22, (0.39)
	Low increasing		0.19, (0.10)	0.15, (0.11)	0.15, (0.11)	0.10, (0.30)	0.10, (0.33)
	High declining		-0.15, (0.15)	-0.20, (0.16)	-0.20, (0.16)	-0.16, (0.23)	-0.16, (0.25)
	High persistent		-0.37, (0.14)	-0.47, (0.15)	-0.48, (0.15)	-0.49, (0.18)	-0.50, (0.19)
Child welfare	Low declining			0.82, (0.06)	0.89, (0.08)	0.74, (0.18)	0.74, (0.27)
	Low increasing			1.20, (0.07)	1.37, (0.10)	1.15, (0.15)	1.22, (0.24)
	High declining			1.32, (0.08)	1.26, (0.15)	1.19, (0.12)	1.16, (0.21)
	High persistent			1.67, (0.08)	1.44, (0.15)	1.56, (0.09)	1.41, (0.16)

Table 5 (continued)

Parameter	Conviction trajectory	Estimate (standard error)					
		Regression model					
		1	2	3	4	5	6
Youth justice	Low declining			1.48, (0.03)	1.49, (0.04)	1.36, (0.18)	1.38, (0.26)
	Low increasing			1.98, (0.04)	2.02, (0.05)	1.77, (0.16)	1.83, (0.22)
	High declining			2.30, (0.06)	2.29, (0.06)	2.23, (0.11)	2.22, (0.15)
	High persistent			2.44, (0.06)	2.40, (0.07)	2.41, (0.09)	2.36, (0.10)
Youth justice: Child welfare	Low declining				-0.14, (0.12)		0.00, (0.39)
	Low increasing				-0.29, (0.13)		-0.12, (0.33)
	High declining				0.02, (0.18)		0.06, (0.27)
	High persistent				0.26, (0.18)		0.22, (0.20)

Table 6 Regression model parameter estimates, random-effect estimates. As defined in Table 3, models are (in order) Intersectional, Intersectional (extra interaction). Model fit is listed in Table 3

Conviction trajectory	Stratum		Estimate (standard error)	
			Regression model	
	Number	Definition	5	6
Low declining	1	Female:Non-Indigenous:No YJ:No CW	-0.57, (0.22)	-0.58, (0.25)
	2	Male:Non-Indigenous:No YJ:No CW	-0.01, (0.21)	-0.01, (0.25)
	3	Male:Non-Indigenous:YJ:No CW	0.11, (0.21)	0.09, (0.25)
	4	Female:Non-Indigenous:YJ:No CW	-0.04, (0.22)	-0.05, (0.25)
	5	Female:Indigenous:No YJ:No CW	0.29, (0.23)	0.28, (0.26)
	6	Male:Indigenous:No YJ:No CW	0.26, (0.23)	0.27, (0.25)
	7	Female:Non-Indigenous:No YJ:CW	0.23, (0.23)	0.23, (0.26)
	8	Male:Indigenous:YJ:No CW	-0.01, (0.23)	-0.02, (0.26)
	9	Male:Non-Indigenous:No YJ:CW	-0.07, (0.23)	-0.07, (0.25)
	10	Male:Non-Indigenous:YJ:CW	-0.02, (0.22)	-0.01, (0.26)
	11	Female:Indigenous:YJ:No CW	0.02, (0.23)	0.00, (0.27)
	12	Male:Indigenous:YJ:CW	-0.17, (0.24)	-0.15, (0.26)
	13	Female:Non-Indigenous:YJ:CW	0.38, (0.23)	0.38, (0.26)
	14	Female:Indigenous:YJ:CW	-0.23, (0.24)	-0.24, (0.26)
	15	Female:Indigenous:No YJ:CW	-0.04, (0.24)	-0.05, (0.27)
	16	Male:Indigenous:No YJ:CW	-0.08, (0.25)	-0.09, (0.28)
	Intercept		0.32, (0.09)	0.34, (0.10)
Low increasing	1	Female:Non-Indigenous:No YJ:No CW	-0.30, (0.19)	-0.26, (0.21)
	2	Male:Non-Indigenous:No YJ:No CW	-0.16, (0.19)	-0.13, (0.21)
	3	Male:Non-Indigenous:YJ:No CW	0.16, (0.19)	0.14, (0.20)
	4	Female:Non-Indigenous:YJ:No CW	0.03, (0.19)	0.01, (0.20)
	5	Female:Indigenous:No YJ:No CW	0.13, (0.19)	0.16, (0.22)
	6	Male:Indigenous:No YJ:No CW	0.20, (0.19)	0.23, (0.22)
	7	Female:Non-Indigenous:No YJ:CW	-0.02, (0.21)	-0.06, (0.22)
	8	Male:Indigenous:YJ:No CW	0.05, (0.19)	0.02, (0.20)
	9	Male:Non-Indigenous:No YJ:CW	-0.04, (0.20)	-0.07, (0.21)
	10	Male:Non-Indigenous:YJ:CW	0.04, (0.19)	0.07, (0.21)
	11	Female:Indigenous:YJ:No CW	-0.13, (0.20)	-0.15, (0.21)
	12	Male:Indigenous:YJ:CW	-0.23, (0.20)	-0.20, (0.21)
	13	Female:Non-Indigenous:YJ:CW	0.28, (0.20)	0.31, (0.22)
	14	Female:Indigenous:YJ:CW	-0.22, (0.20)	-0.19, (0.22)
	15	Female:Indigenous:No YJ:CW	0.21, (0.21)	0.19, (0.22)
	16	Male:Indigenous:No YJ:CW	-0.02, (0.22)	-0.06, (0.22)
	Intercept		0.26, (0.08)	0.27, (0.09)

Table 6 (continued)

Conviction trajectory	Stratum		Estimate (standard error)	
			Regression model	
	Number	Definition	5	6
High declining	1	Female:Non-Indigenous:No YJ:No CW	-0.01, (0.12)	-0.02, (0.14)
	2	Male:Non-Indigenous:No YJ:No CW	-0.05, (0.12)	-0.07, (0.14)
	3	Male:Non-Indigenous:YJ:No CW	-0.01, (0.11)	-0.01, (0.13)
	4	Female:Non-Indigenous:YJ:No CW	0.00, (0.11)	0.00, (0.14)
	5	Female:Indigenous:No YJ:No CW	0.05, (0.15)	0.06, (0.17)
	6	Male:Indigenous:No YJ:No CW	0.02, (0.12)	0.02, (0.13)
	7	Female:Non-Indigenous:No YJ:CW	0.01, (0.13)	0.02, (0.16)
	8	Male:Indigenous:YJ:No CW	0.02, (0.11)	0.02, (0.13)
	9	Male:Non-Indigenous:No YJ:CW	0.03, (0.13)	0.04, (0.15)
	10	Male:Non-Indigenous:YJ:CW	0.03, (0.11)	0.03, (0.13)
	11	Female:Indigenous:YJ:No CW	-0.01, (0.12)	-0.01, (0.13)
	12	Male:Indigenous:YJ:CW	-0.01, (0.12)	-0.01, (0.14)
	13	Female:Non-Indigenous:YJ:CW	0.00, (0.12)	-0.01, (0.14)
	14	Female:Indigenous:YJ:CW	0.00, (0.11)	-0.01, (0.14)
	15	Female:Indigenous:No YJ:CW	-0.02, (0.14)	-0.02, (0.16)
	16	Male:Indigenous:No YJ:CW	-0.03, (0.14)	-0.04, (0.16)
	Intercept		0.10, (0.08)	0.12, (0.10)
High persistent	1	Female:Non-Indigenous:No YJ:No CW	0.00, (0.07)	0.00, (0.07)
	2	Male:Non-Indigenous:No YJ:No CW	0.00, (0.07)	0.00, (0.07)
	3	Male:Non-Indigenous:YJ:No CW	0.01, (0.07)	0.01, (0.07)
	4	Female:Non-Indigenous:YJ:No CW	0.00, (0.07)	0.00, (0.07)
	5	Female:Indigenous:No YJ:No CW	0.00, (0.08)	0.00, (0.08)
	6	Male:Indigenous:No YJ:No CW	0.00, (0.07)	0.00, (0.07)
	7	Female:Non-Indigenous:No YJ:CW	0.00, (0.08)	0.00, (0.08)
	8	Male:Indigenous:YJ:No CW	-0.01, (0.07)	0.00, (0.07)
	9	Male:Non-Indigenous:No YJ:CW	-0.01, (0.08)	-0.01, (0.08)
	10	Male:Non-Indigenous:YJ:CW	0.00, (0.07)	0.00, (0.07)
	11	Female:Indigenous:YJ:No CW	-0.01, (0.07)	-0.01, (0.08)
	12	Male:Indigenous:YJ:CW	0.01, (0.08)	0.00, (0.08)
	13	Female:Non-Indigenous:YJ:CW	0.00, (0.07)	0.00, (0.08)
	14	Female:Indigenous:YJ:CW	0.00, (0.07)	0.00, (0.08)
	15	Female:Indigenous:No YJ:CW	0.00, (0.07)	0.00, (0.08)
	16	Male:Indigenous:No YJ:CW	0.00, (0.07)	0.00, (0.08)
	Intercept		0.05, (0.05)	0.05, (0.06)

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Declarations

Competing interests None.

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