Intergenerationally Penalized?
The Long-Term Wage Consequences of Parental Joblessness

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Abstract

Studies of intergenerational stratification and mobility have long called for investigation of the joint role of mothers and fathers in affecting labor market outcomes of children. However, long-term effects of parental joblessness—where no co-residing parent is employed at a given time—are not well understood. Using longitudinal data (covering 9,942 person-year observations from 2,281 children) from the Household, Income, and Labour Dynamics in Australia (HILDA) Survey, this study investigates the long-term association between parental joblessness and children's wages during early adulthood. It examines whether these associations are mediated by family income during childhood and adolescence, educational attainment, and subsequent employment inactivity of the child, and whether exposure at earlier ages is associated with more detrimental effects. Multilevel mixed-effects models regressing hourly wages in early adulthood (observed over 2008–2018) on the proportion of time spent living in a household where no parent is employed (observed over 2001–2007) reveal two major findings. First, exposure to parental joblessness during childhood and adolescence is correlated with adverse wage outcomes during early adulthood in addition to previously documented employment penalties, with similar estimates across age groups. Second, mediation analyses indicate that household income, children's educational attainment, and children's own inactivity reduce the magnitude of this wage penalty, but do not completely offset it.

Keywords: parental joblessness; intergenerational relationships; wages; Australia; life course

JEL codes: E24; J62

Introduction

There is mounting evidence that joblessness produces adverse consequences not only for those directly affected, but also for family members, including children (e.g., Bubonya, Cobb-Clark, and Wooden 2017; Coelli 2011; Kalil and Ziol-Guest 2008; Lindo 2011; Pan and Obst 2014; Schaller and Zerpa 2019; Stevens and Schaller 2011). Resource deprivation and socialization are two central mechanisms underpinning this intergenerational disadvantage process (for a review, see Francesconi and Heckman 2016). Family resource deprivation is related to the fragmented nature of parental employment and the ensuing income shocks. This is reflected in, for example, parents' reduced ability to provide children with enriched and stimulating learning environments or the inability to buy educational goods and services that enhance children's education and labor market outcomes (Torche 2015). Very differently, socialization suggests that without employed role models in the household, children may form weaker attachments to the labor market and subsequently imitate the jobless behavior of their parents in adulthood (Wilson 1996).

These key theoretical concepts are based on the assumption that both mother's and father's economic participation *jointly* determine the future achievements of their children. Yet, the large majority of empirical research on the intergenerational effects of parental employment has considered the joblessness of only one parent, usually the father. This may understate the size of negative intergenerational effects when both parents experience overlapping spells of joblessness. With few exceptions—even in recent studies where mothers' and fathers' employment statuses are both considered (e.g., Kalil and Ziol-Guest 2008; Lindemann and Gangl 2019)—the focus has been on the separate effects of a parent's joblessness rather than their *joint* or combined effects for children's labor market outcomes. Furthermore, the majority of existing studies have emphasized the link between the joblessness of one parent and children's contemporaneous or short-term outcomes, such as school performance, school expulsion, grade repetition, child poverty, or children's hospitalization rates (e.g., Ekhaugen 2009; Ermisch, Francesconi, and Pevalin 2004; Hérault and Kalb 2016; Macmillan 2014; Mörk, Sjögren, and Svaleryd 2014; O'Neill and Sweetman 1998; Oreopoulos, Page, and Stevens 2008; Page, Stevens, and Lindo 2009; Rege, Telle, and Votruba 2011). Very few studies have examined the relationship between *dual*-parent joblessness and children's long-term labor market outcomes (Macmillan et al. 2018; Mooi-Reci, Wooden, and Curry 2020; Schoon 2014), and none have investigated children's wages or how these associations vary by age or timing of exposure and gender of the child. Children's wage outcomes during early adulthood are important because they are both an indicator of children's welfare and ability to cope with parents' joblessness and a potential mechanism for the intergenerational transmission of disadvantage that can affect the entirety of children's careers.

We address these gaps in the literature by using household panel data from the Household, Income, and Labour Dynamics in Australia (HILDA) Survey over the period 2001 to 2018 to estimate the association between dual-parent joblessness (in dual-parent households), or parent's joblessness (in single-parent households), and children's wages in early adulthood (when children were between 19 and 33 years old). Parental joblessness is represented by the proportion of time during which the co-residing parent(s) were simultaneously jobless, which is constructed from detailed, contemporaneously collected employment calendar data. This use of calendar data allows us to assess how the intensity of parental joblessness influences children's subsequent wage outcomes with less measurement error than most previous work in this area. The findings from this study have important implications for our understanding of the potential effects of dual-parent joblessness on children's long-term outcomes.

Theoretical Background, Previous Literature, and Hypotheses

Potential mediating mechanisms

Intergenerational transmission processes are usually explained within two general frameworks. The resource-based framework (Becker and Tomes 1986; Blau and Duncan 1967) assumes that parents attempt to maximize their children's skills and talents through investments made in training and education during childhood and adolescence. It follows that parental employment influences the resources and opportunity structures that are available to the child through increased income and wealth, which in turn affect children's future achievements.

Parental joblessness is most obviously associated with loss of income and fewer monetary resources for the family. In the case of dual-parent joblessness, reductions in family's monetary resources will be substantial because the income loss attached to the joblessness of one parent is not mediated by the income of the other parent. Fewer monetary resources will restrict parents' abilities to purchase goods and resources that are beneficial for children's development, such as food security or housing in safe environments (Kalil and Ziol-Guest 2008; Schoon 2014). Relatedly, parental joblessness will also reduce parents' capacity to invest in early education or expose children to environments that are conducive to growth and learning (Ermisch et al. 2004; Mooi-Reci et al. 2019; Stevens and Schaller 2011), which in turn can stunt children's cognitive and non-cognitive skills formation even before compulsory education begins (Heckman 2006). This human capital deficit is then expected to influence outcomes in later life, including future labor earnings. This suggests that with longer exposure to parental joblessness, disparities in children's cognitive levels and educational outcomes become substantial. Consequently, longer exposure to jobless parents may result in children falling further behind in school, increasing the likelihood that the jobs they do find in the future will be low status and low paid. Thus, both household income and children's educational attainment are key mediating mechanisms linking parental joblessness and children's subsequent wages.

The second framework used to explain the intergenerational transmission of joblessness is socialization, where the absence of work role models may affect children's attitudes and behavior toward education and work. A central tenet of socialization theory is that parents' adversity is transmitted intergenerationally through changes in the behavioral and emotional functioning of parents (Bandura 1977; Wilson 1996). Parents play a central role in shaping children's attitudes about work and are a primary source of information; they can verbally express their worries and frustrations about their job loss or economic adversity directly to their children, or they can communicate this indirectly by becoming disengaged, emotionally stressed, and pessimistic about their employment outlook (Barling, Dupre, and Hepburn 1998). As a result, witnessing their mothers and fathers out of the labor market over an extended time may instill negative habits and attitudes in children about the importance of work.[1] This may be reflected in children's disengagement from education and training or detachment from future employment activities, which in turn can have adverse consequences for earnings. If children from jobless households have less overall labor market experience than their more advantaged counterparts, they may accumulate lower levels of human, social, and cultural capital, all of which may contribute to both a higher likelihood of employment inactivity and relatively low wages once employment is found. Thus, the employment history of the child is another potential key link between dual-parent joblessness and children's subsequent wages.

Other important mechanisms relate to emotional distress. Numerous studies from social psychology have found support for the basic relationship between job loss and emotional

[1] For a review of the literature on the intergenerational transmission of work values, see Cemalcilar, Secinti, and Sumer (2018).

distress, revealing that after long bouts of unemployment or worklessness, people withdraw socially, display more depressive symptoms, decrease their occupational aspirations, and become less attached to work (e.g., Benati 2001; Bjørnstad 2006; Boyce et al. 2015; Daly and Delaney 2013; Dieckhoff 2011; Hyggen 2008; Jahoda, Lazarsfeld, and Zeisel 1971; Wanberg 2012). The level of emotional distress associated with joblessness and job instability more generally has been found to be particularly high among parents (for a review, see Conger, Conger, and Martin 2010), which in turn adversely affects children's educational and behavioral outcomes through the acquisition of pessimistic views about the world of work (e.g., Barling et al. 1998; Leininger and Kalil 2014). Due to data limitations, however, our study is unable to test the mediating role of emotional stress or changing work ethics on children's wage outcomes.

Heterogeneous effects of parental joblessness

The potential mechanisms discussed above may vary depending on the child's characteristics. Research focused on children's cognitive and non-cognitive skill formation and development has typically concluded that economic disadvantage experienced at young ages is more detrimental for children's future outcomes than economic disadvantage experienced later, as early disadvantage can compound throughout a child's development (Francesconi and Heckman 2016). However, little is known about how parental joblessness influences labor market outcomes of children who are exposed to parental joblessness at younger or older ages. The lack of attention on older children is potentially of large importance given that it is during teenage years that children develop clearer understandings of work, which in turn may influence their subsequent labor market behavior and wage outcomes as adults (Barling et al. 1998; Barni et al. 2013; Cemalcilar et al. 2018). If parental joblessness depresses children's labor market outcomes primarily by reducing parental investments in children leading to deficits in the development of cognitive and non-cognitive (or soft) skills, early exposure to parental joblessness may be most harmful. On the other hand, if psychosocial stress, family dynamics, and socialization around work are relatively more important, exposure to parental joblessness during adolescence may prove more impactful.

Intergenerational effects of parental joblessness: Previous evidence

There is a small but growing number of studies on the effects of involuntary job loss or unemployment on children's subsequent earnings, all of which are concerned with paternal joblessness. These studies attempt to use some form of exogenous employment shock to assess the impact of parental earnings losses on children's earnings outcomes. For example, Oreopoulos et al. (2008), Page et al. (2009), and Bratberg, Nilsen, and Vaage (2008) all use plant closures as sources of exogenous job loss. Oreopoulos et al. (2008) and Page et al. (2009) find that children's earnings decrease in response to a father's job displacement in Canada and the United States, respectively. The effects, however, seem to be heterogeneous, concentrated among those already at the bottom of the earnings distribution. Gregg, Macmillan, and Nasim (2012) use changes in father's industrial sector and rates of contraction within each sector during the 1980s recession in Great Britain to identify fathers who likely experienced involuntary job losses during that downturn. They also find sizeable negative point estimates for the effect of father's displacement on children's earnings that are in a similar range to those reported by Oreopoulos et al. (2008) and Page et al. (2009). However, their estimates are imprecise, which they argue is a function of relatively small sample sizes. By contrast, Bratberg et al. (2008) do not find evidence for similar effects in Norway, though they note that Norway's smaller father–son earnings correlations, its free higher education system, and lower returns to education may all be factors that explain the divergence in findings. Finally, Hilger (2016) uses U.S. tax return data, which allows comparisons of those who claim unemployment insurance with those who worked in firms that laid off others but were not themselves displaced. Hilger (2016) finds no evidence for a substantive effect of father's involuntary job loss on children's earnings in early adulthood (through to age 25). Together, these studies provide mixed evidence on whether a father experiencing an involuntary job loss has an adverse effect on the earnings of their children once they reach adulthood.

A key limitation of this research is its focus on the joblessness experience of the father as the treatment variable, a weakness that characterizes most research on intergenerational transmission of labor market outcomes. Extant research that has focused on the intergenerational effects of employment at the household or family levels has mostly investigated children's contemporaneous outcomes, finding, for example, that parental joblessness is associated with increased child poverty (e.g., de Graaf-Zijl and Nolan 2011; Nickell 2004). In recent years, however, a few studies have attempted to examine the relationship between parental joblessness—defined by the absence of any working parent in the household or family—and children's outcomes in early adulthood. Schoon (2014) used longitudinal survey data to examine whether parental joblessness in the UK, observed at three points in time between 2004 and 2006, was associated with the duration of time that their children spent neither in employment nor in education or training between 2007 and 2009 (when aged 16 to 20). Macmillan et al. (2018) used multi-country data from Europe, but from cross-sectional sources, and examined associations between a retrospective, self-reported measure of living in a jobless household at age 14 or 15 and measures of joblessness and poverty as an adult. Curry, Mooi-Reci, and Wooden (2019) and Mooi-Reci et al. (2020) both used longitudinal data from Australia and the United States to examine whether the proportion of time spent living with jobless parents during adolescence was associated with early adult employment. Yet, none of these studies have looked at the mediating role of children's own inactivity on their wages or investigated differences by age at exposure. Our study addresses these gaps.

Parental joblessness and wages in the Australian context

An institutional feature of Australia's labor market is relatively high levels of minimum wages. Its national minimum wage level is one of the highest in the world,[2] but more importantly, sets a floor to an array of minimum wages for different job classifications, prescribed in "awards" (which set out minimum employment conditions and pay rates for different industries and occupations). Persons under 21 years of age, however, may be paid at lower youth rates (generally a set percentage of the normal adult award rate, that increases with age until reaching parity at 21). Each of these wage rates is set and mandated by the Fair Work Commission, the Federal Government's industrial relations tribunal. In 2018, 21% of all employees were paid at a minimum award rate (Australian Bureau of Statistics 2019, Data Cube 9). Furthermore, so-called casual employees, who do not have many of the protections and entitlements offered to regular employees, receive higher wages (though compliance may not be uniform). In theory, these relatively high wage floors should result in a compression of the wage distribution early in careers.

Australia's welfare system as it relates to unemployment is also atypical. Because it is not an insurance system, the monetary benefit offered to unemployed workers—the "Newstart Allowance"[3]—is not dependent on their prior wages or work history. This leads to lower initial net replacement rates—the proportion of forgone earnings the unemployed can claim in benefits—than in most OECD countries (OECD 2017, Figure 4.2). However, young

[2] According to data assembled by the OECD (and available on https://stats.oecd.org), in 2019 the OECD country with the highest real hourly minimum wage (measured in US purchasing power parity terms) was Australia.

[3] Newstart Allowance was renamed the JobSeeker Payment in 2020, after the latest wave of data used in this study was collected.

people that have never been employed are entitled to the same Newstart Allowance as those with long work histories. By contrast, a system characterized by an insurance model, such as in the United States, would favor unemployed workers with longer work histories and higher prior wages. Further, unlike insurance systems, Newstart Allowance payments are not time limited: subject to meeting program requirements (e.g., active job search or training), unemployed people can remain in receipt of the Newstart Allowance indefinitely. As a result, the level of income support provided to the long-term jobless (while still low in absolute terms) will tend to be relatively generous in Australia compared with many other countries.

Hypotheses

We hypothesize that spending a greater proportion of one's childhood and adolescence with jobless parents will be associated with lower wages conditional on employment (H1). Expectations for this hypothesis are based on both parental investment theory and socialization theory.

We also predict that household income during childhood and adolescence, children's educational attainment, and children's own employment inactivity should explain the association between parental joblessness and wages (H2). If parental joblessness affects wages entirely through resources and investment in education, we would expect no direct association between parental joblessness and wages after controlling for parental income and the child's education. If, on the other hand, wage disparities based on parental joblessness remain, this might point to the importance of other mechanisms, namely socialization or psychosocial stress models. Among those who experience parental joblessness, we expect that earlier ages of exposure will carry stronger wage penalties (H3). This follows from resource-based theories suggesting that disadvantages experienced early in childhood may compound over the course of the child's development.

Method

Data and sample

We use data from the first 18 waves of the Household, Income, and Labour Dynamics in Australia (HILDA) Survey (https://melbourneinstitute.unimelb.edu.au/hilda), an annually conducted nationally representative household panel survey, which began in 2001 (Watson and Wooden 2012). The HILDA Survey provides extensive information about labor market outcomes for all respondents aged 15 years or older, which allows us to consider parents' and children's employment and wages over the course of many years. A total of 11,693 households were identified as in-scope at wave 1, with interviews completed with adult members (defined as persons aged 15 years or older on the 30th June preceding the interview date) of 7,682 of these households (providing an initial responding sample of 13,969 persons). Further interviews were then sought every subsequent year with the members of these original households, along with any other persons (aged 15 years or over) who were subsequently living with them.[4]

The analytic sample began with 8,945 children born between 1985 and 1999. Of these, 6,748 would go on to become responding sample members during the period 2008 to 2018. To be included the "child" then had to report earning income from wages or salaries in at least one of the years 2008 to 2018, reducing the sample to 5,706 persons.[5] We further exclude any individuals where the respondent was only ever observed as a full-time student or had not reached 19 years of age, reducing the sample to 4,789 persons. Finally, we also restrict the sample to those who were not missing on any of the covariates used in the model, yielding an analysis sample of 2,281 unique individuals providing 9,942 observations at the

[4] A refreshment sample was added in 2011 but is not used in this analysis.
[5] Of the observations dropped at this stage, 50.9% come from full-time students.

person-year level. The decline in sample size at this last step is almost entirely due to missingness on the parental joblessness variable (accounting for 93% of the sample loss). This, in turn, is mainly the result of the absence of complete labor market histories over the 2001 to 2007 period for some parents. Some cases, however, are omitted because we set a further requirement that children be observed co-residing with their parents for a minimum of two years during the 2001 to 2007 period to be retained.

Members of the sample were between ages 19 and 33 when their wage outcomes were measured, with a mean age of 24.2 years. Table 1 shows the distribution of sample members by the number of wage observations they contributed, as well as the average age. It shows that over three-quarters of the sample members contributed multiple observations, and that the average age for those who contributed very few wage observations was slightly younger than those who contributed more wage observations.

Observations contributed	Individuals	Person-years	Mean age	SD
1	441	441	21.279	2.498
2	340	680	22.110	2.387
3	305	915	22.379	2.130
4	267	1,068	23.273	2.166
5	207	1,035	23.950	2.093
6	182	1,092	23.781	1.814
7	133	931	24.603	1.983
8	129	1,032	25.001	1.838
9	108	972	25.127	1.596
10	83	830	26.116	1.517
11	86	946	26.263	1.280

Table 1. Age Structure of Observations

Notes: Data are from the HILDA Survey, 2001 to 2018. Sample comprises 2,281 unique individuals providing 9,942 observations.

Analytic strategy

We estimate multilevel mixed-effects regressions predicting logged hourly wages. Because our data contains wage measures for several years for the majority of respondents, we include a random intercept and a random slope for time, measured by survey year at the individual level. Furthermore, because individual respondents are clustered within families, we also include a random intercept at the family level. Respondents are grouped by family depending on the modal co-habiting parent(s) from 2001 through 2007, when parental joblessness was observed. That is, respondents are considered to belong to the same family if their modal single parent or coupled parents are the same for 2001–2007. This leaves us with three nested levels: person-year observations (level 1) are nested within individuals (level 2), which are nested within families (level 3). Including random intercepts for individuals and families and the random slope at the individual level accounts for the nested structure of observations within individuals and individuals within families who may be exposed to common time-invariant factors, such as parental personality, that could bias estimates if excluded from our analyses. This method also provides estimates of coefficients for the observable factors that are time-invariant over the period 2008 to 2018, when children's wages are measured, and allows individuals to contribute one or more person-year observations to the sample without considering each observation to be independent, which would bias the estimated coefficients.

This nested structure is summarized by the following equations:

$$\text{Level 1:}\quad y_{tij} = b_{0ij} + b_{1ij}\,(TIME_{tij}) + b_{2ij}\,x_{tij} + \varepsilon_{\text{tij}} \tag{1}$$

$$\text{Level 2:}\quad b_{0ij} = \delta_{00j} + u_{0ij} \tag{2}$$

$$b_{1ij} = \delta_{10j} + u_{1ij} \tag{3}$$

$$\text{Level 3:}\quad \delta_{00j} = \gamma_{000} + v_{00j} \tag{4}$$

In equation (1), y_{tij} represents the log of real hourly wages observed at time t for individual i, nested within family j. The covariate matrix of controls, x_{tij}, and the corresponding vector of coefficients, b_{2ij}, characterize the effects of observable explanatory variables included in the model, with ε_{tij} representing the residual at the person-year level (i.e., level 1). Equations (2) and (3) specify the random intercept, b_{0ij}, and the random slope, b_{1ij}, for each individual as functions of the average family-specific intercept and slope, denoted by δ_{00j} and δ_{10j}, and individual-level error terms for the intercept and slope, u_{0ij} and u_{1ij}. Finally, in equation (4), the family-level random intercept, δ_{00j}, is a function of the overall intercept, γ_{000}, and the error term for each family, given by v_{00j}.

Dependent variable: Children's real hourly wages

The outcome variable is the log of real hourly wages measured over the period 2008-2018, adjusted to 2015 AUD using the consumer price index. Hourly wages are derived by dividing usual gross weekly wages and salary from all jobs by the number of hours worked during a usual week in all jobs (where working hours include both paid and unpaid overtime).

Key independent variable: Parental joblessness

The primary explanatory variable is the proportion of time co-residing with jobless parents from 2001 to 2007, with the caveat that children be age 18 or younger at the time. In the HILDA Survey, respondents report their labor force status not only at time of interview, but also for three periods of roughly ten days per month over the preceding financial year (July to June) and all subsequent months until date of interview (a period of anywhere from 13 to 20 months long). We considered the 1st, 11th, and 21st of each month as the start points of a new period and counted the number of days in a given spell of employment or non-employment. To calculate these spells, we use labor force status calendar data provided by the co-residing parents of respondents. Both parents are required to be jobless in the same period for a household to be considered jobless; we do not distinguish between unemployment and being out of the labor force. The strict requirement that, in two parent households, the mother and father both be jobless simultaneously means that our reference category includes households with parents who have been continuously employed in the same periods and households in which only one parent works. Parents' employment statuses are only calculated during waves in which they co-reside with respondents. Thus, non-resident parents' employment status does not factor into our proportion variable. And, as noted earlier, we only consider respondents for whom at least two years (72 periods) of parental joblessness data exist.

Mediators: After-tax household income, children's educational attainment, and inactivity

We expect three main variables to mediate the association between parental joblessness and children's wage outcomes. The first potential mediating variable is household income during childhood and adolescence, represented here by the log of average annual real after-tax household income over the period 2001 to 2007 (but only for the years in which the child was living with at least one parent). While household income during childhood and adolescence is often used as a control variable to account for socioeconomic origins, we treat it as a potential mediator in our series of nested regression models given household income is affected by parental employment status and offers a proxy for the financial resources available to children. The second potential mediator is education, captured by a time-varying measure of the respondent's highest level of educational attainment. Educational attainment is divided into four groups: Completed less than high school; High school; Diploma / Certificate Level III or IV; and Bachelor's degree or higher qualification. The third category of education, "Diploma / Certificate level III or IV," contains vocational certificates provided by non-baccalaureate tertiary institutions. Finally, we measure inactivity using a time-varying measure of the proportion of time since age 15 that children were simultaneously not enrolled in full-time education and not employed. Short periods of inactivity which result from school breaks (periods of inactivity of four months or less, surrounded on each side by full-time educational enrollment) were recoded as if respondents were continuously enrolled in education.

Variables	Mean	SD
Log hourly wages (2015 AUD)	3.189	0.408
Parental joblessness proportion	0.090	0.233
Female	0.479	0.500
Age	24.156	3.443
Year of birth	1989.697	3.315
Born in Australia	0.952	0.213
Number of siblings	1.961	1.141
State of residence during childhood		
New South Wales	0.314	0.464
Victoria	0.253	0.435
Queensland	0.194	0.396
South Australia	0.092	0.290
Western Australia	0.082	0.274
Tasmania	0.031	0.173
Northern Territory	0.008	0.087
Australian Capital Territory	0.026	0.160
Single-parent household	0.186	0.351
Parent's highest educational qualification		
Less than high school	0.134	0.341
High school	0.074	0.262
Diploma / Certificate level III or IV	0.441	0.497
Bachelor's degree or higher	0.351	0.477
Log after-tax annual household income (2015 AUD)	11.422	0.503
Child's highest educational qualification		
Less than high school	0.143	0.350
High school	0.352	0.478
Diploma / Certificate level III or IV	0.272	0.445
Bachelor's degree or higher	0.233	0.422
Ever inactive	0.105	0.136
Inactivity proportion	0.775	0.417

Table 2. Descriptive Statistics: Means and Standard Deviations (SD)

Notes: Data are from the HILDA Survey, 2001 to 2018. Sample comprises 2,281 unique individuals providing 9,942 observations.

Control variables

Demographic control variables include gender, number of siblings, age and its square, the first observed state of residence during childhood, nativity, and dummy variables for birth cohort. Socioeconomic controls include the percentage of time over 2001 to 2007 that children spent living in single-parent households (conditional on living with a parent) and the highest level of education completed by a co-residing parent of the respondent. Descriptive statistics for all variables are provided in Table 2.

Results

Associations between parental joblessness and children's wages

Results from the multilevel mixed-effects regression are displayed in Table 3. We report results from four models. In Model 1, we include terms for the proportion of time spent with jobless parents and the set of demographic controls. Consistent with our first hypothesis, parental joblessness is negatively associated with logged wages, conditional on employment. This suggests that differences in demographic background do not fully account for the negative relationship between parental joblessness and wages. The magnitude of this coefficient ($b = -0.128$, $p < .001$) suggests that a ten percent increase in parental joblessness proportion is associated with a decrease of 1.3 percent in respondents' wages after controlling for demographic background and the random intercept for families and the random intercept and slope for individuals across survey waves. In Model 1, wages increase with age in a curvilinear fashion. There are also some significant differences by State of residence, with those in New South Wales (the reference State) earning higher wages than those in Victoria, but lower wages than those in Western Australia. The higher wages observed in Western Australia may be a product of the mining boom that this State experienced for much of the period over which wage outcomes were measured.

The mediating role of household income

One of the primary proposed mediating mechanisms that links parental joblessness during childhood and adolescence to children's wages during adulthood is household income, which we capture through the log of real (after-tax) household income over the period in which children are observed living with jobless parents. As expected, Model 2 in Table 3 shows a positive and significant association between household income and children's wages (b = 0.038, p = .016), all else equal. Thus, children raised in high-income households have higher wage prospects than those from families that were financially less well off. Model 2 also shows that household incomes explain some of the negative association between parental joblessness and wages, reducing the magnitude of the association by about 16%. However, parental joblessness intensity is still negatively associated with wages even after controlling for the demographic and socioeconomic factors included in Model 2. Parental joblessness therefore seems to affect wages either directly or through some means other than parents' incomes. The other notable result in Model 2 is that after controlling for household income, having lived with a single parent is now associated with slightly higher wages. While those who grew up living with single parents experienced more parental joblessness than those from dual-parent households, this result suggests that family structure does not confound the relationship between parental joblessness and children's subsequent wages.

	Base results (Model 1)		+ Household income (Model 2)		+ Child's education (Model 3)		+ Inactivity (Model 4)	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Parental joblessness	-0.128***	(0.032)	-0.107**	(0.033)	-0.106**	(0.032)	-0.077*	(0.032)
Age	0.149***	(0.013)	0.149***	(0.013)	0.133***	(0.013)	0.132***	(0.013)
Age^2	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
Female	-0.026*	(0.013)	-0.025*	(0.013)	-0.040**	(0.013)	-0.039**	(0.013)
Australian born	-0.016	(0.032)	-0.019	(0.032)	-0.013	(0.031)	-0.020	(0.031)
Siblings	0.006	(0.006)	0.005	(0.006)	0.007	(0.006)	0.007	(0.006)
State of residence [a]								
Victoria	-0.044*	(0.018)	-0.042*	(0.018)	-0.045*	(0.018)	-0.042*	(0.017)
Queensland	0.019	(0.019)	0.023	(0.019)	0.022	(0.019)	0.023	(0.019)
South Australia	-0.012	(0.025)	-0.006	(0.025)	-0.008	(0.024)	-0.003	(0.024)
Western Australia	0.066**	(0.026)	0.070**	(0.026)	0.071**	(0.025)	0.069**	(0.025)
Tasmania	-0.061	(0.038)	-0.058	(0.038)	-0.051	(0.038)	-0.037	(0.037)
Northern Territories	0.092	(0.080)	0.090	(0.080)	0.102	(0.078)	0.106	(0.077)
Australian Capital Territory	0.016	(0.045)	0.010	(0.045)	0.001	(0.044)	-0.002	(0.043)
Parent's education [b]								
High school	0.003	(0.031)	-0.001	(0.031)	-0.011	(0.030)	-0.019	(0.030)
Diploma / Cert III or IV	0.010	(0.021)	0.008	(0.021)	0.003	(0.021)	-0.001	(0.020)
Bachelor's degree or higher	0.029	(0.022)	0.019	(0.022)	-0.000	(0.022)	-0.005	(0.022)
Single parent	0.039	(0.021)	0.052*	(0.022)	0.060**	(0.022)	0.058**	(0.021)
Log household income			0.038*	(0.016)	0.032*	(0.016)	0.027	(0.016)
Respondent's education [b]								
High school					-0.007	(0.018)	-0.024	(0.018)
Diploma / Cert III or IV					0.038*	(0.018)	0.023	(0.018)
Bachelor's degree or higher					0.118***	(0.021)	0.097***	(0.021)

Inactivity							-0.240***	(0.040)
Constant	1.017***	(0.165)	0.580*	(0.246)	0.853***	(0.245)	0.970***	(0.244)
Random-effects parameters								
Family intercept	0.007***	(0.003)	0.007***	(0.003)	0.006***	(0.002)	0.006***	(0.002)
Individual intercept	0.023***	(0.005)	0.023***	(0.005)	0.023***	(0.005)	0.024***	(0.004)
Wave	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Residual variance	0.083***	(0.001)	0.083***	(0.001)	0.083***	(0.001)	0.083***	(0.001)
Fit statistics								
AIC	6711.6		6707.9		6649.1		6615.2	
BIC	6971.0		6974.4		6937.3		6910.6	

Table 3. Mixed-Effects Regression Results

Notes: Data are from the HILDA Survey, 2001 to 2018. Sample comprises 2,281 unique individuals providing 9,942 observations. Year of birth dummies are not displayed.
[a] New South Wales is reference category for state of residence.
[b] Less than high school is the reference category for parent's and respondent's education.
* $p < .05$, ** $p < .01$, *** $p < .001$.

The mediating role of children's educational attainment

Children's educational attainment is closely tied to both their socioeconomic origins as well as their future socioeconomic attainment (Blau and Duncan 1967). We therefore expect the child's educational attainment to partially mediate the relationship between parental joblessness and the respondent's wages in adulthood. We also expect the observed positive correlation between household income during childhood and adolescence and children's subsequent wages in early adulthood to work in part through children's educational attainment. In Model 3, we include a categorical measure of the respondent's highest level of educational attainment in our wage prediction equation. As expected, the level of respondent's (i.e., child's) educational attainment has both a large and significant positive association with wages. There is no significant effect of completing a high school education in our sample, but significant returns to completing a vocational qualification or a university degree, with the latter offering a substantially larger return. Despite these relatively large associations, the inclusion of child's educational attainment has very little impact on the coefficient for parental joblessness.

Interestingly, after controlling for education, the wage disadvantage experienced by women strengthens, suggesting that their higher levels of educational attainment are not rewarded by similar increases in hourly wages. We also note a small increase in the size of the positive coefficient for single parenthood, suggesting that those who go on to obtain high levels of educational qualifications despite having single parents may be positively selected. Finally, household income while respondents co-resided with parents from 2001–2007 still appears positively associated with 2008–2018 wages, but its magnitude decreased by roughly 16%.

The mediating role of prior inactivity

As discussed earlier, we test the mediating effect of prior inactivity by including a measure of the proportion of time (since age 15) in which the respondent was neither enrolled in full-time education nor employed. This proportion is allowed to fluctuate across person-year observations within individuals. Model 4 in Table 3 shows a large wage penalty associated with prior inactivity. The inclusion of the inactivity variable also reduces the magnitude of the parental joblessness wage penalty by over 27%. However, the coefficient for parental joblessness remains significantly below zero, suggesting that a residual wage penalty exists even after controlling for socioeconomic and demographic background, as well as potential mediators like parental income, educational attainment, and prior labor market attachment. This finding suggests, contrary to our second hypothesis, that even if it were possible to reduce any educational or employment activity deficits experienced by children with chronically jobless parents, a small wage differential would likely persist.

In auxiliary analyses, available upon request, we tested whether any changes to the order of inclusion of mediating variables substantially changed the coefficient for parental joblessness by running mixed-effects regressions where all five additional possible sequences of household income, child's education, and inactivity were added to the base model. In each of these permutations, the patterns described above remain, with the association between parental joblessness and children's wages being most sensitive to the inclusion of inactivity.

Investigating heterogeneity by age of exposure

In our main analyses, we report relatively robust wage penalties associated with parental joblessness, though they are modest in magnitude. Table 4 tests hypothesis 3, which states that the relationship between parental joblessness and children's wages may vary with age of exposure. Here we construct a continuous variable for the earliest observed age at which children were exposed to parental joblessness. We replicate the above models, but with our new age at exposure measure instead of the parental joblessness proportion, though in Table 4 we only report results for Model 1. These analyses are restricted to those who experienced at least one period of parental joblessness. While the sample size is reduced due to this restriction (659 individuals contributing 2,581 total observations), there is no observable pattern by earliest age of exposure in any of the models. However, given the smaller sample size and the incomplete coverage (since children are not able to be observed for their entire childhood), this finding should be interpreted cautiously.

	Coeff.	SE
Youngest age of exposure	0.004	(0.007)
Age	0.158***	(0.027)
Age^2	-0.003***	(0.001)
Female	-0.034	(0.026)
Australian born	0.016	(0.056)
Siblings	-0.000	(0.012)
Parent's education [a]		
High school	0.036	(0.053)
Diploma / Cert III or IV	0.035	(0.036)
Bachelor's degree or higher	0.047	(0.041)
Single parent	0.020	(0.033)
Constant	-0.103*	(0.042)
Random-effects variances		
Household intercept	0.003	(0.005)
Individual intercept	0.048***	(0.011)
Wave	0.000***	(0.000)
Residual variance	0.089***	(0.003)

Table 4. Mixed-Effects Regression Results: Youngest Age of Exposure to Parental Joblessness

Notes: Data are from the HILDA Survey, 2001 to 2018. Sample comprises 659 unique individuals providing 2,581 observations. Year of birth and state dummies are not displayed.
[a] Less than high school is the reference category for education.
* $p < .05$, ** $p < .01$, *** $p < .001$

	Background controls		+ Household income & child's education		+ Inactivity	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Parental joblessness	-0.121**	(0.041)	-0.099*	(0.043)	-0.080	(0.043)
Age	0.244***	(0.036)	0.233***	(0.036)	0.231***	(0.036)
Age^2	-0.004***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)
Female	-0.027	(0.016)	-0.036*	(0.016)	-0.036*	(0.016)
Australian born	-0.052	(0.046)	-0.044	(0.045)	-0.052	(0.045)
Siblings	0.000	(0.008)	-0.001	(0.008)	-0.002	(0.007)
Parent's education [a]						
High school	-0.020	(0.041)	-0.033	(0.040)	-0.039	(0.040)
Diploma / Cert III or IV	0.001	(0.028)	-0.006	(0.027)	-0.012	(0.027)
Bachelor's degree or higher	0.003	(0.029)	-0.023	(0.030)	-0.028	(0.030)
Single parent	0.049	(0.029)	0.068*	(0.029)	0.067*	(0.029)
Log household income			0.038	(0.025)	0.030	(0.025)
Respondent's education [a]						
High school			-0.017	(0.024)	-0.032	(0.024)
Diploma / Cert III or IV			0.021	(0.025)	0.008	(0.025)
Bachelor's degree or higher			0.089**	(0.029)	0.073*	(0.029)
Inactivity					-0.165***	(0.050)
Constant	-0.001	(0.413)	-0.280	(0.505)	-0.133	(0.505)
Random-effects variances						
Household intercept	0.009†	(0.004)	0.008†	(0.005)	0.009†	(0.004)
Individual intercept	0.029***	(0.009)	0.029***	(0.009)	0.030***	(0.008)
Wave	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Residual variance	0.091***	(0.002)	0.091***	(0.002)	0.092***	(0.002)
Fit statistics						
AIC	3665.0		3646.1		3637.3	
BIC	3865.5		3872.4		3870.0	

Table 5. Additional Analyses: Restricting to 1990–1999 Birth Cohort

Notes: Data are from the HILDA Survey, 2001 to 2018. Sample comprises 1,458 unique individuals providing 4,750 observations. Year of birth and state dummies are not displayed.
[a] Less than high school is the reference category for education.
* $p < .05$, ** $p < .01$, *** $p < .001$

Additional analyses

In further analyses, we add a range of constraints to our sample and model to check the robustness of our main finding. One potential concern is that the respondent's labor market histories, which influence their observed wages, may start prior to some observed spells of parental joblessness. We address this concern in two ways. First, in Table 5 we exclude the oldest members of the sample, re-estimating models only for those born between 1990 and 1999. This sub-sample of 4,750 person-year observations (1,458 individuals; 970 family groups) comprises persons aged 2–17 in the period 2001–2007, when parental joblessness was measured. Using this younger sample, we continue to find negative associations between parental joblessness and wages of similar magnitudes. One notable difference is that, while the final columns of both Table 3 and Table 5 report nearly identical point estimates on the coefficient for parental joblessness, the estimate with the younger subsample is less precise, resulting in a lack of statistical significance. In a separate analysis, we used the full sample to interact parental joblessness with a cubic function of age at the time that wages were measured for each observation, again finding no support for a significant interaction effect. And in yet another separate analysis, we interacted parental joblessness with age dummies. The resulting marginal effects showed no significant rise or fall across the age distribution of the sample. We can thus find no evidence to suggest that the association between parental joblessness and children's wages varies significantly with age within the early career (i.e., from age 19 to 33).

Our second type of robustness check is to restrict the observation of parental joblessness in 2001–2007 only to periods before the respondent (child) reported earnings for the first time (N = 8,541 observations; 2,082 individuals; 1,210 families). Therefore, parental employment statuses for periods after the child first enters the labor market are not factored into the analysis, even if children continue to cohabitate with their parent(s). Results are reported in Table 6, and again we find a significant negative association between parental joblessness and wages after controlling for education, demographic and socioeconomic background, and random intercepts at the individual and family levels (column 1: $b = -0.116$, $p < .001$). The slightly smaller magnitude, however, may suggest that a small part of the observed association between parental joblessness intensity and 2008-2018 wages is due to a negative correlation between children's unmeasured characteristics and their parents' subsequent joblessness. And as with our main models, adding mediating variables like household income, education, and especially prior inactivity, all reduce, but do not eliminate, the wage penalty associated with parental joblessness intensity.

	Background controls		+ Household income & child's education		+ Inactivity	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Parental joblessness	-0.116***	(0.032)	-0.093**	(0.033)	-0.069*	(0.033)
Age	0.139***	(0.015)	0.122***	(0.015)	0.122***	(0.015)
Age^2	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
Female	-0.028*	(0.013)	-0.041**	(0.013)	-0.041**	(0.013)
Australian born	-0.017	(0.034)	-0.012	(0.033)	-0.018	(0.033)
Siblings	0.006	(0.006)	0.006	(0.006)	0.006	(0.006)
Parent's education [a]						
High school	0.001	(0.033)	-0.013	(0.032)	-0.022	(0.032)
Diploma / Cert III or IV	0.013	(0.022)	0.005	(0.022)	0.000	(0.022)
Bachelor's degree or higher	0.030	(0.023)	0.000	(0.024)	-0.006	(0.023)
Single parent	0.035	(0.023)	0.053*	(0.023)	0.053*	(0.023)
Log household income			0.031	(0.017)	0.026	(0.017)
Respondent's education [a]						
High school			0.002	(0.019)	-0.016	(0.019)
Diploma / Cert III or IV			0.051**	(0.019)	0.036	(0.019)
Bachelor's degree or higher			0.120***	(0.022)	0.098***	(0.023)
Inactivity					-0.228***	(0.041)
Constant	1.051***	(0.191)	0.893**	(0.274)	1.018***	(0.273)
Random-effects variances						
Household intercept	0.006*	(0.003)	0.004	(0.003)	0.003	(0.003)
Individual intercept	0.026***	(0.005)	0.027***	(0.005)	0.029***	(0.005)
Wave	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Residual variance	0.084***	(0.001)	0.084***	(0.002)	0.084***	(0.001)
Fit statistics						
AIC	5928.5		5878.5		5849.9	
BIC	6182.4		6160.6		6139.0	

Table 6. Additional Analyses: Parental Joblessness Measured Prior to Respondent's First Employment

Notes: Data are from the HILDA Survey, 2001 to 2018. Sample comprises 2,082 unique individuals providing 8,541 observations. Year of birth and state dummies are not displayed.
[a] Less than high school is the reference category for education.
* $p < .05$, ** $p < .01$, *** $p < .001$

In addition to issues of timing, family composition is also a potential confounder. Single-parent households are at greater risk of experiencing parental joblessness than dual-parent households since any loss of parental employment in a single-parent family results, by definition, in parental joblessness. It is thus possible that our results are driven mainly by those who grew up in single-parent families. To test for this, we simply repeated our analyses after including an interaction between our parental joblessness measure and the dummy variable identifying whether the respondent was living in a single-parent household when young. The results are reported in Table 7 and reveal coefficients on the interaction term that are not significantly different from zero at the conventional 95% confidence level. Furthermore, even if we ignore this lack of significance, the coefficients on these interaction terms have the “opposite” sign. In summary, the worry that the observed effect of parental joblessness is actually due to single parenthood causing both low wages for children and higher instances of parental joblessness is not supported by the data. Indeed, Table 7 suggests that dual-parent joblessness is more harmful than living with a single parent who is jobless.

Finally, we also investigate whether differences can be detected in the relationship between parental joblessness and men’s and women’s wages. We test this by interacting parental joblessness with gender while accounting for family-level random effects in the full sample (not shown but available upon request). The interaction term is essentially zero, well short of statistical significance ($b = 0.004$, $p = .933$), suggesting that the observed association between parental joblessness and wages does not differ significantly by gender after controlling for the observable covariates.

	Background Controls		+ Household income and child's education		+ Inactivity	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Parental joblessness	-0.191***	(0.049)	-0.153**	(0.050)	-0.123*	(0.049)
Single parent	0.022	(0.024)	0.046	(0.024)	0.045	(0.024)
Parental jobless*Single parent	0.111	(0.066)	0.081	(0.065)	0.079	(0.064)
Age	0.149***	(0.013)	0.132***	(0.013)	0.132***	(0.013)
Age^2	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
Female	-0.026*	(0.013)	-0.040**	(0.013)	-0.039**	(0.013)
Australian born	-0.016	(0.032)	-0.013	(0.031)	-0.020	(0.031)
Siblings	0.006	(0.006)	0.007	(0.006)	0.007	(0.006)
Parent's education [a]						
High school	0.008	(0.031)	-0.007	(0.030)	-0.016	(0.030)
Diploma / Cert III or IV	0.012	(0.021)	0.005	(0.021)	0.001	(0.020)
Bachelor's degree or higher	0.031	(0.022)	0.002	(0.022)	-0.003	(0.022)
Log household income			0.030	(0.016)	0.025	(0.016)
Respondent's education [a]						
High school			-0.006	(0.018)	-0.024	(0.018)
Diploma / Cert III or IV			0.038*	(0.018)	0.023	(0.018)
Bachelor's degree or higher			0.117***	(0.021)	0.096***	(0.021)
Inactivity					-0.240***	(0.040)
Constant	1.020***	(0.165)	0.874***	(0.246)	0.990***	(0.244)
Random-effects variances						
Household intercept	0.007**	(0.003)	0.006*	(0.003)	0.005*	(0.002)
Individual intercept	0.023***	(0.004)	0.023***	(0.004)	0.024***	(0.004)
Wave	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Residual variance	0.083***	(0.001)	0.083***	(0.001)	0.083***	(0.001)
Fit statistics						
AIC	6710.8		6649.6		6615.7	
BIC	6977.4		6945.0		6918.3	

Table 7. **Additional Analyses: Interacting family structure and parental joblessness**
Notes: Data are from the HILDA Survey, 2001 to 2018. Sample comprises 2,281 unique individuals providing 9,942 observations. Year of birth and state dummies are not displayed.
[a] Less than high school is the reference category for education.
* $p < .05$, ** $p < .01$, *** $p < .001$

Discussion

This study uses 18 annual waves of longitudinal data from Australia to test whether the proportion of time that respondents experienced parental joblessness during childhood and adolescence affected their wages during early adulthood. Using theoretical arguments from resource deprivation and socialization, we expected that parents' joblessness would be both related indirectly to children's subsequent wages (through its influence on parental resources, child's education and child's own inactivity) and directly (through children's internalization of their parents' work attitudes and behavior). We deployed a series of multilevel mixed-effects models to test our central hypotheses.

Our first set of results indicate that the intensity of parental joblessness is negatively associated with children's subsequent wages, conditional on employment. These results are consistent with previous research documenting widespread effects of parents' unemployment on children's school performance, school-to-work transitions and employment outcomes (e.g., Ekhaugen 2009; Ermisch et. al. 2004; Hérault and Kalb 2016; Macmillan 2014; Rege et al. 2011). Furthermore, the wage penalties associated with parental joblessness remain significant even after controlling for household income during childhood and adolescence, children's educational attainment and their employment inactivity, though all of those factors were independently correlated with wages themselves. Consistent with models of parental investment (Becker and Tomes 1986), this finding provides evidence that resources available to children are a key mechanism that links parental joblessness to children's subsequent wages. Parents who have long spells of joblessness and as a consequence, low incomes, may be unable to invest in their children's education or provide other resources that stimulate development and eventually enable children to obtain high-paying jobs in the future (Johnson, Kalil, and Dunifon 2012; Oreopoulos et al. 2008; Stevens and Schaller 2011).

In addition, we find that children's own inactivity during adolescence and early adulthood may help explain lower wage outcomes for those raised in jobless households. This finding suggests that children from jobless households may accumulate lower levels of human, social, and cultural capital, all of which may contribute to lower wages for those who are employed. It is also consistent with predictions from theories of cumulative advantage that expect disadvantages experienced earlier in life to compound over time. Against our predictions, associations between parental joblessness and children's wages did not vary with age of exposure to parental joblessness. While this portion of the analysis would clearly benefit from a larger sample, the null finding with regard to age of exposure suggests that parental joblessness may lead to reduced wages no matter when children experience it. Finally, we find a significant, though modest, residual association between parental joblessness and children's wages after controlling for household income, children's education and their own inactivity. This pattern of results is consistent with socialization theory and the propositions that children socialized in environments where jobless parents become discouraged and reduce attachment to work may themselves lower their occupational aspirations, leading ultimately to weaker attachment to the labor market and lower wages. An alternative explanation is that family distress or parental conflict associated with parental joblessness, which were not observed, may work to inhibit children's life chances.

Our analysis is not, however, without limitations. First, estimates may be influenced by life-cycle bias, which results because father–son earnings correlations depend on when sons' earnings are measured, with these correlations tending to increase throughout sons' early careers (Haider and Solon 2006). Given the timing of the HILDA Survey and the age requirements for our analyses, we are only able to observe wages between ages 19 and 33. Since parent–child resemblance in labor market outcomes is typically weakest at the time children commence their employment careers, our results may understate the extent to which parental joblessness is associated with lifetime earnings. In analyses reported in Table 5 that restrict the sample to later age cohorts, however, we do not find substantially different (i.e., smaller) estimates of the coefficient for parental joblessness. Similarly, interacting age with parental joblessness did not yield parental joblessness–wage correlations that varied markedly with age in our sample. That said, these results should be interpreted with caution.

Most obviously, this auxiliary analysis would benefit from larger cell sizes. Furthermore, if life-cycle patterns work to increase the magnitude of the coefficient for parental joblessness among older respondents, other factors, like the age at which respondents were exposed to parental joblessness, may be working in the opposite direction, increasing the magnitude among younger respondents. Similarly, if attrition over time is strongest for those who both experienced parental joblessness and have relatively low wages, the remaining older respondents may be positively selected on wages, thereby reducing the parental joblessness coefficient in a manner that might offset life-cycle wage variation. Thus, life-cycle variation may be present but obscured by other age- or cohort-related factors. To help identify and deal with any effects from life-cycle bias, we need to wait for more waves of data, which would allow longer measurement periods for both parental joblessness during childhood and wages in adulthood.

Second, our analyses were restricted to respondents who reported wages during the observation period, giving rise to the possibility of selection bias. A priori, the direction of such bias is uncertain. One the one hand, if persons are excluded because of the inability to obtain employment then, given a negative correlation between parental joblessness and children's subsequent employment chances, our results can be expected to underestimate the true association between parental joblessness and wages. On the other hand, if the non-observation of earnings is a function of educational attendance, we would expect the bias to work in the other direction. Furthermore, as with all studies relying on longitudinal survey data, non-random attrition across waves is a concern. Though the effect sizes tend to be quite small, there is some evidence that attrition in the HILDA Survey is greater for those at the bottom of the income distribution relative to those in the middle (Watson and Wooden 2009). While inclusion in our sample is conditional on reporting wages, which omits many of those with very low incomes, attrition over time is still a general risk that analyses based on panel data face, particularly those that rely on long time periods and many waves of data collection.

A third issue is the difficulty in determining the causal impact of parental joblessness. Obviously, parental joblessness is not distributed randomly among children. Furthermore, natural experiments that use plant closings or other exogenous sources of parental joblessness may suffer from limited sample sizes because such studies would be required to account for both parents' employment and to follow children for enough time to observe their adult labor market outcomes. These constraints mean we are unable to rule out spurious associations arising from unobserved factors that may correlate with both parental joblessness and children's wages, such as genetic endowments. Furthermore, while we observe parental income over up to a seven-year period while parental joblessness is measured, we are unable to control for all the resources available to children, which might include household income outside of that window, wealth, and other resources available to the child from extended family or other non-parental sources. Thus, the extent to which parental joblessness is associated with children's subsequent wages via the resources channel may be understated. An alternative strategy would be to use family-level fixed effects, where differences between siblings in the amount of time spent with jobless parents are leveraged to provide variation in parental joblessness exposure while holding constant characteristics of parents that siblings share. However, because most siblings experience similar if not identical levels of parental joblessness throughout their childhoods, identifying a suitable sample will be difficult. Furthermore, even this fixed-effects methodology may suffer from similar limitations because changes in exposure to certain unobserved parental behaviors may affect parents' joblessness as well as children's subsequent wages.

Our findings have important implications for further research around potential public policy interventions in this area. First, our study suggests that even the children from jobless households who find employment experience persistent wage disadvantages that last throughout the early career, if not longer. This suggests that policies that successfully reduce children's exposure to household joblessness may provide an outsized return by reducing long-term, intergenerational disadvantages that affect both parents and children. Second, the finding that parental joblessness reduces wages in part by increasing children's inactivity during adolescence and early adulthood, while unsurprising, suggests that reducing this group's barriers to employment may be a particularly efficient intervention. In this context, developing early job placement initiatives, to the extent that they are successful, could lead to faster transitions to employment and therefore ameliorate some of the negative effects of parental joblessness. These, however, remain empirical questions that require further systematic investigation. Future work that assesses cross-national differences in the structural resources available to jobless families may further illuminate potential policy mechanisms to reduce the negative consequences of growing up with jobless parents.

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