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The Intergenerational Transmission of Worklessness in the UK

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The Intergenerational Transmission of Worklessness in the UK

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Abstract
This research analyses the magnitude of the intergenerational correlation in worklessness in the UK using the two British birth cohorts. By using the British Cohort Study of those born in 1970, the magnitude of the intergenerational correlation of worklessness can be assessed for a new cohort for the first time in the UK and the trend in intergenerational worklessness can be considered across time. Two empirical identification strategies commonly used in the literature are applied to UK data and a third empirical strategy, utilising the recession of 1981 is introduced to attempt to identify causality. The intergenerational correlation in worklessness in the UK is large and has increased across time, although the differences in the coefficients are not statistically significant. When a more restrictive measure of sons' worklessness is introduced, this difference becomes statistically significant. This suggests supportive evidence of the intergenerational mobility literature for the UK. There are no statistically significant findings on causality in intergenerational worklessness, driven by either measurement issues or a lack of causality.

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1. Introduction

The level of intergenerational income mobility in a country can be thought of as the extent to which an individual coming from the poorest compared to the richest backgrounds have equal opportunities to succeed in life, given their ability. Previous estimates of intergenerational income mobility in the UK are often based on earnings in the sons' generation measured at certain points in time as access to administrative data is limited. This puts constraints on the sample we are able to measure mobility for as to have earnings you have to be in employment. Therefore the majority of intergenerational income mobility measures capture the intergenerational correlation of the employed. This research aims to analyse the other side to this story by considering the intergenerational correlation of worklessness. In particular, it questions the scale of this correlation and to what extent the transmission of worklessness from one generation to the next is transmitted through observable confounding factors across families, unobservable heterogeneity or causal processes.

The transmission of worklessness from one generation to the next can possibly work through a number of different channels, some causal and some non-causal. Corak (2004) cites research by Roemer (2004), stating that parents influence their children through three main channels; (1) Through connections to education and jobs; (2) Through parenting that encourages skills, motivation and belief; and (3) Through a transmission of innate ability. Becker and Tomes (1986) set out a theoretical framework for the intergenerational transmission of income based on an intergenerational transmission of endowments. They argue that some children have a distinct advantage over other children by coming from families where not only is there a genetic transmission of greater ability but also other favourable cultural attributes such as better attitudes to education and work. Characteristics and attributes of parents are therefore passed onto their children both genetically and environmentally through the behaviour, attitudes and preferences of the parents. If the parent is of low ability they will likely have an occupation that is less well paid and less secure than their higher ability counterparts. If the child is also low ability they will also find themselves in less secure jobs and a correlation between workless spells will arise across the generations. In this case however, the intergenerational correlation would not be causal. Schemes to change the employment status of the parent would have no direct impact on the likely employment status of the child as it is not the work, or lack of it, itself that is creating this correlation across generations. It is the underlying confounding characteristics and attributes of the family, be it observable or unobservable.

This chapter first aims to add to the current research in this area by analysing the magnitude of the correlation in worklessness across the two British birth cohorts. There have been questions raised over the validity of the income measures used to measure income mobility in this data and this will provide further analysis on the differences in mobility across time using measures less prone to reporting error. To then ascertain whether any of this correlation may be causal, two methods commonly used in this literature and the welfare dependency literature will be assessed using new data from the United Kingdom. In addition, a new method is introduced to the literature, utilising the recession of the early 1980's as an external shock to the work status of the parents of the British Cohort Study cohort members, born in 1970. I argue in the next section that worklessness could be causally transmitted from one generation to the next through four main channels; through changing tastes and attitudes of parents, the implicit poverty associated with being out of work, through the associated stress and depression from spells out of work and through 'social capital' or informal social networks. However, identifying which of these channels, if any, causality is flowing through is beyond the scope of this chapter,

This is a timely addition to the literature on worklessness given the current economic downturn with the unemployment level at 2.22 million by March 2009 (ONS), the largest level and rate rise since 1981. If the recession hits the most vulnerable hardest in terms of their likelihood of experiencing spells out of work and there is a causal impact of worklessness across generations, the penalty of the rising unemployment we are witnessing today could be paid not only by the current generation in terms of scarring within this generation but also by the next generation. Previous literature by Gregg (2001) on the effects of unemployment on future unemployment within the same generation finds a causal impact of youth unemployment spells on the likelihood of unemployment later in adulthood. Johnson and Reed (1996) motivate the need for this research by arguing that the 'exclusion from society' of individuals who are from the poorest groups in society makes them of interest for a variety of economic, social and political reasons. An intergenerational transmission of worklessness may be of far more concern to policy makers than any movement or lack of movement around the middle or top parts of the mobility distribution. If the worklessness of today’s parents also has a causal impact on workless spells in the child’s generation the causal scars measured previously could be the tip of the iceberg.

Worklessness is considered here instead of unemployment as the definition of unemployment is very narrow, often defined as those who are actively seeking work. This therefore only captures a transitory state of being out of work but trying to get back into work. This is difficult to measure if we only observe individuals at a point in time and only captures part of the story for those who are out of work. Worklessness on the other hand captures a wider group of individuals; both those who are out of work and are not seeking to be in work as well as those in transitory unemployment. This work adds to a base of research which has been scarce over the past decade, particularly in the UK. O’Neill and Sweetman (1998) appear to be the last authors to consider the magnitude of the intergenerational transmission of worklessness in the UK with more recent work by Corak et. al. (2000), Beaulieu et. al. (2005) and Ekhaugen (2009) addressing this and similar issues of intergenerational welfare dependency for Finland, Canada and Norway.

The next section will discuss in more detail the previous literature on this topic and the associated topic of intergenerational welfare dependency. Section 3 will then give a description of the empirical strategies used to answer the main questions asked and a summary of the data that will be used to implement these strategies will be provided in section 4. Section 5 will discuss the results of the empirical analysis and some robustness checks and section 6 will conclude.

2. Background literature

Motivation

As mentioned, the current literature in the UK in terms of intra-generational worklessness provides cause for concern given the rising levels of worklessness that we face today. Gregg (2001) finds evidence of structural dependence for those experiencing unemployment spells in early adulthood. Using local area unemployment rates to instrument for endogeneity, he finds causal impacts of early unemployment on later unemployment. In addition, in the UK this worklessness is becoming more polarised within certain specific groups of society. Gregg and Wadsworth (2001) find that 'the current workless household rate is now more than double that of the late seventies' and 'more than 1 in 6 children are growing up in a household that does not work'. If workless experiences of parents not only causally influence their own later workless experiences but also the workless experiences of their children, and this is becoming more restricted to a specific group of society, then the impact of rising unemployment in the UK at present will not be fully measurable in this generation. It will have scarring effects on the labour market experiences of the children of today.

The previous literature on this topic gives a wide range of motivations as to why we might expect a positive causal relationship between the employment status of the parent and the child. If the parent has specific tastes to work or attitudes towards work, for example, a taste for leisure over work, and these tastes are transmitted through learnt behaviours to the child, an intergenerational correlation of worklessness will arise from this. If the action of getting the parent into work directly alters these tastes or attitudes for work, there will be a causal impact of changing the employment status of the parent on the future employment status of the child. Alternatively, if the poverty associated with workless spells experienced by the parent adversely affects the resources and education that the parent is able to provide for their child, the act of moving the parent to employment will alleviate some of these constraints and causally influence the likelihood of the child experiencing future workless spells[1]. It is important to note that this research does not seek to disentangle a separate 'wealth effect' but simply capture the entire causal process from a transition into work, be it through the impact of actually working or the increased income that work brings.

[1] Benefit levels have remained constant in real terms across the period considered hence having a similar influence on the labour supply decisions of all cohorts considered

Alleviating poverty by moving parents into work and hence increasing resources and education is not the only channel that would causally influence the child's probability of experiencing future worklessness. The 'Family stress model' (Conger et. al (2000)) suggests that parents who experience specific stresses such as spells out of work and the associated lack of income may disadvantage their children in their parenting behaviours towards them. The model implies that spells out of work can lead to dysfunction within the family between the adults, often caused by depression and feelings of worthlessness, that can have complex adverse affects on the children both directly and indirectly through reduced warmth and support, inconsistencies in parental behaviour and a lack of control over the child. The child is therefore more likely to act out at school and suffer behavioural problems leading to lower outcomes and a higher propensity towards unemployment themselves. The act of moving the parents into work may therefore reduce some of this stress within families and therefore increase the likelihood of more effective parenting hence increasing the child's outcomes and reducing the likelihood of them experiencing unemployment in adulthood.

O'Neill and Sweetman (1998) and Corak and Piraino (2008) frame the motivation for this causal link in the job-search theory literature. If job searching is costly and the likelihood of a child entering into a job is the multiplicative effect of their exposure to the job and the probability of choosing that specific job given that they have been exposed to it, children are likely to enter into the same occupations of their parents. If the child of a teacher is more likely to become a teacher, the child of a workless individual is likely to become workless themselves. Ioannides and Loury (2004) advise that the reason transactions in the labour market are not the same as transactions in the goods market is down to the fact that idiosyncrasies arise due to social networking. The information provided by family and close networks in searching for jobs has a huge influence on the outcome of search, particularly for those out of work. The authors find, using the US PSID data that 15.5% of unemployed individuals in 1993 looked to 'informal' networks for information and contacts compared to only 8.5% of employed individuals. Corak and Piraino (2008) find that 40% of the sons they consider have worked at some point for the same employer as their father. The direct action of changing the employment status of a parent in this context would alter the likely employment status, and occupation, of the child in the future and increase the information available to the child through informal networks.

Ekhaugen (2009) adds some scope for a negative causal relationship across generations. She argues that workless spells of the parents could conversely reduce the child's likelihood of experiencing workless spells in the future by the parent having more time to invest in the human capital of the child hence reducing their probability of entering into less secure occupations in the future. Alternatively, the perceived 'risky behaviours' associated with long periods of worklessness such as poverty and depression could deter the child from wanting the same existence in adulthood. They could, in effect, learn from their parents mistakes. In both of these cases parents experiencing higher levels of worklessness could reduce the child's likelihood of experiencing future worklessness.

Previous findings and methodology

As mentioned, there is very little previous literature on the intergenerational transmission of worklessness in the UK to date. Johnson and Reed (1996), in an attempt to quantify the scale of the links in unemployment across generations in the UK, found that 19.1% of sons in the National Child Development Study (NCDS) who experienced a year or more out of work between the ages of 23-33 had a father out of work at 16 compared to the sample average of 9.9%. Similarly, O'Neill and Sweetman (1998) use the same data source and find that a father's participation in unemployment has a significant effect on the probability that the son will become unemployed. Sons from fathers with some experience of unemployment when the son is 11 or 16 are twice as likely to experience their own unemployment spells as sons from fathers that were in work when observed. Ekhaugen (2009) uses Norwegian administrative data and finds that sons with parents who have experienced a spell of unemployment during the son's teenage years face probabilities of experiencing unemployment themselves in their mid-20's that are 8-13 percentage points higher than those sons with parents who do not experience any spells of unemployment. Once family observables such as parental income, parental education and region are controlled for, this difference falls by around 50%.

Gottschalk's (1996) much cited paper on the correlation of welfare participation between mothers and daughters across generations in the US offers two different methods for attempting to identify causality that will be analysed in this research, using UK data. The first is that used by Ekhaugen (2009) and Corak, Gustafsson and Osterberg (2000) utilising the timing of spells of welfare receipt or unemployment to identify unobserved family heterogeneity. This method is based on a number of assumptions; that the parent cannot learn from the child, the child only learns from the parent, and that the child can only be causally affected by the parent's experience in childhood. When the son becomes an adult he can no longer be causally affected. The correlation between parental worklessness in the son's childhood and the son's own workless experience is therefore composed of two parts; that which is causal and that which is reflecting some underlying heterogeneity common to both the parent and child. If parental worklessness is also observed when the son is an adult and parental worklessness can no longer causally affect the son's own workless experiences, the correlation between this and the son's worklessness would be capturing pure unobservable heterogeneity. By therefore including both the parents' worklessness 'before' the son leaves home and the parental worklessness 'after' the son leaves home in a model, the causal impact can be identified as the difference between these two effects. This methodology will be assessed in greater detail in the next section.

Corak, Gustafsson and Osterberg (2000) contrast the participation in Unemployment Insurance (UI) use in Canada and Sweden across generations. Identifying causality from parental future participation in UI they find that in Canada, 81% of sons whose fathers have ever used UI claim UI themselves at some point up to the age of 31, compared to 70% of sons whose fathers never used UI[2]. In Sweden the comparable figures were 68% and 57% respectively. All of this difference between these sons can be attributed to unobservable differences across families in Sweden whereas in Canada about half is attributable to observed and unobserved differences across families and half is estimated to be causal.

A recent paper by Ekhaugen (2009) has asked similar questions on the intergenerational transmission of worklessness for the Norwegian population. This paper adds to the literature by using this methodology directly and a variation of this methodology using a siblings-difference method to control for unobserved heterogeneity by measuring differences within families. The framework is based on the assumption that unobserved family heterogeneity is identical across siblings. By then examining siblings where only one of the siblings has been exposed to parental unemployment, the other having left the family home by the time the parents were made unemployed, the estimated differences in outcomes across the siblings will give the causal estimate of parental unemployment on the child's unemployment. This is

[2] Over 75% of Canadian men relied on UI at some stage before reaching the age of 31 compared to 60% of Swedish men

a desirable empirical strategy but very difficult to apply in the UK given the need for longitudinal data on siblings and their parents. There are some concerns with such a strategy in assuming identical unobservable characteristics between siblings as often they are not identical on observable characteristics. The author finds no significant causal effect. Ekhaugen speculates that this indicates that there is either no or a small insignificant causal relationship between parental unemployment and child unemployment or that there are both positive and negative causal effects and that the net of these effects is to cancel the other one out.

The second method proposed by Gottschalk (1996) is that also used by O'Neill and Sweetman (1998), Beaulieu, Duclos, Fortin and Rouleau (2005), and Corak, Gustafsson and Osterberg (2000) to identify causality. In this empirical strategy, welfare participation or unemployment of the parent and son are both modelled jointly, allowing for a correlation between the two error terms to model any unobserved cross-family heterogeneity. Gottschalk (1996) and Corak, Gustafsson and Osterberg (2000) have panel data available and hence utilise a random effects logit model to capture causality in welfare dependence across generations. O'Neill and Sweetman (1998) and Beaulieu, Duclos, Fortin and Rouleau (2005) only have longitudinal data available and hence are restricted to using a bivariate probit model for identification. Given the data available in the UK, the bivariate probit model is the only available option for this research. However, this strategy is purely identified by its functional form without the use of an exclusion restriction. It also imposes some strict assumptions on the distribution of the error terms given that unobservable heterogeneity is explicitly modelled. This will also be discussed in greater detail in section 3.

Beaulieu, Duclos, Fortin and Rouleau (2005) consider the intergenerational correlation of reliance on the Canadian social assistance program using administrative data from Quebec. They simultaneously model the welfare participation of parents and children to control for unobservable heterogeneity within families by allowing the error terms to be correlated. They argue that Wilde (2000) illustrates that the dichotomous and hence non-linear nature of the model means that this framework requires no exclusion restrictions. The 'recursive structure' of the model rules out the potential for reverse causality, given that parents can influence children but children can not influence parents, whilst the non-linearity means that no additional exogenous variation is required in the estimation of the parental worklessness model to identify the affect of prior parental worklessness on future son's worklessness. The entire non-causal element of worklessness is captured by the joint estimation of a parent and child's workless model controlling for observables with controls and unobservables through the correlation across the two errors.

The authors find a significant positive causal effect of parental participation on son's future participation; a one percent increase in parental participation in the social assistance program during their son's childhood increases the likelihood of the son participating in the social assistance program by 0.29%. These results are however conditional on the parent's having some participation in social assistance and therefore difficult to generalise to the whole population if those who claim social assistance are thought to differ from the average non-claiming individual.

O'Neill and Sweetman (1998) used the NCDS to examine the intergenerational transmission of unemployment in the UK from 1974 to 1991. This is the only attempt to capture the causality in worklessness across generations in the UK given the need for longitudinal or preferably panel data sources for such tasks. They use a bivariate probit model to jointly estimate the father's and the son's unemployment probabilities but argue, in contrast to the argument by Beaulieu et. al. (2005), that the model is not identified unless there is either no correlation between the two error terms in the parent and son's workless models or some exclusion restrictions are included.

They attempt to identify causality by introducing additional exogenous variation to the model by including a number of exclusion restrictions. Father's education, father's social class and local unemployment rates when the son was aged 7 and 11 are included in the father's workless model but not in the son's. For these to be valid, there should be no significant effect of these variables on son's worklessness other than through the father's own employment experiences. They suggest that all three of their exclusion restrictions are questionable but do not present tests on this matter. They find that magnitude of the correlation remains but they find no significant causal impact of father's unemployment on the son's unemployment in adulthood.

To summarise, previous literature on the intergenerational transmission of worklessness utilizes two empirical strategies to identify the causal impact of parental worklessness on the next generations' worklessness. From the literature reviewed none of the research on the intergenerational transmission of worklessness has been able to identify a causal impact of parental worklessness on their child's own workless experiences despite all research finding large positive correlations across the generations. The literature on welfare dependency has been more successful in identifying a causal relationship across generations for Canada and the US but as yet no evidence has been found of a significant causal relationship in Europe. This leads to two possible conclusions a priori; the two estimation strategies used in all of these studies place strong assumptions on the data that may not hold, which will be assessed in greater detail in the following section, hence leading to imprecise estimations of causal effects. Alternatively, there is no causal relationship between parental and child worklessness with the large positive correlations being driven by unobservable or un-measurable family heterogeneity.

This chapter adds a third methodological attempt to estimate a causal impact of worklessness across generations by utilising the hard-hitting recession of the early 1980's. This methodology follows the lead of those who analyse the causal impact of income on child outcomes using father's displacements due to plant closures as an exogenous shock (Oreopolous, Page and Stevens (2005), Bratberg, Nilsen and Vaage (2008) and Rege, Telle and Votruba (2007). Utilising 3 digit industry level data from 1980 and 1983 on industries that were particularly hard hit during the recession in terms of employment loss, an instrument is created to extract exogenous variation in employment shocks in an attempt to identify a causal impact of fathers' worklessness on their sons' workless experiences.

Oreopolous, Page and Stevens (2005) attempt to analyse the causal impact of family income on the earnings of the son in adulthood using a sample based on Canadian children of fathers who worked continuously for the same firm from 1978 to 1981, controlling for average family income, regional location, industry and firm size for the four years. The authors argue that this allows a comparison across outcomes of children who would have had the same level of permanent income if the treatment fathers had not been displaced with a sample size of over 60,000 observations. They do not instrument income but instead argue that income has a causal impact on the sons' earnings by using a two-stage procedure. Firstly, they demonstrate that displacement has substantive long-lasting impact on family income to satisfy the relevance assumption and secondly they use this information to include displacement in an intergenerational regression including prior income, proving that once future income is included, all of the displacement effect is working through future income levels. Bratberg, Nilsen and Vaage (2008) carry out a similar exercise using Norwegian administrative data and find the reduction in family resources due to fathers' being displaced has a significant impact on the education of the child but not on the earnings of the child in adulthood.

The crucial distinction between this attempt to identify causality and that within the job displacement literature is that Oreopolous, Page and Stevens (2005), Bratberg, Nilsen and Vaage (2008) and Rege, Telle and Votruba (2007) all have information on whole plant closures, or almost complete plant closures. They can all therefore argue that the shock was completely exogenous of any characteristics of the family, once industry, occupation and regional controls are included. With information on changes in employment at industry level being the only information available in this case, there is the potential that there is selection into those industries that are hardest hit by less productive or less able parents and through the genetic transmission, their sons' are also likely to be less productive or less able and hence more likely to experience worklessness. The instrument in this case would not be truly exogenous. One way of dealing with this endogeneity is to select the sample of the 'hit' and 'non-hit' group by matching their observable characteristics. This will all be discussed further in section 3.

3. Empirical strategy

The relationship of interest in this research is that captured in equation (1) where y_i^{*son} is a latent variable capturing the propensity of son *i* to experience a workless spell in adulthood and y_i^{parent} is a binary variable indicating whether the head of the household *i* has experienced any workless spells during the son's childhood.

$$y_i^{*son} = \alpha + \beta y_i^{parent} + u_i \qquad (1)$$

The coefficient β will capture the intergenerational correlation between parental worklessness and the son's workless experiences in adulthood.

Given that the dependent variable is a latent variable taking the value

$$y_i^{son} = 0 \quad \text{if} \quad y_i^{*son} \leq 0$$
$$y_i^{son} = 1 \quad \text{if} \quad y_i^{*son} > 0$$

the OLS estimation technique can not be used here as taking conditional expectations of equation (1) gives the Linear Probability model (LPM) and β therefore captures the marginal effects rather than the OLS coefficients. The predicted probabilities calculated from this model should be bound between zero and one; however this is difficult to ensure using the LPM, particularly as the number of explanatory variables increases.

An index function model can instead be used, where taking conditional expectations of equation (1) gives us $E(y_i^{son} \mid y_i^{parent}) = P(y_i^{son} = 1 \mid y_i^{parent}) = F(\beta y_i^{parent})$ where $F(\beta y_i^{parent})$ only takes values in the interval [0,1] and is continuously differentiable. Given the requirements on $F(\beta y_i^{parent})$, a cumulative distribution function is chosen and in this case, the Standard normal distribution $F(\beta y_i^{parent}) = \Phi(\beta y_i^{parent})$ and therefore the probit model will be used to estimate this relationship.

The main estimation problem with this setup is that equation (1) only captures the intergenerational correlation of worklessness. If any policy conclusions about the impact of parental worklessness on the son's own workless experiences are to be drawn from this research, an attempt must be made to identify any causal relationship that may exist. The problem with identifying the causal relationship between parental worklessness and the child's own workless experiences is that there are many things that lead to the worklessness of the child, such as low innate ability, that are linked to but not caused by the parents' workless experiences. In an ideal situation, a counterfactual would exist where the same family could be observed over the same period in two different states, in work and workless, so that the difference in outcomes between these two states would give a true causal relationship of worklessness. Arguably the most effective but also most difficult and costly alternative would be to run a randomised experiment, splitting a population of families randomly into a control and treatment group. By making one group work and one group not, the difference between the impacts on the children's own employment experiences would identify the causal relationship between parent's workless experiences and that of the child. The cost and moral issues associated with forcing one group into employment and one group out of employment prevent such an experiment becoming a reality.

If all of the non-causal components that lead to worklessness of the child and are linked to worklessness of the parent were observable, these could be controlled for in a regression and the true causal effect of parental worklessness on child's worklessness would be identified by the coefficient β in equation (2).

$$y_i^{*son} = \alpha + \beta y_i^{parent} + \mathbf{x}_i \lambda + u_i \tag{2}$$

If $\mathbf{x}_i$ is a vector of family background characteristics and captures all of the components that lead to worklessness of the child and are linked to worklessness of the parent and given that everything is observable, the error term is uncorrelated with parental worklessness, $E(u_i \mid y_i^{parent}) = 0$, $p\lim \hat{\beta} = \beta$, $\hat{\beta}$ is a consistent estimator of β. However, if, as is often the case, there are components that are not observable and therefore not captured by $\mathbf{x}_i$, such as heterogeneity amongst the parents in the form of a lower emphasis on the importance of going to work. If these lead to worklessness of the child and are linked to the workless experiences of the parents, these would be captured in the error term, u_i, violating the assumption $E(u_i \mid y_i^{parent}) = 0$. The coefficient $\hat{\beta}$ will therefore give a biased estimate of β due to omitted variable bias. The direction of this bias is dependent on the correlations between the unobserved components and the parental worklessness. If they are positively correlated, $Cov(u_i y_i^{parent}) > 0$, the coefficient on parental worklessness is biased upwards.

In an attempt then to capture the observed heterogeneity within families, equation (2) can be estimated including controls for observable family background characteristics. Given the previous discussion on the need to use an index function model, equation (2) will again be estimated using a probit model with the intergenerational correlation being captured by $\Phi(\beta + \mathbf{x}_i \lambda) - \Phi(\mathbf{x}_i \lambda)$ at the average values of the observable characteristics. An important note is that only observable confounding factors should be included in $\mathbf{x}_i$ as the inclusion of controls that any causal impact could be transmitted through would reduce the estimated causal impact of intergenerational worklessness.

In an attempt to identify causality this research will firstly consider two methods used widely across the literature, introduced by Gottschalk (1996) to attempt to identify a causal relationship between mother and daughter's welfare participation. The first method is also used by Corak et. al. (2000) and Ekhaugen (2009). The model I want to estimate is

$$y_i^{*son} = \alpha + \beta y_i^{parent} + \mathbf{x}_i \lambda + \mathbf{z}_i \delta + u_i \qquad (3)$$

where y_i^{son} represents the workless experiences of the child, y_i^{parent} captures the parental workless experience, $\mathbf{x}_i$ is a vector of all observable confounding factors, $\mathbf{z}_i$ is a vector of all other unobserved components and u_i is a random disturbance term. As $\mathbf{z}_i$ is unobservable, this model cannot be estimated and therefore an alternative strategy is needed.

There may be something about the family that increases their risk of exposure to workless spells, such as having a low innate ability and therefore only being able to obtain work in low-pay less secure jobs. Parents from these families are more at risk to workless spells than those parents from higher ability families and through the intergenerational transmission of ability, the same will be true of their children. This unobserved correlation in worklessness can therefore be used as a proxy for the unobserved components, $\mathbf{z}_i$. If the child can only be causally affected by the parent's experience in childhood, the correlation between parental worklessness in the son's childhood and the son's own workless experience, controlling for observable confounders, contains two parts; that which is causal and that which is reflecting some unobservable confounding factors. If parental worklessness observed when the son is an adult can no longer causally affect the son's own workless experiences then this component by assumption can only be capturing unobservable confounding factors. By therefore manipulating the timing of parental workless experiences using two periods of workless experiences of the parents, one 'before' the child leaves home and one 'after' the child leaves home, the causal impact of parental worklessness on the child's workless experiences can be captured by $\beta - \delta$ from equation (4).

$$y_i^{*son} = \alpha + \beta y_{i,before}^{parent} + \mathbf{x}_i \lambda + \delta y_{i,after}^{parent} + u_i \qquad (4)$$

As mentioned previously, there are some assumptions that have to be made for this causal relationship to be identified. The first, most crucial, identifying assumption is that the child can only be causally affected by the parent's experience before they leave home. Only the 'before' period can therefore contain any causality. The 'after' period should only be measuring family specific heterogeneity. As Gottschalk points out, this assumption may be questionable if the observed 'before' and 'after' period are sufficiently close in time. With an outcome such as worklessness this is particularly problematic as the 'after' period is not clearly defined. If the outcome was instead education obtained at 16 for example, this methodology would be much cleaner as the 'after' period would be firmly defined as 'after' the exams took place. Robustness tests will be applied to the distance between the 'before' and 'after' period to address such concerns.

In addition, it must be assumed that only children learn from their parents, the parents cannot learn from the child's experiences to remove the concern of reverse causality. It could be thought that in terms of worklessness, this assumption is likely to be valid as it is unlikely a parent would choose to leave employment if they see their child not working.

A further identifying assumption is that the relationship between the unobserved heterogeneity that this method attempts to proxy for and the parental workless spells in both the 'before' and 'after' period are equal. One problem with this assumption is the findings of Gregg (2001) that unemployment causally impacts future unemployment. This evidence indicates that there is likely to be an element of persistence in the 'after' period of the parent caused by the 'before' period, violating this assumption. This may bias the effect of the 'after' period upwards and hence the causal impact downwards as a result of the timing.

The second method often used in the literature to identify a causal relationship between parental worklessness and the workless experiences of their sons is a version of the alternative method used by Gottschalk (1996) and that used by Beaulieu et. al. (2005) and O'Neill and Sweetman (1998). This method utilises the fact that the relationship of interest can instead be thought of as

$$y_i^{*parent} = \alpha + \mathbf{x}_i \lambda + u_i^{parent} \quad (5)$$

$$y_i^{*son} = \alpha + \beta y_i^{parent} + \mathbf{x}_i \lambda + u_i^{son} \quad (6)$$

where the likelihood of sons experiencing workless spells in their own generation and the likelihood of parents experiencing workless spells are captured by the two equations (5) and (6). Note that the controls for observable heterogeneity are parental family background controls and the same set are used in both equations, hence there is no exclusion restriction for identification. This is consistent with Beaulieu et. al. (2005)[3]. The dependent variables are again latent variables of the form

$y_i^{son} = 0$ if $y_i^{*son} \leq 0$

$y_i^{son} = 1$ if $y_i^{*son} > 0$

and

$y_i^{parent} = 0$ if $y_i^{*parent} \leq 0$

$y_i^{parent} = 1$ if $y_i^{*parent} > 0$

[3] Child characteristics could instead be used in equation (6) as in O'Neill and Sweetman (1998) but these are viewed as a transmission mechanism through which parental worklessness could impact on child's worklessness. Hence their inclusion in the model would reduce the estimate of the causal impact.

If the two equations are estimated together, there are now four possible outcomes of the model; head of the household workless, son workless; head of the household not workless, son workless; head of the household workless, son not workless; and head of the household not workless, son not workless. The main advantage of this new structure is that it gives a 'recursive' simultaneous equations model which Wilde (2000) and Beaulieu et. al. (2005) argue allows for the endogeneity of parental worklessness in equation (6) to be ignored given the non-linear functional form. If the model was linear, adding (5) and (6) together would remove parental worklessness from the equation and the model would not be identified. However, given that the model is not estimated in a linear form, they argue that this problem is removed. The model is therefore only semi-parametrically identified; it relies on its non-linear form for identification. The main issue with this identification strategy is that the non-linear identification only holds at the tails of the distribution, where the CDF of the probit function deviates from a linear function. As will be seen in the following section, the levels of worklessness in the data used are not situated around the tails of the distribution but more central, around the area of the distribution where the probit distribution and a linear distribution would appear identical. It is therefore highly unlikely this model will identify causality in this data. However, for completeness, this will be estimated and the results analysed. The model is therefore

$$P(y_i^{son} = 1, y_i^{parent} = 1 \mid \mathbf{x}_i) = \Phi_2(\beta y_i^{parent} + \mathbf{x}_i\lambda, \mathbf{x}_i\lambda, \rho) \tag{7}$$

where $\rho = Cov(u_i^{parent}, u_i^{son})$ and is modelled explicitly to control for unobserved family level heterogeneity and $\mathbf{x}_i$ is a vector of all observable components.

This model is based on the important assumption that the child can only learn from the parent, the parent can not learn from the child and therefore this removes any concerns of reverse causality. In addition the two error terms u_i^{parent} and u_i^{son} are assumed to be bivariate normal distributed. Any unobservable family specific components are common to both parent and son and hence captured in the error term in both equations by the correlation ρ. The likelihood function to be maximised is then

$$L = \Pi(P_{11}^{y_i^{son} y_i^{parent}} . P_{10}^{y_i^{son}(1-y_i^{parent})} . P_{01}^{(1-y_i^{son}) y_i^{parent}} . P_{00}^{(1-y_i^{son})(1-y_i^{parent})}) \quad (8)$$

where

$P_{11} = P(y_i^{son} = 1, y_i^{parent} = 1) = \Phi_2(\beta y_i^{parent} + \mathbf{x}_i \lambda, \mathbf{x}_i \lambda, \rho)$

$P_{10} = P(y_i^{son} = 1, y_i^{parent} = 0) = \Phi_2(\mathbf{x}_i \lambda, -\mathbf{x}_i \lambda, -\rho)$

$P_{01} = P(y_i^{son} = 0, y_i^{parent} = 1) = \Phi_2(-(\beta y_i^{parent} - \mathbf{x}_i \lambda), \mathbf{x}_i \lambda, -\rho)$

$P_{00} = P(y_i^{son} = 0, y_i^{parent} = 0) = \Phi_2(-\mathbf{x}_i \lambda, -\mathbf{x}_i \lambda, \rho)$

Maximum likelihood estimation can then be used to attempt to identify any causal affect of parental worklessness on sons' workless experiences. Therefore this process of jointly estimating equations (5) and (6) removes any of the family specific unobserved heterogeneity by modelling this explicitly with the correlation ρ and the remainder of this is attempting to extract the causal estimate of parental worklessness on sons' workless experiences.

The third methodology that will be used in an attempt to estimate a causal relationship between father and sons' worklessness will utilise the impact of the 1981 UK recession. The recession of the early 1980's was widely unanticipated and hit certain sectors, such as manufacturing much harder than other sectors such as the public sector. The hard hit industries saw large falls in the proportions employed within that industry between 1980 and 1983 (see figure 1). The detailed description of the instrument will follow in the data section but the methodology behind utilising the recession employment shock data is to create a dummy indicating fathers' who were working in hard hit industries just before the recession. These fathers', given that there was no selection into these industries, were at a higher risk of experiencing worklessness in 1986 than those in non-hit industries due to an exogenous shock to their specific industry. By definition, this therefore places a requirement on the data that the father was in work before the recession. This methodology therefore is attempting to capture causality in a less permanent form of worklessness than that of the rest of the analysis of this research.

An instrumental variable technique is implemented to attempt to extract exogeneity in fathers' worklessness through a first stage regression shown in equation (9) and this exogenous variation is then used to estimate a causal relationship between father and sons worklessness as shown in equation (10).

$$y_i^{*parent} = \alpha + \gamma hit + \mathbf{x}_i \lambda + u_i^{parent} \tag{9}$$

$$y_i^{*son} = \alpha + \beta \hat{y}_i^{parent} + \mathbf{x}_i \lambda + u_i^{son} \tag{10}$$

The crucial assumption for identifying any causality through an exogenous instrument is that those in the treatment group, or those defined as working in a hard hit industry in 1980 in this case, were not necessarily different in terms of observable and unobservable characteristics from those in the control group; those working in an industry that was not hit hard. This is the excludability restriction that the instrument should not be capturing something which would predict the probability of the sons' workless status, apart from the impact that it has on the fathers' workless status. There may be some concern that those who worked in hard hit industries in 1980 were more at risk to worklessness regardless of the industry that they worked in. In order to ensure that this crucial assumption holds, a form of propensity matching can be implemented by predicting the likelihood of working in a hard hit industry in 1980 based on a vector of observable characteristics.

$$hit_i^{parent} = \alpha + \mathbf{x}_i \lambda + u_i^{parent} \tag{11}$$

The predicted probabilities from a probit model shown in equation (11) of working in a hard hit industry are used to match fathers in the treatment and control groups. By performing this sample selection on observable characteristics, it is assumed that any differences in underlying unobservable characteristics are minimized.

A further assumption required for working in a hard hit industry in 1980 to be used as a valid instrument is the relevance assumption; working in these hard hit industries must predict the increased probability of the father becoming workless. An F-test on the instrument in equation (10) can clarify the relevance assumption but given that there is only one instrument and hence the model is exactly identified, tests can not be carried out to prove the exogeneity of the instrument. Therefore, for this methodology to be capturing any causality, the assumption must hold that the once the two samples are matched, those fathers' working in those industries defined as 'hit' are identical to those fathers' working in those industries defined as ‘not-hit’ apart from that they are at a higher risk of worklessness, given the employment shock, to satisfy the exclusion restriction. Robustness tests will be carried out on the definition of industries that are hard hit.

4. Data

Three main sources of British data are used for this research. The two British cohort studies, the National Child Development Study (NCDS) of those born in 1958 and the British Cohort Study (BCS) of those born in 1970 with original samples of around 9,000 boys in each, and the British Household Panel Survey (BHPS), a panel survey of 10,000 representative households recorded annually from 1991.

The three data sources all have strengths and weaknesses for this research and so each are used to their strengths. The cohort studies have detailed longitudinal information, following the child and parent from birth to 16. They have been the main source of data for analysing intergenerational mobility in the UK and are broadly comparable across time. However, they do not follow the parents after the child is 16 and hence can not be used for the first identification method which requires parental work history after the child has left home.

The BHPS on the other hand does follow all members of the household so we have information on parents work history after the son has left the home. However, we have more limited work history data for the sons that are measured quite differently to that of the cohort studies. For this reason the use of the BHPS is restricted to illustrating the first methodology explored to ascertain causality in intergenerational worklessness and will not be used in any comparative manor. In addition, as it is a household panel survey the sample sizes for each age group are small which makes statistical inference difficult.

All three surveys were nationally representative when the original sample was taken, eliminating the likely downward bias discussed by Solon (1992) caused by sample selection. There are attrition problems however, particularly in the cohort studies, as the final samples are reduced by about half to around 4,500 sons and therefore an external source will be used to validate the employment characteristics of the remaining fathers to assess the direction of any biases.

National Child Development Study

The NCDS obtained data at birth and ages 7, 11, 16, 23, 33, 42 and 46 for children born in a week in March 1958. The employment measures of the father are available if present when the son is age 11 (1969) and age 16 (1974). Various different father and head of household (hoh) employment measures have been tested and will be discussed in the robustness section but the main focus of the analysis will be on the father and the son as employment patterns for women are subject to different participation decisions making them harder to measure precisely. The dichotomous variable indicating fathers' worklessness is coded as 1 if the father is observed as workless at 11 (1969) or 16 (1974), or in both periods[4]. The base category is that the father is observed as employed at 11 (1969) or 16 (1974), or in both periods. This stringent definition of worklessness was designed to capture a more persistent workless level rather than just a temporary shock.

Table 1 indicates the samples of those fathers' only ever seen as out of work when observed, 2.2% of the total sample. Given that this definition of worklessness may be subject to measurement error as not all fathers' are observed in both periods, the analysis of the is repeated for a more restrictive measure and sub-sample of the father being workless in both periods and observed in both periods respectively. The results will be discussed in the next section. To assess whether the workless rates observed are nationally representative, given attrition, the first panel of table A1 compares the workless rates of both the father-son pair sample and the hoh-son pair sample to the workless rates from the Family Expenditure Survey (FES) in both 1969 and 1974 for fathers and head of households with sons aged 10-16. The rates of worklessness are reassuringly very similar across the two surveys for the corresponding years suggesting that the attrition in the sample is not adversely affecting the observed levels of worklessness for fathers or head of households. As the fathers vary in age, quadratic age controls are included in all of the analysis to remove any life cycle bias of worklessness.

For the sons, work history data is available for the cohort members for every month from ages 16 to 42 (Galindo-Rueda (2002)). From the measure of sons' worklessness, varying

[4] The NCDS ask about the father's occupation at 11 and 16, requesting that if not currently working to put 'not working'. These are coded as workless. For the mother, at 11 it asks the number of weeks worked in the past year and is coded workless if this is zero. At age 16 the question is 'Does the mother do paid work' and is coded workless if the answer is 'no'. Father assumed head of the household unless missing.

intensities of binary employment variables are computed[5] from leaving full time education to age 30 for comparability with the BCS. Leaving full time education was chosen as the starting point to observe workless spells rather than a fixed date so as to not bias upwards the predicted probabilities of experiencing worklessness for those entering into higher education. The focus of the main results will be on sons experiencing a year or more concurrent spells out of work but a more intense measure of worklessness will also be considered in the robustness section for those sons who have spent two years or more in concurrent workless spells. Table 2 clearly shows a distinction in sons' workless levels by their father's workless experiences. For sons from families where the father was observed only in employment, there was a 13.2% chance that they would experience a year or more in concurrent workless spells after leaving full time education. If the father was observed out of work at either 11 or 16, the chances of the son experiencing a year or more out of work increases to 21.6%. For sons from families where the father was only observed as workless throughout the son's childhood, the corresponding percentage was 35%.

To control for observable differences across families, information on parental education, father's social class when the son is aged 11[6], the region the family live in at 11 and housing tenure at 11 are all available. The education and social class of the parents are likely to capture family heterogeneity in exposure to worklessness by the type of job that the parent obtains. They are also likely to capture the socio-economic status of the parent, as will the housing tenure of the family, which will be negatively associated with the likelihood of experiencing workless spells in both generations. The region controls are included to capture any region specific employment shocks that are likely to effect the correlation assuming children often stay in the same region as their parents' in adulthood.

British Cohort Study

The BCS originally included all those born in Great Britain between 4th and 11th April 1970. Information was obtained about the sample members and their parents at birth and at ages 5, 10 and 16 and then the sample members only at ages 26, 30 and 34. Employment measures are available for the parents at ages 10 (1980) and 16 (1986) and in a similar fashion to those

[5] Binary outcomes were chosen to fit into the framework used in the literature on intergenerational worklessness and welfare dependency. O'Neill and Sweetman (1998) examine different methods by using the continuous truncated sons' workless variable.
[6] 36% of those defined as workless have missing social class information.

created in the NCDS, the employment experiences of the father at these two ages are used to create the explanatory variable of interest[7]. The dichotomous workless variable is coded as 1 if the father is only ever observed as workless and 0 if the father is observed as in employment at 10 or 16.

A can be seen from the second panel of table 1, 6.37% of fathers are considered workless in this sample. As in the NCDS, whilst the main focus will be on father-son pairs, the head of household-son pair is also considered for robustness in the next section. In addition, a more restrictive measure and sample of worklessness; those fathers observed workless at 10 and 16 and observed in both periods will also be considered for robustness. The second panel of table A1 repeats the exercise of comparing the workless rates of father-son pairs and hoh-son pairs in 1980 and 1986 with a similar sample of fathers and head of households in the FES. The data on father-son pairs looks very similar for 1980 but there is slightly more fathers worklessness in the cohorts in 1986 compared to the FES. For head of household-son pairs, the opposite is true; the data from 1986 on head of household worklessness looks very similar but the cohorts seem to experience less worklessness in 1980. Although these differences are slightly concerning, the fact that these trends are different would suggest there is not any systematic bias in parental worklessness in the cohort study.

For the employment shock analysis, the father must be in work at 10 to be working in a hard hit industry and so this is a minimum restriction placed on the explanatory variable (90% of previous sample). This moves the analysis from a more permanent form of worklessness, to attempting to capture any causal impact of worklessness in a shock to the fathers' work status. The fathers' workless variable therefore becomes defined as 1 if the father was in work at 10 and is not observed in work at 16 and 0 if the father is observed as in work in both periods. A more restrictive version of this variable is also used in line with the previous definition of worklessness where the fathers workless variable is re-defined as 1 if the father is employed at 10 but then observed out of work at 16 and again 0 if the father is employed at 10 and 16.

[7] The questions about the employment status of the mother and the father are identical in the BCS at age 10 and 16 with both asking the 'current (present) employment situation' of each the father and the mother. Both are coded as workless if the response is anything but 'regular paid job' or 'works occasionally'. Father assumed head of household unless missing.

Work history information is available for the sons for every month between the ages of 16 and 30 and so comparable outcome variables are created on whether the son has experienced one year or two years in concurrent spells out of work from leaving full time education to age 30. The main focus will be on sons who spent a year or more out of work but the more restrictive measure will be considered in the robustness section. Comparable family background measures are available in the BCS in the form of parental education, father's social class at age 10[8], region of residence at 10 and housing tenure at 10. Table 2 again indicates a large distinction in sons' workless levels by their father's workless experiences. For sons' of fathers' who were only ever observed out of work while the son was aged 10 and 16, the percent experiencing a year or more in concurrent workless spells in adulthood is nearly 40%. For those whose father was observed out of work at either 10 or 16 this percentage falls to 20%. In contrast, those sons' with a father observed as employed at 10 or 16, only 13% experience a year or more out of work after leaving full time education.

For the more restrictive employment shock methodology, the first row of table 3 summarises the rate of sons' worklessness by fathers' workless experience at 16 given that they are employed in 1980. As to be expected it is clear that the differential levels of sons' worklessness by fathers' worklessness are smaller than those seen in table 2. For those sons with fathers' observed in work in both periods the proportion workless in adulthood is 10%. If the father isn't observed in work the proportions of sons' worklessness in adulthood are 19 and 15% respectively for the father observed workless or not observed at age 16. This is in contrast to 40% of sons experiencing worklessness with fathers' only ever observed as workless. The intergenerational correlation of worklessness for this specific analysis will therefore be around half the size of that analysed using a more permanent definition of fathers' worklessness. The bottom row of table 3 illustrates those fathers' employed in 1980 without an industry code. Given that the definition of the instrument is reliant on observing the industry of the father in 1980, these sons' are dropped from this sample. Reassuringly, the rates of sons' workless by each grouping of fathers' work status are very similar to those in the entire sample; hence this selection is not likely to bias the results.

The instrument for an exogenous shock to the father is defined based on industry level information from 1980 and 1983. Working in a 'hit industry' is defined as whether the

[8] 55% of those defined as workless have missing social class information

industry that the father worked in when observed in 1980 was in the top 40% of 'hit industries'; defined as the proportion employment change using 3 digit industry level employment data from the Employment Gazette for 1980 and 1983[9]. Rows 2 and 3 of table 3 illustrate the differences in the percentage of sons' experiencing worklessness by the fathers' employment status in 1986 and the defined instrument. As can be seen, in all three outcomes of the father, those in the hard hit industries were more likely to have a son who experienced a year or more out of work in adulthood.

As discussed in section 3, there may be some concern over selection into the hard hit industries. To address this problem, a form of propensity matching is introduced to ensure that the treatment and control group are similar based on observable characteristics. For this, the same family background controls discussed above are used to predict working in a hard hit industry. Those in the control group with predicted probabilities below the minimum observed in the treatment group are then dropped from the sample under the 'no common support' assumption[10]. The predicted probabilities of working in a hard hit industry were then standardised and those with particularly low probabilities of being in hit industries in the control group were dropped[11] until the mean predicted probability of working in these industries based on observable characteristics was the same for the control group and the treatment group. This sample selection is carried out to ensure that the two samples appear similar and minimize the risk of unobservable differences across the treatment and control groups.

British Household Panel Study

The BHPS is a panel survey of households recorded from 1991 onwards. Given that the first methodology requires that sons be observed along with their parents at only a specific time during their lives (a window from late childhood until preferably late 20's) the sample of individuals that the BHPS allows is limited. However, given the household nature of the survey, the parents of the sons are still observed once the son enters the survey at 16 and in subsequent periods of the son's life. As noted, the definitions of worklessness are different from the cohort studies. A workless spell in the BHPS is defined as the main labour force

[9] 20% and 60% cut off points are also analysed for robustness
[10] 28 observations dropped in main sample
[11] 690 further observations dropped in main sample

status reported by the father or son in the given year of interview. The definition of a period out of work for the father and the son is reporting anything other than 'employed' as their main labour force status at the time of interview. The BHPS sample are interviewed in all but one survey in the same three months of each year (September to December) so there should be no concern over any seasonal variation affecting the reporting of the main economic status.

Two distinct periods are defined for this analysis, a 'before' and 'after' period. The father's worklessness in childhood is defined as the father experiencing any spell out of work in the 'before' period which is from the first observation up until either the child is age 18 or the age the child leaves home if this happens first. The sons' worklessness is defined as experiencing a spell out of work in the 'after' period which is the time from the end of the 'before' period until the last observation. Parental worklessness after the child has left home is defined as the father experiencing any workless spell in the 'after' period. The length of the 'before' and 'after' periods are not stable across the sample observed and so restrictions are placed on the minimum number of 'before' and 'after' periods required to enter into the sample. The parents and sons must therefore be observed for at least three periods in the 'before' period and at least three periods in the 'after' period.

To make the data as comparable as possible with the two earlier cohort studies information is used on boys who have parents in the survey from when the son is age 10/14 onwards. This allows fathers worklessness to be observed during the childhood of the son, along with family background measures in their first observed time period including parental education, the father's social class, region of residence and housing tenure despite the son not entering the survey until the age of 16.

5. Results

The unconditional intergenerational correlation

To quantify the magnitude of the raw intergenerational correlation of worklessness, table 4 shows the estimates from a probit model on equation 1. The table indicates that the predicted probability of a son whose father has not been observed in work during the son's childhood spending a year or more out of work themselves between leaving full time education and age 30 is 0.33 in the NCDS. This is in contrast to the predicted probability of a son from a family where the father is observed to be in work at least once at 11 or 16 spending a year or more out of work themselves between leaving full time education and age 30 of 0.14. The intergenerational correlation or difference between the predicted probabilities for the two different types of family is 0.196.

In the BCS, the predicted probability of a son spending a year or more in concurrent spells out of work between leaving full time education and age 30 is 0.39 if they are from a family where the father has is not observed in work at 10 or 16 compared to 0.14 if they are from a family where the father is observed to be in work at least once in these two periods. This produces an intergenerational correlation of 0.25. This indicates that between the cohort born in 1958 and those born in 1970 there has been an increase in persistence in the intergenerational correlation in worklessness, in line with the findings on intergenerational mobility. The fathers' employment status for those sons' born in 1970 is a stronger predictor of their own workless status than the father's employment status for those sons' born in 1958 although the difference between the two coefficients is not statistically significant.

To begin to move towards a causal estimate in the intergenerational transmission of worklessness, equation (2) can be estimated, controlling for the observable family background characteristics. As discussed in the previous section, by controlling for all observable characteristics it is unlikely that the casual effect will be identified given the high likelihood of an unobserved family specific component remaining in the error term and hence biasing the estimates. However, this can be thought of as a first step in a movement towards a causal estimate. Column 4 of table 4 presents the intergenerational correlation of sons' worklessness and fathers' worklessness conditional on these parental background controls. In the NCDS, 31% of the unconditional correlation in sons' experiencing at least a year out of work can be accounted for by these observable differences across families. In the BCS 29% of the unconditional intergenerational correlation between fathers' worklessness and their son's experiencing at least a year out of work can be accounted for by these parental background controls.

Table 5 repeats the analysis in table 4 for the BCS cohort for a restricted sample of fathers' who are employed in 1980. As discussed, within the instrumental variable analysis there is a restriction on the data that the father must be employed in 1980 and hence the focus shifts from a more permanent form of fathers' worklessness to a shock to the father's work status. As predicted, the raw intergenerational correlation is almost four times smaller for this restricted sample of individuals. If the predicted probabilities are considered, the probability of the son being workless in adulthood given that his father was employed in both periods is very similar to that of the predicted probability from table 4 of a son with a father observed to be working in at least one period. The main difference across the two tables comes from the large fall in the predicted probability of the son experiencing a year or more out of work in adulthood given that the father is employed at 10 but not observed in work at 16. This probability is just 0.186 compared to 0.385 for those sons whose father is never observed as employed; over twice the size when the more permanent measure of fathers' worklessness is used. 38% of this smaller unconditional correlation is accounted for by observable characteristics across families.

Before moving on to examine the causal impact of parental worklessness, appendix tables A2, A3 and A4 examine further the correlation across the cohorts considering different levels of fathers' worklessness and sons' worklessness intensities. Table A2 repeats the correlations in table 4 using instead a more restrictive measure of fathers' worklessness. In this case the sample is restricted to individuals observed at both 11(10) and 16 and the workless measure is defined as 1 for those fathers observed out of work in both periods to reduce any measurement error brought about by including those not observed in both periods. There is very little difference in the unconditional predicted probabilities and intergenerational correlations in either cohort. In the NCDS the intergenerational correlation is slightly higher, driven by an increase in the predicted probability of sons' experiencing worklessness in adulthood with fathers' observed as workless in both periods. In the BCS the correlation is marginally higher and this is instead driven by a decrease in the predicted probability of the sons' experiencing worklessness from fathers' who are employed at either 10 or 16.

There are some noticeable differences however in both cohorts in the amount of the correlation that can be accounted for by the same set of observable characteristics when this more restrictive fathers' workless measure is used. The observable family characteristics can now account for 42% of the intergenerational correlation in the NCDS and 48% in the BCS, an improvement from that accounted for with the less restrictive measure. This is reassuring as it suggests that this more restrictive measure and the observable characteristics are both capturing something permanent about the families.

Table A3 repeats table 5 for the instrumental variable analysis sample, restricting the measure of fathers' worklessness as in table A2 to only those fathers' observed workless in 1986. Again, there is very little difference in the predicted probabilities and the unconditional intergenerational correlation. The correlation is slightly higher due to a slight increase in the predicted probability of sons from fathers' observed not in work at 16 experiencing worklessness in adulthood and a slight decrease in the probability of sons from fathers employed at 10 and 16 experiencing worklessness in adulthood. The magnitude of the unconditional correlation remains significantly smaller than that of the more permanent workless measure used in table A2. The conditional correlation is almost identical to that from the less restrictive measure of worklessness for this sample seen in table 5 with a larger proportion, 55% for this measure, of the unconditional correlation being accounted for by observable characteristics.

Appendix table A4 instead places restrictions on the intensity of worklessness of the son so that the dependent variable is now defined as 1 if the son spends 2 or more years in concurrent spells out of work from leaving full time education until the age of 30. In the NCDS, the unconditional correlation is around half the size of that from table 4 but for the BCS the correlation remains of a similar magnitude. The underlying predicted probabilities of experiencing these spells out of work are lower in all cases as would be expected but the probability of experiencing two or more years out of work for sons' with fathers' who were only observed workless remains high in the BCS with a predicted probability of 0.31. The corresponding probability in the NCDS has almost halved which is driving the substantial differences in the intergenerational correlation. The unconditional and conditional correlations are now twice the size in the later cohort, again, consistent with the literature on intergenerational mobility that finds an increase in persistence in family background in predicting child outcomes across time. The increase in persistence in this case is statistically significant. When family background characteristics are controlled for, there remains a significant correlation in the NCDS, with 38% of the unconditional correlation accounted for and in the BCS, with 43% of the unconditional correlation being accounted for by observables.

Table A5 assesses the issue of selecting father-son pairs rather than head of household-son pairs for this analysis by repeating table 4 for the head of household sample rather than fathers alone. The results indicate that for the NCDS, the head of household measure generates an intergenerational correlation around 25% lower than that found for the father sample. In the BCS however, the results are very similar to those found in the analysis on fathers' only. The difference in the results in the NCDS appears to be driven by the decrease in the predicted probability of sons' from households' where the head of household was only observed workless being 0.05 lower than for sons' from the fathers sample. All other coefficients remain very stable to those of the sample of fathers only. This result could be driven by the fact that being brought up without a father was less common for those born in 1958 and mothers' in general tended to work less and hence were more likely to be observed workless, without necessarily impacting on their sons' future workless experiences.

The causal impact of intergenerational worklessness

To estimate the causal impact of fathers' worklessness on son's worklessness using the first identification strategy discussed in section 3 requires observing fathers' worklessness both during the sons' childhood, or 'before' the son leaves home and once the son is in adulthood, or 'after' the son leaves home. Given that observations of the fathers' are only available in the birth cohorts up until age 16, there is no observable 'after' period for these two cohorts. However, the BHPS allows us to observe the father in both periods. Table 6 gives results from this identification strategy starting in column (1) with the raw intergenerational correlation as discussed for the cohorts in table 4, and introducing the 'after' period of fathers' worklessness to control for unobserved heterogeneity in column (2). As can be seen from table 6, while the addition of the 'after' period reduces the coefficient on the 'before' period, there is no significant difference between the two coefficients indicating that there is no causal relationship between fathers' worklessness and sons' worklessness. The p-value on the test of equality of the two coefficients of 0.7342 indicates that the null that the two coefficients are statistically equal can not be rejected.

Columns 3 and 4 of table 6 repeat this procedure for the regressions conditional on parental background controls. Column 3 shows the conditional intergenerational correlation (as observed for the cohorts in column 4 of table 4) with the ‘after’ period of parental worklessness included in column 4. The coefficient on fathers’ worklessness in the sons’ childhood in the conditional regression has increased compared to the coefficient in the unconditional regression, indicating some negative correlation between the controls, the sons’ worklessness measure and the fathers’ worklessness measure. The coefficient on fathers’ worklessness after the son has left home has diminished slightly. This is reassuring given that the ‘after’ period is used to control for unobserved heterogeneity and therefore is likely to be correlated with any observable heterogeneity that is controlled for in column 4. There is now a larger difference between the ‘before’ and ‘after’ coefficients indicating a positive causal impact of parental worklessness on son’s worklessness but this is not statistically significant. The p-value from the test of equality of the coefficients of 0.5181 again infers that we can not reject the null that the two coefficients are equal and hence there is no causal relationship.

Gottschalk (1996) suggested that this method may be subject to bias if the ‘before’ and ‘after’ periods are close together as the assumption that children only learn from their parents in the ‘before’ period could be invalid. The ‘after’ period could also therefore contain both heterogeneity and some additional causal element, biasing up the ‘after’ period and down the true causal estimate. Tables 7 considers this issue by restricting the ‘after’ period to three years after the ‘before’ period ends. As the ‘after’ period moves further away from the ‘before’ period, this increases the chances that there is no causal element of worklessness remaining in the ‘after’ period, moving to a cleaner measure of heterogeneity. The coefficient on the ‘after’ period should therefore decrease the further away from the ‘before’ period this becomes and hence the estimated causal impact should increase. Given the additional restrictions on the data the sample is reduced but comparing table 6 to table 7, the coefficients on the ‘before’ period remain remarkably stable. What is noticeable by comparing the second and fourth column in each table is the dramatic reduction in the coefficient of parents’ worklessness ‘after’ the child leaves home along with the p-value on the test for equity of the coefficients. Although in table 7 there is still no significance in causality, the direction of the coefficients are certainly working towards a significant positive causal effect. Further movement of the 'after' period would reduce the samples further but given the scope for further years of data in the future there may be a suggestion of positive causality with additional sample members.

Moving onto the second identification strategy discussed, this strategy does not place as many constraints on the data as the first and can therefore be used to attempt to estimate causality within the cohort studies. As discussed in the methodology section, given the levels of worklessness observed in the data for the cohorts, this methodology is highly unlikely to be identified as the part of the distribution that it is working from is likely to be linear and this methodology is only identified by its non-linearity in the absence of an exclusion restriction. Table 8 shows the coefficients from the conditional univariate probit model used to calculate the conditional marginal effects, or intergenerational correlation, in column 4 of table 4. In both cohorts the Wald test statistic indicates that the null that rho is equal to zero cannot be rejected. However, the standard errors and confidence intervals on rho are very large; suggesting as expected that this model is not well identified. No further conclusions can be drawn about the causality in intergenerational worklessness using this methodology.

The third strategy used to identify causality in intergenerational worklessness shifts the focus from permanent worklessness to a shock to the work status of fathers' and the impact this has on the sons' workless experiences in adulthood. As seen from table 5, this less permanent form of worklessness is predicting a smaller unconditional and conditional intergenerational correlation in worklessness as would be expected. As discussed in the previous sections, the two identifying assumptions behind this methodology are firstly that the instrument is relevant, which can be tested, and secondly that the instrument is excludable, which, given that the model is exactly identified, is not testable as there are not enough degrees of freedom.

A method of matching can be applied to the control and treatment groups to attempt to minimize differences in the predicted probability of the fathers' being in a hit industry as opposed to a non-hit industry based on their observable characteristics. This works toward the assumption that the only distinction between being in the hit group as apposed to the non-hit group is the exogenous increased risk of being made workless associated with the employment change in the fathers' industry. Table 9 repeats the analysis of table 5 for the unmatched and matched sample of fathers. As can be seen, the predicted probabilities of sons' experiencing worklessness in adulthood and the unconditional and conditional correlations are all very similar for the matched and unmatched samples. This suggests that there may not be an endogeneity problem with the instrument given the small differences between the matched and unmatched sample.

Table 10 presents the first and second stage results, unconditional and conditional from an instrumental variable regression using an indicator for working in a hit industry in 1980 to instrument the father's employment status at 16 for the unmatched sample. In the unconditional first stage regressions the probability of the father being observed workless in 1986 increases 12% if they work in a hit industry as apposed to a non-hit industry. In the conditional regression this is reduced to 8%. The corresponding F statistics are 49 and 21 respectively, suggesting that the instrument is relevant. The second stage result for the unconditional regression is a large increase in the intergenerational correlation of worklessness, significant at a 99% level of confidence. For the conditional regression, the coefficient is half the size and not significantly different from zero given the large standard error, but still 5 times the magnitude of the conditional correlation.

If the main concern in measuring causality in intergenerational worklessness is omitted variable bias, a priori the second stage effects should be lower than the unconditional and conditional correlations seen in table 9 given the assumption of a positive correlation between the unobservable heterogeneity and endogenous variable, father's worklessness. The second stage results are, however, five to six times the size of the estimated intergenerational correlation in worklessness.

Table 11 repeats the analysis in table 10 for the sample of matched fathers'. The first and third columns of table 11 indicate that the instrument again satisfies the relevance assumption with an F statistic of 16.04 and 15.06 in the unconditional and conditional first stage regressions respectively. The marginal effect of being in a hit industry predicts fathers' worklessness to be 8% higher than if the father is not in a hit industry, very similar to that of the unmatched conditional regression in column 3 of table 10. The two effects are stable despite the addition of background controls, indicating that once a matched sample is used this instrument is indeed measuring something exogenous rather than any confounding factors across families. As in table 10, the coefficients from the second stage regression are much larger than the intergenerational correlations from table 9. Both the unconditional and conditional effects are statistically insignificant but this is again due to the large robust standard errors rather than the point estimate.

One possible explanation for this is that given the nature of the selection of the workless variables to include those not observed in work at 16, measurement error could be present in the data leading to attenuation bias, biasing the correlations towards zero. By using an exogenous instrument, this could be removing any such error from the data. To check as to whether this may be driving the results, a more restrictive measure of fathers' worklessness, having to be observed out of work at 16, can be used to replicate this methodology. If the instrument is dealing with any error in the data, the more restricted fathers' workless variable would be subject to less measurement error and hence the estimated second stage effect should be higher in the more restricted data as it is subject to less attenuation bias.

Table 12 replicates table 10 using the more restricted sample. For the unconditional regression the first stage marginal effect is around half the size of that seen in table 10 with an F statistic of 15.25, suggesting the instrument is still relevant. The second stage coefficient is larger than that seen in table 10 as would be expected given less error. The conditional regression has a lower effect in the first stage regression and a lower F statistic of 4.23 suggesting the instrument is now becoming less effective at predicting fathers' workless status. This could be driven by the sample size as the degrees of freedom on the F statistic are more constrained. The second stage coefficient however has a point estimate very close to the conditional point estimate from table 10 and 11. Although none of the conditional point estimates are statistically significantly different from zero, they are all in the same range and it is only the large standard errors that prevent significance.

A number of robustness tests were carried out on the definition of the instrument to ensure that the instrument is exogenous. One robustness check is to test different definitions of the cut off point for being in a 'hit industry'. If the cut off point is too low, the instrument will fail the relevance assumption by not predicting enough variation in fathers' worklessness. If the cut off point is too high, the instrument will be endogenous as it won't be selective enough. Tables A6 and A7 consider both of these points by reducing the cut off point to the worst 20% hit industries in table A6 and the worst 60% industries in table A7. In table A6, as expected, the marginal effect of being in a hit industry does not predict fathers' workless status. The marginal effect is not statistically significantly different from zero in either the unconditional or conditional regressions. The F statistics are therefore very low at 2.37 and 1.95 respectively. In table A7, the instruments are statistically significantly predicting the endogenous variable but the F statistics are also very low, at 3.88 and 4.52 in the unconditional and conditional regression respectively. This is likely to be driven by the fact that the instrument is not selective enough and is therefore endogenous. The 60% cut off is therefore suffering from weak instrument specification and the results are unreliable.

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6. Conclusions

This research adds to the currently sparse literature on the intergenerational transmission of worklessness in the UK in a number of ways. By introducing new data, the magnitude of the intergenerational correlation of worklessness can be assessed for a new cohort born in 1970 and the intergenerational correlation in worklessness can be compared across time in the UK for the first time. In addition, this research replicates two commonly used methods of identifying causality in the literature identifying the strengths and weaknesses in each, often not observed in other research. Finally, this research adds a third methodology to the literature by introducing an exogenous shock to fathers' employment utilising the recession of 1981 to capture causality in the intergenerational transmission of worklessness.

The results indicate that there is a large correlation in workless experiences between fathers' and sons' in the UK. Son's from both cohorts are over twice as likely to experience workless spells themselves if they come from a family where the father was not observed in work throughout childhood compared to a father observed as employed at either 11(10) or 16. Across time, this correlation has increased from those born in 1958 to those born in 1970. The intergenerational correlation is 5% higher in the BCS than the NCDS; the difference in the probability of experiencing worklessness between sons' from families with workless fathers' as apposed to sons from families with a father employed at 11(10) or 16 has widened across time although the difference is not statistically significant in this case. Increasing the intensity of the sons' workless measures leads to an even larger increase across cohorts with the intergenerational correlation doubling from the NCDS to the BCS with the difference becoming significant across time. This is consistent with an increase in persistence of the impact of family income on sons' adult earnings predicted in the mobility literature. Controlling for observable characteristics accounts for 30% of the intergenerational correlation in the two cohorts and the use of more intensive workless measures of the father increases this percentage to 42% and 48% in the NCDS and BCS respectively.

The first empirical strategy used to estimate causality in the BHPS finds no significant causal relationship between father's worklessness and son's worklessness. It is likely, given evidence provided using a more restrictive method, that this result may be driven by a lack of data. Creating a sizeable gap between the two periods defined produces remarkably stable coefficients for the 'before' period and pushes the 'after' period towards zero. Given the sample sizes are decreasing with the increasing demand on the data this method can not be explored further until further data becomes available. The second empirical strategy often used in the literature to explore causality is shown here to be not well identified. Despite the use of this strategy without any exclusion restriction in other research, the levels of worklessness in the cohort data violate the non-linearity identification strategy. These results can not therefore be used to infer any additional information about intergenerational worklessness.

The new strategy introduced by this research utilises the recession of the 1980's to attempt to identify causality in intergenerational worklessness. The instrument is defined as the father working in the bottom 40% of hit industries in 1980, based on the proportion change in 3 digit industry level employment from 1980 to 1983. Given that the father must be employed in 1980 a less permanent measure of worklessness is examined with an intergenerational correlation around 1/5 of the size of that found using the more permanent measure of fathers' worklessness. The evidence from an instrumental variable regression using this instrument suggests that whilst there is not a statistically significant causal impact of intergenerational worklessness, the point estimates from the conditional regressions are very stable across the unmatched, matched and restrictive sample and are as large as those predicted using a more permanent measure of worklessness. The standard errors however are also very large.

To conclude, whilst not being able to make any strong statement about causality in the intergenerational transmission of worklessness, this research has been informative on the trends in the correlation of worklessness across time, the role of observable characteristics, the strengths and weaknesses of the methodologies commonly used in the literature and finally it has introduced a new attempt at identifying causality. Despite not finding statistical significant results in these point estimates, the instrument appears valid and the point estimates large.

Table 1 Sample composition of fathers' defined as workless in the NCDS and the BCS cohorts

NCDS

16 / **11**	Father employed	Father workless	Missing	**TOTAL**
Father employed	2932 (63.20)	123 (2.65)	1032 (22.25)	**4087 (88.10)**
Father workless	39 (0.84)	41 (0.88)	35 (0.75)	**115 (2.48)**
Missing	410 (8.84)	27 (0.58)	0 (0.00)	**437 (9.42)**
TOTAL	**3381 (72.88)**	**191 (4.12)**	**1067 (23.00)**	**4639**

Shaded region represents those counted as workless. Actual figures reported. Percentage of total sample in parenthesis.

BCS

16 / **10**	Father employed	Father workless	Missing	**TOTAL**
Father employed	1855 (39.93)	213 (4.58)	2100 (45.20)	**4168 (89.71)**
Father workless	27 (0.58)	39 (0.84)	213 (4.58)	**189 (4.07)**
Missing	245 (5.27)	44 (0.95)	0 (0.00)	**289 (6.22)**
TOTAL	**2127 (45.78)**	**296 (6.37)**	**2223 (47.85)**	**4646**

Shaded region represents those counted as workless. Actual figures reported. Percentage of total sample in parenthesis.

		Main sample workless
		Restricted sample workless

Table 2 Descriptive statistics of sons' workless rates in adulthood by fathers' workless experience in childhood in the NCDS and BCS cohorts

	Percentage son's workless by father's employment status		
Cohort (year son born)	**Father only observed workless**	**Father employed and workless**	**Father only observed employed**
NCDS (1958)	34.95	21.60	13.19
BCS (1970)	39.21	20.42	12.86

Sons workless defined as cohort members observed as out of work for 12 or month consecutive months from leaving full time education to age 30

Fathers' employment status defined from measures of employment at cohort members age 11(10) and 16.

Table 3 Descriptive statistics of sons' workless rates in adulthood by father's workless experience in childhood for fathers' employed in 1980 in the BCS cohort

	Percentage son's workless by father's employment status		
16 **10**	Father employed	Father workless	Missing
Father employed	10.35 [1855]	19.25 [213]	15.38 [2100]
No hit	9.29 [936]	17.04 [88]	14.42 [853]
Hit	12.78 [485]	21.74 [92]	17.47 [727]
No ind at 10	9.91 [434]	18.18 [33]	14.04 [520]

Sample size in parenthesis – Total N – 4168. Father must be employed at 10.
Sons workless defined as cohort members observed as out of work for 12 or month consecutive months from leaving full time education to age 30
Fathers' employment status defined from measures of employment at cohort members age 10 and 16.
Hit - fathers' working in hard hit industries in 1980 defined as the bottom 30% of industries by employment change 1980-1983

		Main sample workless
		Restricted sample workless
		Dropped from analysis

Table 4 Predicted probabilities of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood for the NCDS and BCS cohorts

	Unconditional			**Conditional**
Cohort (year son born)	**Father only observed workless**	**Father employed at 11 (10) or 16**	**Difference in predicted probabilities by worklessness**	
	Predicted probabilities		Intergenerational Correlation	
NCDS (1958)	0.3330	0.1369	0.1961 [0.046]***	0.1351 [0.043]***
BCS (1970)	0.3854	0.1402	0.2452 [0.035]***	0.1752 [0.033]***
Age, age squared	√	√	√	√
Parent background controls				√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample sizes 4639 and 4646 in the NCDS and BCS respectively
Intergenerational correlations = predicted probability of 'any workless' – predicted probability of 'no workless'.
Conditional controls include parental education, fathers' social class, housing tenure and region at age 11 (10) in the NCDS (BCS)

Table 5 Predicted probabilities of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood in the BCS given that the father is in work in 1980

	Unconditional			Conditional
Cohort (year son born)	**Father not observed in work at 16**	**Father employed at 10 & 16**	**Difference in predicted probabilities by worklessness**	
	Predicted probabilities		Intergenerational Correlation	
BCS (1970)	0.1864	0.1336	0.0528 [0.012]***	0.0329 [0.012]***
Age, age squared	√	√	√	√
Parent background controls				√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 3181
Intergenerational correlations = predicted prob of 'father workless at 16' – predicted prob of 'father not workless at 16'
Conditional controls include parental education, fathers' social class, housing tenure and region at age 10 in the BCS

Table 6 Probit estimates of sons' worklessness and fathers' worklessness in the BHPS using both 'before' and 'after' the son leaves the household

	(1)	(2)	(3)	(4)
Father workless before				
Marginal effects	0.2030 (0.053)***	0.1552 (0.056)***	0.2093 (0.071)***	0.1760 (0.073)**
Coefficient	*0.5745 (0.143)****	*0.4445 (0.155)****	*0.6003 (0.195)****	*0.5093 (0.202)***
Father workless after				
Marginal effects		0.1231 (0.056)***		0.1086 (0.058)*
Coefficient		*0.3569 (0.157)****		*0.3217 (0.167)***
P test for equality (causality)		0.7342		0.5181
Age, age squared	√	√	√	√
Parent background controls			√	√
N	454	454	454	454

Marginal effects reported. Robust standard errors in parenthesis. Coefficients in italic , *significant at 10%, ** significant at 5%, ***significant at 1%
P-test for equality is a test for equality of regression coefficients, not marginal effects.
Parental background controls: parental education, fathers' social class, housing tenure and region when household first observed (child age 10-14)
Sample: Boys only. 'Before' – child age 10 or when first observed until age 18 or when left home if left home 16/17. Must be observed for at least 3 'before' periods. 'After' – year after before period ends until up to 9 yrs later. Must be observed for at least 3 'after' periods.

Table 7 Probit estimates of sons' worklessness and fathers' worklessness in the BHPS using both 'before' and 'after' the son leaves the household – moving 'after' period to **three years** from 'before' period

	(1)	(2)	(3)	(4)
Father workless before				
Marginal effects	0.2006	0.1744	0.1915	0.1743
	(0.060)***	(0.064)**	(0.082)**	(0.085)**
Coefficient	*0.5376*	*0.4690*	*0.5188*	*0.4734*
	*(0.158)****	*(0.169)****	*(0.218)***	*(0.226)***
Father workless after				
Marginal effects		0.0756		0.0553
		(0.066)		(0.069)
Coefficient		*0.2068*		*0.1540*
		(0.178)		*(0.190)*
P test for equality (causality)		0.3577		0.3310
Age, age squared	√	√	√	√
Parent background controls			√	√
N	350	350	350	350

Marginal effects reported. robust standard errors in parenthesis. Coefficients in italic , *significant at 10%, ** significant at 5%, ***significant at 1%
P-test for equality is a test for equality of regression coefficients, not marginal effects.
Parental background controls: Parental education, fathers' social class, housing tenure and region when household first observed (child age 10-14)
Sample: Boys only. 'Before' – child age 10 or when first observed until age 18 or when left home if left home 16/17. Must be observed for at least 3 'before' periods. 'After' – three years after before period ends until up to 6 yrs later. Must be observed for at least 3 'after' periods.

Table 8 Bivariate probit estimates of sons worklessness on fathers worklessness in the NCDS and BCS cohorts

Cohort (year son born)	**Univariate model**	**Bivariate model**	ρ
NCDS (1958)	0.5444	-0.3620	0.4066
	[0.135]***	[0.922]	[0.415]
BCS (1970)	0.6233	0.7167	-0.0480
	[0.099]***	[0.459]	[0.226]
Age, age squared	√	√	√
Parent background	√	√	√

Coefficients reported, robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample sizes 4639 and 4646 in the NCDS and BCS respectively
Conditional controls include parental education, fathers' social class, housing tenure and region at age 11 (10) in the NCDS (BCS)

Table 9 Predicted probabilities of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood given that the father was in work in 1980 in the BCS cohort

	Unconditional			Conditional
Cohort (year son born)	**Father not observed in work at 16**	**Father employed at 10 & 16**	**Difference in predicted probabilities by worklessness**	
	Predicted probabilities		Intergenerational Correlation	
Unmatched sample	0.1864	0.1336	0.0528 [0.012]***	0.0329 [0.012]***
Matched sample	0.1929	0.1492	0.0437 [0.014]***	0.0282 [0.015]*
Age, age squared	√	√	√	√
Parent background controls				√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 3181 unmatched and 2463 matched
Intergenerational correlations = predicted prob of 'father workless at 16' – predicted prob of 'father not workless at 16'
Conditional controls include parental education, fathers' social class, housing tenure and region at age 10 in the BCS

Table 10 Instrumental variables regression of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood given that the father was in work in 1980 in the BCS cohort instrumented by father working in a 'hit industry' in 1980

	Unconditional		Conditional	
Dependent variable	**First stage – Hit industry**	**Second stage**	**First stage – Hit industry**	**Second stage**
Father not observed in work at 16	0.1229 [0.018]***		0.0828 [0.018]***	
Son workless for a year or more		0.3142 [0.109]***		0.1501 [0.160]
F-test	48.96		20.61	
Age, age squared	√	√	√	√
Parent background controls			√	√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 3181
Hit - fathers' working in hard hit industries in 1980 defined as the bottom 30% of industries by employment change 1980-1983
Conditional controls include parental education, fathers' social class, housing tenure and region at age 10 in the BCS

Table 11 Instrumental variables regression of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood given that the father was in work in 1980 in the BCS cohort instrumented by father working in a 'hit industry' in 1980 for a matched sample of fathers.

	Unconditional		Conditional	
Dependent variable	**First stage – Hit industry**	**Second stage**	**First stage – Hit industry**	**Second stage**
Father not observed in work at 16	0.0788 [0.020]***		0.0759 [0.020]***	
Son workless for a year or more		0.2268 [0.188]		0.1986 [0.194]
F-test	16.04		15.06	
Age, age squared	√	√	√	√
Parent background controls			√	√

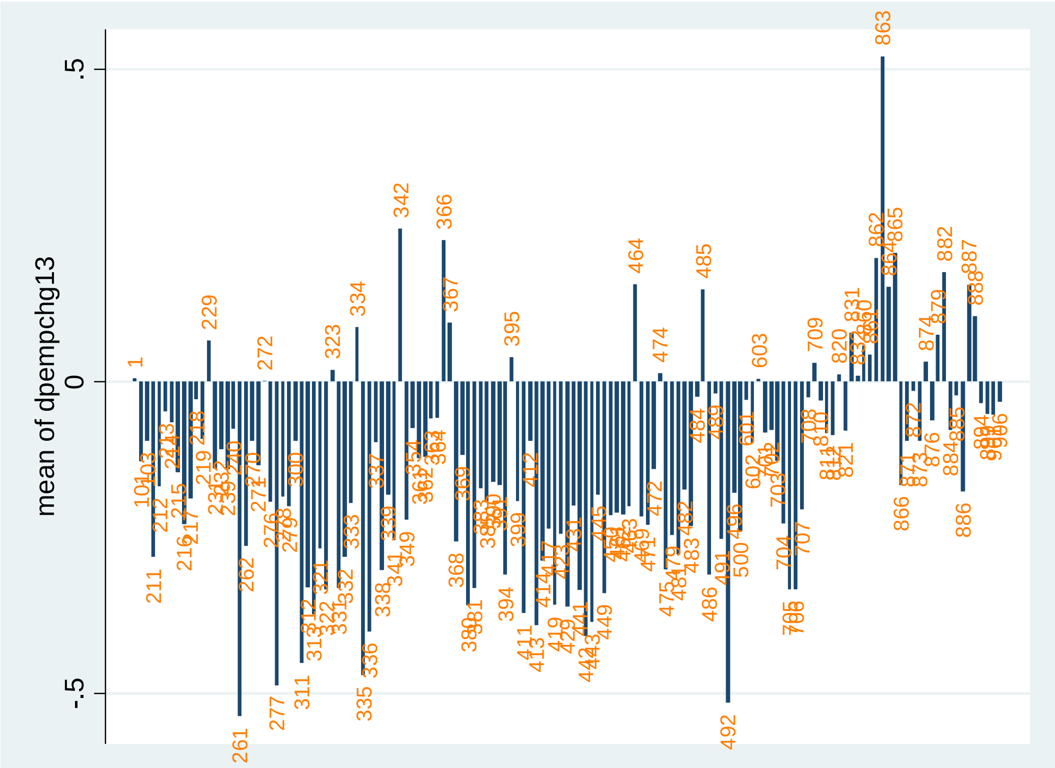
Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 2463
Hit - fathers' working in hard hit industries in 1980 defined as the bottom 30% of industries by employment change 1980-1983
Conditional controls include parental education, fathers' social class, housing tenure and region at age 10 in the BCS

Table 12 Instrumental variables regression of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood given that the father was in work in 1980 in the BCS cohort instrumented by father working in a 'hit industry' in 1980 for a more restrictive sample of fathers'

	Unconditional		Conditional	
Dependent variable	**First stage – Hit industry**	**Second stage**	**First stage – Hit industry**	**Second stage**
Father not observed in work at 16	0.0675 [0.017]***		0.0360 [0.017]***	
Son workless for a year or more		0.5932 [0.286]**		0.2192 [0.503]
F-test	15.25		4.23	
Age, age squared	√	√	√	√
Parent background controls			√	√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 1601
Hit - fathers' working in hard hit industries in 1980 defined as the bottom 30% of industries by employment change 1980-1983
Conditional controls include parental education, fathers' social class, housing tenure and region at age 10 in the BCS

Figure 1 Variation in the proportion change in employment by 3 digit industry code from 1980 to 1983



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Appendix

Table A1 Attrition analysis for the cohorts - workless rates from the cohorts and FES

	Cohorts	FES	Cohorts	FES
	Father-son pairs		**HOH-son pairs**	
NCDS				
1969	2.74	2.90	4.01	5.41
1974	5.35	3.70	6.96	7.14
BCS				
1980	4.34	4.18	6.99	10.98
1986	12.22	9.36	14.97	15.59

FES rate for Fathers / HOH with a son aged 10-16 in the household

Table A2 Predicted probabilities of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood for the NCDS and BCS cohorts for more restrictive measures of fathers' worklessness

	Unconditional			**Conditional**
Cohort (year son born)	**Father observed as workless at 11 (10) and (16)**	**Father employed at 11 (10) or 16**	**Difference in predicted probabilities by worklessness**	
	Predicted probabilities		Intergenerational Correlation	
NCDS (1958)	0.3728	0.1320	0.2408 [0.075]***	0.1403 [0.068]**
BCS (1970)	0.3705	0.1178	0.2527 [0.078]***	0.1330 [0.069]**
Age, age squared	√	√	√	√
Parent background controls				√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample sizes 3,135 and 2,134 in the NCDS and BCS respectively
Conditional controls include parental education, fathers' social class, housing tenure and region at age 11 (10) in the NCDS (BCS)

Table A3 Predicted probabilities of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood in the BCS given that the father was in work in 1980 for more restrictive measures of fathers' worklessness

	Unconditional			**Conditional**
Cohort (year son born)	**Father observed as workless at 16**	**Father employed at 10 & 16**	**Difference in predicted probabilities by worklessness**	
	Predicted probabilities		Intergenerational Correlation	
BCS (1970)	0.1954	0.1124	0.0830 [0.031]***	0.0359 [0.026]
Age, age squared	√	√	√	√
Parent background controls				√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 1601
Intergenerational correlations = predicted prob of 'father workless at 16' – predicted prob of 'father not workless at 16'
Conditional controls include parental education, fathers' social class, housing tenure and region at age 11 (10) in the NCDS (BCS)

Table A4 Predicted probabilities of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood for the NCDS and BCS cohorts for more restrictive measures of sons' worklessness

	Unconditional			**Conditional**
Cohort (year son born)	**Father only observed workless**	**Father employed at 11 (10) or 16**	**Difference in predicted probabilities by worklessness**	
	Predicted probabilities		Intergenerational Correlation	
NCDS (1958)	0.1825	0.0630	0.1195 [0.038]***	0.0656 [0.029]***
BCS (1970)	0.3069	0.0825	0.2245 [0.033]***	0.1395 [0.029]***
Age, age squared	√	√	√	√
Parent background controls				√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample sizes 4639 and 4646 in the NCDS and BCS respectively
Sons' worklessness defined as at least two years out of work
Intergenerational correlations = predicted probability of 'any workless' – predicted probability of 'no workless'
Conditional controls include parental education, fathers' social class, housing tenure and region at age 11 (10) in the NCDS (BCS)

Table A5 Predicted probabilities of sons experiencing a year or more concurrent spells out of work in adulthood by the head of households' workless experience in childhood for the NCDS and BCS cohorts

	Unconditional			Conditional
Cohort (year son born)	**HOH only observed workless**	**HOH employed at 11 (10) or 16**	**Difference in predicted probabilities by worklessness**	
	Predicted probabilities		Intergenerational Correlation	
NCDS (1958)	0.2772	0.1372	0.1400 [0.038]***	0.0989 [0.036]***
BCS (1970)	0.3636	0.1454	0.2282 [0.028]***	0.1629 [0.028]***
Age, age squared	√	√	√	√
Parent background controls				√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample sizes 4812 and 4930 in the NCDS and BCS respectively
Intergenerational correlations = predicted probability of 'any workless' – predicted probability of 'no workless'
Conditional controls include parental education, fathers' social class, housing tenure and region at age 11 (10) in the NCDS (BCS)

Table A6 Instrumental variables regression of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood given that the father was in work in 1980 in the BCS cohort instrumented by father working in a 'hit industry' in 1980 defined as the worst 20% of industries in terms of employment change

	Unconditional		Conditional	
Dependent variable	**First stage – Hit industry**	**Second stage**	**First stage – Hit industry**	**Second stage**
Father not observed in work at 16	0.0362 [0.022]		0.0307 [0.022]	
Son workless for a year or more		0.5347 [0.547]		0.7217 [0.735]
F-test	2.73		1.95	
Age, age squared	√	√	√	√
Parent background controls			√	√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 3181 unmatched and 2269 matched
Hit - fathers' working in hard hit industries in 1980 defined as the bottom 20% of industries by employment change 1980-1983
Conditional controls include parental education, fathers' social class, housing tenure and region at age 10 in the BCS

Table A7 Instrumental variables regression of sons experiencing a year or more concurrent spells out of work in adulthood by fathers' workless experience in childhood given that the father was in work in 1980 in the BCS cohort instrumented by father working in a 'hit industry' in 1980 defined as the worst 60% of industries in terms of employment change

	Unconditional		**Conditional**	
Dependent variable	**First stage – Hit industry**	**Second stage**	**First stage – Hit industry**	**Second stage**
Father not observed in work at 16	0.0422 [0.021]***		0.0453 [0.021]***	
Son workless for a year or more		0.2777 [0.378]		0.3022 [0.0361]
F-test	3.88		4.52	
Age, age squared	√	√	√	√
Parent background controls			√	√

Robust standard errors in parenthesis, *significant at 10%, ** significant at 5%, ***significant at 1%
Sample size 3181 unmatched and 2634 matched
Hit - fathers' working in hard hit industries in 1980 defined as the bottom 60% of industries by employment change 1980-1983
Conditional controls include parental education, fathers' social class, housing tenure and region at age 10 in the BCS