

Where you go depends on where you come from: the influence of father's employment status on young adult's labour market experiences

Wouter Zwysen

Institute for Social and Economic Research
University of Essex

No. 2013-24
November 2013



INSTITUTE FOR SOCIAL
& ECONOMIC RESEARCH

Non-technical summary

Most of the literature on intergenerational social mobility focuses on the transmission of income or social status, thereby ignoring whether parents and/or their children work in the first place. As the proportion of unemployed and non-working people increases, it becomes more important to study both aspects: employment and job quality. Previous studies have shown that a father's worklessness is associated with lower aspirations in education and on the labour market, as well as with a higher risk of worklessness for the child later on.

We add to the literature by looking at the effect of having a father who did not work when their children were aged 14 on multiple aspects of young adult's labour market experiences. We study not only whether these children are working, but also look at their job characteristics when employed. We find that growing up with a non-working father has negative effects on the labour supply of these young adults. They are 16% less likely to be employed and when working work around 3 hours less per week and work part-time more often. This is also the case when we only compare children whose fathers did not work with those whose fathers worked in lower paying occupations. Young adults whose fathers did not work are also more likely to report dissatisfaction with their work, even though they do not earn less or have less secure contracts.

We test several possible explanations of why a father's working situation would impact on their children's labour market experiences. We find no evidence that the young adults suffered psychological scarring in their youth, nor that they are at a disadvantage because their fathers had less useful social networks. We do however find some support for the idea that young adults whose fathers were not working when they were younger experience being out of work differently. For young adults whose fathers worked, even in a lower paid job, being out of work is associated with lower happiness and wellbeing. We found the reverse pattern for young adults whose fathers had not worked when they were aged 14. They are on average less dissatisfied when out of work than when working.

Where you go depends on where you come from: the influence of father's employment status on young adult's labour market experiences

Wouter Zwysen*

*Institute for Social and Economic Research, University of Essex
contact: wzwyse@essex.ac.uk

Abstract

The transmission of economic (dis-)advantage over time should take into account the probability of employment as well as employment conditions, especially given the recent increase in the proportion of non-working people. We study the effect of young people experiencing their father not working on a range of labour market outcomes as young adults using the UKHLS. We find that children of non-working fathers are less likely to work themselves and are less satisfied when working despite similar experiences to their peers in terms of wages and contract. Testing several mediators, we find indications that these young adults experience worklessness as a less negative experience.

Keywords: intergenerational transmission; worklessness; family background

Introduction

This paper studies the effect of paternal worklessness on young adults' labour market experiences in the UK and the mechanisms through which this effect occurs. The study of the intergenerational effects of worklessness becomes more relevant as unemployment and worklessness increase. Eurostat estimates the youth unemployment rate in the UK between 2010 and 2012 to be around 20%. The total unemployment rate is a bit below 8% (Eurostat, 2013). A recent report commissioned by the department of education shows that a range of negative outcomes regarding delinquency and school behaviour which affect later labour market experiences are related to parental worklessness (Schoon et al., 2012). While social mobility in general receives increased interest a lot remains unknown regarding the effects of paternal worklessness on their children's later outcomes.

Most of the literature on social mobility focuses on intergenerational mobility in occupations or wages, ignoring the probability of being employed as well as other aspects of job quality (Bowles et al., 2005; Erikson and Goldthorpe, 2010; Lee and Solon, 2009). A smaller literature shows a positive correlation between unemployment or worklessness of children and their parents (Ekhaugen, 2009; Macmillan, 2010; O'Neill and Sweetman, 1998). These research traditions remain mostly separate however. Stewart (2007) shows a dynamic link between unemployment and low job quality, indicating the relevance of studying them together.

We extend on the literature by studying the effect of experiencing paternal worklessness when aged 14 not only on employment itself but also on the type of employment young adults obtain. We nuance the distinction between working and non-working fathers by separating the working fathers into those working in a lower paid occupation and the others. Comparing children whose fathers did not work with those whose fathers worked in a lower paying occupation can help disentangle the effects of fathers' worklessness from those of financial disadvantage.

Father's worklessness may influence their children's labour market experiences through different pathways. Human capital investment, mental health and wellbeing, attitudes, social networks and a sense of stigma towards being out of work are mentioned in the literature as possible mediators, but have not yet been tested (Ekhaugen, 2009; Macmillan, 2010). It is

important to understand the pathways through which worklessness can be transmitted over generations as this may provide tools to diminish this continuation of disadvantage.

We find that young adults whose fathers did not work at age 14 tend not to work or work less often themselves and are more often dissatisfied with their job even though their pay and type of contract are no worse than their peers whose fathers worked. We find no strong support for any of the mediating mechanisms that we test except possibly that experiencing paternal worklessness at a young age changes the attitude towards work and worklessness relative to their peers. A decreased stigma towards being out of work may lead them to remain out of work longer or to work fewer hours.

Worklessness and disadvantage over generations

Much of the social mobility literature has followed one of two approaches. A more sociological approach concerns itself with the transmission of social class or status, most often occupation-based, from parents to children (Erikson and Goldthorpe, 2010; Jonsson et al., 2007). This approach tends to group together very different experiences of economic position however. Economists studied the correlation in life earnings or wealth (Lee and Solon, 2009; Mazumder, 2005; Solon, 1999). While this allows for finer differentiation, income is but one aspect of job quality (Kalleberg, 2011; Leontaridi and Sloane, 2001). The literature focuses on single and one-dimensional aspects of job quality for those who work while not paying much attention to the question whether people work in the first place (Jonsson et al., 2011). A smaller and mostly economic literature consistently shows a positive relation between the labour market attachment of parents, mostly fathers, and their children (Johnson and Reed, 1996; Macmillan, 2010, 2012; O'Neill and Sweetman, 1998; Payne, 1987). We present selected studies on the intergenerational transmission of unemployment and worklessness in the UK. The non-UK studies find positive correlations of unemployment that are comparable to the British studies (Ekhaugen, 2009; Osterbacka, 2004).

Intergenerational correlation in worklessness and unemployment

Payne (1987) was among the first to show a concentration of unemployment within families. Using the General Household Survey in 1980-1981 she found that unemployed young people aged 16-19 had almost double the odds that the head of their household was unemployed as well. The odds that other young adults in their household, such as siblings, would also be unemployed were even higher.

Johnson and Reed (1996) showed that children whose fathers were out of work or in the lowest quintile of earnings were more likely to have been out of work for more than a year at age 33 and were more likely to be in the lowest income quintile. They used the National Child Development Study (NCDS), a cohort study of British children born in one week in 1958. This indicates the link between worklessness and low wages, supporting later work by Stewart (2007) stating that unemployment and low income are connected in a dynamic process.

O'Neill and Sweetman (1998) also made use of the NCDS. They showed that father's worklessness at ages 11 or 16 led to a higher probability of experiencing unemployment between ages 21 and 33, but not to longer lasting unemployment spells. This is an important difference as it may indicate that the job search process does not take longer.

More recently, Macmillan (2010) showed that the strength of the intergenerational correlation in worklessness between fathers and sons increased over time. She used the NCDS as well as the British Cohort Study (BCS) which is a cohort of children born in 1970, and the British Household Panel Study which ran from 1991 to 2008 and is a representative longitudinal household panel study. Using several econometric techniques she could not establish whether this correlation was a causal effect of father's worklessness (Macmillan, 2010).

In later work Macmillan (2012) used a set of cognitive and non-cognitive characteristics, combined with information on education and behaviour to explain the correlation between worklessness of father and son in the BCS. This set of characteristics accounted for 12% of the correlation in worklessness while it has been shown to account for about 40% of the transmission in income. This indicates different processes may be at work in explaining whether a person works or not and the type of job and income associated with it.

Different labour market outcomes

The literature consistently finds that children of non-working fathers are less likely to be employed themselves. The effects of father's worklessness on their children's type of work are not known however. Schoon et al. (2012) showed that experiencing father's worklessness is associated with other adverse effects such as lower educational outcomes and labour market aspirations. This indicates that there are several outcomes besides the child's employment that can be influenced by father's worklessness. Their study was restricted to aspirations however and did not look at labour market outcomes themselves. It is important to

study two aspects to discern the effect of family background on labour market outcomes: first of all access to the labour market and secondly the quality of work.

This study addresses these two aspects partly by looking at the effect of father's worklessness on young adults' labour supply and the characteristics of their work if employed. We are first of all interested in whether experiencing a father being out of work when aged 14 lowers the probability of employment and whether it affects the hours worked and the probability of working part-time when employed. Second we also want to know whether employed children of non-working fathers work on average in lower quality jobs. This follows the idea of segmentation into dual labour markets. The first labour market offers better-paid jobs where employers aim to retain their employees for a longer time while the second segment consists of less desirable jobs with fewer prospects (Leontaridi and Sloane, 2001). We test whether father's worklessness is associated with a less desirable position in terms of lower wages and less security through a fixed-term contract. The final outcome we look at is the children's satisfaction with their job.

Mechanisms through which father's worklessness affects children

There are several possible reasons why children of non-working fathers are more at risk of not working themselves. First of all parents and children share many characteristics that may affect their labour market experiences and these shared characteristics could lead to the observed correlation in worklessness, without the father not working being the cause. O'Neill and Sweetman (1998) name this a transmission of preferences or a transmission of constraints. There is an established correlation in educational achievement between parents and their children for instance, which could constrain the probabilities of employment for both (Heineck and Riphahn, 2007). There are some indications that parental job loss can lead to a decrease of schooling and grades however (Andersen, 2011; Stevens and Schaller, 2011).

Being out of work is rarely the only type of disadvantage to which these children are exposed while growing up. Other types such as parental ill health or poverty often accompany it (Schoon et al., 2012). A qualitative study by Shildrick et al. (2012) tested the presence of a 'culture of worklessness' within households where parents and their children experienced long periods out of work. They found no evidence for such a culture and found that the persistence of worklessness was often caused by multiple deprivations and not by a cultural adherence to worklessness.

Lower income and human capital investment

Job loss is associated with a loss in income which could influence the human capital investment in children, lowering their desirability on the labour market (Becker and Tomes, 1994). Parental poverty rather than worklessness then leads to disadvantage for the children. O'Neill and Sweetman (1998) tested whether children of unemployed fathers got sent to private schools less often. This was included as a proxy variable for human capital investment, but including it did not explain a substantial part of the intergenerational correlation in unemployment however.

We divide the working fathers in those who worked in low paying jobs and the others and make two comparisons in order to disentangle the effect of father's worklessness from that of a lower family income. First of all children whose fathers were not working when the children were aged 14 are compared with their counterparts whose fathers were working. This is the comparison that the previous literature makes. In a second step we compare children of non-working fathers with their counterparts whose fathers worked in a lower paying occupation. In both comparisons the effect of father's worklessness will be similarly important, but in the latter the income difference between the two groups is smaller. Comparing both results therefore indicates the relative importance of income and worklessness. We use this method as we have no information on parental income while growing up.

If children of non-working fathers have on average fewer resources and lower human capital we expect them to be employed less often or for fewer hours as well as face worse conditions in terms of wage and job security.

Lower wellbeing and mental health

Second, parental job loss could also lead to lower well-being and psychological health for the parent, which may influence the well-being of the child directly as well as through decreased parenting skills, lowering their success on the labour market. Studies have shown that job insecurity and unemployment as an extreme case of job insecurity lead to lower wellbeing both for the adult with the insecure job and for the children (Burchell, 1994; Larson et al., 1994). This lower psychological wellbeing of the child may then influence their labour market experience. Frijters, Johnston and Shields (2010) show that a one standard deviation decrease in mental health lowers someone's probability of entering a job by 17%. This means that if children's mental health indeed decreases due to their father's worklessness this may influence their labour market participation.

Like the effects of lower human capital investment, we expect that lower wellbeing and worsened mental health would make children of non-working fathers less desirable on the labour market. They would be expected to be less likely to be employed and if employed face worse conditions and work part-time more often.

Social networks

A third possible causal explanation consists of depreciation of an unemployed parent's social network. Bramoullé and Saint-Paul (2010) and Gallie, Gershuny and Vogler (1994) showed that the unemployed tend to have fewer social contacts that can be useful to find a job. Since a useful social network is often maintained through working, unemployed fathers can be expected to have less useful social networks on average (Cingano and Rosolia, 2012). Indirect referral through social contacts is an important mechanism of job search and many young adults also make use of their parent's networks (Corak and Piraino, 2011; Granovetter, 1995; Holzer, 1988; Loury, 2006). These networks can be expected to be more important in explaining the duration of spells of not working, rather than the incidence of not working. O'Neill and Sweetman (1998) found that sons of unemployed fathers were more likely to be out of work, but did not need more time to exit unemployment. This would indicate that the social networks are less important.

This pathway is different from the others in that it would only matter if the father's social network was lower, due to his worklessness, at the time the child is actively looking for a job. If the father was out of work when the child was aged 14 but regained more employed social contacts since, there is no reason why the child would be hindered in their job search. We know from literature on scarring however that being out of work once is a good predictor for being out of work again (Gregg and Tominey, 2005). Therefore fathers who were out of work when the child was aged 14 may also be more likely to be out of work when the child is looking for a job and may then have lower social networks as a consequence of that. If any effect of paternal worklessness is due to a comparative disadvantage in job search through less useful social networks of a workless father we expect a lower probability of being employed. Once a job is found however, this pathway should not affect its' quality.

Change in attitudes and decreased stigma

A final pathway considered here is that the experience of worklessness of the parent influences the child's attitudes. First of all there could be a change in the attitude towards being out of work. A young adult who experiences parental worklessness would then be less bothered by the stigma attached to not working (Ekhaugen, 2009; Macmillan, 2010).

Ekhaugen (2009) suggests that seeing a father not working may also lead the children to work more and try harder to avoid unemployment. A negative correlation in worklessness between generations has not been found however. In a study on the effect of unemployment insurance on unemployment duration Tatsiramos (2006) shows that a longer time spent in unemployment leads on average to longer employment spells afterwards which he explains as the result of a longer and better search process. In this case young adults who experienced their father being out of work when they were younger may be less bothered by being out of work themselves, and therefore feel less pressure to accept just any job. If experiencing a father's worklessness changes the evaluation of work and the sense of stigma of being out of work, we expect these young adults to work less, but not face worse conditions when working.

We cannot measure attitudes towards being out of work directly, but we can study the consequences of being out of work. It is well established that not working, either in inactivity or unemployment, is associated with lower life satisfaction (Green, 2011). In her study on the psychological effects of unemployment, Jahoda (1982) states that working provides latent functions such as structure and a sense of value and belonging which cause depression when lost. She noted that the time freed up through not working is not at all the same as leisure time as it brings no satisfaction. If children of workless parents do not derive as much of their self-value from work, we can expect that they would enjoy the free time that is available due to not working as leisure time. We can therefore compare the satisfaction with leisure time between working and not working children whose fathers did not work when they were aged 14 with those whose fathers did work. We expect that young adults whose father did not work are less dissatisfied with their leisure time when not working. More broadly, if not working carries less of a stigma, we also expect that being out of work is associated with a smaller reduction in life satisfaction.

Father's worklessness may also influence their children's experiences on the labour market through effects on general attitudes and behaviour. Schoon et al. (2012) find that children of workless parents have less positive attitudes towards school which can also affect the attitude towards the labour market. They are less likely to believe they can be successful which in turn influences their labour market opportunities. A study by Armstrong (2012) states that children make a choice on education based on their belief in a just world which is influenced by their parents' beliefs. If they grow up to believe that hard work is seldom rewarded they may be prone to take up less education. An experience such as being out of work could

impact strongly on this belief. Dohmen et al. (2012) show that parents and their children share a propensity to trust people or take risks which has strong effects on labour market outcomes. These attitudes are formed while growing up and can be influenced by witnessing a father's worklessness. We expect that these general attitudes and beliefs would influence the labour supply as well as the working conditions through lowering motivation and making these young adults comparatively less desirable.

The next section presents the methods and data that we use to test these hypothesized relations.

Data and methods

Data

We use the UK Household Longitudinal Study, or "Understanding Society" (UKHLS). This is a large household panel survey in the United Kingdom which started in 2009. Around 40,000 households were selected and every adult household member is sampled and interviewed yearly. We use the first two waves (2009-2010 and 2010-2011) and only selected respondents who answered in both waves. This is necessary since some of the variables we use are measured in the first wave and some in the second wave. We measure all outcomes in the second wave. To deal with attrition the results are weighted by longitudinal weights. Since our study concerns young adults we select respondents aged 16-25 in the first wave and we only select those for whom we have information on their education and father's occupation or lack of work at age 14. We also drop 1,411 young respondents who were in full-time education in the second wave. This leaves us with 2,441 respondents. In addition to the UKHLS, we also make use of information from the Labour Force Survey (LFS) for the United Kingdom. The LFS is a nationally representative sample in the UK with about 60,000 households, maintained by the Office for National Statistics (ONS). It is a rotating sample where each respondent is interviewed for 5 consecutive quarters. It provides no information on family background however. We use the quarterly LFS databases from 2002 through to 2010 to calculate median hourly wages for different groups.

We study first of all whether a respondent is employed or not. If employed, there are 7 other outcomes of interest. All of these outcomes are measured in the second wave. First we will explain the main independent variable and the general methodology that is used and then each of these dependent variables is explained in more detail, along with important control

variables. Afterwards we present the issues regarding missing variables and our use of multiple imputations to deal with this.

Father's employment situation when aged 14

We study the father's working situation when the child was 14 years old. A father's working situation is divided into three categories, depending on whether the father was reported to be working or not at age 14 and if working, what 3-digit occupation the father worked in. These occupations were divided in two groups. Based on the LFS we calculated the weighted median hourly wage by occupation. We use information from 2002 onwards as the occupational coding in the LFS changed then. These median wages were ranked in each quarter. We then averaged out those rankings from 2002 up to 2010. Those occupations with an average ranking below the first quartile are categorized as low-paying, and all the rest are the average or good jobs. We had to resort to this occupation-based categorization since there is no information on the actual wage, social status or class for the father in the UKHLS. Of the 2,441 respondents, 338 (14%) reported having a father who did not work at age 14 and 627 (26%) had a father who was working in an occupation within the lowest quartile of median wage. Since our choice for the lowest quartile of average hourly earnings is arbitrary, we carry out robustness tests by comparing children of fathers who did not work with children of fathers who were in either the lowest decile of average earnings, or in the lower half. Our findings are robust to changes of this threshold.

Estimation of average treatment effect for treated (ATT)

In order to estimate the effect of having a father who did not work at age 14 we would need to know what the outcomes for their children would have been had their father worked. The difference between the observed outcome and these potential outcomes for children of workless fathers is then the average effect of treatment for the treated (ATT) (Schafer and Kang, 2008). The problem with evaluating this effect of father's worklessness is that we only observe one outcome for each respondent. The potential outcome must therefore be estimated (Rubin, 1979). Schafer and Kang (2008) discuss several methods through which this can be done. Regression or matching on a propensity score is most often used. We estimate the potential outcome by estimating an appropriate regression model for the relevant outcome in the control group and predicting the outcome for the children whose father did not work using this equation (Schafer and Kang, 2008). We then compare the average observed outcome for children whose fathers did not work with the predicted outcomes we obtained for them using the control group regression equation. This is done using a paired sample T-test.

Equation 1 presents this, with T indicating treatment and Y indicating the outcome for group i. \widehat{Y}_0 indicates the predicted outcome for the treated group based on the equation estimated in the control group (T=0). We first use all respondents whose fathers worked as control group. In a second step we restrict the control group to those respondents whose fathers worked in a low paying occupation.

$$1. \text{ ATT} = \frac{\sum_i T_i (Y_i - \widehat{Y}_{i0})}{\sum_i T_i}$$

We include both men and women in this analysis and control for gender. It is plausible that a father's employment status has different effects for sons and daughters. Due to small sample size we pool them however. We do perform a robustness check where the analysis is separated for men and women. There are some differences in the importance of father's worklessness on the outcomes, but our main conclusions are supported.

Labour market outcomes

Outcome: working or not

We study whether the child is employed or not as a young adult and estimate the potential outcome through a binary logistic regression. Respondents are classified as working if they did paid work in the last week or if they had a paid job despite not working in the last week. All other cases are classified as out of work and respondents in full-time education are not included. 1,748 (71.6%) of the respondents were working.

Since a father and child can share many characteristics that make them both more likely to be employed or not we control for a number of variables. First of all we account for the respondent's socio-demographic background by controlling for gender, age and highest obtained educational qualification. We include a dummy variable indicating the difference between white and non-white ethnicity, control for whether the respondent is born in the UK and whether English is the respondent's native language. We control for the respondent cohabitating or being married and for the presence of children as this may influence labour supply. Having poor health is controlled for as health is related to the transmission of socio-economic status (Bianchi et al., 2005; Smith, 2004). We also control for the strength of the relationship between the respondent and their father by including how often the respondent sees their father and whether the child lived with the father at age 16. To account for the general employment situation when the child was aged 14 we include the UK-wide

unemployment rate in the year the child was aged 14 acquired from the OECD¹ as this could influence the children's attitude towards unemployment (Ochsen and Welsch, 2011). We include the current age of the father and whether the father and mother had a higher educational degree since parental education may influence the child's labour market outcomes (Andersen, 2011).

Outcome: weekly hours worked

As a further indicator of labour supply we measure how many hours the respondent works on average per week. We estimate the potential outcomes through ordinary least squares (OLS) with the same control variables as when estimating the probability of being employed.

Outcome: working part-time

For employed respondents, we distinguish between those who work full-time and those who work part-time by including a dummy for part-time work. This is also an indicator of labour supply and is estimated using binary logistic regression with the same control variables as when estimating the probability of employment.

Outcome: working on a fixed-term contract

We include a dummy variable indicating that someone works on a fixed-term contract, rather than having a permanent job. Working on a fixed-term contract increases job insecurity and is therefore an important part of the quality of the job. The potential outcome is estimated using binary logistic regression using all control variables as above, except whether the respondent cohabitates or has children. Socio-demographic background, family background and relation to father as well as unemployment rate when aged 14 are still included.

Outcome: wage position given age, gender and education

In order to assess the quality of employment we include a dummy indicating whether the respondent's earnings are lower than those of his/her peers. We calculated the median gross hourly wage by age category (16-17; 18-19; 20-22; 23-25), gender and highest educational degree. This is calculated in the LFS from 2009 to 2010, weighted appropriately. A dummy indicates that the respondent's gross hourly wage, calculated from the UKHLS, lies below the nationally representative median hourly wage for people of similar age, gender and educational qualifications. The potential outcome is estimated through binary logistic regression on all controls except cohabitating and being a parent. We also include working

¹ From OECD: <http://stats.oecd.org/#>, statistics on Economic outlook in the UK from 1998-2009

part-time and working on a fixed-term contract as controls as someone's position in the wage distribution may depend on the type of contract someone has.

Outcome: wage position given age, gender and occupation

We make use of another operationalisation of peer group for which we want to know the respondent's relative wage position. This dummy indicates that the respondent's earnings are lower than the median hourly wage by age category, gender and 3-digit occupation, again calculated using the LFS. This indicator of job quality indicates that the respondent has a wage in the lower half of earnings compared to people of the same age and gender who work in the same occupation. We estimate the predicted relative wage in a similar equation as with wage position given age, gender and education.

Outcome: gross monthly labour market income

We test the effect of paternal worklessness on their children's gross monthly labour market income if employed. This is the most straight-forward measure of job quality and relates directly to the financial dimension of job quality (Kalleberg, 1977). The counterfactual labour market income for children whose fathers did not work is estimated through an OLS regression of gross monthly labour market income on all control variables that are used in estimating whether someone works on a fixed-term contract, with the addition of the average hours worked per week.

Outcome: dissatisfied with job

The final labour market outcome we study is the self reported job satisfaction of working respondents indicating how the young adult experiences their work (Kalleberg, 1977). Respondents in the UKHLS are asked how satisfied they are with their job and can respond from 1 completely dissatisfied to 7 completely satisfied. If respondents reported to be somewhat dissatisfied (3) or less this was classified as being dissatisfied on a dummy variable. We use binary logistic regression to estimate the counterfactual job satisfaction using all controls used for monthly wage with the inclusion of all other labour market outcomes. This variable can capture the undesirability of a job in ways we did not measure with the other variables. It may also indicate different expectations of a job and therefore different evaluations of the available work conditions on average.

Table 1 below summarizes the different control variables that are used for each separate outcome.

Table 1: Explanatory variables used in the different regressions

	Job	Hours	Part - time	Fixed - term	Wage position educ.	Wage position occ.	Wage	Dissatisfied
Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
White	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Not UK	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
English	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Couple	Yes	Yes	Yes	No	No	No	No	No
Parent	Yes	Yes	Yes	No	No	No	No	No
Poor health	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
See father	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Living age 16	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unemployment rate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Father age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Father education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother education	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job hours	No	No	No	No	No	No	Yes	Yes
Wage	No	No	No	No	No	No	No	Yes
Fixed-term	No	No	No	No	Yes	Yes	No	Yes
Wage by education	No	No	No	No	No	No	No	Yes
Wage by occupation	No	No	No	No	No	No	No	Yes
Monthly wage	No	No	No	No	No	No	No	Yes
Part-time job	No	No	No	No	Yes	Yes	No	Yes

Mediation

Apart from presenting the differences in labour market outcomes of young adults depending on their father's occupation at age 14, we also test some of the mechanisms through which worklessness is transmitted over generations. We expect that part of the effect of paternal worklessness on their children's probability of employment is indirect through some other, mediating variable. We will test the role played by mental health and wellbeing; attitudes; and father's social networks, comparing children of non-working fathers with their peers whose fathers worked in lower paying jobs to limit the income differences.

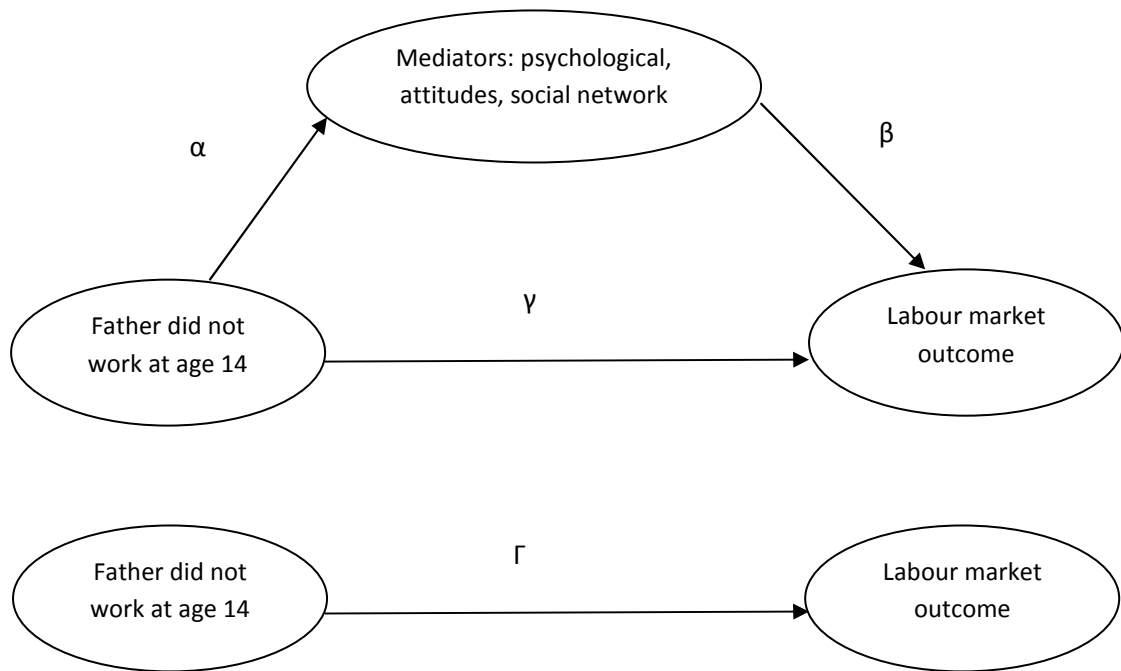
For a concept such as for example mental health to mediate the effect of paternal worklessness on the child's probability of employment two conditions must be met. First the respondent's mental health must be affected by their father's worklessness when aged 14. Second this mental health must have an independent effect, when controlling for father's employment status at age 14, on the child's probability of being employed.

Figure 1 presents the causal scheme of mediation that we test. The interesting parameters are the total effect " Γ " of having a father who did not work on whether the respondent works or not, but also the direct effect " γ " after controlling for the appropriate mediator. To check whether there is a real mediating effect we also estimate " α " by regressing the mediator on whether the father did not work at age 14, and " β " by regressing whether the respondent works or not on the mediator, controlling for whether the father worked or not at age 14. We use OLS regression for continuous dependent variables and binary logistic regression for dichotomous variables.

It is not very straightforward to check the proportion of the total effect " Γ " that is mediated through the indirect effect " $\alpha*\beta$ " as we have binary outcomes and some binary mediators, meaning that the scale in which the coefficients are expressed differ (Hicks and Tingley, 2011). We follow Macmillan (2012) in estimating all parameters with OLS, meaning we estimate a linear probability model for binary outcomes. We can then easily calculate the proportion of the total effect " Γ " that is accounted for through the indirect effect " $\alpha*\beta$ ".

We estimate this for each mediator separately with all relevant control variables for working or not included. We also run a model where all indicators for one pathway are included to estimate the explanatory power of that transmission mechanism.

Figure 1: causal scheme of mediation variables (Mackinnon and Dwyer, 1993)



Respondents' psychological wellbeing as mediator of father's worklessness

The respondent's psychological wellbeing is measured through two dummy variables. The first one indicates mental health and equals 1 if the respondent scores in the top quartile of the Likert-scale general health questionnaire (GHQ). This is a validated scale for recent changes in mental health status where a higher score indicates higher probability of mental problems (Goldberg et al., 1997). While this mostly captures recent changes in mental health it may also indicate a more precarious general mental health. We also include a dummy indicating that the respondent felt completely, mostly or somewhat dissatisfied with life in general. 12% of our respondents feel at least somewhat dissatisfied. Both of these variables, measured in the first wave, capture subjective well-being (Warr, 1990). This well-being has been shown to be influenced by parental job loss (Larson et al., 1994). The correlation between the two dummies is 0.31 and significant at $p < 0.05$ which is not too high.

Respondent's attitudes as mediator of father's worklessness

Schoon et al. (2012) state that attitudes towards education and the labour market are influenced by parental worklessness and may influence later labour market experiences. We use 7 variables to capture attitudes or non-cognitive skills that are expected to play a mediating role. We measure a factor built from 7 items that indicate a positive outlook on life

and self-confidence² which are measured on a 1 to 5 scale with a higher score indicating a more positive outlook. This scale had a Cronbach's alpha of 0.86. Groves (2005) found that locus of control, a feeling of control over what happens, explained about 11% of the intergenerational transmission in income. Armstrong (2012) showed that even early decisions regarding education are influenced by this sense of control which parents can transmit to their children. We capture this through three dummy variables that indicate that someone feels moderate or strong powerlessness regarding whether what happens in life is beyond personal control, whether someone has control over things at home, and whether there are too many demands made on the respondent. The feeling of powerlessness in general and the feeling that too many demands are made on the respondent correlate with a coefficient of 0.38 which is high but not too high. The feeling of control at home and control in life are correlated with a coefficient of -0.05. Dohmen et al. (2012) showed that attitudes towards risk and trusting people influenced economic outcomes and are strongly transmitted from parents to children. We include three variables to capture this. We include a dummy indicating that the respondent thinks you can't be too careful rather than believing most people can be trusted. We also include two variables which indicate whether the respondent is prepared to trust strangers and prepared to take risks in general on a scale from 0 to 10. These two have a correlation of 0.38. The willingness to trust and the dummy indicating that you can't trust anyone are correlated with a coefficient of -0.19. These 7 variables will be included separately to test their mediating role in the transmission of worklessness. They will then be put in together to judge how much of the intergenerational correlation in worklessness can be accounted for by the respondent's non-cognitive skills.

Father's social networks as a mediator for father's worklessness

We use the same methodology to test the mediating effect of paternal social networks, albeit on a restricted sample of young adults who lived with their fathers in at least one of the waves of the UKHLS. The father of 801 (33%) of the respondents is also included as a respondent in the survey. We create a scale that measures a sense of belonging and being embedded in the neighbourhood³. These items are measured on a 1 to 5 scale with a higher score indicating stronger ties with the neighbourhood. The Cronbach's alpha of this scale was 0.88. We also include a second scale composed of three questions regarding the respondent's relationship to

² The items are: 'feeling optimistic about the future'; 'feeling useful'; 'feeling relaxed'; 'dealing with problems well'; 'thinking clearly'; 'feeling close to others'; 'able to make up own mind'.

³ The items are: 'belong to neighbourhood'; 'local friends mean a lot'; 'advice obtainable locally'; 'can borrow things from neighbours'; 'willing to improve neighbourhood'; 'plan to stay in neighbourhood'; 'am similar to others in neighbourhood'; 'talk regularly to neighbours'

his/her friends⁴ which is only asked if the respondent reported having friends. This scale is coded from 1 to 4 with 4 indicating a stronger relationship with friends. The Cronbach's alpha of this scale was 0.84. If the respondent reported having no friends (6%) this was coded as 0 on the scale. Because of the smaller sample we do not look at the model with both measures included but only include them one at a time. This leaves a sample of 628 respondents for the effect of father's friends and 615 for father's neighbourhood embeddedness. When restricting the sample to only include those whose fathers either did not work or worked in lower paying occupations when the child was aged 14 we are left with respectively 197 and 183 respondents. These measures are not perfect because they will mostly capture the strong ties of the father rather than the extent of his network, which is more useful in job search (Lin, 2001).

Change in respondent's attitude towards work through father's worklessness

We test whether respondents whose fathers did not work experience worklessness differently than their peers whose fathers worked by looking at the association of being out of work with satisfaction with leisure time and overall wellbeing. We use dummy variables indicating the respondent is mostly or completely dissatisfied with the amount of leisure time or life in general. If worklessness is experienced differently we expect a smaller difference in dissatisfaction with leisure time between working and not working for children whose father did not work than for children whose fathers worked in a lower paying job. The latter are expected to report more dissatisfaction when out of work.

We estimate two binary logistic regressions; one where being dissatisfied with leisure time is the dependent variable and one studying having low overall life satisfaction. The independent variables are the same in both models: whether the respondent is employed or not and the father's employment status when the respondent was aged 14. We also include whether the respondent was employed in the previous wave of the UKHLS as well as the control variables also used in the equation regarding employment. We then estimate a further model including an interaction term between the employment status of the respondent in the second wave and of the father at age 14. If being out of work is experienced differently in terms of dissatisfaction with life or leisure time by respondents depending on their father's employment status while growing up we expect a significant interaction term.

⁴ items are: how much do they understand, how much can you rely on them, how much can you open up

Missing observations and descriptive statistics

There are many missing observations among these variables which is problematic as the sample is quite small. For three of the variables, age of the father (49% missing), education of father (17% missing) and education of mother (14%) we can rely on the structure of the UKHLS to impute missing values. When the father and/or mother are present as respondents we can use their information on age and/or education and reduce the missing observations to respectively 18%, 11% and 6%.

Table A1 in the appendix presents the means and standard deviations of the variables that are included in this analysis. We also report the number of missing observations. Our total sample consists of 2,441 respondents, but only 1,747 of those have a job and can therefore have labour market outcomes. We also present the likelihood ratio test of the binary logistic regression of a dummy indicating a respondent has a missing value on that variable on father's occupation, age and education of respondent. This statistic is chi square distributed with 8 degrees of freedom. Knowing if a missing value can be predicted is important to decide the strategy of dealing with the missing cases. The commonly used method consists of listwise deletion, dropping all cases that have at least one missing value. This assumes that the missing pattern is completely at random (MCAR) (Enders, 2010). We use multiple imputation. Table A1 also presents the mean and standard deviation of all variables after multiple imputations of the missing values.

Multiple imputation is considered one of the best ways to deal with the problem of missing data (Enders, 2010). Multiple imputation consists of three phases. In a first phase an imputation model is built where the available information in the dataset is used to offer plausible values for the missing variables. The benefit of multiple imputation over any single imputation technique is that it accounts for the uncertainty connected to the missing data by creating several datasets that hold plausible values. The imputation model needs to contain all the variables and relations that will be used in the final analysis but is not restricted to this (Enders, 2010). The next step is performing the preferred analysis on all datasets and in a final step Rubin's combination rules are used to pool the estimates. These have been shown to be unbiased if the data are missing at random (given the observed variables used in the imputation model) (Enders, 2010). We use multiple imputation by chained equations. Each dataset is created through an iterative process where all variables are used to impute all the others through sequential imputations (Royston and White, 2011). We use all the variables specified in table 1 in the imputation model, as well as the labour market outcomes in the first

wave. It is not a problem and even necessary to include all variables that will be independent variables to impute among others the dependent variable (Enders, 2010). As a rule of thumb it is advised to use at least as many imputations as the percentage of missing data that needs to be imputed. For the question on how often the respondent sees their father 48% of the responses are missing. We therefore create 50 datasets. In order to test the quality of the imputation we compare the means and standard deviations after imputation with those of only the observed cases and see they are very similar.

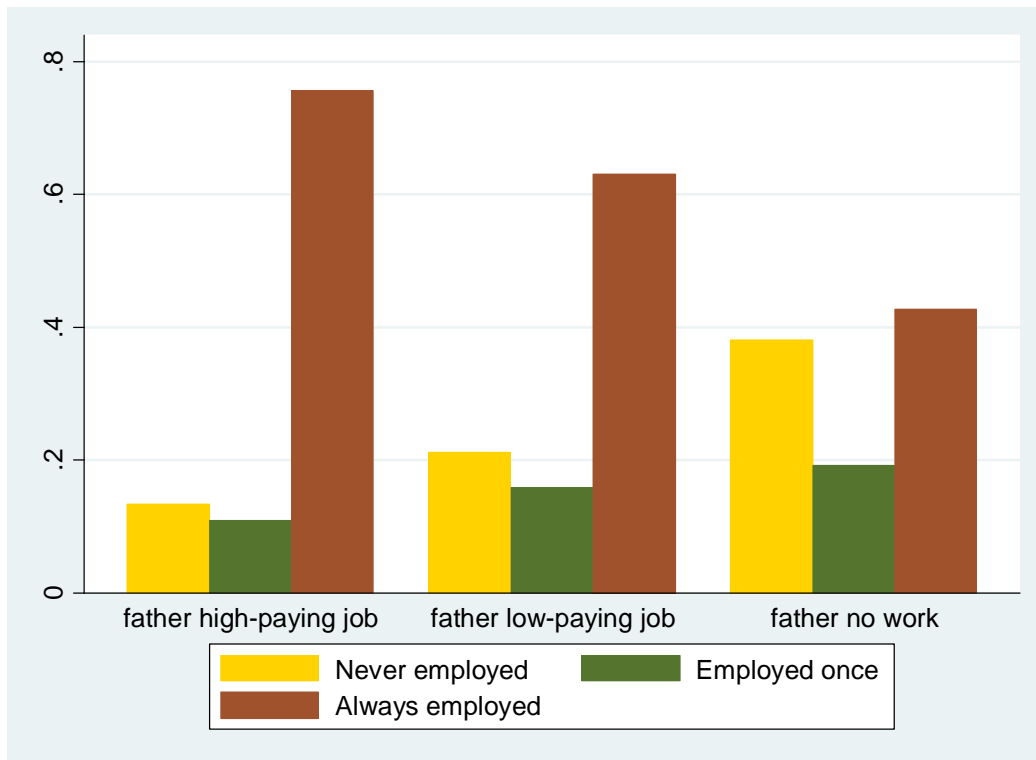
As a robustness test we compare the outcomes we find using the multiply imputed data with the data on the smaller subsample of complete cases. We find comparable results with much more precision for the multiple imputations which strengthens our confidence in the results.

Results

Difference in employment

Figure 2 below illustrates employment differences between children depending on their father's occupational status while they grow up. The proportion of young adults who reported being employed in none, one or both of the waves of the UKHLS is presented by the father's occupational status. The percentage of children who worked in both waves decreases as father's occupational status becomes less advantageous. The vast majority of respondents with fathers in well paying occupations were employed in both waves. Respondents whose fathers did not work are almost as likely to be out of work in both waves as they are to be continuously employed. The fact that children of fathers who were workless at some point are less likely to be employed themselves is important and follows the findings in the literature (Macmillan, 2010). Children of workless fathers are clearly distinct from those whose fathers worked, even if there is a difference depending on whether the respondent's father worked in a lower or higher paying job.

Figure 2: *employment status of children in 2009-2010 and 2010-2011 depending on father's occupational status*



Estimated treatment effect of experiencing father's worklessness

In this section we estimate the effect of their father's worklessness for young adults whose fathers did not work when they were aged 14. This is done through a comparison of the average outcome for these respondents and their predicted scores had their fathers been employed (Schafer and Kang, 2008). The regression coefficients used to obtain the counterfactual labour market outcomes are presented in table A2 in the appendix.

Table 2 below presents the observed and counterfactual outcomes and the difference between them: the average treatment effect. We find that experiencing parental worklessness when aged 14 lowers the probability of being employed significantly by 16%. Even when employed these young adults work on average 2 hours fewer per week and earn £96 gross less per month, controlling for hours worked. This could be due to a selection into lower paid work as they are not more likely to have a lower hourly wage relative to their peers. On top of these effects we also find that young adults whose father was out of work when they were aged 14 are more likely to be dissatisfied while working even when controlling for all the labour market outcomes we study. This may indicate a different evaluation of objective job characteristics or it may indicate that there are some aspects, such a job security or

environment in which they work that we do not measure but are worse for respondents whose fathers did not work. These differences are statistically significant.

Table 2: estimated effect of father not working rather than working

Outcome	Nr. treated	Nr. Control used	Average observed (Std. Error)	Average counterfactual (Std. Error)	Difference (Std. Error)
Working	338	1877	0.52 (0.03)	0.68 (0.01)	-0.16 (0.03)***
Work part-time	175	1396	0.39 (0.04)	0.32 (0.01)	0.07 (0.04)*
Hours/week	175	1396	28.52 (0.89)	30.72 (0.33)	-2.20 (0.83)***
Low job satisfaction	175	1396	0.21 (0.03)	0.13 (0.00)	0.09 (0.03)***
Fixed-term contract	175	1396	0.13 (0.03)	0.17 (0.01)	-0.03 (0.03)
Low hourly wage given occupation	175	1396	0.58 (0.04)	0.57 (0.01)	0.01 (0.04)
Low hourly wage given education	175	1396	0.57 (0.04)	0.58 (0.01)	-0.01 (0.04)
Gross monthly labour market income	175	1396	934.92 (46.73)	1030.88 (44.83)	-95.96 (41.80)**

*: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$

Respondents whose fathers did not work will on average also grow up in families with fewer financial means. This makes it harder to disentangle the effects of paternal worklessness from those of a low family income. Restricting the control group to respondents whose fathers worked in lower paying occupations ought to limit this difference in financial means between the treated and control group. We use the regression coefficients from models estimated for respondents whose fathers worked in lower paying occupations to estimate the counterfactual score. These coefficients are presented in table A3 in the appendix.

Table 3 presents the results. They are similar to those shown in table 3 with the exception that the penalty of paternal worklessness in monthly labour market income is reduced from £96 to £53 and is no longer statistically significant. This indicates that at least part of the effect of paternal worklessness on monthly labour market income was due to the family's financial means while the respondent was 14 and not to the father's employment status. Some of the association between paternal worklessness and the child's labour market income shown in table 3 could hence be due to a decreased opportunity for human capital investment that is experienced by fathers who did not work and by those who earned less (Becker and Tomes, 1994). On the other hand, the difference in time spent working when employed has increased

a little bit. Children whose fathers did not work are statistically significantly more likely to work part-time if employed. The other effects do not change substantially.

Table 3: estimated effect of father not working rather than working in lower paid occupation

Outcome	Nr. treated	Nr. Control used	Average observed (Std. Error)	Average counterfactual (Std. Error)	Difference (Std. Error)
Working	338	545	0.52 (0.03)	0.68 (0.01)	-0.16 (0.03)***
Work part-time	175	378	0.39 (0.04)	0.31 (0.01)	0.08 (0.04)**
Hours/week	175	378	28.52 (0.89)	31.98 (0.27)	-3.46 (0.85)***
Low job satisfaction	175	378	0.21 (0.03)	0.13 (0.01)	0.09 (0.03)***
Fixed-term contract	175	378	0.13 (0.03)	0.14 (0.01)	-0.01 (0.03)
Low hourly wage given occupation	175	378	0.58 (0.04)	0.62 (0.02)	-0.04 (0.04)
Low hourly wage given education	175	378	0.57 (0.04)	0.62 (0.02)	-0.05 (0.04)
Gross monthly labour market income	175	378	934.92 (46.73)	988.07 (60.35)	-53.16 (0.30)

*: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$

To summarize, our results show that father's worklessness has strong effects on their children's probability of being employed as young adults. This is not all however, as young adults who experienced their father's worklessness are less likely to work full-time and are less satisfied with their jobs. We find no effect of experiencing paternal worklessness on the quality of a job seen as the probability of working on a fixed-term contract or of earning less than the median in their wage distribution. Respondents whose fathers did not work earn less on average, but only when comparing them to all children of working respondents. If the control group is restricted to only those children whose fathers worked in a lower paying occupation the difference is no longer statistically significant.

Mediation through psychological well-being, social networks or attitudes

We test the role of mediating factors in the transmission of worklessness from fathers to children. Table 5 presents the impact of our mediating variables and the degree to which they account for this intergenerational association. In a first step we regress the mediator on whether the father was working or not. We present the part of the effect of father's worklessness that is due to an indirect effect through the mediator as the proportion of the indirect effect on the total effect. The indirect effect is measured as the product of the coefficient of the mediator on father's worklessness and the outcome on the mediator and

father's worklessness in linear probability models (Macmillan, 2012). The last column shows the proportion of the total effect of father's worklessness on the probability of being employed that is explained by each separate variable and by the blocks of psychological well-being or attitude variables. The mediating role of the father's social network is analysed using a smaller sample. The sample sizes vary as we can only use the non-missing observations.

Table 4: mediation between father's worklessness and respondent's employment

Mediators	N	Effect father not working on mediator	Effect mediator on working or not (odds ratios)	% effect father not working explained
GHQ score high (binary)	844	1.42 (0.19)*	0.46 (0.21)***	7.33%
Low life satisfaction (binary)	844	1.24 (0.21)	0.53 (0.26)**	2.21%
Well-being	844			7.49%
Low trust (binary)	844	1.19 (0.19)	0.85 (0.19)	0.65%
Control over life (binary)	844	0.89 (0.18)	0.71 (0.21)*	-1.53%
Control at home (binary)	844	1.02 (0.20)	1.27 (0.31)	0.11%
Experience many demands (binary)	844	0.88 (0.18)	0.87 (0.23)	-0.85%
Positive outlook (continuous)	844	-0.07 (0.06)	1.58 (0.14)***	3.83%
Prepared to take risks (cont.)	844	-0.46 (0.24)*	1.04 (0.04)	2.10%
Risk to trust (cont.)	844	0.03 (0.24)	1.10 (0.04)**	-0.31%
Attitudes	844			2.36%
Father embedded in neighbourhood	183	-0.24 (0.11)**	1.07 (0.42)	2.94%
Father's relation with friends	197	0.13 (0.23)	1.02 (0.30)	0.29%

*: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$, controlled for gender, age, education, race, born in UK, speaking English, cohabitation, having children, having poor health, contact with father, lived home at age 16, unemployment rate when aged 14, age of father, father's education, mother's education, on respondents whose father did not work or worked in a lower paying occupation. Standard errors are presented in parentheses

Children of fathers who were not working at age 14 tend to be significantly more averse to taking risks. This is in line with expectations as being prepared to take risks is associated with better economic outcomes and respondents who experienced their father's worklessness may aim to avoid finding themselves in the same situation (Dohmen et al., 2012; Ekhaugen, 2009). Respondents whose fathers did not work are also more likely to report mental health

problems which can be due to increased stress when they were aged 14 which may have longer lasting effects (Ochsen and Welsch, 2011). Those respondents who reported worse mental health are also statistically significantly less likely to be employed when controlling for father's working situation at age 14. This mediation mechanism accounts for 7% of the total effect of father's worklessness which is rather low. The odds of father's worklessness on respondent's employment rise from 0.44 to 0.46 when including respondent's mental health in the first wave. While very small, it is the largest mediating effect we find.

Life satisfaction, a sense of control over life and being likely to trust people as well as having a positive outlook on life have independent effects on the probability of employment but do not mediate the effect of father's worklessness. Table 4 therefore offers a weak indication that father's worklessness may influence children's employment probabilities through their mental health, but it does not account for any substantial part of the effect of father's worklessness. We therefore find no strong indication that children of non-working fathers are less likely to be employed than those whose fathers worked as a result of psychological issues or a change in general attitudes towards the world.

Fathers who did not work when their child was aged 14 have on average a worse relation with their neighbourhood. Neither of the father's social network variables mediates between father's employment status at age 14 and the child's probability of being employed however. This can be due to the indicators of social network not being very appropriate. It would be better to measure the number of employed friends of the father, but we did not have this information (Cappellari and Tatsiramos, 2011; Cingano and Rosolia, 2012).

We cannot test directly whether the transmission of worklessness from father to child is due to the child experiencing worklessness differently and having a stronger attachment to leisure as a result. We can however test this indirectly by looking at the differences in how worklessness is experienced by children whose fathers did not work when the children were aged 14 and by those whose fathers worked in a lower paying job.

Different experience of worklessness depending on father's occupation

We expect non-working respondents to report higher dissatisfaction with their leisure time than working respondents as it comes to be experienced negatively (Jahoda, 1982). If young adults who experienced their father's worklessness when they were aged 14 are less negatively influenced by being out of work we expect less dissatisfaction with their leisure time while out of work. If children of workless fathers suffer less from being out of work we

also expect a lower association between life satisfaction and being out of work. We test this by estimating the interaction term between having a job and father's employment status on both outcomes in binary logistic regression models. If the association between employment and dissatisfaction with life and/or leisure time differs for respondents by their father's employment status the interaction term would be statistically significant. Table 5 presents these coefficients in odds ratios.

None of the variables of interest have a statistically significant effect on the probability of being dissatisfied with leisure, but the direction of the coefficients does follow our expectations. Being employed is associated with a lower probability of being dissatisfied with leisure time for respondents whose father worked in a lower paying occupation. For respondents whose fathers did not work being employed increases the probability of being dissatisfied with leisure time.

Table 5: odds ratios of being employed, father's employment status and their interaction on being dissatisfied with leisure time and life

N=698	Dissatisfied with leisure	Dissatisfied with life
Have a job	0.88 (0.35)	0.64 (0.34)
Father did not work at age 14	0.82 (0.36)	0.88 (0.33)
Interaction	1.78 (0.45)	2.59 (0.43)*

**: $p < 0.05$, weighted and controlled for gender, age, education, race, born in UK, speaking English, cohabitation, having children, having poor health, contact with father, lived home at age 16, unemployment rate when aged 14, age of father, father's education, mother's education and employment in wave 1 on respondents whose father did not work or worked in a lower paying occupation. Standard errors are presented in parentheses.*

The interaction term is statistically significant when explaining dissatisfaction with life overall. The odds of being dissatisfied with life for employed respondents whose fathers worked in a lower paying occupation when they were aged 14 are 0.64 times those of their peers who are not working. For respondents whose father did not work however, the odds of being dissatisfied when employed are 1.66 ($0.64 * 2.59$) times higher than when out of work.

This indicates that on average, respondents whose father did not work at age 14 are more dissatisfied with their life when employed than when out of work. This may indicate that children whose fathers did not work at age 14 are already more familiar with being out of work and therefore suffer less when out of work themselves. Table 6 therefore indicates that experiencing paternal worklessness at age 14 might lead to employment and worklessness

being experienced differently as a young adult. This could be a possible reason for the finding that young adults whose fathers were out of work are less likely to be employed themselves and work fewer hours. Their labour supply might be lower as worklessness is not seen as such a bad experience. This may mean they take more time looking for a good job (Tatsiramos, 2006).

Sensitivity and robustness

Sensitivity to inclusion of a binary unobserved confounder

Regression models assume that there are no unobserved covariates correlated with the predictors and the outcomes. This is problematic as fathers and their children share a wide range of characteristics that may influence their success on the labour market. The literature puts forward characteristics such as intelligence and motivation as important characteristics that can be related over generations (Ekhaugen, 2009; Macmillan, 2010).

We do not deal with this unobserved heterogeneity directly. We can however test the robustness of our conclusions to unobserved characteristics through a sensitivity analysis. Groenwold et al. (2010) review three applications of sensitivity analyses. They all make assumptions about the type of unobserved characteristics, such as the relation with the independent variable of interest and the strength of the relation with the outcome, to estimate the true effect of the treatment correcting for that confounder. By changing these characteristics the plausibility of an unobserved covariate of sufficient strength to change the conclusions regarding the treatment effect can be evaluated. We use a method first proposed by Lin et al. (1998). They show a straight-forward correction factor to adjust the estimated effect of having a father who did not work, based on three parameters. First, the odds of the unobserved binary confounder on the outcome (Γ); second, the probability that the confounder is present in the treatment group ($P1$); and third the probability that the confounder is present in the control group ($P0$). They show analytically that the true effect of the treatment, R , equals R^* , the observed treatment effect in a reduced model without unobserved covariates, divided by an adjustment factor A . Equations 2 and 3 present this (Lin et al., 1998). The same adjustment factor can be used on the boundaries of the confidence interval so we can assess the significance of the results. Groenwold et al. (2010) state that this method is a more conservative estimate as the correlations between the unobserved covariates and the observed covariates are not taken into account.

$$2. R = R^*/A$$

$$3. A = \frac{\Gamma_1 P_1 + (1 - P_1)}{\Gamma_0 P_0 + (1 - P_0)}$$

We assume a binary unobserved confounder which is positively related with the respondent being employed and negatively related to the father not working when the child was aged 14. This could be a concept such as capability or motivation for work. If we assume $\Gamma=2$, meaning that someone with the unobserved confounder has odds that are twice as high of being in work than someone without, the unobserved confounder would have to be very unequally distributed to make the effect of having a father who did not work insignificant. If all of those whose father worked in a lower paying job would have the unobserved confounder, at most 20% of those whose father did not work can have the unobserved confounder for the effect to no longer be significant. When assuming an unlikely high $\Gamma=6$ the required difference is smaller. If 30% of the children whose father worked possessed the unobserved confounder versus at most 10% of the children whose father did not work, the effect would no longer be significant when including this covariate. Tables A4 to A9 in appendix 2 present the odds ratio effect of having a father who did not work on their children's probability of employment, corrected for different levels of Γ , P_1 and P_0 .

In order to assess the likely strength of these confounders, we can compare them with the effect and prevalence of observed confounders that are likely to be important. The odds of having a higher education degree rather than no qualifications at all on the probability of being employed are 2.34 when including no control variables. Only 5.9% of the children whose father did not work have a higher degree, versus 12.3% of those whose fathers worked in a lower paying occupation. Introducing an unobserved confounder with a similar relation to the treatment and outcome to the model would correct the odds of having a non-working father from 0.44 to 0.46 and it would still be significant at $p<0.05$. This indicates that our results are robust to the inclusion of an unobserved confounder which is at least as strong as the difference between having a higher education degree versus no degree at all which inspires confidence.

Different specifications

We perform several other robustness tests. The results of these tests for the different outcomes are shown in table A10 in the appendix. As already described we try out different thresholds to categorize a father's occupation as a lower paying occupation. Instead of selecting occupations that ranked in the lowest quartile of hourly wage from 2002-2010, we

redo the analyses with occupations ranking in the lowest half and in the lowest 10%. In the latter we could not obtain an estimate for job satisfaction as due to the smaller sample size some variables predicted a low job satisfaction perfectly and had to be dropped which lead to inconsistency in the sample size between imputations. We find the same effect on labour supply and job satisfaction as when using the lowest 25% earning occupations. When restricting the sample to only the lowest 10% it is estimated that growing up with a non-working father leads to a 13% lower probability of earning less than the median hourly pay given age, gender and education. When using a less restrictive sample there is still an estimated difference in monthly wage showing that this difference becomes smaller as the financial advantage of the control group becomes smaller. On the whole however, the main conclusions are similar.

We also perform a complete cases analysis to compare these results to the ones obtained through multiple imputations. As there are too many missing values on the variable regarding how often the respondent sees their father this is left out when comparing complete cases analysis with multiple imputation. When dropping missing cases listwise we retain 60 treated and 712 control units. The coefficients are larger but we draw very similar conclusions as in the multiple imputation model. The main differences are that respondents whose fathers did not work are statistically significantly more likely to work part-time and are also more likely to have a wage that is less than the median given their age, gender and occupation in the complete cases analysis.

As the main labour market outcome we look at whether the respondent is working or not. In a robustness test we take the slightly more restrictive distinction of having reported being in employment rather than unemployed as main activity. This leaves us with 2,025 respondents of whom 81% are employed. There are no substantial or statistically significant differences between these two operationalisations of working or not.

We measure the labour market outcomes in the first wave rather than the second. This leads to quite different results however. Respondents whose fathers did not work are still less likely to be employed, but are also less likely to work part-time and work no fewer hours than respondents whose fathers worked in lower paying occupations. They are also not significantly less satisfied with their jobs. This suggests that it would be good to study these outcomes more dynamically rather than looking at only one wave.

Osterbacka (2004) found that the intergenerational transmission of unemployment differed by gender with men being more influenced by their family background and women more by their current family situation. To test whether our main conclusions hold for both men and women we estimated the main comparison between respondents whose father did not work and what their outcomes would have been had their father worked in a lower paying occupation, separately for men and women. We find that both men and women are likely to be less often employed and to work fewer hours on average when employed if their father did not work at age 14. Paternal worklessness does seem to affect them differently in terms of being dissatisfied with their job and working part-time however. Men whose father did not work at age 14 are 16% more likely to work part-time while the difference for women is much smaller at 7% and is not significant. It has to be noted however that 44% of women whose father did not work are in a part-time job versus 31% of men whose father did not work.

Finally we compare the outcomes of children whose fathers did not work to what their outcomes would have been had their father worked in a lower paying occupation, estimated through propensity score matching. Propensity score matching is shown to be less biased than regression if there are large initial biases and if the covariates and relations between them are not correctly modelled. We therefore use it as a robustness test for the functional form of the model (Schafer and Kang, 2008). The propensity score is a predicted score of belonging to the treatment category which is estimated on all the control variables we use for the different outcomes. We can then compare each respondent whose father did not work to one or more control respondents with fathers who worked in lower paying occupations and who have a similar propensity to have a father that did not work. By balancing on this propensity score we compare respondents with very similar characteristics in that they have an equal or similar predicted probability of having a father who did not work (Caliendo and Kopeinig, 2008). Following Mitra and Reiter (2010) we calculated the propensity score using the multiply imputed datasets and then used this propensity score to match on the original dataset. We evaluate the matching in terms of the non-missing variables. Radius matching with a calliper of 0.1 had the lowest remaining bias after matching for most of the outcomes. We matched on the same variables that were controlled for. When comparing respondents whose fathers did not work with their counterparts whose fathers worked in lower paying occupations we found similar results as when using regression to estimate the ATT which strengthens the

confidence in our results. Respondents whose fathers did not work are estimated to earn about £101 less per month however and this is statistically significant.

To conclude, we can state that the effect of father's worklessness on the probability of being employed is robust and strong. We also find that in 2010-2011 children of non-working fathers are more likely to work part-time and to work fewer hours. They are also more likely to be dissatisfied. This is not replicated in the first wave however.

Discussion and conclusion

As unemployment and worklessness rises, especially among young people, it becomes more important to take the probability of employment as well as aspects of job quality into account when studying intergenerational economic (dis-)advantage. We extend on previous studies by assessing the effects of experiencing a father out of work when aged 14 on several labour market outcomes as a young adult. This is especially important as being out of work is linked to a range of adverse outcomes that may have long-term effects.

This paper shows that young adults whose father did not work when they were aged 14 are less likely to be employed themselves. When employed, they tend to work fewer hours and work part-time more often than their counterparts whose fathers did work even if they worked in lower paid occupations. On average young adults whose fathers did not work do not have lower wages or less secure contracts. They are however more often dissatisfied with their job.

We tested several mediating mechanisms that may account for the difference in employment: decreased human capital investment through lower financial means, mental health and wellbeing, attitudes, social networks and a sense of stigma towards being out of work. Financial losses associated with being out of work explained why children of non-working fathers earned on average £100 less per month than their peers whose fathers worked. This partly supports the idea that non-working fathers are less able to invest in their children's human capital, leading them to experience less success on the labour market. They do not seem to play an important role in explaining why children of non-working fathers are less likely to be employed however. Decreased well-being or having less beneficial attitudes and behaviours did not account for more than 7% of the association between a father not working and his child being out of work when aged 16-25. We also found no support for a father's social networks playing an important role.

We do find indications that young adults whose fathers did not work experience being out of work differently. While in the general population not working is associated with a higher dissatisfaction than working, we find it is the reverse for young adults whose fathers did not work when they were younger. They are more likely to state being dissatisfied when employed than when out of work. As being out of work is coupled with fewer negative feelings, having already experienced your father's worklessness while being younger may

decrease the stigma of not working. This could lead to a different evaluation of the time that needs to be spent working, as well as lead to less suffering from being out of work.

Our paper indicates the importance of taking family background into account when studying labour market experiences. It also shows that the high unemployment rates that occur now may have longer-term repercussions later on as these workless young adults have children of their own. A good starting point for further analyses is to look at the experiences of unemployment. Our paper indicates that children of non-working fathers differ from their peers in the way they experience being out of work. It exacts less of a psychological toll and might be preferred over work. It would be interesting to see whether these effects hold for all jobs or whether children of non-working fathers are more often selected into a certain type of job that has a disadvantage we did not capture here. It might also be fruitful to study these different labour market outcomes over time to get a clearer view of the effect of family background on different labour market trajectories.

References

- Andersen, S.H. (2011). Common Genes or Exogenous Shock? Disentangling the Causal Effect of Paternal Unemployment on Children's Schooling Efforts. *Eur. Sociol. Rev.* *0*, 1–12.
- Armstrong, A. (2012). Belief in a Just World and Children's Cognitive Scores. *Natl. Inst. Econ. Rev.* *222*, R7–R19.
- Becker, G.S., and Tomes, N. (1994). Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education. G.S. Becker, ed. (The University of Chicago Press), pp. 257–298.
- Bianchi, S.M., Casper, L.M., and King, R.B. (2005). Complex Connections: A Multidisciplinary Look at Work, Family, Health and Well-Being Research. In *Work, Family, Health, and Well-Being*, S.M. Bianchi, L.M. Casper, and R.B. King, eds. (London: Lawrence Erlbaum Associates, Publishers), pp. 1–17.
- Bowles, S., Gintis, H., and Groves, M.O. (2005). Introduction. In *Unequal Chances: Family Background and Economic Success*, S. Bowles, H. Gintis, and M.O. Groves, eds. (New York, Princeton and Oxford: Russell sage foundation and Princeton University Press), pp. 1–22.
- Bramoullé, Y., and Saint-Paul, G. (2010). Social networks and labor market transitions. *Labour Econ.* *17*, 188–195.
- Burchell, B. (1994). The Effects of Labour Market Position, Job Insecurity, and Unemployment on Psychological Health. In *Social Change and the Experience of Unemployment*, D. Gallie, C. Marsh, and C. Vogler, eds. (Oxford University Press), pp. 188–211.
- Caliendo, M., and Kopeinig, S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *J. Econ. Surv.* *22*, 31–72.
- Cappellari, L., and Tatsiramos, K. (2011). Friends' networks and job finding rates. *ISER Work. Pap. Ser.* *2011-21*, 1–48.
- Cingano, F., and Rosolia, A. (2012). People I know: Job Search and Social Networks. *J. Labor Econ.* *30*, 291–332.
- Corak, M., and Piraino, P. (2011). The intergenerational Transmission of Employers. *J. Labor Econ.* *29*, 37–68.
- Dohmen, T., Falk, A., Huffman, D., and Sunde, U. (2012). The Intergenerational Transmission of Risk and Trust Attitudes. *Rev. Econ. Stud.* *79*, 645–677.
- Ekhaugen, T. (2009). Extracting the causal component from the intergenerational correlation in unemployment. *J. Popul. Econ.* *22*, 97–113.
- Enders, C.K. (2010). The Imputation Phase of Multiple Imputation. In *Applied Missing Data Analysis*, (New York: The Guilford Press), pp. 187–216.
- Erikson, R., and Goldthorpe, J.H. (2010). Has social mobility in Britain decreased? Reconciling divergent findings on income and class mobility. *Br. J. Sociol.* *61*, 211–230.
- Eurostat (2013). *Europe in figures - Eurostat yearbook*.

- Frijters, P., Johnston, D., and Shields, M. (2010). Mental health and labour market participation: Evidence from IV panel data models. IZA Discuss. Pap. Ser.
- Gallie, D., Gershuny, J., and Vogler, C. (1994). Unemployment, the Household, and Social Networks. In *Social Change and the Experience of Unemployment*, D. Gallie, C. Marsh, and C. Vogler, eds. (Oxford University Press), pp. 231–263.
- Goldberg, D.P., Gater, R., Sartorius, N., Ustun, T.B., Piccinelli, M., Gureje, O., and Rutter, C. (1997). The validity of two versions of the GHQ in the WHO study of mental illness in general health care. *Psychol. Med.* 27, 191–197.
- Granovetter, M. (1995). *getting a job* (The University of Chicago Press).
- Green, F. (2011). Unpacking the misery multiplier: How employability modifies the impacts of unemployment and job insecurity on life satisfaction and mental health. *J. Health Econ.* 30, 265–276.
- Gregg, P., and Tominey, E. (2005). The wage scar from male youth unemployment. *Labour Econ.* 12, 487–509.
- Groenwold, R.H.H., Nelson, D.B., Nichol, K.L., Hoes, A.W., and Hak, E. (2010). Sensitivity analyses to estimate the potential impact of unmeasured confounding in causal research. *Int. J. Epidemiol.* 39, 107–117.
- Groves, M.O. (2005). Personality and the Intergenerational Transmission of Economic Status. In *Unequal Chances: Family Background and Economic Success*, S. Bowles, H. Gintis, and M.O. Groves, eds. (New York, Princeton and Oxford: Russell sage foundation and Princeton University Press), pp. 208–231.
- Heineck, G., and Riphahn, R.T. (2007). Intergenerational transmission of educational attainment in Germany - the last five decades. *SOEPpapers Multidiscip. Panel Data Res.* 37, 1–37.
- Hicks, R., and Tingley, D. (2011). Causal mediation analysis. *Stata J.* 11, 605.
- Holzer, H.J. (1988). Search Method Use by Unemployed Youth. *J. Labor Econ.* 6, 1–20.
- Jahoda, M. (1982). *Employment and unemployment: a social-psychological analysis* (Cambridge: Cambridge University Press).
- Johnson, P., and Reed, H. (1996). intergenerational mobility among the rich and poor: results from the national child development survey. *Oxf. Rev. Econ. Policy* 12, 127–142.
- Jonsson, J.O., Grusky, D.B., Carlo, M.D., Pollack, R., and Brinton, M.C. (2007). *Micro-Class Mobility Social Reproduction in Four Countries*.
- Jonsson, J.O., Grusky, D.B., Pollak, R., Di Carlo, M., and Mood, C. (2011). Occupations and Social Mobility: Gradational, Big-Class, and Micro-Class Reproduction in Comparative Perspective. In *Persistence, Privilege, and Parenting*, T.M. Smeeding, R. Erikson, and M. Jäntti, eds. (New York: Russell Sage Foundation), pp. 138–172.
- Kalleberg, A.L. (1977). Work Values and Job Rewards: A Theory of Job Satisfaction. *Am. Sociol. Rev.* 42, 124.

- Larson, J.H., Wilson, S.M., and Beley, R. (1994). The impact of job insecurity on marital and family relationships. *Fam. Relations* 138–143.
- Lee, C.-I., and Solon, G. (2009). Trends in Intergenerational Income Mobility. *Rev. Econ. Stat.* 91, 766–772.
- Leontaridi, R., and Sloane, P. (2001). Measuring the Quality of Jobs. *Low. Work. Pap.* 7, 5–42.
- Lin, N. (2001). *Social Capital* (Cambridge University Press).
- Lin, D.Y., Psaty, B.M., and Kronmal, R.A. (1998). Assessing the Sensitivity of Regression Results to Unmeasured Confounders in Observational Studies. *Biometrics* 54, 948–963.
- Loury, L.D. (2006). *Informal Contacts and Job Search Among Young Workers* (Department of Economics, Tufts University).
- Mackinnon, D.P., and Dwyer, J.H. (1993). Estimating Mediated Effects in Prevention Studies. *Eval. Rev.* 17, 144–158.
- Macmillan, L. (2010). The Intergenerational Transmission of Worklessness in the UK. *Cent. Mark. Public Organ. Work. Pap.* 52.
- Macmillan, L. (2012). The role of non-cognitive and cognitive skills, behavioural and educational outcomes in accounting for the intergenerational transmission of worklessness. pp. 1–38.
- Mazumder, B. (2005). The apple falls even closer to the tree than we thought: new and revised estimates of the intergenerational inheritance of earnings. In *Unequal Chances: Family Background and Economic Success*, S. Bowles, H. Gintis, and M.O. Groves, eds. (New York, Princeton and Oxford: Russell sage foundation and Princeton University Press), pp. 80–99.
- Mitra, R., and Reiter, J.P. (2010). A comparison of two methods of estimating propensity scores after multiple imputation. *Stat. Methods Med. Res.*
- O’Neill, D., and Sweetman, O. (1998). Intergenerational Mobility in Britain: Evidence from Unemployment Patterns. *Oxf. Bull. Econ. Stat.* 60, 431–447.
- Ochsen, C., and Welsch, H. (2011). The social costs of unemployment: accounting for unemployment duration. *Appl. Econ.* 43, 3999–4005.
- Osterbacka, E. (2004). *It Runs in the Family: empirical analyses of family background and economic status*. Abo Akademi University Press.
- Payne, J. (1987). Does Unemployment Run in Families? Some Findings from the General Household Survey. *Sociology* 21, 199–214.
- Royston, P., and White, I.R. (2011). Multiple imputation by chained equations (MICE): implementation in Stata. *J. Stat. Softw.* 45, 1–20.
- Rubin, D.B. (1979). Using Multivariate Matched Sampling and Regression Adjustment to Control Bias in Observational Studies. *J. Am. Stat. Assoc.* 74, 318.
- Schafer, J.L., and Kang, J. (2008). Average causal effects from nonrandomized studies: A practical guide and simulated example. *Psychol. Methods* 13, 279–313.

Schoon, I., Barnes, M., Brown, V., Parsons, S., Ross, A., and Vignoles, A. (2012). Intergenerational transmission of worklessness: Evidence from the Millennium Cohort and the Longitudinal Study of Young People in England.

Smith, J.P. (2004). Unraveling the SES-Health Connection. *Popul. Dev. Rev.* 30, 108–132.

Solon, G. (1999). Intergenerational Mobility in the Labor Market. In *Handbook of Labor Economics*, (Amsterdam: Elsevier), pp. 1761–1796.

Stevens, A.H., and Schaller, J. (2011). Short-run effects of parental job loss on children's academic achievement. *Econ. Educ. Rev.* 30, 289–299.

Stewart, M.B. (2007). The interrelated dynamics of unemployment and low-wage employment. *J. Appl. Econ.* 22, 511–531.

Tatsiramos, K. (2006). Unemployment Insurance in Europe: Unemployment Duration and Subsequent Employment Stability. *IZA Discuss. Pap. Ser. no.2280*, 1–43.

Warr, P. (1990). The measurement of well-being and other aspects of mental health. *J. Occup. Psychol.* 63, 193–210.

Appendix:

Appendix 1: regression tables for different outcomes

Table A1: descriptive statistics of variables before and after imputation and log-likelihood ratio (df=8) of predicting missing by age, father's employment and education for whole sample

Variables	Mean (std. Dev)	Observed	Imputed	LR (df=8), by age, father's employment and education	Mean (std. Dev) from 50 imputations
Father not working	0.14	2441	0		0.14
Father working low occupation	0.26	2441	0		0.26
Father working other occupation	0.60	2441	0		0.60
Have a job	0.72 (0.45)	2441	0		0.72 (0.45)
Part-time job	0.27 (0.44)	1621	126	22.38*	0.28 (0.45)
Low job satisfaction	0.14 (0.35)	1622	125	21.11*	0.13 (0.33)
Temporary job	0.14 (0.35)	1743	4	5.17*	0.15 (0.35)
Low hourly wage given occupation	0.50 (0.50)	1362	385	260.69*	0.48 (0.50)
Low hourly wage given education	0.50 (0.50)	1382	365	334.82*	0.48 (0.53)
Hours worked	32.19 (11.47)	1661	86	13.31*	31.92 (11.62)
Monthly labour income	1204.65 (942.61)	1747	0	4.98	1184.07 (973.24)
Dissatisfied with leisure	0.10 (0.29)	1967	474	13.37*	0.09 (0.26)
Dissatisfied with life	0.14 (0.34)	1959	482	13.35*	0.14 (0.31)
General outlook	3.54 (0.64)	2073	368	12.72	3.53 (0.65)
Low mental health	0.27 (0.44)	2080	361	12.33	0.27 (0.41)
Don't trust people	0.51 (0.50)	2079	362	14.00*	0.51 (0.46)
Control life	0.31 (0.46)	1958	483	15.49*	0.32 (0.42)
Control at home	0.14	1968	473	14.90*	0.15 (0.32)

	(0.35)				
Too many demands	0.22 (0.41)	1938	503	14.80*	0.22 (0.37)
Take risks	6.21 (2.42)	2080	361	16.44*	6.17 (2.26)
Risk to trust	3.68 (2.46)	2081	360	16.44*	3.63 (2.30)
Age	21.54 (2.66)	2441	0		21.50 (2.72)
Father's age	51.73 (7.10)	2014	427	28.03*	51.83 (6.59)
Living with father age 16	0.72 (0.45)	2347	94	13.44*	0.74 (0.43)
Native English speaker	0.89 (0.32)	2347	94	13.44*	0.88 (0.32)
Not born in UK	0.12 (0.32)	2441	0		0.12 (0.33)
White (rather than non-white)	1.21 (0.41)	2347	94	13.44*	1.21 (0.41)
Have children	0.03 (0.16)	1999	442	188.58*	0.04 (0.15)
Poor health	0.12 (0.33)	2440	1		0.13 (0.33)
Live as a couple	0.30 (0.46)	2076	365	14.84*	0.28 (0.42)
Father high education	0.39 (0.49)	2168	273	39.69*	0.37 (0.46)
Mother high education	0.35 (0.48)	2303	138	23.82*	0.34 (0.46)
Qualifications: degree	0.17 (0.37)	2441	0		0.15 (0.36)
Qualifications: other higher	0.09 (0.28)	2441	0		0.08 (0.27)
Qualifications: A level	0.33 (0.47)	2441	0		0.33 (0.47)
Qualifications: GCSE	0.32 (0.47)	2441	0		0.33 (0.47)
Qualifications: other	0.02 (0.12)	2441	0		0.02 (0.13)
Qualifications: none	0.08 (0.27)	2441	0		0.08 (0.28)
How often see father (1-6)	3.00 (1.52)	1266	1175	166.96*	2.83 (1.18)
National unemployment rate (when child aged 14)	5.44 (0.50)	2441	0		5.45 (0.51)
Male	0.44 (0.50)	2441	0		0.44 (0.50)

*: $p < 0.10$

Table A2: regressions of labour market outcomes on control sample of all working fathers

Coefficients	Working (logit)	Job hours (OLS)	Part-time (logit)	Fixed-term (logit)	Low by occ. (logit)	Low by ed. (logit)	Monthly wage (OLS)	Low job sat. (logit)
Age	0.04	1.56	-0.30	-0.28	0.05	0.08	54.39	0.05
Father age	0.00	-0.04	0.00	-0.01	-0.01	-0.01	9.35	-0.01
Live age 16	0.27	0.24	0.04	-0.34	0.09	-0.10	73.18	-0.49
English native speaker	0.10	4.03	-1.18	-1.11	0.27	-0.46	103.07	0.32
Not UK	0.09	1.92	0.09	-0.38	-0.16	-0.36	196.31	-0.01
White	-0.64	-3.87	0.58	0.27	0.18	-0.04	-141.50	-0.61
Poor health	-0.66	-1.58	0.46	-0.85	0.25	0.31	-56.11	0.14
Father education	0.27	-0.26	-0.10	-0.27	-0.21	-0.19	116.22	0.21
Mother education	-0.07	-0.74	0.14	-0.07	-0.03	0.24	-112.75	-0.11
Qual.: degree	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Qual.: other high	-0.24	-2.92	0.27	-0.08	-0.17	-0.32	-269.39	-0.21
Qual.: A level	-0.43	-2.19	0.23	-0.34	-0.03	-0.26	-134.78	0.05
Qual.: GCSE	-1.24	-2.23	0.28	-0.82	0.10	-0.23	-305.94	-0.06
Qual.: other qual	-2.03	-4.25	-0.27	-0.25	0.30	0.13	-308.68	0.00
Qual: none	-2.29	-1.69	0.31	-0.40	0.74	0.45	-518.04	0.13
How often see father	-0.10	0.24	-0.12	0.15	0.12	0.03	-3.38	0.09
Unemployment rate age 14	0.18	-3.14	0.57	0.15	1.17	0.99	87.29	0.09
Male	0.43	5.35	-1.04	-0.07	0.05	0.21	172.60	0.05
Parent	-0.85	-3.23	1.56					
Couple	-0.22	0.19	0.20					
Job hours							38.13	0.02
Monthly wage								0.00
Fixed-term					0.70	0.34		-0.27
Part-time					0.03	0.84		0.26
Low by education								0.31
Low by occupation								-0.31
Constant	0.66	17.05	2.99	4.86	-7.24	-6.03	-2025.04	-2.36
N	1877	1396	1396	1396	1396	1396	1396	1384

*bold coefficients are significant at $p < 0.10$, controlled for appropriate controls and weighted

Table A3: regressions of labour market outcomes on control sample of fathers working in low paying occupations

Coefficients	Working (logit)	Job hours (OLS)	Part-time (logit)	Fixed-term (logit)	Low by occ. (logit)	Low by ed. (logit)	Monthly wage (OLS)	Low job sat. (logit)
Age	-0.16	1.14	-0.24	-0.15	-0.04	0.00	57.07	0.13
Father age	0.00	0.00	0.00	-0.07	-0.00	-0.00	8.52	-0.01
Live age 16	0.30	-0.42	0.36	-0.25	-0.52	-0.49	12.72	-0.23
English	0.59	1.16	-0.77	-0.98	-0.50	-1.01	168.15	-0.07
Not UK	0.05	-1.33	0.80	0.31	-0.47	-0.40	-98.55	0.13
White	-0.10	-0.46	-0.58	0.10	0.41	0.06	-154.08	-0.16
Poor health	-0.76	-1.34	0.56	-0.99	0.81	0.98	-192.53	0.33
Father education	0.18	1.42	-0.02	-0.28	-0.22	0.38	394.70	-0.19
Mother education	0.32	-2.27	0.36	-0.45	0.09	0.14	-228.34	-0.46
Qual.: degree	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Qual.: other high	0.17	-4.91	0.70	-1.03	-0.28	-0.44	-300.45	0.20
Qual.: A level	-0.79	-3.55	0.43	-0.76	-0.02	-0.62	1.73	-0.47
Qual.: GCSE	-1.55	-3.65	0.45	-1.40	-0.04	-0.43	-490.80	0.30
Qual.: other qual	-1.32	- 11.65	0.09	-1.05	0.15	-0.77	247.93	0.00
Qual: none	-2.81	-2.28	0.32	-0.79	1.08	1.23	-777.87	-0.22
How often see father	-0.08	-0.02	-0.08	0.06	0.06	-0.02	-28.62	0.10
Unemployment rate age 14	0.75	-4.05	0.94	0.33	2.07	1.41	173.70	-0.65
Male	0.98	4.96	-1.05	0.36	-0.15	-0.17	318.41	0.33
Parent	-1.18	-3.96	1.08					
Couple	0.21	0.81	0.18					
Job hours							48.86	0.00
Monthly wage								0.00
Fixed-term					1.32	1.30		-0.18
Part-time					0.03	0.40		0.24
Low by education								-0.08
Low by occupation								0.30
Constant	0.78	31.08	0.02	5.00	-9.74	-5.91	-2670.61	-0.10
N	545	378	378	378	378	378	378	372

*bold coefficients are significant at $p < 0.10$, controlled for appropriate controls and weighted

Appendix 2: tables for sensitivity analysis on inclusion binary unobserved confounder

Table A4: estimated odds of being employed in second wave for father not working when adjusted for unobserved confounder with $\Gamma=2$, bold indicates significant at $p<0.05$

P1/P0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.44	0.48	0.52	0.56	0.60	0.64	0.68	0.72	0.76	0.81
0.2	0.41	0.44	0.48	0.52	0.55	0.59	0.63	0.66	0.70	0.74
0.3	0.37	0.41	0.44	0.48	0.51	0.55	0.58	0.61	0.65	0.68
0.4	0.35	0.38	0.41	0.44	0.47	0.51	0.54	0.57	0.60	0.63
0.5	0.32	0.35	0.38	0.41	0.44	0.47	0.50	0.53	0.56	0.59
0.6	0.30	0.33	0.36	0.39	0.42	0.44	0.47	0.50	0.53	0.55
0.7	0.29	0.31	0.34	0.36	0.39	0.42	0.44	0.47	0.49	0.52
0.8	0.27	0.30	0.32	0.34	0.37	0.39	0.42	0.44	0.47	0.49
0.9	0.26	0.28	0.30	0.33	0.35	0.37	0.40	0.42	0.44	0.47

Table A5: estimated odds of being employed in second wave for father not working when adjusted for unobserved confounder with $\Gamma=6$, bold indicates significant at $p<0.05$

P1/P0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.44	0.59	0.74	0.89	1.03	1.18	1.33	1.48	1.62	1.77
0.2	0.33	0.44	0.55	0.66	0.77	0.89	1.00	1.11	1.22	1.33
0.3	0.27	0.35	0.44	0.53	0.62	0.71	0.80	0.89	0.97	1.06
0.4	0.22	0.30	0.37	0.44	0.52	0.59	0.66	0.74	0.81	0.89
0.5	0.19	0.25	0.32	0.38	0.44	0.51	0.57	0.63	0.70	0.76
0.6	0.17	0.22	0.28	0.33	0.39	0.44	0.50	0.55	0.61	0.66
0.7	0.15	0.20	0.25	0.30	0.34	0.39	0.44	0.49	0.54	0.59
0.8	0.13	0.18	0.22	0.27	0.31	0.35	0.40	0.44	0.49	0.53
0.9	0.12	0.16	0.20	0.24	0.28	0.32	0.36	0.40	0.44	0.48

Table A6: estimated odds of being employed in second wave for father not working when adjusted for unobserved confounder with $\Gamma=10$, bold indicates significant at $p<0.05$

P1/P0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.44	0.65	0.86	1.07	1.28	1.49	1.70	1.91	2.12	2.33
0.2	0.30	0.44	0.59	0.73	0.87	1.01	1.15	1.30	1.44	1.58
0.3	0.23	0.34	0.44	0.55	0.66	0.77	0.87	0.98	1.09	1.20
0.4	0.18	0.27	0.36	0.44	0.53	0.62	0.70	0.79	0.88	0.96
0.5	0.15	0.23	0.30	0.37	0.44	0.52	0.59	0.66	0.73	0.81
0.6	0.13	0.19	0.26	0.32	0.38	0.44	0.51	0.57	0.63	0.69
0.7	0.12	0.17	0.22	0.28	0.33	0.39	0.44	0.50	0.55	0.61
0.8	0.10	0.15	0.20	0.25	0.30	0.35	0.39	0.44	0.49	0.54
0.9	0.09	0.14	0.18	0.22	0.27	0.31	0.36	0.40	0.44	0.49

Table A7: estimated odds of being employed in second wave for father not working when adjusted for unobserved confounder with $\Gamma=0.5$, bold indicates significant at $p<0.05$

P1/P0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.44	0.42	0.40	0.37	0.35	0.33	0.30	0.28	0.26	0.23
0.2	0.47	0.44	0.42	0.39	0.37	0.34	0.32	0.30	0.27	0.25
0.3	0.49	0.47	0.44	0.42	0.39	0.36	0.34	0.31	0.29	0.26
0.4	0.53	0.50	0.47	0.44	0.42	0.39	0.36	0.33	0.30	0.28
0.5	0.56	0.53	0.50	0.47	0.44	0.41	0.38	0.35	0.32	0.30
0.6	0.60	0.57	0.54	0.51	0.47	0.44	0.41	0.38	0.35	0.32
0.7	0.65	0.61	0.58	0.55	0.51	0.48	0.44	0.41	0.37	0.34
0.8	0.70	0.66	0.63	0.59	0.55	0.52	0.48	0.44	0.41	0.37
0.9	0.76	0.72	0.68	0.64	0.60	0.56	0.52	0.48	0.44	0.40

Table A8: estimated odds of being employed in second wave for father not working when adjusted for unobserved confounder with $\Gamma=0.17$, bold indicates significant at $p<0.05$

P1/P0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.44	0.40	0.36	0.32	0.28	0.24	0.20	0.16	0.12	0.08
0.2	0.49	0.44	0.40	0.35	0.31	0.27	0.22	0.18	0.13	0.09
0.3	0.54	0.49	0.44	0.39	0.34	0.30	0.25	0.20	0.15	0.10
0.4	0.61	0.55	0.50	0.44	0.39	0.33	0.28	0.22	0.17	0.11
0.5	0.70	0.63	0.57	0.51	0.44	0.38	0.32	0.25	0.19	0.13
0.6	0.81	0.74	0.66	0.59	0.52	0.44	0.37	0.30	0.22	0.15
0.7	0.97	0.89	0.80	0.71	0.62	0.53	0.44	0.35	0.27	0.18
0.8	1.22	1.11	1.00	0.89	0.77	0.66	0.55	0.44	0.33	0.22
0.9	1.62	1.48	1.33	1.18	1.03	0.89	0.74	0.59	0.44	0.30

Table A9: estimated odds of being employed in second wave for father not working when adjusted for unobserved confounder with $\Gamma=0.1$, bold indicates significant at $p<0.05$

P1/P0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0.1	0.44	0.40	0.36	0.31	0.27	0.22	0.18	0.14	0.09	0.05
0.2	0.49	0.44	0.39	0.35	0.30	0.25	0.20	0.15	0.10	0.05
0.3	0.55	0.50	0.44	0.39	0.33	0.28	0.22	0.17	0.12	0.06
0.4	0.63	0.57	0.51	0.44	0.38	0.32	0.26	0.19	0.13	0.07
0.5	0.73	0.66	0.59	0.52	0.44	0.37	0.30	0.23	0.15	0.08
0.6	0.88	0.79	0.70	0.62	0.53	0.44	0.36	0.27	0.18	0.10
0.7	1.09	0.98	0.87	0.77	0.66	0.55	0.44	0.34	0.23	0.12
0.8	1.44	1.30	1.15	1.01	0.87	0.73	0.59	0.44	0.30	0.16
0.9	2.12	1.91	1.70	1.49	1.28	1.07	0.86	0.65	0.44	0.23

Table A10: Difference (observed-predicted) for respondents whose father did not work and those whose father worked in lower occupation at different operationalisations

	1.		2		3		4		5	
Difference:	Lowest 50%	Lowest 10%	First wave with lowest 25%	Propensity score with lowest 25%	Lowest 25%, employed vs. unemployed	Men	Women			
Working	-0.16 (0.03)*	-0.23 (0.03)*	-0.17 (0.03)*	-0.14 (0.03)*	-0.17 (0.03)*	-0.23 (0.04)*	-0.11 (0.03)*			
N treated	338	311	271	330	260	137	201			
N control	1086	172	455	627	445	236	309			
Work part-time	0.08 (0.04)*	0.15 (0.04)*	-0.08 (0.04)*	0.09 (0.04)*	0.08 (0.04)*	0.16 (0.06)*	0.07 (0.05)			
Hours/week	-2.50 (0.85)*	-4.81 (0.92)*	-0.28 (1.12)	-3.16 (0.92)*	-3.30 (0.88)*	-4.46 (1.44)*	-3.77 (1.24)*			
Low job satisfaction	0.08 (0.03)*	/	-0.05 (0.04)	0.08 (0.03)*	0.06 (0.03)	-0.06 (0.06)	0.13 (0.05)*			
Fixed-term	-0.04 (0.03)	-0.00 (0.03)	-0.04 (0.03)	0.00 (0.03)	-0.00 (0.03)	-0.07 (0.05)	-0.01 (0.03)			
Relative low wage by occupation	-0.01 (0.04)	-0.08 (0.04)	0.03 (0.05)	0.04 (0.05)	-0.05 (0.05)	-0.06 (0.07)	0.00 (0.06)			
Relative low wage by education	-0.04 (0.04)	-0.13 (0.05)*	-0.03 (0.06)	0.06 (0.05)	-0.04 (0.04)	-0.08 (0.07)	-0.01 (0.06)			
Gross monthly income	-92.21 (43.86)*	42.88 (42.13)	-8.74 (85.21)	-101.36 (46.36)*	-49.75 (43.57)	-22.52 (121.95)	-34.31 (50.30)			
N treated	175	163	109	147-176	162	62	91			
N control	754	130	292	347-438	358	183	195			

*: $p < 0.05$, controlled for all appropriate control variables and weighted, due to perfect prediction no estimates could be got for low job satisfaction compared to the lowest 10%.