Parental Links and Labor Market Outcomes: Evidence from the UK

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Abstract

Do parental links influence labor market outcomes of individuals? We answer this question by exploiting monthly job histories and rich information from the British Household Panel Survey. We improve upon the literature by linking each individual to his family members and measuring the correlations between labor market outcomes of parents and individuals. In order to motivate our econometric specification, we first postulate a stylized model of intergenerational transmission of networks in the labor market. Our empirical strategy includes both difference-in-differences specification and linear regressions controlling for individual fixed effects. Our results indicate that, on average, those whose father is employed rather than unemployed experience an employment rate that is about 8 percentage points higher, with job finding rates which are higher by 5 percentage points and job separation rates which are lower by 0.3 p.p.. Instead, we do not find similar patterns for mothers. Individuals who choose to search for a job or to work in occupations similar to the one of their father experience even better labor market outcomes. Among the possible mechanisms we consider, the empirical evidence suggests that such results are indeed due to informational advantages rather than human capital transmission, direct hiring or common shocks.

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1 Introduction

We explore how parental links affect labor market outcomes of individuals; more specifically, we look at how the job finding and job separation rate are affected by the fact that parents are employed rather than unemployed. We construct detailed monthly job histories using information from the British Household Panel Survey and exploit information on household structure and friends from the same dataset. In particular, we improve upon the existing literature by linking each individual to his family members, and measuring how the labor market outcomes of an individual are affected by the labor market status of any of his relatives or his spouse. Finally, we compare the strength of family ties with that of other relevant ties such as friends.

The importance of social networks in determining labor market outcomes has been recognized in the literature in the last decades. Rees [1966] and Granovetter [1973] were the first ones to investigate the important role played by social networks in labor markets. Montgomery [1991] proposed a simple model to capture the features of a labor market with personal connections. More recently, Calvó-Armengol and Jackson [2004] studied the dynamic implications of networks, shedding new light on the possible effects of policy. Networks are a common way to alleviate information frictions, largely used by both workers (Holzer [1988] and Pellizzari [2010]) and firms (Ioannides and Loury [2004] and Topa [2011]).

Our work looks at the workers' side, i.e. individual transitions from unemployment to employment and viceversa. Several papers have tried to quantitatively assess how belonging to a particular network affects labor market variables such as the job finding, job separation and the wage. For instance, Topa [2001], Munshi [2003], Beaman [2012]. One usual shortcoming of the data is that only indirect measures of networks are available. Some researchers tried to rely on estimates of the social networks, in order to assess their impact. As a consequence, the estimates produced by these studies are likely to be affected by measurement error, due to the impossibility of exactly identifying the network members. Our work uses direct information on social contacts, thus limiting the extent of measurement error.

The main focus of this work is on parental links. Fathers and mothers are commonly recognized to be strong ties in the network literature, and it is therefore interesting to analyze the extent to which parents can influence the labor market choices and outcomes of their offsprings. Moreover, such influence is likely to affect the intergenerational persistence of social and economic status. In this sense, the choice of the data is particularly appealing for our analysis: among developed countries, the UK ranks relatively high in terms of socio-economic persistence across generations[1].

Our primary ojective is to measure how important parental links are for the determination of labor market outcomes of individuals. We consider as links both fathers and mothers, allowing for the possibility that these effects might be different along gender lines. For the sake of concreteness, we are interested in the effect that having one parent employed has on the standard search variables of individuals. In order to motivate our econometric specification, we first postulate a stylized model of intergenerational transmission of networks in the labor market. Our empirical strategy includes both difference-in-differences specification and linear regressions controlling for individual fixed effects. In order to make a sense out of the correlations we find, we test whether these are magnified when the individual ends up finding a job in the same occupation of the father. Although one might think that parental ties play the most important role in the very first job of the offspring, we show that large and persistent differences in the job finding and job separation rate are related to father's labor market variables for a number of years, rather than only at the beginning of one's career.

To the best of our knowledge, we are the first ones to analyze how parental links affect transitions from unemployment to employment and viceversa. We are also the first to document the existence of a strong positive effect of father's employment on such transitions in the UK labor market by exploiting direct information on such links. We also document patterns of intergenerational occupational mobility, shedding some light on the sources of persistence in economic status across generations.

We document that in the UK occupations tend to be persistent across generations; for instance, sons are from 20 % to 260 % (depending on the sector) more likely to end up working in similar occupations

[1] For instance, the intergenerational correlation of income is about 0.27, compared to 0.28 in the US (Blanden et al. [2005]). The intergenerational earnings elasticity in UK is estimated to be about 0.5, one of the highest among developed countries, again very similar to that of the US, which ranges from 0.5 to 0.6 depending on the estimation method (Corak [2010]).

as their fathers, with some exceptions. Similar considerations apply to daughters and mothers.

We find that those who have an employed (rather than unemployed) father experience an employment rate that is about 8 percentage points higher, with a job finding rate higher by at least 5 percentage points, compared to an average in-sample job finding rate of 11 %. Moreover, if an individual searches for a job in the same sector in which his father is currently employed, the job finding rate increases by a further 3 percentage points. Women appear to be more affected by the employment status of the father. Such results are robust to alternative specifications and to several robustness checks. Moreover, having an employed father decreases the job separation rate by 0.3 percentage points and working in the same sector decreases it by a further 0.2 percentage points, compared to an average in-sample job separation rate of 0.8 %. We do not find similar effects for mothers, except for the case of job separation rate when individuals are employed in the same sector (-0.2 %). For the sake of comparison, an additional employed friend increases the job finding rate by 1 - 3 % depending on the estimation method, and decreases the job separation rate by 0.3 - 0.5 %. Conversely, spouse's employment status has a strong effect on the job finding rate (with a similar magnitude to the father's one) and a negligible one on the job separation rate.

The rest of the paper is organized as follows. Section 2 surveys the literature in greater detail, emphasyzing the differences between our work and the others. In section 3 we introduce the data, along with some descriptive statistics of interest. In Section 4 we present a stylized model of intergenerational networks, in order to justify the empirical models employed for the analysis (explained in Section 5). Results are shown in section 6 and discussed in section 7. We performs some robustness checks in Section 8 and conclude in Section 9.

2 Related Literature

We offer direct evidence of the positive impact of family ties' employment on labor market transitions. Several studies in the literature have tackled the issue of understanding the effects of networks by means of a theoretical model. One of the first papers to include personal contacts in a job search framework was Mortensen and Vishwanath [1994]. In their model the information about vacancies comes from two different sources: direct application to employers or indirect contact through friends. As a consequence, better connected individuals have more chances to find a job. Similarly, Montgomery [1991] finds that well connected workers perform better in the labor market, both in terms of wages and of higher job finding rates. Calvó-Armengol and Jackson [2004] also develop a model where workers can obtain information through an explicitly modeled network of social contacts. In their model, belonging to a network with less employed members implies worse employment prospects, and this effect is persistent over time. Other models of networks and job search are in Fontaine [2008] and Calvó-Armengol and Zenou [2005], with a particular focus on networks' dynamics.

A distinctive feature of all these works is that networks exhibit a positive effect on labor market outcomes of individuals. In our paper we do not directly test for such predictions, as we neither focus on the size of social networks nor on the general level of employment within a network. However, these studies constitute the theoretical ground on which we base the interpretation of our results.

Many empirical studies try to identify the effect of belonging to a particular network on labor market outcomes. Several papers rely on indirect measures of networks. For instance, Topa [2001], Bayer et al. [2008] and Schmutte [2010] use geographical proximity and group affiliation as proxies for social interactions. Beaman [2012] uses data on political refugees resettled in the US and proxies for networks using nationality. Overall, these studies find evidence of positive effects of social interactions on labor market outcomes. Similarly, Khan and Lehrer [2013] use a random assignment to a unique intervention to identify the impact of changes in the size of a social network. Access to the program succesfully led to gains in the number of weak ties but these changes did not translate into improved employment outcomes. Herault and Kalb [2009] look instead at parental links; using retrospective parental information from Australian data, they find significant persistence in employment across generations.

Our paper is more closely related to that strand of this literature that exploits direct identification of network members.

O'Regan and Quigley [1993] study the correlation of employment status of urban youth with the employment status of their family members (parents and siblings) in the US, finding strong and positive correlations. Further, they observe that the industry affiliation of the network members is a good predictor of the industry affiliation of the individual. Magruder [2010] examines to which extent parents help children in finding jobs in South Africa. He finds that fathers help sons (but not daughters), while mothers are not helpful in finding jobs. Differently from these works, our analysis is dynamic and focuses on transitions from unemployment to employment and viceversa, rather than on employment status versus nonemployment. Also, our data allows us to employ different estimation techniques and to compare parental effects to similar effects by other strong ties. Skamarz and Skans [2011] investigate parental networks at the firm-level. They analyze Swedish graduates, finding that it is quite frequent that their first job is in the same plant where their parents work. With respect to their paper, rather than focusing only on the entry in the labor market, we follow individuals over their life-cycle, investigating whether the advantages derived from their network persist over time.

Finally, Pistaferri [1999] uses Italian data and finds that informal networks use is associated with higher job finding rates and lower wages. Similarly, Bentolila et al. [2010] find that individuals who use social contacts to find their job are characterized by higher job finding rate (lower unemployment duration) and slightly lower wages. They suggest that the trade-off between job finding rate and wage could still make individuals choose to enter the same sector as their network members. Indeed, we document patterns of intergenerational persistence in occupations; along with our regression results, this is consistent with a model of occupational choice in the spirit of Bentolila et al. [2010].

Closely related to our work is the study of Cappellari and Tatsiramos [2011], who also use data from the BHPS and a similar methodology. Nonetheless, some relevant traits differentiate the two works: first, we focus on parental links, instead of friendship ones; second, we identify monthly transitions (rather than yearly); third, we look at transitions within the labor force while they consider transitions from non-employment to employment; fourth, we document how belonging to the same occupational sector magnifies the partial correlations we find.

3 The Data

We use data from the British Household Panel Survey, a representative sample from the UK following individuals since 1991. The BHPS is a yearly survey taken by about 10,000 individuals per year and the last available wave for this study is 2008. The follow-up rate is very high and the great majority (more than 90%) of the individuals who enter the sample are interviewed also in the subsequent year. Besides these, every year a certain number of new individuals enter the sample. A total of 32,377 individuals are interviewed in the BHPS in the period 1991-2008. Even though the survey is yearly, individuals report their job history in the last year, listing all the employment (unemployment) spells along with several characteristics of each job. This allows us to identify monthly transitions and build very long time series for each individual, up to 216 periods. Details on how we construct job histories for individuals are included in Appendix A.

We retrieve the employment status of individuals exploiting the job histories, distinguishing between employees and self employed. The employment status of individuals is assigned at the monthly frequency. Differently from other studies, we do not consider individuals who are out of the labor force in our transitions. We define the job finding rate as the probability of transiting from unemployment (rather than non-employment, as for instance in Cappellari and Tatsiramos [2011]) to employment. The job separation rate is defined accordingly. We restrict our sample to individuals aged between 16 and 65[2], as it is standard in the literature, we drop armed forces and registered disabled. Eventually we are left with 27,278 individuals, for a total of 2,232,528 monthly observations. [3]

Along with a very detailed job history, for each individual it is typically available a large amount of

[2]That is, our intergenerational sample will include couples of parents and offsprings if and only if both are in this age range.

[3]We also check whether our final sample is representative of the UK economy between 1991 and 2008. We compute the in-sample unemployment rate and compare it with the harmonized unemployment rate according to OECD statistics (figure 6 in the Appendix). The average unemployment rate of our sample replicates quite well the pattern of the OECD series.

information including sex, age, education, occupation, race, marital status, region of residence and much more. More interestingly, for a share of individuals the identification number of their parents and their spouse is available, allowing us to connect them to their family members and follow them together over time[4]. In addition to this, the data include information on the employment status of the three closest friend and the occupation of the first closest friend. This information is collected only every second wave, starting in 1992. At the core of the analysis, we consider the relationship between the employment status (and the occupation) of the parents and the labor market outcomes of respondents. We also compare parental effects to similar effects by spouse and friends. Since friends' job histories are not reported, in order to keep the monthly frequency we extend their employment status and occupation in the following 12 months after each observation. Furthermore, we use a simple procedure to attribute the occupational sector to unemployed and to extend non-varying or spell-dependent variables, as described in Appendix A. Especially for the occupation, the data contain many missing values, both for respondents and connected individuals: we assume that these values are missing at random and simply exclude the incomplete observations from the estimation, when it is not possible to replace them according to the procedure described in Appendix A. The final size of the estimating sample varies, depending on the dependent variable we use in each regression[5].

Table 1 displays some descriptive statistics of interest for our analysis. As we can see, the period 1991-2008 is characterized by a generally low level of unemployment in the UK. More than 93% of the population in the labor market has a job, 12% of which is self employed. The average monthly job finding rate, that is the probability of transition from unemployment to employment, is slightly above 7%. Conversely, the average job separation rate is relatively small (0.4%). This implies that in the period considered the UK economy was characterized by a high level of security for those who had a job. On the other hand, it was somewhat hard to find an occupation for those who were unemployed: on average, the expected waiting time in unemployment was at least one year. In other words, the reason

[4]Unfortunately, it is possible to do so only for about 19% of the whole sample for fathers and 25% for mothers (those who report the parental PID numbers).

[5]By its own nature, the job finding rate (job separation) is defined only over unemployment (employment) spells.

behind the low unemployment rate is the tightness of the monthly outflow from employment rather than a large inflow from unemployment. Compared to other OECD countries, the UK economy has an average performance in terms of search variables[6]. A comparison among genders shows that females in the labor force tend to have slightly better outcomes than males.

Table 1. Summary statistics of labor market outcomes. Source: BHPS (1991-2008).

Variable	**Subsample**	**Mean**	**N**
Unemployment Rate	All Sample	6.15	1685930
	Males	7.24	865469
	Females	5.00	820051
Job Finding Rate	All Sample	7.21	99532
	Males	7.15	60356
	Females	7.32	39121
Job Separation Rate	All Sample	0.42	1549143
	Males	0.49	786531
	Females	0.34	762282

About 53% of our sample is female and the average individual is aged 39. We define four educational groups and nine occupational sectors, following the SOC aggregation by major groups as established by the Employment Department Group and the Office of Population Censuses and Surveys. We identify an occupational sector $O_{i,t}$ for each individual (parents included), for both unemployed and employed individuals. When employed, the occupational sector is defined in a straightforward manner. When unemployed, the occupational sector is interpreted as the sector in which the individual seeks for a job, and is assumed to be the one in which the individual eventually finds a job. For instance, if an individual i starts being unemployed at time t, is unemployed for 10 months and then finds a job in sector 3, we assume that the individual was indeed searching in sector 3 for those 10 months: $O_{i,t} = O_{i,t+1} = ... = O_{i,t+10} = 3$. If we have no information on the occupation of arrival, for instance because the individual exits the sample or goes out of the labor force, we use the occupation prior to the unemployment spell when available. The rationale behind our choices and further details are explained in Appendix A. The distribution of workers across occupational sectors is shown in Table 2, along with

[6]For a cross-country comparison of estimates of the standard search variables see Hobijn and Sahin (2007). As it is known by other studies, the European economies perform much worse than the US to this extent. For instance, the job finding rate is estimated to be at least 50% in the US.

several labor market statistics of the sectors. First of all, we see that all the sectors are comparable in terms of size. Some of them are definitely bigger than the others, but for each of them we have a number of observations included between 150,000 and 300,000. This is important for our study, as we should not expect any dramatic change in the estimating sample size when performing the analysis by sector rather than on the aggregate. Second, labor market outcomes are not independent on sectors. One would definitely expect that high-skilled jobs are better paid, while the relatively large differentials in terms of unemployment rate (and search variables) are somewhat more puzzling. One possible explanation is a relative scarcity of high-skilled workers in the UK in those years, compared to the high profitability of those sectors (managerial and professional). In the first three sectors the unemployment rate ranges between 1.8% and 2.1%, with a job finding rate of 10-12% and a job separation rate of about 0.2%. On the other hand, we also notice that restricting the sample to the observations for which the occupation is available induces some degree of sample selection. The average job finding rate (unemployment rate) is indeed higher (lower) than in the whole sample. This happens because originally all the individuals assigned to a sector are employed, and our sector imputation only considers the next and the last labor spell. Therefore, due to the large number of missing values for occupation, we lose many observations of unemployed (typically, the long-term unemployed) when imputing the sector. Unfortunately, without making any stronger assumptions than the ones we already make, it is not possible to get rid of this issue. However, notice that the sample selection problem only affects the unemployment rate and the job finding rate, as shown in Table 2.

3.1 Patterns of Occupational Mobility across Generations

While many studies on occupational mobility across generations rely on single observations for the occupation of parents, the BHPS allows us to follow parents over time. In this way, besides the answer to "What was your parents' occupation when you were 14?", we are provided with a better source of information on parents' side. Furthermore, the availability of two different ways to assess occupational

Table 2. Distribution of workers across sectors and sectoral labor market statistics. Source: BHPS (1991-2008)

Occupational Sector	Abs. Freq.	Rel. Freq.	Unempl. Rate	JF Rate	JS Rate
Managers & Administrators	221396	14.88	2.08	10.15	0.25
Professional	147698	9.92	1.82	11.96	0.20
Associate Professional & Technical	174160	11.70	2.59	11.18	0.22
Clerical & Secretarial	235157	15.80	4.35	12.16	0.43
Craft & Related	178628	12.00	6.22	8.10	0.53
Personal & Protective Service	170551	11.46	6.72	8.03	0.52
Sales	108502	7.29	6.39	10.59	0.62
Plant & Machine	131936	8.86	7.82	8.95	0.67
Agriculture & Elementary	120345	8.09	9.66	7.55	0.73
Total	1488373	100.000	4.94	9.38	0.43

mobility provides us a possible way to disentagle different sources of intergenerational correlations. First of all, we compare the distributions of parents and offsprings across sectors. Table 3 shows the distribution of sons and daughters, parents when offsprings (respondents) were 14 and parents who are followed over time. We immediately notice that a large degree of sex segregation characterizes the distribution across sectors. Managerial and craft occupations are typically covered by men, while secretarial and sales jobs are more intensively taken by women. This phenomenon seems to be persistent over generations, given that no relevant differences can be detected when comparing the distribution of offsprings and parents to this extent. Another interesting feature is the large structural change that characterized the UK economy in the last decades. Sectors such as craft or machine occupation shrunk significantly in relative terms, while managerial, professional and especially technical occupations employ nowadays a larger share of the working force than before. For this reason, the distribution of offsprings is more directly comparable with the distribution of parents who are followed over time, as in this way we are comparing occupational choices within the same economy.

In order to investigate the degree of occupational mobility across generations we build Markov matrices, computing the transition probabilities from a sector to another. As parental occupation, we use both the current one and the one as reported when offsprings were 14. If individuals rarely switch occupation over the life cycle, the two sources of information on parental occupation will be highly correlated. Consistently with the degree of sex segregation that we found in the data, we report the tables for

Table 3. Distribution of sons and parents across sectors, relative frequencies. Source: BHPS (1991-2008)

Occupational Sector	**Offsprings 1991-2008**		**Parents when offsprings 14**		**Parents 1991-2008**	
	Sons	**Daughters**	**Fathers**	**Mothers**	**Fathers**	**Mothers**
Managers & Administrators	18.92	11.96	16.81	7.36	22.48	9.90
Professional	10.23	10.60	8.05	6.04	8.69	9.19
Associate Professional & Technical	10.83	13.35	4.05	7.61	7.11	9.19
Clerical & Secretarial	7.91	24.39	5.00	19.16	6.41	25.61
Craft & Related	21.12	2.12	27.44	5.40	22.43	2.20
Personal & Protective Service	5.90	16.55	5.11	14.90	4.70	18.06
Sales	4.60	9.81	3.71	11.66	4.36	10.87
Plant & Machine	13.41	3.29	18.26	7.84	18.35	3.82
Agriculture & Elementary	7.07	7.93	11.58	20.03	5.46	11.16
Total	100.00	100.00	100.00	100.00	100.00	100.00

couples of the same gender: fathers with sons, and mothers with daughters. For males, even though with some heterogeneity, we note that there is a general level of persistence in the same sector as their father's one as reported when respondents were 14. Table 4 reveals that the persistence is particularly high at the top (managerial and professional occupations) and at the bottom (plant and machine occupations) of the distribution, with another peak for craft occupations. Instead, when considering the contemporaneous occupation, persistence drops significantly at the top while it strongly increases in the mid-sectors.

Table 4. Markov matrix of occupational mobility: fathers-sons, relative frequencies. Source: BHPS (1991-2008)

Father's sector when son is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**31.99**	13.76	12.42	6.44	12.56	5.10	4.38	8.30	5.06
2	23.72	**26.11**	21.35	7.55	6.51	4.04	3.38	4.65	2.69
3	25.86	15.75	**17.53**	7.84	12.67	5.16	3.35	8.72	3.13
4	16.98	16.94	13.80	**12.07**	16.71	4.97	3.26	9.69	5.57
5	16.65	9.55	9.32	7.43	**27.86**	5.31	3.76	13.73	6.40
6	18.26	11.61	11.81	10.02	17.87	**8.68**	5.33	11.73	4.68
7	25.09	9.73	13.27	8.88	15.46	2.52	**8.42**	11.55	5.07
8	15.06	7.03	8.38	6.50	24.20	6.50	3.66	**22.13**	6.55
9	14.52	5.47	6.44	7.43	25.18	4.49	4.63	19.37	**12.47**
Father's sector contemporaneous	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**13.46**	7.51	13.11	11.80	22.34	6.94	10.26	5.49	9.09
2	10.77	**13.32**	19.95	16.82	13.02	5.97	10.71	4.46	4.98
3	9.22	7.92	**19.74**	18.96	15.47	5.18	8.36	10.00	5.16
4	13.65	7.85	16.44	**16.03**	17.37	3.82	8.18	10.20	6.46
5	7.99	1.64	8.78	10.95	**40.49**	5.39	7.32	10.28	7.16
6	12.20	1.76	11.69	18.40	17.66	**16.93**	6.87	6.64	7.86
7	7.76	6.47	14.77	13.22	21.95	8.95	**9.95**	11.89	5.03
8	8.95	2.26	6.70	8.50	30.91	7.89	5.51	**20.89**	8.39
9	6.16	4.61	13.16	12.31	23.45	5.35	5.65	8.18	**21.13**

When considering women (in Table 5), similar considerations can be made: for instance, the per-

Table 5. Markov matrix of occupational mobility: mothers-daughters, relative frequencies. Source: BHPS (1991-2008)

Mother's sector when daughter is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**18.77**	12.38	15.46	20.77	1.94	15.32	9.03	1.06	5.26
2	13.96	**30.97**	17.75	19.36	0.58	9.26	4.83	0.56	2.73
3	14.72	12.54	**21.03**	21.81	1.28	15.51	6.20	1.95	4.96
4	13.78	16.87	16.28	**29.64**	1.74	11.70	5.51	1.09	3.40
5	12.44	8.30	10.85	22.72	**2.92**	16.39	11.65	4.39	10.33
6	10.86	8.15	13.39	23.85	2.03	**20.11**	9.43	2.57	9.60
7	12.79	8.55	11.93	29.41	1.71	14.61	**11.92**	3.15	5.92
8	10.32	5.02	8.97	26.61	2.76	17.93	10.25	**6.98**	11.15
9	8.89	6.29	13.21	21.58	1.98	20.26	11.50	4.18	**12.12**
Mother's sector contemporaneous	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**16.74**	13.52	9.61	21.04	0.58	19.90	10.83	1.27	6.51
2	13.50	**15.91**	17.27	25.06	1.93	11.80	10.59	0.53	3.41
3	10.01	9.99	**14.89**	25.73	1.30	23.05	9.59	1.35	4.08
4	10.75	7.51	10.45	**37.10**	0.87	18.49	11.01	0.44	3.37
5	6.00	9.25	0.89	23.13	**9.65**	19.29	24.80	3.74	3.25
6	8.07	7.17	10.85	25.41	1.19	**24.59**	16.28	1.15	5.29
7	5.60	3.25	6.02	31.47	2.74	23.57	**18.31**	5.30	3.74
8	6.54	0.94	4.79	23.47	5.87	24.61	13.01	**10.92**	9.84
9	14.12	5.04	9.23	30.27	1.03	19.23	13.98	2.78	**4.31**

sistence with mother's sector as reported when daughters were 14 is strikingly high for managerial and professional occupations. Again, when we look at the contemporaneous occupation, the persistence at the top almost disappears while it becomes more substantial in the middle and at the bottom of the distribution. Overall, women are very attached to clerical and secretarial occupations: the probability of falling into that category is very high regardless of parental background.

The large differentials in the patterns of persistency obtained by using retrospective instead of current information on parental occupations implies the existence of a substantial degree of occupational mobility of parents over their life cycle. Tables 6 and 7 show that fathers and mothers have a sizeable probability of moving between occupations during their worklife. Studies that focus only on retrospective information on parental occupations cannot account for this important feature of the data.

In the next subsection, in order to understand and interpret the patterns of occupational persistence, we study whether parental labor market variables (such as their employment status and their sectoral belonging) affects individuals' labor market outcomes.

Table 6. Markov matrix of occupational mobility: fathers when sons are 14-fathers over their life-cycle, relative frequencies. Source: BHPS (1991-2008)

Father's sector when son is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**59.32**	4.41	6.16	7.32	6.31	1.63	6.33	7.10	1.42
2	16.03	**68.07**	9.13	3.07	0.72	0.33	1.12	0.66	0.86
3	11.72	11.11	**54.46**	10.82	4.28	0.18	4.85	1.01	1.58
4	14.72	2.10	2.60	**49.86**	3.38	8.08	15.22	4.04	0.00
5	5.16	2.54	3.89	1.85	**65.88**	3.19	0.37	12.75	4.37
6	9.54	0.19	18.41	21.96	3.61	**38.66**	1.94	3.51	2.18
7	27.79	0.00	1.59	9.95	4.58	0.00	**33.60**	18.49	4.01
8	8.24	3.47	1.08	1.11	8.91	1.86	1.15	**70.11**	4.07
9	14.81	15.68	0.50	4.16	12.28	5.45	4.18	22.36	**20.59**

Table 7. Markov matrix of occupational mobility: mothers when daughters are 14-mothers over their life-cycle, relative fequencies. Source: BHPS (1991-2008)

Mother's sector when daughter is 14	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1	**46.01**	0.00	6.78	21.68	0.00	16.29	1.54	6.36	1.33
2	0.98	**62.87**	19.81	7.57	0.00	0.94	0.00	2.29	5.53
3	1.61	7.20	**69.76**	4.66	0.72	10.90	0.76	0.68	3.70
4	17.05	3.21	5.88	**62.81**	0.88	2.11	5.04	0.27	2.75
5	2.25	0.00	3.56	43.34	**12.66**	9.10	16.60	6.94	5.53
6	13.49	2.59	6.14	12.88	0.23	**46.58**	6.44	1.68	9.97
7	7.61	5.80	1.91	12.83	4.92	13.02	**40.40**	0.81	12.70
8	3.02	0.98	13.06	28.24	9.71	3.59	8.00	**28.41**	4.98
9	7.08	4.60	5.21	6.17	0.28	12.29	12.83	3.19	**48.34**

3.2 Labor Market Outcomes across Generations

Before entering the regression-based analysis, we look at the relationship between labor market performances across generations. In particular, we compute the average unemployment rate and search variables of individuals conditional on the employment status of parents. We also investigate whether these intergenerational correlations vary when individuals are in the same occupational sector as their parents.

Table 8 reveals the existence of strong correlations across generations. Having employed (rather than unemployed) parents is associated with better labor market outcomes. For instance, the average unemployment rate -that is 21% for those whose father is unemployed- drops to 8% for those whose father is employed, decreasing further up to less than 5% when the father is in the same sector as the offspring. Similar percentages characterizes the mother's employment status, with the difference that there does not seem to exist any additional effect linked to sector belonging. The job finding rate more

Table 8. Intergenerational Correlations. Labor Market Outcomes conditional on parental employment status. Source: BHPS (1991-2008).

Variable	**Subsample**	**Father**			**Mother**		
		Unemployed	**Employed**	**Same Sector**	**Unemployed**	**Employed**	**Same Sector**
Unemployment Rate	All Sample	20.67	7.84	4.74	17.86	7.86	7.38
	Males	24.14	9.11	5.02	20.83	9.18	8.02
	Females	14.35	6.23	4.01	15.17	6.28	6.87
Job Finding Rate	All Sample	4.85	11.02	15.23	7.45	11.05	12.89
	Males	4.88	10.58	14.85	7.65	10.64	14.17
	Females	4.86	11.82	16.13	7.20	11.79	11.68
Job Separation Rate	All Sample	1.16	0.75	0.58	1.23	0.74	0.79
	Males	1.34	0.85	0.58	1.42	0.84	0.94
	Females	0.87	0.62	0.57	1.07	0.63	0.66

than doubles on average (it increases from 4.9 to 11%) when the father is employed, while the effect of the mother's employment status is less pronounced but still large (from 7.4 to 11%). Again, when the father is employed in the same sector, individuals experience an even higher job finding rate on average (about 15%). Interestingly, the job finding rate of males appears to be affected also by having the mother in the same sector. Finally, the job separation rate is also correlated with parents' employment status in the same direction. It is roughly 1.1% for those with unemployed father and it drops to 0.75% for those whose father is employed. Mother's employment status has approximately the same effect on this conditional average. An extra reduction in the job separation rate is found when the sector of the offspring coincides with the one of the father, while no relevant differences with respect to the sector of the mother.

Overall, significantly better the labor market performances are found to be associated with the employment status of the parents. Such advantages are larger when individuals are in the same occupational sector as their father. The additional premium is about 40-50% the size of the effect of having an employed father. Remarkably, we do not find that these patterns are substantially different by gender. We investigate whether the differences between these two groups change over the life cycle. Remarkably, we find that especially for the very young the difference is very large. Figure 1 shows that having the father employed is associated with up to 20 to 30 percentage points more in the average employment rate. This difference steadily declines over the life cycle and eventually disappears at the age of 35.

The higher employment rate can be generated by higher job finding rates, lower job separation rates or a combination of the two. Figure 2 and 3 reveal that the job finding rate is driving the bulk of the difference, yielding large and persistent variations across groups. Conversely, the job separation is substantially lower for offsprings of employed fathers especially at early ages, whereas the gap greatly reduces later on in the life cycle. Nevertheless, small differences in absolute value are actually large in relative terms and have a strong impact on individual worklife.

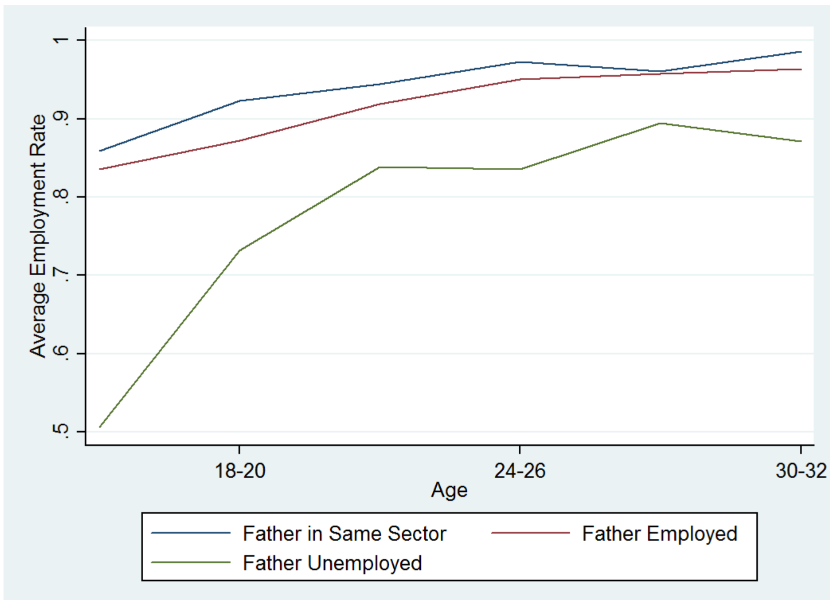

Figure 1. Employment Status (Employed 1, Unemployed 0) as a function of age: cross sectional averages. Source: BHPS.

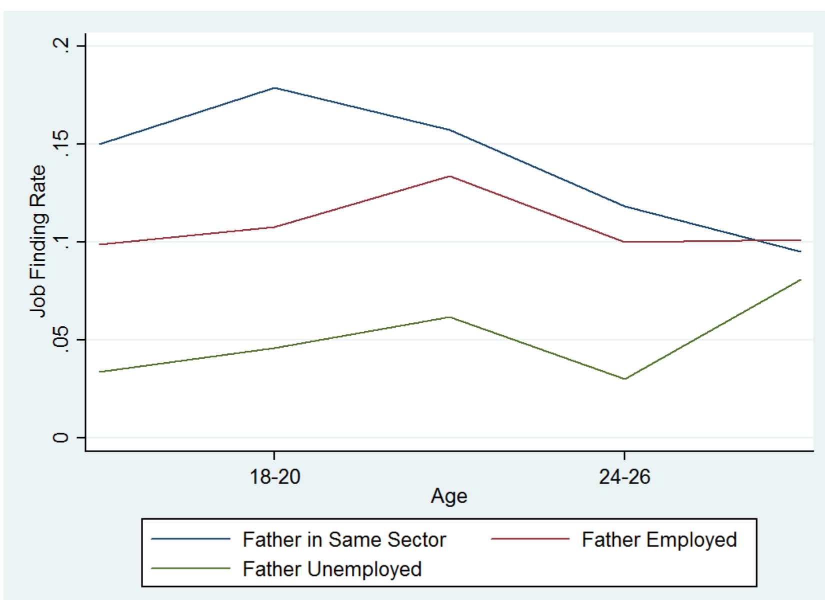

Figure 2. Job Finding Rate as a function of age: cross sectional averages. Source: BHPS. Ages 30-32 are cut because of limited availability of observations.

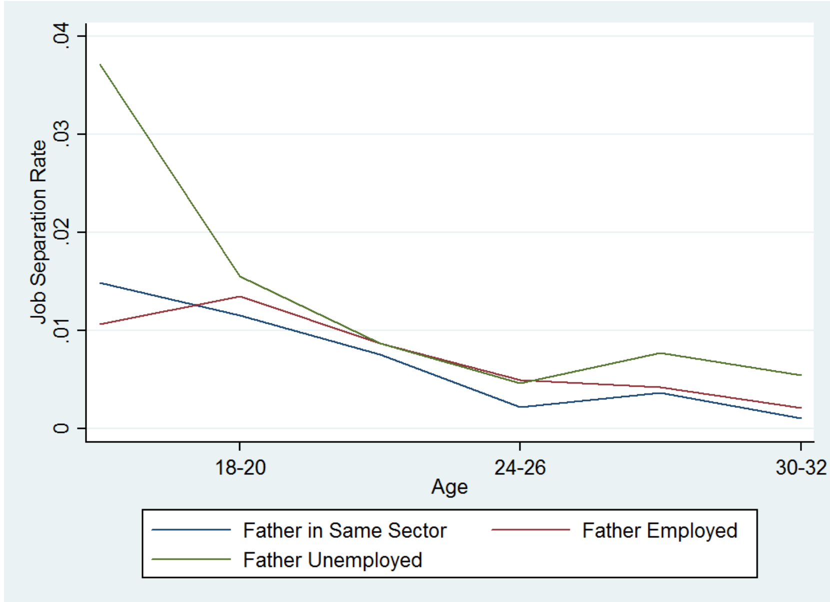

Figure 3. Job Separation Rate as a function of age: cross sectional averages. Source: BHPS.

The correlations found so far are interesting per se, even though they do not necessarily represent any direct effects of parents on offsprings' labor market outcomes. Several other correlations, for instance educational attainment, human capital accumulation or genetical transmission, might well explain these differences in the conditional averages. Moreover, it could also be the case that respondents' outcomes affects parental ones, instead of the other way around. In the next section we outline our empirical strategy to address these and other related issues, in order to try to establish a causal relationship and estimate the effect of parental ties on offsprings' labor market outcomes.

4 A Simple Model of Intergenerational Networks

In order to fix ideas and motivate our difference-in-difference strategy, we explain the source of variation we aim to identify by means of a stylized model of intergenerational networks.

Suppose the economy is populated by identical workers, indexed by worker i, family j and age t. Every period, all workers of age 20 have an offspring of age 0. At the first period of their lives ($t = 0$), agents do not have useful work connections, but inherit a fraction of those of their fathers. Hence we write

$$n^j_{i+1,0} = \beta n^j_{i,20} + \epsilon^j_{i+1,0} \tag{1}$$

where $i+1$ represent the offspring of father i within family j, $n^j_{i,t}$ denotes the natural logarithm of work connections held by worker i in family j at time t, and $\epsilon^j_{i+1,0}$ is an i.i.d normally distributed shock to initial networks.

Workers can be in either of two states $S \in \{E, U\}$, employed or unemployed. When employed, they lose their job with constant probability γ. Work connections positively affect the probability of finding a job, as such connections allow workers to reduce informational frictions. Hence we have that, when unemployed, the job finding probability f is

$$f^j_{i,t} = 1 - e^{-N^j_{i,t}} \tag{2}$$

where $N_{i,t} = e^{n_{i,t}}$. Networks evolve stochastically according to

$$n^j_{i,t+1} = \begin{cases} \alpha + (1-\delta^E)n^j_{i,t} + \epsilon^j_{i,t} & \text{if} \;\; S^j_{i,t} = E \\ (1-\delta^U)n^j_{i,t} + \epsilon^j_{i,t} & \text{if} \;\; S^j_{i,t} = U \end{cases} \tag{3}$$

where $\epsilon^j_{i,t} \sim \mathbb{N}(0, \sigma^\epsilon)$. These equations encompass the idea that a worker gains useful connections while working, and may randomly lose/gain more connections every period. While not working, however, such connections depreciate every period because workers progressively lose contact with their former colleagues. There is no reason to believe that the rates of depreciation $\{\delta^E, \delta^U\}$ are equal, but the difference between them is not important for our results.

It is clear that the correlation between labor market outcomes of fathers and offsprings is highest for $t = 0$; at the initial period, connections of offsprings are mainly defined by those of their fathers because the former did not have the opportunity yet to form many useful work connections. As time goes by, the careers of fathers and offsprings evolve independently and those that were common contacts at the

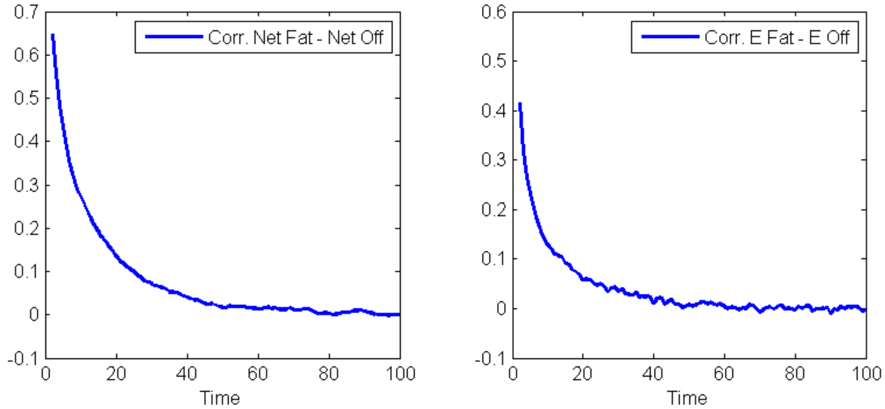

Figure 4. Simulated correlation between fathers and offsprings **network** (left) and **employment status** (right). $\alpha = 0.05, \beta = 0.3, \delta^E = 0.03, \delta^U = 0.05, \gamma = 0.05$.

beginning might be still useful contacts for one, but lost touch with the other. As a consequence, the correlation between labor market outcomes fades out along with the correlation between parental and offspring's networks.

Showing in general that the covariance between fathers and offsprings dies out over time is not straightforward, because the correlation at one point depends on the whole history of employment/unemployment. We carry out the algebra for some special cases in Appendix C. However, we provide simulation results to show that indeed such correlation fades out as workers get older. These results are shown in Figure 4, in which we assign values to the parameters of the model and report the results of our simulations.

Another way to see that differences induced by initial networks vanish over time is to look at the probability of being employed over the life cycle, by different initial conditions. Figure 5 shows how individuals with high, rather than low, initial networks have a higher probability of being employed at the beginning of their careers; as time goes by, such difference goes to zero, as we observe in the data.

This motivates our strategy of looking at the difference in correlation of employment status between ages 20-30 and later ages. As careers evolve independently, the correlation fades out and offsprings after age 30 constitute a proper control group for identifying the effect of networks early on.

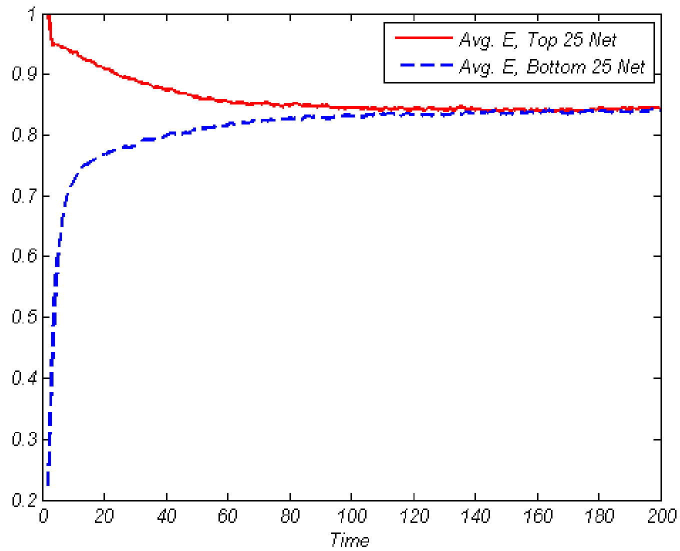

Figure 5. Simulated paths of average employment status for individuals with **high** (red line) and **low** (blue line) initial networks. $\alpha = 0.05, \beta = 0.3, \delta^E = 0.03, \delta^U = 0.05, \gamma = 0.05$.

5 Empirical Strategy

We are interested in understanding the partial correlation between individual labour market outcomes[7] and the employment status of a parent. First of all, we define an employment status variable $E_{i,t}$ using information on job histories. $E_{i,t}$ is equal to 1 if individual i is employed at time t, and 0 in case of unemployment. In all periods of different labor market status (retired, in further education etc.), $E_{i,t}$ is not defined.

Then we define the transition variables $J^f_{i,t}$ and $J^s_{i,t}$, respectively the job finding and job separation events for an individual. $J^f_{i,t}$ is a dummy variable that takes value 1 if individual i moves from unemployment to employment at time t (that is, $E_{i,t-1} = 0, E_{i,t} = 1$), and 0 if the individual remains unemployed ($E_{i,t-1} = E_{i,t} = 0$). In all periods of employment or labor market status different from unemployment, $J^f_{i,t}$ is not defined. Conversely, $J^s_{i,t}$ takes value 1 in case of transitions from employment to unemployment and zero otherwise.

Next, we link individuals and parents using personal identification numbers of relatives provided in the BHPS. For all individuals i for which such information is available, we associate a father, a mother, a spouse and three friends. Call $E^{\textbf{father}}_{i,t}$ the employment status of the father of individual i at time t

[7]As of now, the focus of our analysis is exclusively on individual employment status and transitions from unemployment to employment (and viceversa). In a future version, we are planning to include the wage in our analysis

and similarly for the mother, the spouse and all friends.

In principle we could just use the raw employment status data in our regressions. However, since we have monthly job histories, we are not capable of determining precisely whether jobs ending at time t are covering the full month representing time t or only a small portion of it. The problem is relevant because a correct identification of the timing of spells is crucial to correctly estimate the partial effect of interest: suppose for instance that a father is employed until December 20th when he becomes unemployed, while his offspring obtains a job on December 10th. Since job histories are written in monthly format, it is possible that the father will result unemployed in December, while his offspring will result employed from December onwards. However, it is not clear whether we should have considered the father employed rather than unemployed, since the labor market spell of his offspring began during his employment spell. In order to exclude these controversial cases, we consider only labor market statuses that are unambiguously assigned in a given month, that is we exclude those cases in which the labor market spell changes between two months. Basically, instead of using $E_{i,t}^{\textbf{Father}}$ as defined above, we use

$$E_{i,t}^{\textbf{Father, ongoing}} = \begin{cases} E_{i,t}^{\textbf{Father}} & \text{if } E_{i,t+1}^{\textbf{Father}} = E_{i,t}^{\textbf{Father}} \\ \\ \textit{missing} & \text{if } E_{i,t+1}^{\textbf{Father}} \neq E_{i,t}^{\textbf{Father}} \end{cases}$$

We construct similar variables for mothers and, for comparison purposes, spouses.

5.1 Difference-in-Differences Estimation

In order to identify the effect of parental networks on labor market outcomes, we divide our sample in two groups, one of which is assumed not to be affected by parental networks. Consistently with the stylized model presented in Section 4, the control group is made up by all those workers who are not very young anymore. In particular, we employ an age threshold of 27 for discriminating between control and treatment group[8]. As the rationale behind the definition of the control group in this way is that individuals accumulate social contacts while working, an alternative definition of the control group

[8] Results are robust to changes in the threshold age. Using any age between 25 and 29 yields a coefficient that yields between 6 and 8 p.p., that is significantly different from zero

is made according to the experience of the individuals. That is, we define the control group as those workers who have at least a given number of months of experience (defined as months on a job) in the labor market. In the results shown later on we employ a threshold of 50 months.[9] For both definitions of control group, we run linear[10] regression models of the form

$$Y_{i,t} = \beta_0 + \beta_1 E_{i,t-1}^{\textbf{Father, ongoing}} + \beta_2 T_{i,t} + \beta_3 T_{i,t} E_{i,t-1}^{\textbf{Father, ongoing}} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{4}$$

where $T_{i,t}$ takes the value 1 if the individual belongs to the treatment group (as explained before). The employment status of the father $E_{i,t-1}^{\textbf{Father, ongoing}}$ has a one period lag, in order to avoid problems of double causality (i.e. when the offspring is employed, the father becomes employed thanks to the offspring). $\mathbf{X}_{i,t}$ is a vector of control variables and the dependent variable $Y_{i,t}$ will be, alternatively, the employment status, the job finding rate $J_{i,t}^f$ and the job separation rate $J_{i,t}^s$. Controls will include a third degree age polynomial, dummies for gender, education, occupational sector (observed for employed, imputed for unemployed), marital status, ethnic group, smoking behaviour, region of residence and quarterly dummies. We are interested in the estimation of β_3, which will give us the effect of parental networks on labor market outcomes. The identifying assumption is that all other factors affecting the outcome variable other than parental networks affect the offsprings of employed and unemployed in the two groups in the same way. That is, we only need that the relative difference in the way these factors affect individuals remains unchanged across the treatment and the control group. Under this assumption, our estimator $\hat{\beta}_3$ will identify the effect we are looking for.

$$\hat{\beta}_3 = (\bar{Y}_{T,E^F=1} - \bar{Y}_{T,E^F=0}) - (\bar{Y}_{C,E^F=1} - \bar{Y}_{C,E^F=0}) \tag{5}$$

[9] Again, results are substantially robust to changes in the months threshold (we tried with 30,40,60).

[10] In principle, linear models are not ideal for analyses that involve probability because they might predict negative or bigger than one probabilities. We choose linear models over probit/logit formulations because of the easier interpretability of marginal effects. When we run similar logistic regressions, we obtain substantially the same results. Results are now available upon request and will be included in the Appendix of a future version of the paper.

5.2 Other Linear Probability Models

In order to check that our results hold changing the model specification, we also employ other three different types of regressions: Pooled Ordinary Least Squares, Random Effects GLS and Fixed Effects. In this case we do not use any control group and our identification strategy with FE estimation estimation crucially depends on the time-invariance of the other factors affecting the outcome variables. The estimating model is a reduced version of the previous one and reads as follows

$$Y_{i,t} = \beta_0 + \beta_1 E_{i,t-1}^{\textbf{Father, ongoing}} + \gamma \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{6}$$

We are interested in the estimation of the coefficient β_1. While the POLS is the standard empirical baseline, we are more interested in empirical models that exploit the time structure of the data. In particular, the time-invariant individual heterogeneity captured by the Fixed Effects estimator might affect our results significantly if fixed individual characteristics not captured by controls $\mathbf{X}_{i,t}$ are correlated with labor market outcomes of parents. We run such regressions for both parents and, for comparison purposes, spouses and the three best friends.[11]

For a more in-depth analysis, we restrict to those individuals who have employed parents only: that is, an observation is included in the sample if and only if $E_{i,t-1}^{\textbf{Father, ongoing}} = 1$.

Using the occupations $O_{i,t}$, defined for both employed and unemployed individuals as explained in the Data subsection, we compute a new variable $S_{i,t}$, where S stands for "same" sector:

$$S_{i,t} = \begin{cases} 1 & \text{if } O_{i,t} = O_{i,t}^{\textbf{Father}} \\ 0 & \text{if } O_{i,t} \neq O_{i,t}^{\textbf{Father}} \\ \textit{missing} & \text{otherwise} \end{cases}$$

Such variable captures whether an unemployed individual is assumed to be (or not) seeking a job

[11] Although we would like to run the same regressions for all these variables at the same time, the low amount of data for which all variables are available does not allow us to do so; in a future version, we will try to address this issue and understand the extent to which results are robust to the inclusion of all independent variables.

in the same sector of his employed father, or whether an individual is currently working (or not) in the same sector of his employed father.

We run regressions similar to those explained above, where the job finding events $J^f_{i,t}$ and the job separation events $J^s_{i,t}$ are regressed on the same sector indicator $S_{i,t}$. Notice that in this case the sample will include only those individual whose parents are employed, meaning that any correlation associated to $S_{i,t}$ will be *additional* to those obtained when looking at the correlation with the employed status of parents.

In the Robustness section we question our empirical strategy, allowing for a more flexible specification; we show that our strategy yields the most "conservative" estimates, and we argue that what seems to be the most "obvious" approach leads to upward biased estimates of the marginal effects. Furthermore, the more flexible specification yields negligible gains in efficiency.

6 Results

6.1 Difference-in-Differences Estimation

	Dependent Variable		
	(1) Emp.Status	(2) Job Finding	(3) Job Separation
Father's emp. status (2m, lagged)	-0.00329	-0.0439	-0.000594
	(0.016)	(0.048)	(0.002)
Younger than 27	-0.0745***	-0.131**	0.00162
	(0.023)	(0.052)	(0.003)
Younger than 27*Father's emp. status (2m, lagged)	0.0822***	0.114**	-0.00253
	(0.023)	(0.049)	(0.003)
N	115823	7912	105727
R^2	0.066	0.040	0.006

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9. Difference-in-differences regressions of Employment Status, Job Finding and Job Separation. The control group is given by individuals aged at least 27. We report the coefficient of the **employment status of father**, of **belonging to the treatment group** and the **interaction term** (the effect we want to estimate). All regressions include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

In Table 9 we report the results of our diff-in-diff specification. The estimates indicate that having a father employed (rather than unemployed) is associated with an increase in the individual employment rate of about 8 p.p.. We then decompose this result between an higher job finding rate and a lower job separation, simply by running the same regression changing the dependent variable. Column 2 and 3 of Table 9 shows that the bulk of the economic advantage lies in a much higher job finding rate (the effect estimates is 11 p.p.). We want to stress how the effects estimated by our regression are very large and significant. Unfortunately, it is not possible to include individual fixed effects in these regression, due to the limited availability of individuals who belong both to the tratment and the control group in our sample. Nonetheless, in the next sections we report the results of other linear probability models in which we do control for unobserved heterogeneity.

6.2 Job Finding Rate - Parental Links

Table 10 shows that having the father employed rather than unemployed has a strong and significant effect on the job finding rate of the offspring, perfectly in line with the results outlined above. The partial correlation observed in POLS models, including all relevant controls, lays in the region of 5-6 p.p. These effects are quite large (to be compared with a 12% in-sample average job finding rate) and robust to several model specifications. Panel regressions with RE yield a similar coefficient (6.4 p.p.). Importantly, the coefficient keeps the same size and it is estimated with a similar precision even in fixed effects models. This suggests that the effects captured by the coefficient do not depend on fixed factors (e.g. genes) that might be transmitted across generations. Notice that the in-sample average job finding rate is higher than the average job finding rate of the overall sample, consistently with the lower average age of the estimating sample. We estimate the baseline POLS regression separately by gender, finding that the father has a larger effect on females than on males. This is somewhat puzzling, as the gender segregation in occupations would suggest an opposite pattern.

Conversely, mothers do not appear to have any significant effect on the job finding rate of offsprings, neither for males nor for women. The coefficients are ranging between 3 and 4 p.p. but their estimates

Panel A Dep. Variable: Job Finding

	(1) POLS	(2) POLS (men)	(3) POLS(women)	(4) GLS	(5) FE
Emp. Status (father, lagged)	0.0643***	0.0559***	0.0965***	0.0645***	0.0565**
	(0.014)	(0.018)	(0.028)	(0.020)	(0.023)
Avg. Age (in-sample)	22.1	22.4	21.6	22.1	21.7
Avg. JF rate (in-sample)	0.120	0.114	0.131	0.120	0.119
N	7772	5051	2721	7772	8527
R^2	0.041	0.052	0.061		0.029
N of groups				753	860

Panel B Dep. Variable: Job Finding

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. Status (mother, lagged)	0.0365**	0.0457*	0.0498	0.0365	0.0274
	(0.018)	(0.025)	(0.035)	(0.023)	(0.026)
Avg. Age (in-sample)	22.6	22.8	22.2	22.6	22.2
Avg. JF rate (in-sample)	0.123	0.118	0.131	0.123	0.124
N	7384	4640	2744	7384	7943
R^2	0.045	0.052	0.078		0.032
N of groups				703	799

Panel C Dep. Variable: Job Finding

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. Status (Father, lagged)	0.0835***	0.0870***	0.110***	0.0921***	0.0742*
	(0.021)	(0.030)	(0.033)	(0.033)	(0.040)
Emp. Status (Mother, lagged)	-0.000429	-0.0192	0.0195	0.00135	-0.00275
	(0.023)	(0.035)	(0.037)	(0.032)	(0.036)
Avg. Age (in-sample)	22.1	22.3	21.8	22.1	21.8
Avg. JF rate (in-sample)	0.126	0.119	0.137	0.126	0.127
N	5420	3473	1947	5420	5871
R^2	0.047	0.062	0.082		0.035
N of groups				573	652

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. Linear regressions of Job Finding Rate (transition from Unemployed to Employed); coefficient for **employment status of father** and **mother** (1 for employed, 0 for unemployed), standard error (clustered at individual level), average age and average job finding rate in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

are less precise, even when we use the data as repeated cross-sections (Table 10, panel B).

As the employment status of couples is likely not to be indipendently distributed, our models might be suffering from omitted variable bias. In order to control for correlations between the employment status of the father and of the mother, we estimate the model including both regressors. The results shown in Table 10 (panel C) confirm the patterns shown in the separate regressions, yielding the father's employment status as the only important predictor of offspring's transitions. This is consistent with other studies as for instance Magruder [2010]. The effect of having the father employed ranges between 7.4 and 11 p.p., while the effect of the mother is not stable across specifications and never significantly different from zero. This suggests that the positive effects of mother's employment status -shown in panel B of Table 10- were almost entirely driven by within-couple correlation in employment status. Notice that, even though standard errors rise in fixed effects estimation, the father's coefficient keeps having the same size (or even higher). This indicates that such effects do not depend on within-household correlation in employment status.

In order to get further insights on the father effects found so far, we test whether these are magnified when the occupational sectors of the offspring and of the father coincide. That is, we investigate whether individuals who search for a job in the same sector where their father is employed have additional advantages. As shown in Table 11, such additional advantages are estimated to be in the region of 3 to 5 p.p.. The size of the coefficient is again robust to the inclusion of individual fixed effects. This implies that having the father employed in the same sector where individuals are looking for jobs generates an effect of about 1.6 times the magnitude of having the father employed in some other sector. This is a substantial difference and it might be one of the main factors driving the occupational persistence across generations that we find in the data.

We do not find similar effects for mothers, consistently with our previous findings. Mothers' employment status does not appear to provide any advantages to offsprings, not even when their job is

Panel A	Dep. Variable: Job Finding				
	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (father)	0.0422**	0.0447**	0.0497	0.0447**	0.0366
	(0.018)	(0.020)	(0.034)	(0.019)	(0.023)
Avg. Age (in-sample)	22.0	22.2	21.7	22.0	21.7
Avg. JF rate (in-sample)	0.130	0.123	0.144	0.130	0.131
N	6257	4038	2219	6257	6864
R^2	0.045	0.057	0.069		0.029
N of groups				666	764

Panel B	Dep. Variable: Job Finding				
	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (mother)	-0.00344	0.00482	-0.0236	-0.00526	0.00653
	(0.011)	(0.015)	(0.017)	(0.014)	(0.018)
N	9419	5942	3477	9419	10571
R^2	0.036	0.042	0.070		0.021
N of groups				953	1139

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11. Regressions of Job Finding; coefficient for **father in same sector** and **mother in same sector** (0 employed in other sector, 1 employed in same sector), standard error (clustered at individual level), average age and average job finding rate in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

similar to the one their offsprings are looking for (the associated regression table is shown in Appendix B).

6.3 Job Finding Rate - Other Links

In this section we consider the employment status of the three closest friends and of the spouse, investigating whether these effects are similar in magnitude to the parental ones we documented in the previous section. To ease the comparison we employ the same empirical strategy and model specifications. The only difference is that we do not distinguish between males and females in the regressions.

In the first model, we consider the number of employed friends[12], among the three closest as reported by individuals. Table 12 reveals that friends' employment status has a significant impact on the probability of transition from unemployment to employment. Having an additional employed (rather than unemployed) friend raises on average the individual job finding rate by 3 p.p. Notice that this coefficient is significantly smaller than the father's coefficient (about half in magnitude). Moreover, the friends' coefficient drops with the inclusion of fixed effects in the model, suggesting that individual characteristics are producing a bias in the baseline regressions. Some fixed factors are positively correlated with both the ability of finding a job and having good (employed) friends. Our estimates are in line with those of Cappellari et al. (2010), who find an effect of about 7.4 p.p. on yearly transitions.

As Table 12 shows, spouse links seem to be stronger than those of friends. According to regression results, individuals whose spouse is employed experience a job finding rate that is 5-6 p.p. higher than that of individuals who are married to an unemployed spouse. One possible concern is assortative mating, i.e. the fact that people who are more likely to be employed tend to marry among them. However, the fact that the effect is robust to fixed effects estimation strategies suggests that this mechanism is not driving the results. Summing up, spouse effects are comparable in size to father's ones, while friendship ties seem to be a less important factor in the determination of the job finding rate.

[12] We follow the same strategy as Cappellari and Tatsiramos [2011].

Panel A	Dep. Variable: Job Finding				
	(1)	(2)	(3)	(4)	(5)
	POLS	POLS (men)	POLS (women)	GLS	FE
Num. Employed Friends (lagged)	0.0287***	0.0260***	0.0324***	0.0275***	0.0113
	(0.003)	(0.004)	(0.005)	(0.005)	(0.007)
Avg. Age (in-sample)	33.5	33.3	33.8	33.5	33.0
Avg. JF rate (in-sample)	0.101	0.099	0.105	0.101	0.102
N	14127	9241	4886	14127	14897
R^2	0.028	0.030	0.045		0.031
N of groups				1919	2066

Panel B	Dep. Variable: Job Finding				
	(1)	(2)	(3)	(4)	(5)
	POLS	POLS (men)	POLS (women)	GLS	FE
Emp. Status (spouse, lagged)	0.0527***	0.0595***	0.0549***	0.0690***	0.0613***
	(0.010)	(0.015)	(0.014)	(0.018)	(0.024)
Avg. Age (in-sample)	43.3	44.5	41.9	43.3	43.3
Avg. JF rate (in-sample)	0.100	0.104	0.095	0.100	0.100
N	10580	5737	4843	10580	10621
R^2	0.027	0.036	0.037		0.021
N of groups				1075	1085

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12. Regressions of Job Finding Rate (transition from Unemployed to Employed); coefficient for **number of employed friends** (from 0 to 3) **employment status of spouse** (0 or 1), standard error (clustered at individual level), average age and average job finding rate in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

When considering the occupational sector, we find that on average one has no advantage (in terms of job finding rate) by searching for a job in the same sector as his spouse. The regression table is shown in Appendix B.

Instead, friends' sector appears to be an important predictor of the individual job finding rate in POLS estimation. However, this result is not robust to the use of panel methods estimation, especially to the inclusion of fixed effects. Remarkably, when including individual fixed effects the coefficient turns negative. This suggests that individuals who usually have better chances of finding jobs might be more likely to find employment in the same sector of their best friend, for instance because they also have better social skills.

6.4 Job Separation Rate - Parental Links

The evidence on the effect of the employment status of the father on the job separation rate (summarized in Table 13) is in the same direction of the evidence for the job finding rate. The coefficient is in the region of -0.3%, without notable differences among men and women, keeping the same size when using regression techniques that exploit the panel structure of the data. Overall, regressions suggest that having an employed father reduces the probability of a separation from the present job, even though the estimates are not very precise.

When we restrict our attention to individuals who have an employed father (table **??**), we find that those who work in the same occupational sector as their father experience a further decrease (about -0.2 %) in the job separation rate. Such result is robust across different specifications, although it appears to be significantly lower in the sample of women.

As in the case of the job finding rate, we do not find statistically and economically significant effects of having a mother employed/unemployed on the job separation rate. However, having the mother employed in the same sector does seem to affect the job separation rate of individuals significantly (-0.2 %).

Panel A	Dep. Variable: Job Separation				
	(1) POLS	(2) POLS (men)	(3) POLS(women)	(4) GLS	(5) FE
Emp. Status of father (lagged)	-0.00203	-0.000606	-0.00315	-0.00358*	-0.00354*
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Avg. Age (in-sample)	24.3	24.5	24.1	24.3	24.1
Avg. JS rate (in-sample)	0.007	0.008	0.006	0.007	0.008
N	103826	56146	47680	103826	109460
R^2	0.006	0.008	0.008		0.003
N of groups				1801	2080

Panel B	Dep. Variable: Job Separation				
	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. Status of father (lagged)	0.00246	0.00319	0.00302	0.00413	0.00414
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Emp. Status of mother (lagged)	-0.00164	-0.00334	-0.000417	0.00171	0.000920
	(0.004)	(0.006)	(0.004)	(0.003)	(0.003)
_cons	0.000824	-0.0314	0.0302	0.0691*	0.198
	(0.037)	(0.059)	(0.043)	(0.040)	(0.154)
N	76441	41207	35234	76441	80815
R^2	0.006	0.008	0.009		0.003
N of groups				1491	1706

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13. Linear regressions of Job Separation; coefficient for **father's employment** and **mother's employment** (0 for unemployed, for 1 employed), standard error (clustered at individual level), average age and average job separation in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

Panel A	Dep. Variable: Job Separation				
	(1)	(2)	(3)	(4)	(5)
	POLS	POLS (men)	POLS(women)	GLS	FE
Emp. in Same Sector (father)	-0.00199**	-0.00222**	-0.00127	-0.00167	-0.00137
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Avg. Age (in-sample)	24.3	24.6	24.1	24.3	24.1
Avg. JS rate (in-sample)	0.007	0.008	0.006	0.007	0.007
N	95148	51190	43958	95148	100317
R^2	0.006	0.008	0.008		0.003
N of groups				1670	1933

Panel B	Dep. Variable: Job Separation				
	(1)	(2)	(3)	(4)	(5)
	POLS	POLS (men)	POLS (women)	GLS	FE
Emp. in Same Sector (mother)	-0.00181**	-0.00225*	-0.00137	-0.00224**	-0.00175*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Avg. Age (in-sample)	24.2	24.5	23.8	24.2	23.9
Avg. JS rate (in-sample)	0.008	0.009	0.007	0.008	0.008
N	119056	65382	53674	119056	127838
R^2	0.006	0.008	0.007		0.003
N of groups				2233	2662

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14. Regressions of Job Separation; coefficient for **Father in same sector** and **Mother in same sector** (0 employed in other sector, 1 employed in same sector), standard error (clustered at individual level), average age and average job separation in the sample of the regression.Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

6.5 Job Separation Rate - Other Links

In the same spirit of the previous section, we compare the father's and mother's coefficients with those of friends and spouse (Table 15). Interestingly, we find that the correlation between job separation and having an employed spouse is weak and unstable across specifications. Coefficients are in the region of -0.1 % for POLS estimation, but become virtually zero when adding individual fixed effects, suggesting that spouse's partial effects are weaker than those of the father, and that selection mechanisms shape results substantially.

Panel A Dep. Variable: Job Separation

	(1) POLS	(2) POLS (men)	(3) POLS(women)	(4) GLS	(5) FE
Emp. Status (spouse, lagged)	-0.00117*	-0.00238**	-0.000306	-0.000176	-0.0000269
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Avg. Age (in-sample)	44.4	45.5	43.4	44.4	44.4
Avg. JS rate (in-sample)	0.002	0.002	0.002	0.002	0.002
N	456732	222971	233761	456732	463224
R^2	0.001	0.002	0.001		0.000
N of groups				6069	6208

Panel B Dep. Variable: Job Separation

	(1) POLS	(2) POLS (men)	(3) POLS(women)	(4) GLS	(5) FE
N. of Emp. Friends (lagged)	-0.00506***	-0.00616***	-0.00379***	-0.00405***	-0.00302***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Avg. Age (in-sample)	38.4	38.6	38.2	38.4	38.1
Avg. JS rate (in-sample)	0.004	0.005	0.003	0.004	0.004
N	333391	189926	143465	333391	345870
R^2	0.005	0.006	0.005		0.001
N of groups				10468	11418

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15. Regressions of Job Separation; coefficient for **spouse's employment** (0 for unemployed, for 1 employed), standard error (clustered at individual level), average age and average job separation in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

We find that having an additional employed friend decreases the job separation rate by 0.5 % in the pooled regression. The coefficient changes magnitude across specifications, being approximately -0.4 % in the random effects model and -0.3 % in the fixed effects model, suggesting that correlation between friends' and individual characteristics might be relevant issues for this kind of partial correlation. The magnitude of the coefficient for an additional employed friend is comparable to that of having the father employed rather than unemployed. Interestingly, having the spouse employed in similar occupations does not affect significantly the job separation rate of an individual, as was the case for the father's employment. Instead, having the best friend employed in the same sector lowers the job separation rate by approximately 0.2 percentage points.

Panel A Dep. Variable: Job Separation

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (spouse)	-0.000259	-0.000211	-0.000462*	-0.000204	-0.000138
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Age (in-sample)	TO ADD				
Avg. JS rate (in-sample)	TO ADD				
N	435082	213959	221123	435082	436362
R^2	0.001	0.002	0.001		0.001
N of groups				5840	5896

Panel B Dep. Variable: Job Separation

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (best friend)	-0.00138***	-0.00158***	-0.00105***	-0.00178***	-0.00175***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Age (in-sample)	39.3	39.4	39.2	39.3	39.2
Avg. JS rate (in-sample)	0.004	0.005	0.003	0.004	0.004
N	294789	148595	146194	294789	299344
R^2	0.004	0.005	0.003		0.001
N of groups				12235	12671

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16. Regressions of Job Separation; coefficient for **spouse in same sector** and **best friend in same sector** (0 employed in other sector, 1 employed in same sector), standard error (clustered at individual level), average age and average job separation in the sample of the regression.Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

7 Discussion

In this section we discuss our results and provide some possible mechanisms that can explain the partial correlations observed in the data. The focus of our discussion is exclusively on the effects of fathers' variables on offsprings' job finding rates, which we consider as the most important of our results. At a first glance, these positive effects are consistent with the standard models of networks in the labor market. Information flow on vacancies and job opportunities probably represents one of the main channels through which individuals belonging to the same social network help each other. Of course, the partial correlations uncovered by our regressions possibly include several other mechanisms.

Genetical and Human Capital Transmission

For instance, genetical and human capital transmission across generations might be driving the results. To this respect, we have to consider that for each of the models we estimate, we always include fixed effects as the last specification. In this way we capture fixed individual characteristics that have an effect on the dependent variable and are possibly correlated with the explanatory variables of interest. Genetical endowments are an example of such individual characteristics that are properly controlled for in fixed effects models, assuming that their effect is linear and non time-varying. With respect to human capital, even though it could -at least in part- be assimilated to fixed factors in adult individuals, this is certainly not true for young individuals. Human capital is a time-varying factor that can be potentially relevant in our estimates. The presence of educational group dummies in our regression attenuates this problem, as education is a good proxy for human capital. However, If the effects were due to the transmission of human capital or work ethics, then we should find that the exact timing of the employment status (or the sectoral belonging) of the father does not matter much. Indeed, such transmission mechanisms are supposed to be long-lasting, and it is also reasonable to think that they take some time in order to produce their effects. Hence, as a further robustness check we include in our regression several lags of the employment status of the father. Interestingly, columns 1-4 of Table 17 reveals that only the contemporaneous employment status and sector of the father have an effect. The coefficient of the lags considered (3, 6 and 12 months) are actually negative or not significative, indicating that human capital transmission is not a relevant factor in our estimates. Since strong collinearity might be causing a bias in our coefficients, we also estimate a regression including only the 12-months lag of our variables of interest (columns 2 and 4 of Table 17). We find this to have, if anything, a slightly negative effect on the job finding rate. Repeating the same test for both the employment status and the occupational sector provides a test for, respectively, a general and an occupation-specific human capital interpretation. As we can see, the empirical evidence is strongly at odds with this interpretation. The fact that the coefficients of the current variables are even higher now reveals that in the baseline models these coefficients were picking up the negative correlations of the lagged variables, which are serially correlated.

Direct Hiring

Second, another possible channel is direct hiring of individuals by their father. Even though it is unclear whether this should be considered as an informational advantage or another kind of mechanism, we investigate whether a major part of the effects we find can be attributed to this channel. We study whether having a father who hires employees (rather than employee or self-employed without employees) boosts the advantages in terms of job finding rate. Column 5 of Table 17 shows that, if anything, having a father who is an employer has a negative effect on the individual job finding rate. This is strongly inconsistent with an interpretation of our results as direct hiring.

Local Labor Market Conditions

Another possibility is the existence of common shocks affecting both parental employment status and offsprings' performances. For instance, if an individual and his father both live in a region that has experienced a positive shock, their employment statuses will be correlated as they will be caused by the same fundamental shock. Similar considerations can be made with respect to the occupational sector. If the partial correlations we find are due to local labor market conditions, then we should expect these correlations to be stronger when the offspring lives together with his father. To this purpose, we

Dep. Variable: Job Finding

	(1) Lags	(2) Lag 12 only	(3) Sector lags	(4) Sector lag 12 only	(5) Fat. Hires Employees
Emp. Status (father, lagged)	0.0866**				0.0577***
	(0.037)				(0.022)
Emp. Status (father, 3 months lag)	-0.0415				
	(0.041)				
Emp. Status (father, 6 months lag)	-0.0161				
	(0.033)				
Emp. Status (father, 12 months lag)	0.00719	-0.0148			
	(0.026)	(0.023)			
Father in Same Sec. (lagged)			0.0758**		
			(0.035)		
Father in Same Sec. (3 mths lag)			-0.00615		
			(0.033)		
Father in Same Sec. (6 mths lag)			-0.0247		
			(0.031)		
Father in Same Sec. (12 mths lag)			0.00972	-0.00866	
			(0.026)	(0.021)	
Father Hires Employees					-0.106**
					(0.048)
N	6918	7891	5039	6039	8563
R^2	0.025	0.024	0.033	0.030	0.027
N of Groups	672	740	568	643	791

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17. Discussion: Human Capital and Direct Hiring. All regressions are fixed effects estimates. All regressions include all controls discussed in previous sections.

use the region of residence, generating a dummy that takes the value 1 when the region of residence of the offspring does not coincide with the one of the father. Column 1 of Table 18 shows that the partial correlation of father's employment with offsprings' job finding rate is instead magnified when the offspring lives in a different region from his father, even though the estimate of the difference is not very precise. In our regression we control for regional changes of offsprings, to account for the possibility that individuals migrate in order to find a job, which would bias the estimate of the father's employment coefficients. Individuals who belong to different regions definitely belong to different local labor markets, and therefore we have to conclude that local labor market conditions are not an important driver of the correlations we find. In order to control further for local labor market conditions, we also compute the average unemployment rate by sector and by region. We then add these new variables to our regressions as additional controls. As shown in columns 2-5 of Table 18, the partial correlations are unchanged by the inclusion of all these possible controls. In particular, we are including dummies for the sector interacted with the year in column 4 and for the region interacted with the year in column 5, controlling for possible booms or busts of given segments of the labor market. Nonetheless, this does not appear to capture at all the effects outlined so far.

8 Robustness Checks

In this section we explore whether our results are robust to different choices of the sample and to different empirical strategies. First, we want to understand whether the composition of our sample might be driving our estimates. The fact that our estimating sample includes many individuals who are still at school or at the university might be creating problems of sample selection. To control for this possibility, we try to exclude individuals with a college degree from our sample. Column 1 of table 19 presents results of this estimation: although the size of the estimate is somewhat lowered, it still is statistically and economically significant, showing that college-educated individuals are not driving the bulk of the correlations we find.

Dep. Variable: Job Finding

	(1) Local Conditions	(2) Sector Unemp.	(3) Region Unemp.	(4) Sector*Year	(5) Region*Year
Emp. Status (father, lagged)	0.0558**	0.0553**	0.0553**	0.0564**	0.0542**
	(0.024)	(0.022)	(0.022)	(0.024)	(0.024)
Father emp. (in other region)	0.0619				
	(0.040)				
Father unemp. (in other region)	-0.121				
	(0.116)				
Has Changed Region from last year	X				
Unemployment of Sector		X			
Unemployment in Metropolitan Area of residence			X		
Interactions Sector × Year				X	
Interactions Region × Year					X
N	7816	8563	8563	8563	9246
R^2	0.029	0.027	0.029	0.047	0.062
N of Groups	754	791	791	791	828

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18. Discussion: Local Labor Market Effects. All regressions are fixed effects estimates. All regressions include all controls discussed in previous sections.

Then, we consider the possibility that only very young workers (aged 16-20) are affected by the employment status of their father. However, when we include only individuals aged more than 20 years of age in the estimation (column 4), we maintain the size of the coefficient, despite losing more than one-third of our original sample.

Also, we consider the possibility that our assumptions on sectors of search might be important for our results: by using future and past occupations as proxies of current sectors of search, we are de facto excluding those individuals who are always unemployed in the BHPS, or who never report their occupation. To account for this possibility, we exclude controls for occupation from our estimations. Results are reported in column 2: the coefficient is lowered by about 1 percentage point, maintaining statistical and economical significance.

Finally, we question our empirical strategy and consider the possibility that a more flexible model may allow us to better capture the nature of the correlations we find. That is, we do not keep only fathers who are on an ongoing spell but rather all the observations which are not missing. Specifically, we construct four indicators based on the two months of job history of the father during the offspring's transitions: hence we have one dummy for "father unemployed past month and current", one for "father unemployed past month but employed on current" and so on. Column 3 shows the results of such experiment: while the coefficient roughly corresponding to our empirical strategy (employed past month and current) maintains substantially the same magnitude and standard error, the coefficient corresponding to "father unemployed last month, employed today" is strikingly high. Such a coefficient is due to a relatively large number of transitions taking place at the same time (for both fathers and offsprings) and does not correctly capture any direct effect of fathers on offsprings. There are at least two main issues: first, common high-frequency shocks that we are not able to properly control for might be a common cause for these contemporaneous events. Second, there is the possibility that in fact offsprings are affecting fathers (instead of the other way around), producing a large upward bias due to reverse causality.

	(1) No College	(2) No Sectors	(3) Different Model	(4) Age > 20
Emp. Status (father, lagged)	0.0461**	0.0490**		0.0616**
	(0.022)	(0.021)		(0.028)
Father U-E			0.172***	
			(0.050)	
Father E-U			0.0526	
			(0.054)	
Father E-E			0.0632***	
			(0.022)	
N	7826	9246	8644	5889
R^2	0.026	0.024	0.026	0.031
N of groups	671	828	792	576

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 19. Robustness Checks: regression without college graduates (column 1), no sectoral dummies (column 2), more flexible specification (column 3), Only individuals aged > 20 (column 4). Omitted category: Father U-U. All regressions are fixed effects estimates. All regressions include all controls discussed in previous sections.

9 Conclusion

We tested whether parental links affect labor market outcomes of individuals using rich panel data from the British Household Panel Survey. Our results indicate that, on average, those whose father is employed rather than unemployed experience an employment rate that is about 8 percentage points higher, with job finding rates which are higher by 5 percentage points and job separation rates which are lower by 0.3 p.p.. We also show that such difference is larger when individuals work in occupations similar to those of their father. We do not find similar correlations for mothers, and we show that father's effects are similar in magnitude, or larger, to those of other supposedly relevant links. We also document that the job separation rate is on average lower for individuals whose father is employed in similar occupations to theirs.

By means of a number of robustness checks, we show that our results are unlikely to be attributable to human capital transmission, to common shocks driving both outcomes at the same time or to the fact that fathers directly hire their offsprings. Our conclusion is that parental networks are likely to play an important role in determining labor market outcomes.

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Appendix A - The Data

Construction of Job Histories

The BHPS is a yearly survey, and therefore its basic structure contains yearly observations for each individual. Among the available variables, individuals report what their employment status and occupation is at the moment of the interview and when the current spell began. In addition to the main dataset, there is a separate annex in which individuals list their detailed job history in the last 12 months. Each single spell is identified with a start date and an end date. When the month of the start date is missing, we replace it with the month of the interview (if the spell began in the same year) or with December (if the spell began in some previous year). In this way, we partly exploit those spells, that otherwise would be completely missing. For each spell we are provided with the employment status, occupation and other information.

We replace the yearly observations by 12 monthly observations for each individual. Then, we fill in the employment status exploiting the information provided. Constructing correctly the job histories is not a straightforward exercise, as the spells reported by individuals sometimes overlap or conflict with each other. In order to solve this issue, we need to set a hierarchical order of the available information. Importantly, we never replace the variables we copy over time once they are assigned, even if they get into conflict with some future source of information. We give priority to the current spell report, as the amount of recall needed to report it correctly is smaller than for past spells. Therefore, first of all we copy the current employment status over time, from the start date of the current spell to the date of the interview. Second, we use past spells to fill in the remaining missing values. Again, we assume that recalls closer in time are more reliable and therefore we first consider the very last spell, then the second last and so on.

We fix 12 as the maximum number of difference in months between the interview (moment of the recall) and the variable to assign (object of the recall). For individuals who are interviewed every year this choice has virtually no effect, as their employment sequences are constructed simply using for each given year the information provided in the interview of the same year. For the others, this choice is meant to limit the amount of measurement error generated by imperfect recall. We noticed that individuals often change their answer to the lenght of the current spell or modify the order or the nature of a job spell, even after years. This implies that without fixing a maximum time difference for assigning the variables, we would end up with a dataset that included pieces of different spell, oftern misreported, one after the other.

Employment Status Imputation of Friends

Individuals are asked about the employment status of their friends once per two years. What is available in the basic structure of the BHPS is therefore a unique observation. Unfortunately we cannot construct the job histories of friends, as no identification number is reported. In order to keep the monthly frequency, we replicate the information on friends over the following 12 months. This is done also to keep relatively large the sample size. Our imputation procedure is based on the assumption that the employment status features a relatively large degree of persistence over time. This is certainly true for employment spell, as the job separation rate in the sample is small and implies long average job duration. It is also true for unemployment spells, as the average unemployment spell duration is above one year. By replicating the employment status in the following 12 months we are simply assuming that those spells of friends are average ones. The only risk we bear is to misplace them in time.

Sector Imputation of Unemployed

The unemployed, by definition, do not belong to any occupational sector. One might even argue that unemployed are simply looking for some job, regardless of any occupational classification. Instead, we believe that we gain useful insights by imputing sector of search to the unemployed. From the data we see that individuals do not change occupational sector often and, even when they do so, the change is usually not dramatic (e.g. movements from sector 2 to sector 3). Moreover, it seems reasonable to think that individuals target their job search to some particular sector of the economy, consistently with their educational level, qualifications and past occupations. Therefore we treat unemployed workers -for which the sector is in principle missing- as if they were still belonging to some occupational sector. Furthermore, for the purpose of our analysis we need to assign them to some sector.

The problem is that we do not really know in which sector they are seeking jobs. The idea behind our imputation is very simple: by logic, the sector where an unemployed worker finds a job is just the sector where he was seeking jobs. The only limitation is that we assign the whole unemployment spell to that particular sector, without allowing for movements across sectors within the spell. When the sector after the unemployment spell is not reported, then we use the previous sector. In any case, to limit the amount of measurement error generated by our imputation, we only consider spells that immediately follow (or precede) the unemployment spell of interest.

Educational and Occupational Classification

For constructing educational groups, we consider the highest educational qualification achieved by individuals. The original variable contains more than ten possible values, with an elevated degree of details. We collpase those ten groups into four. The first group corresponds to those who hold a Bachelor's degree or some higher degree. The second group includes the individuals with a high school diploma or qualifications for teaching or nursing. Individuals with an A level or O level fall into the third group. Finally, the fourth group is for those who hold no qualification whatsoever.

With respect to the occupational classification, we follow the aggregation in major group of the SOC as proposed by the Employment Department Group and the Office of Population Cansuses and Surveys. The BHPS uses the SOC90 (Standard Occupational Classification), a three-digit code, for describing occupations. At the most disaggregated level we have 347 categories, and in order to analyze the persistence across sectors we need to aggregate them. We choose the aggregation in major groups (9 categories) as the one able to preserve some substantial degree of persistence while keeping a satisfactory level of details.

For further details, refer to "Standard Occupational Classification - Structure and Definition of Major, Minor and Unit Groups, Volume 1"

Representativeness of the BHPS sample

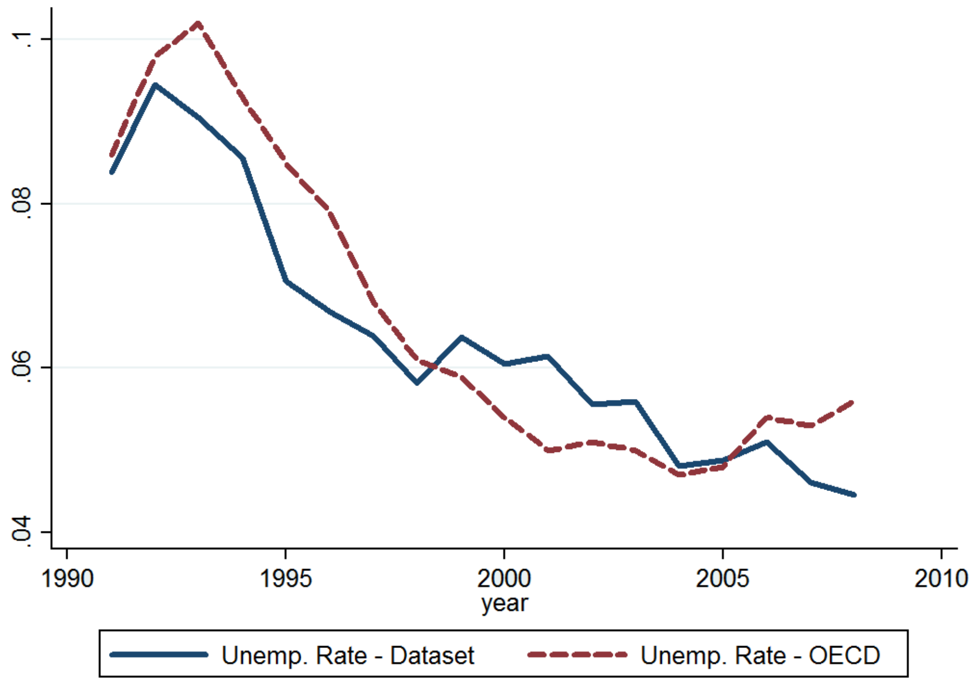

Figure 6. In-sample unemployment rate compared to the Harmonized Unemployment Rate in UK, 1991-2008 (Source: OECD).

Appendix B - Additional Tables

Dep. Variable: Job Finding

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (mother)	-0.00344	0.00482	-0.0236	-0.00526	0.00653
	(0.011)	(0.015)	(0.017)	(0.014)	(0.018)
Avg. Age (in-sample)	22.0	22.0	21.8	22.0	21.6
Avg. JF rate (in-sample)	0.127	0.126	0.130	0.127	0.129
N	9419	5942	3477	9419	10571
R^2	0.036	0.042	0.070		0.021
N of groups				953	1139

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20. Regressions of Job Finding; coefficient for **mother in same sector** (0 employed in other sector, 1 employed in same sector), standard error (clustered at individual level), average age and average job finding rate in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

Dep. Variable: Job Finding

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (spouse)	0.00308	0.0122	-0.00819	0.0104	0.00883
	(0.012)	(0.016)	(0.020)	(0.017)	(0.022)
Avg. Age (in-sample)	43.5	44.5	41.9	43.5	43.5
Avg. JF rate (in-sample)	0.109	0.116	0.101	0.109	0.110
N	9343	5090	4253	9343	9367
R^2	0.014	0.018	0.020		0.008

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21. Regressions of Job Finding; coefficient for **spouse in same sector** (0 employed in other sector, 1 employed in same sector), standard error (clustered at individual level), average age and average job finding rate in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

Dep. Variable: Job Finding

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (best friend)	0.0221***	0.0320***	0.00890	0.0175*	-0.00850
	(0.007)	(0.009)	(0.011)	(0.010)	(0.014)
Avg. Age (in-sample)	34.3	34.5	34.0	34.3	34.1
Avg. JF rate (in-sample)	0.097	0.096	0.098	0.096	0.098
N	14269	8523	5746	14269	14594
R^2	0.022	0.025	0.027		0.033
N of groups				2101	2175

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22. Regressions of Job Finding; coefficient for **best friend in same sector** (0 employed in other sector, 1 employed in same sector), standard error of coefficient (clustered at individual level), average age in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, year, occupation of search or of employment, defined according to the assumptions described in section X.

Dep. Variable: Job Separation

	(1) POLS	(2) POLS (men)	(3) POLS(women)	(4) GLS	(5) FE
Emp. Status (mother, lagged)	-0.00199	-0.00549	0.00102	-0.0000258	-0.000886
	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)
Avg. Age (in-sample)	24.3	24.6	24.0	24.3	24.1
Avg. JS rate (in-sample)	0.007	0.008	0.006	0.007	0.007
N	97755	51355	46400	97755	103471
R^2	0.005	0.007	0.007		0.003
N of groups				1739	1997

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23. Regressions of Job Separation; coefficient for **mother's employment** (0 for unemployed, for 1 employed), standard error of coefficient (clustered at individual level), average age in the sample of the regression. Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, year, occupation of search or of employment, defined according to the assumptions described in section X.

Dep. Variable: Job Separation

	(1) POLS	(2) POLS (men)	(3) POLS (women)	(4) GLS	(5) FE
Emp. in Same Sector (spouse)	-0.000259	-0.000211	-0.000462*	-0.000204	-0.000138
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg. Age (in-sample)	44.3	45.3	43.3	44.3	44.3
Avg. JS rate (in-sample)	0.002	0.002	0.002	0.002	0.002
N	435082	213959	221123	435082	436362
R^2	0.001	0.002	0.001		0.001
N of groups				5840	5896

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24. Regressions of Job Separation; coefficient for **Spouse in same sector** (0 employed in other sector, 1 employed in same sector), standard error (clustered at individual level), average age and average job separation in the sample of the regression.Models 1-3 are pooled OLS regressions, model 4 is a random effects GLS regression, model 5 is a fixed effects regression. All models include a third-degree polynomial in age and dummies for education, gender, region of residence, smoking behaviour, marital status, ethnicity, quarter, occupation of search/employment, defined according to the assumptions described in Appendix A.

10 Apendix C - Initial network's effect dies out over time

This can be illustrated simply by looking at the evolution of an individual's network over time. Given the initial condition, the value of an individual's network at a given time is a function of the whole history of employment spells[13]. Nonetheless, given a history, it is easy to derive an expression for the individual network. It is particularly straightforward to derive an expression for the network under the two extreme scenarios: the one in which an individual is constantly employed (Equation 7), and the opposite one in which he is constantly unemployed (Equation 8). We can interpret these two cases as the best and the worst-case scenario, respectively. These provide an upper and a lower bound for the value of an individual network, given an initial condition.

$$(n^j_{i,T}|S^j_{i,1} = ... = S^j_{i,T} = E; n^j_{i,0}) = \underbrace{(1-\delta^E)^T n^j_{i,0}}_{\text{Discounted initial network}} + \overbrace{\sum_{k=0}^{T-1}(1-\delta^E)^k\alpha}^{\text{New on-the-job contacts}} + \underbrace{\sum_{k=0}^{T-1}(1-\delta^E)^k\epsilon^j_{i,T-k}}_{\text{New random contacts}} \tag{7}$$

$$(n^j_{i,T}|S^j_{i,1} = ... = S^j_{i,T} = U; n^j_{i,0}) = \underbrace{(1-\delta^U)^T n^j_{i,0}}_{\text{Discounted initial network}} + \underbrace{\sum_{k=0}^{T-1}(1-\delta^U)^k\epsilon^j_{i,T-k}}_{\text{New random contacts}} \tag{8}$$

In both of these equations we can notice that as $T \to \infty$, the share of an individual's network accounted for by the initial network he receives tends to zero. In other words, in our model the covariance between an individual's network and its initial condition vanishes over time (the following expression is for simplicity assuming a fixed δ).

$$cov(n^j_{i,T}, n^j_{i,0}) = (1-\delta)^T var(n^j_{i,0}) \to 0 \qquad \text{as } T \to \infty \tag{9}$$

Furthermore, notice that the probability that an individual is employed at any given time T is an increasing function of her job finding rate f^j_i (to derive the following expression, we assume that the job

[13]The number of periods in which the individual was employed rather than unemployed is not sufficient to know the value of the individual's network. The exact timing of each spell is also necessary information.

finding rate does not vary over time), that in turn is an increasing function of her network (Equation 2). We assume that at time 0 (at the entry in the labor market) every individual is unemployed ($S^j_{i,0} = 0 \ \forall j, i$).

$$P(S^j_{i,T} = E) = f^j_i (1 - P(S^j_{i,T-1} = E)) + (1 - \gamma) P(S^j_{i,T-1} = E) \tag{10}$$

Taking as given the employment status at $T - 1$, it is trivial to see that the probability of being employed at T is strictly increasing in f. Iterating backward this argument, one can show that the employment probability at ant time T is strictly increasing in f. Therefore, being f strictly increasing in n, equation 9 implies that also the correlation between the employment status of an individual and the one of his parent dies out over time.