# Like Father, Like Son: Occupational Choice, Intergenerational Persistence and Misallocation

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**Abstract**

We develop a dynamic quantitative model of occupational choice and search frictions with multiple channels of intergenerational transmission (comparative advantage, social contacts and preferences), and use it to decompose the occupational persistence observed in the UK. In the model, workers who choose their father's occupation find jobs faster and earn lower wages, which is consistent with patterns found in UK data. Quantitatively, parental networks account for 79% of total persistence. Shutting down parental networks or the transmission of preferences improves the allocation of workers and thus yields welfare gains, while removing the transmission of comparative advantage generates welfare losses.

**Keywords:** Comparative Advantage, Labor Productivity, Mismatch, Occupational Mobility, Social Contacts.

**JEL Classification Numbers:** J24, J62, J64.

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# 1 Introduction

It is well known that a number of economic outcomes are correlated across generations, most notably income, education and occupational choice. Such persistence is commonly believed to represent a failure of the equality of opportunity principle, besides being potentially symptomatic of an underlying misallocation of resources and talents (Mora, 2009; Caselli & Gennaioli, 2013; Güell *et al.*, 2015). In particular, a large degree of persistence in occupational choice may reflect the presence of barriers of various types in the labour market, implying a suboptimal allocation of workers to jobs. However, a quantitative theory of occupational persistence, that would help us understand whether or not persistence is indeed associated with inefficiencies, has not been developed yet.

In this paper, we study how intergenerational occupational persistence and labor misallocation are related. We demonstrate that when persistence stems from a number of sources, it is crucial to measure the quantitative importance of each and how they interact with one another. To do so, we develop a dynamic model of occupational choice and search frictions that features multiple channels of intergenerational transmission, and use it to decompose the occupational persistence observed in UK data. Our quantitative analysis provides novel insights on the impact of different sources of persistence on the sorting of workers in the labor market, and therefore the aggregate level of efficiency and welfare.

In order to inform the quantitative analysis, we first document a number of facts on occupational persistence and on the labor market performance of those who pursue the same occupation as their parents (*occupational followers*) relative to those who do not (*occupational movers*). Our empirical analysis exploits micro data from the British Household Panel Survey (1991–2008) on male workers and their fathers. This dataset allows us to observe labor market transitions at the monthly frequency, occupation and wages of both fathers and sons, together with a large number of other covariates.

We estimate that the degree of occupational persistence in the UK is substantial: at the 1-digit level, a worker is 72 percent more likely to be employed in a given occupation if his father is also currently employed in that occupation. Turning to labor market outcomes, we find that occupational followers exhibit monthly job-finding rates that are about 5 percentage points higher than those of occupational movers. Given that the average in-sample job-finding probability is about 12.5 percentage points, looking for a job in the same occupation as one's father is associated to a substantial advantage in terms of employment prospects (robust to the inclusion of individual fixed effects). Regarding wages, we find that occupational followers exhibit large discounts (between 8 and 13 log points) relative to occupational movers. These results are shown to be robust to alternative definitions of *occupational followers* that use information on the entire labor market career as well as only contemporaneous information, and to the use of a more detailed (2-digit) occupational classification. Importantly, all our findings hold *within* occupations, in the sense that we compare the labor market outcomes of individuals who work or search for a job in a given occupation, and have fathers who may or may not work in that occupation. Finally, we also document that sons of high-wage fathers are more likely to be occupational followers, a fact that supports a theory based on comparative rather than absolute advantage.

Guided by our empirical evidence, we develop a dynamic model of occupational choice in which abilities (comparative advantage), social contacts and preferences are transmitted across generations. In our model, occupational persistence can indeed be a sign of misallocation if parents help their offspring find a job faster in their current occupation, which is not necessarily where their offspring's comparative advantage lies. However, agents optimally choose their occupation, so that productive occupational mismatch is not necessarily detrimental to welfare.[1] We calibrate the quantitative model in order to match the abovementioned key pieces of empirical evidence, along with several other features of the UK economy. In particular, the parameters governing intergenerational transmission are pinned down as follows: the transmission of social contacts replicates the job-finding rate premium of followers, the transmission of comparative advantage replicates the differential in persistence by parental wage, and the transmission of preferences is the residual channel of occupational persistence.

We acknowledge that, by definition, this notion of parental networks implicitly accounts for all factors that cause offspring to find jobs faster in their father's occupation. This includes fathers helping their offspring in a variety of ways that are specific to their occupation: giving information on vacancies that are otherwise hard to find, providing contacts which can either look more favorably at a prospective applicant or alleviate information frictions, calling in "favors" to increase the probability that the offspring is hired or provide specific knowledge that can help at the application or interview stage.

[1] We study more in depth the welfare implications of the transmission of social contacts across generations in Lo Bello & Morchio (2021).

We investigate the quantitative importance of the three different channels in generating occupational persistence, and find that parental networks can account for about 79 percent of persistence, whereas transmission of comparative advantage and preferences account for 19 percent and 9 percent, respectively.[2] The very large role played by parental networks depends on the fact that they interact with the other two factors generating persistence, thus acting as a multiplier. We also find that the impact on welfare of occupational persistence can be either positive or negative, depending on the driving source. When we shut down parental networks or the transmission of preferences, welfare improves: workers align their occupational choice more often with their comparative advantage, thus output per worker increases and firms react by posting more vacancies. In contrast, when we shut down the transmission of abilities, the reduction in persistence is accompanied by a reduction in welfare, driven by a larger degree of productive mismatch, which in turn also leads to less firm entry. However, the changes in welfare are relatively small: when we shut down parental networks, welfare improves by 0.3 percent in consumption equivalent variation. The other counterfactuals deliver even smaller changes. Interestingly, most of the qualitative results are accounted for by the partial equilibrium reaction of workers, but general equilibrium forces reinforce the results: for instance, when we shut down parental networks, unemployment is lower and output is higher if optimal vacancy posting (firm entry) is accounted for.

To confirm the importance of the three transmission channels, we demonstrate that a model in which only productive abilities are transmitted across generations (which we call the *restricted model*) falls short at accounting for several key pieces of evidence, and in general provides a worse fit to the data. We also investigate the role of search frictions and find that the impact of parental networks on the allocation becomes negligible as equilibrium unemployment tends to zero; also, a decrease in the equilibrium job-finding rate in our model simultaneously generates a rise in the unemployment rate and a drop in labor productivity, via more mismatch. Finally, in our model more generous unemployment benefits imply that workers are less likely to choose the same occupation as their father in order to reduce the probability of unemployment. This implies that, in addition to reducing occupational persistence, increasing benefits can potentially be welfare-improving, since the allocation of the workforce may also improve. Nonetheless, we find that an increase in unemployment benefits triggers a reallocation towards preferences rather than comparative advantage. Therefore,

[2] The sum of the effects of the three transmission channels exceeds 100 percent because they are endogenously correlated.

the overall effect on welfare is slightly negative. For instance, an increase in unemployment benefits of 25 percent yields a decrease in welfare of 0.6 percent in consumption equivalent variation.

While there is a significant amount of research on income persistence across generations,[3] work on occupational choice is far scarcer in the literature.[4] We contribute to this literature along several dimensions: First, we add to the empirical literature on occupational persistence across generations (Constant & Zimmermann 2004, Hellerstein & Morrill 2011, Ermisch & Francesconi 2002, Di Pietro & Urwin 2003, Long & Ferrie 2013) by documenting new facts on labor market outcomes of occupational followers. We show that, relative to other observationally equivalent workers, they find jobs faster but earn lower wages.[5] Moreover, we provide new estimates of the likelihood of belonging to the same occupational category as one's father using contemporaneous information based on monthly transitions.

Second, our study bridges the literature on the determinants of occupational choice (Miller 1984; McCall 1991; Keane & Wolpin 1997; Papageorgiou 2014; Carrillo-Tudela & Visschers 2014), its consequences for inequality (Kambourov & Manovskii 2009) and unemployment duration (Wiczer 2015) and the literature on occupational persistence and career following (Laband & Lentz 1983; Doepke & Zilibotti 2017). Our paper adopts a quantitative perspective on occupational choice across generations, providing novel insights into how persistence maps to efficiency and aggregate welfare.[6] We stress that in this paper we focus on the determinants of occupational persistence and how this affects aggregate outcomes, while we do not study the connection between occupational choice persistence and earnings persistence across generations. In this sense, we view our framework as a model of horizontal, rather than vertical, occupational persistence.[7]

Third, we relate to the literature on social networks in the labor market (for instance, see

[3]The first important contribution in the intergenerational literature was Becker & Tomes (1979); more recently, Solon (1992, 2002); Corak (2006); Hertz (2006); Björklund & Jäntti (2009) have documented persistence in income. For persistence in education, see Chevalier *et al.* (2009); and for occupational persistence, see Hout & Beller (2006), Constant & Zimmermann (2004), Escriche (2007), Eberharter (2008) and Dustmann (2004). Two reviews of the literature can be found in Black & Devereux (2010) and Ermisch *et al.* (2012).

[4]The economic literature has primarily focused on the study of income persistence, while the sociological literature, pioneered by Blau & Duncan (1967), has focused on occupational persistence. More recent contributions include Stier & Grusky (1990), Checchi (1997) and Andres *et al.* (1999).

[5]This new finding in the intergenerational context is similar to the patterns shown in Bentolila *et al.* (2010) regarding workers who find jobs through networks.

[6]With a similar perspective, Sinha (2016) studies how borrowing constraints affect occupational choices and how this mechanism can be important in understanding persistence in developing countries.

[7]Modeling earnings persistence and vertical occupational persistence would require us to model persistence in general ability and to allow for heterogeneous occupations, while our model features homogeneous occupations. We leave this question to further research.

Horváth 2014 and Galenianos 2014)[8] and particularly the transmission of contacts or related advantages across generations (Corak & Piraino 2011, Kramarz & Skans 2014, Pellizzari *et al.* 2011, Lentz & Laband 1989, Aina & Nicoletti 2014, Bamieh & Cintolesi 2021 and Basso *et al.* 2021). Fourth, our paper investigates the possibility of misallocation of the labor force due to socially suboptimal occupational choice, as in Bentolila *et al.* (2010), Hsieh *et al.* (2013) and Munshi & Rosenzweig (2016). In the intergenerational context, the occurrence of socially suboptimal occupational choice has been studied also in Caselli & Gennaioli (2013), Celik (2015) and Spiganti (2020). Finally, our decomposition exercise is very close in spirit to the quantitative exercises decomposing income persistence across generations, such as Restuccia & Urrutia (2004), Lee & Seshadri (2014), Abbott *et al.* (2013) and Gayle *et al.* (2015).

The rest of the paper is organized as follows: Section 2 presents empirical evidence on occupational persistence and the labor market outcomes of occupational followers and movers. Section 3 outlines the dynamic quantitative model, which is calibrated and used for counterfactual experiments in Section 4. Finally, Section 5 concludes.

# 2 Empirical Evidence

In this Section, we document the degree of occupational persistence across generations in the UK and we study the labor market outcomes of occupational followers and movers. In particular, we focus on differences in job-finding probabilities (a proxy for employment prospects) and wages.[9] To this end, we use the British Household Panel Survey (BHPS) and in particular the dataset constructed by Lo Bello & Morchio (2020). We document two key facts: first, occupational followers tend to find jobs faster than movers; second, they earn lower wages on average.

## 2.1 The Data

The BHPS is a yearly survey covering around 5,500 households (more than 10,000 individuals) per year in the UK. It was first carried out in 1991, and the last available wave for this study is 2008. The survey is characterized by a fairly high follow-up rate, with more than 90 percent of the individuals being interviewed also in the subsequent year, and a number of new households entering the sample

[8] Other contributions include Granovetter (1973), Montgomery (1991), Calvó-Armengol & Jackson (2007), Pellizzari (2010), Cingano & Rosolia (2012), Hensvik & Skans (2013), Topa (2001) and Dustmann *et al.* (forthcoming).

[9] We have also investigated whether there are differentials in job separation rates across followers and movers, finding small differences that are not statistically significant.

each year. In total, 32,377 individuals were interviewed in the BHPS during the period 1991-2008. We restrict our sample to males aged 16–65, and are thus left with 12,982 individuals, for a total of 1,023,888 monthly observations.[10] Individuals report a detailed job history of the previous year, including all the employment/unemployment spells, along with several job characteristics of each job (among them, the occupation). In this way, we are able to construct long labor market histories for each individual (potentially up to 216 months) and, more importantly, we are able to observe transitions at the monthly frequency. Apart from a detailed job history, each individual provides demographic information including gender, age, education, occupation, race, marital status, region of residence, etc. One key feature of the dataset is that it allows us to connect individuals to their fathers and to track them both over time. For our analysis, we will condition on being active in the labor market and also on the father being part of the labor force.[11]

The job-finding probability is defined as the monthly probability of transiting from unemployment to employment. Wages are calculated by dividing the total monthly labor income by the number of hours normally worked per week multiplied by four (the information on hours worked is only available for the current job at the moment of the interview, that is, it is recorded annually).

All of our findings hold *within* occupations, in the sense that we always control for occupation fixed effects. In this way, we are in fact comparing individuals who work or search for a job in a given occupation, and whose father may or may not work in that same occupation. Therefore, we correct for the fact that followers and movers have potentially different distributions across occupations, and for changes in the occupational structure that have occurred across generations.

## 2.2 Intergenerational Occupational Persistence

The data allows us to study the extent of occupational persistence across generations. We compute the distribution of workers across occupations and study the probability that a father and his son work in the same occupation. In order to account for the unequal distribution of workers across occupations and for changes in the occupational structure of the economy over time, we construct

[10] We exclude women from the sample for several reasons: i) employment rates of men and women are substantially different, especially for the parent generations; ii) to maintain comparability to the rest of the literature, which also excludes women; iii) in previous work we found that, although occupational following is also prevalent among women, there is no suggestive evidence that mothers serve as network providers (see Lo Bello & Morchio 2020).

[11] We do this because it is not clear how inactivity spells should be treated: voluntary entry and exit decisions may blurry the assessment of labor market performance.

likelihood ratios.[12] In computing the likelihood ratios, we pool all individual observations together; in this way, each individual contributes to occupational persistence for the actual number of periods (months) in which he has worked in the same occupations as his father.

Let $\mathcal{P}_j$ define the likelihood ratio, i.e. the ratio between the probability of working in occupation $j$ conditional on the father also working in it, and the unconditional probability of working in occupation $j$:

$$\mathcal{P}_j = \frac{P(o = j | o^F = j)}{P(o = j)} ,$$

where $o$ represents an individual's occupation and $o^F$ his father's one. In our baseline results, we follow the Standard Occupational Classification (SOC) aggregation by major group (the 1-digit level), as established by the Employment Department Group and the Office of Population Censuses and Surveys. Nonetheless, the most important results of our analysis are repeated and confirmed at the 2-digit level (see the Online Appendix). Results for the likelihood ratios at the 1-digit level are shown in Table I:

**Table I.** Occupational persistence (likelihood ratios)

| **Occ. code** | **Occupational group (contemporaneous)** | **Likelihood Ratio** | **# of offspring** | **# of pairs** |
|---|---|---|---|---|
| 1 | Managers and administrators | 1.29 | 6214 | 1764 |
| 2 | Professional | 2.60 | 3179 | 669 |
| 3 | Associate professional & technical | 1.62 | 7388 | 931 |
| 4 | Clerical and secretarial | 1.26 | 7645 | 666 |
| 5 | Craft and related | 1.55 | 15917 | 5276 |
| 6 | Personal and protective services | 1.58 | 2898 | 205 |
| 7 | Sales | 1.34 | 4917 | 277 |
| 8 | Plant and machine | 1.94 | 6620 | 2640 |
| 9 | Agriculture and elementary | 2.67 | 4915 | 619 |
| | Average (unweighted) | 1.76 | | |
| | Average (weighted) | 1.72 | | |

*Source:* BHPS (1991–2008). *Note:* The occupation is defined at the 1-digit level.

We find a substantial degree of occupational persistence. The estimated likelihood ratios of

[12] We do this because occupational concentration mechanically increases occupational persistence. For instance, if all workers had a job in the same occupation, the occupations of parents and offspring would always be the same. By using likelihood ratios, we are also able to adjust for the fact that employment occupational shares might be growing or shrinking over time. The intuition is that when an occupation changes in size, fewer or more individuals will work there, affecting both the numerator and the denominator of the likelihood ratio. Moreover, by using contemporaneous information on both the father's and the son's occupation, we limit the extent to which structural change biases downwards our measures of persistence. Intuitively, if fathers have been affected by structural change themselves, the occupation in which they worked decades ago is not necessarily a good predictor of their current occupation.

occupational persistence are greater than 1, indicating that a worker is more likely to work in a given occupation if his father also works in it. The average weighted likelihood ratio is estimated to be 1.72, implying that an individual is 72 percent more likely to work in a given occupation if his father does as well; this excess probability ranges from 29 percent to 167 percent, depending on the occupation. Interestingly, persistence does not appear to vary systematically with the occupation's skill level or pay.[13] Repeating the same exercise at the 2-digit level, we find that the average unweighted and weighted likelihood ratios are 5.69 and 4.71, respectively (see Online Appendix A), showing that occupational following is relatively more likely at a detailed level.[14]

Our estimates are robust to the inclusion of several control variables. We estimate linear probability models which regress the probability of working in a given occupation – as opposed to any other – on a number of covariates (see Panel a of Figure 1 and the corresponding regression Table in Online Appendix A), and find that a worker is *ceteris paribus* between 1.59 and 15.1 percentage points more likely to work in the same occupation as his father (at the 1-digit level). These are large probability differences and are highly statistically significant in each of the occupations, suggesting that covariates do not play a major role in explaining occupational persistence.[15] These results are also confirmed at the 2-digit level: the conditional excess probability is positive and statistically significant in 36 out of 48 occupations (see Panel b of Figure 1).

Moreover, we provide some suggestive evidence that our estimates of occupational persistence are not primarily related to regional factors, such as the average development level or the occupational structure. In principle, if the distribution of occupations differs across regions, this might mechanically increase the likelihood ratio. In that case, we would not be comparing the conditional probability to the *correct* unconditional probability. To evaluate this, we compute the region-specific likelihood ratios and compare them in a cross-region fashion against the average regional wage (a proxy for development level) and the Herfindahl index (a measure of occupational concentration). In Online Appendix A we show that neither variable can predict persistence, providing reassurance

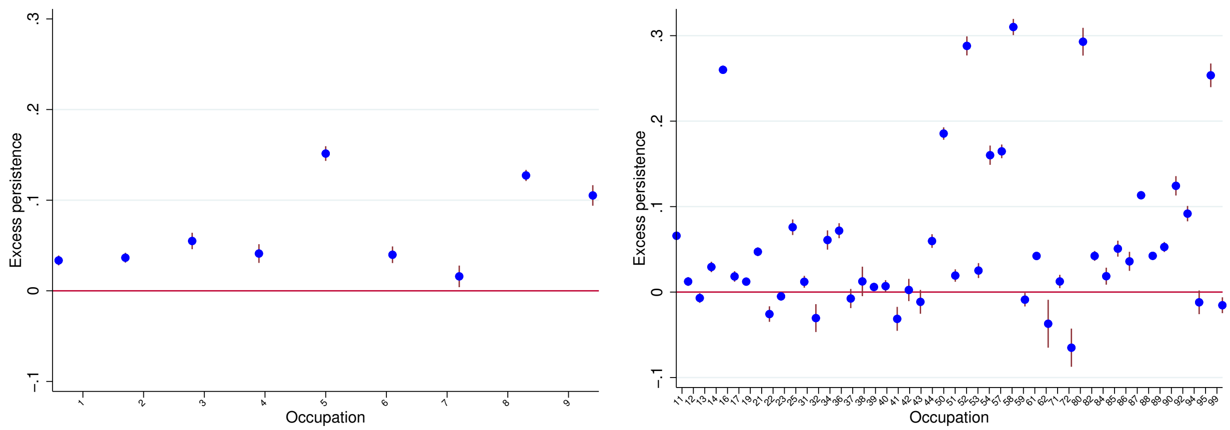
[13] This seems to suggest that borrowing constraints are not playing a major role in occupational choice. We also investigated whether likelihood ratios vary by the father's income within an occupation. Our results show that unconditional occupational persistence decreases only slightly with the father's wage. For instance, if we only consider the top 1/3 of earners in each of the occupations, the average likelihood ratio drops to 1.64 (see Online Appendix A).

[14] We also investigate what proportion of 1-digit level persistence is accounted for by 2-digit level persistence, by computing the likelihood ratios at the 1-digit level while discarding the cases in which the occupation is also the same at the 2-digit level. We find that most of the persistence at the 1-digit level vanishes when 2-digit persistence is discarded (the weighted average drops from 1.72 to 1.09; see Table IX in Appendix A). This shows that occupational following is highly concentrated at the level of detailed occupations.

[15] The average conditional likelihood ratio implied by these estimates is only slightly higher than the unconditional one.

**Figure 1.** Conditional occupational persistence

**(a)** 1-digit classification **(b)** 2-digit classification




*Source:* BHPS 1991–2008. *Note:* Coefficient of excess persistence after controlling for covariates, by occupation.

that regional factors are not playing a major role in determining our results.[16]

Finally, we relegate a number of additional results to the Online Appendices A and E, namely: i) that intergenerational occupational persistence does not exhibit a clear life-cycle profile; ii) that occupational followers tend to stay longer in their first occupation; and iii) that they tend to switch occupations less frequently throughout their lives. Taken together, these results suggest that intergenerational occupational persistence is not a transient phenomenon that interests only young workers, but instead it is a potential determinant of the allocation of workers to occupations throughout their career. Having established a large and persistent degree of occupational persistence, we now turn to the analysis of labor market outcomes.

## 2.3 Occupational Persistence and Labor Market Outcomes

In this Section, we study how occupational following relates to labor market outcomes, focusing in particular on job-finding probabilities and wages.

To deal with occupational mobility over the life-cycle, we construct three different indicators of occupational persistence, which we consider informative of different aspects of the phenomenon. First, we define $\pi_{i,t}$ as a dummy variable that takes the value 1 if the worker $i$ is in the same

[16] An important caveat is that our geographic variable is quite coarse, consisting of only have 19 regions: it is possible that the relevant level of aggregation for the father-son transmission is finer than that. Our data's sample size does not allow us to estimate occupation-specific indexes of persistence at a more detailed regional level.

occupation as his father at time $t$ and 0 otherwise. We view this as a natural definition of persistence based on contemporaneous information; moreover, this definition has the advantage of allowing us to control for fixed unobserved heterogeneity, since it varies over time.

Second, we construct an index of how long each individual has spent in the same occupation as his father during his working life. We do this for two reasons: first, it is useful to construct groups that do not change over the life-cycle of individuals; and second, as far as wages are concerned, it is generally unclear whether we should look at the father's occupation at the moment of the wage observation or at the start of each job spell. Thus, we define $\bar{\pi}_i$ as the fraction of months of employment that individual $i$ spent in the same occupation as his father: $\bar{\pi}_i = \frac{\sum_t \pi_{i,t}}{\sum_t E_{i,t}}$, where $E_{i,t}$ is a dummy variable taking the value 1 if the individual $i$ is employed in period $t$ and 0 otherwise. The index $\bar{\pi}_i$ ranges from 0 to 1, and it measures the share of months (out of those in which he was employed) during which his occupation coincided with his father's.

Third, we assign to each individual (and his father) the occupation in which he spent the majority of his working life, and define a new occupational persistence dummy variabile $\phi_i$, that takes value 1 if the two most frequent occupations coincide. If the degree of occupational mobility over the life-cycle is limited, these three measures will be strongly correlated.

We show the summary statistics of our persistence measures in Table II. The sample means of $\pi_{i,t}$ and $\bar{\pi}_i$ coincide by construction, but their degree of dispersion differs. Moreover, assigning workers to their most frequent occupations ($\phi_i$) implies an increase in measured occupational persistence, possibly reflecting the fact that occupational attachment is higher among occupational followers. Turning to the correlation across these variables, Table III shows that the correlations are large and positive, but far from perfect, ranging between 0.5 and 0.75.[17] This implies that, owing to occupational mobility, these measures indeed capture different aspects of persistence.

We now study the labor market outcomes of occupational followers *vis-a-vis* the ones of movers. When studying job-finding probabilities, the occupation of an unemployed individual is assumed to be the one in which a job will be found at the end of the unemployment spell. In Figure 2, we plot the average job-finding probability and the wage profiles of two groups, defined by the intensity of occupational following: we split those with $\bar{\pi}_i > 0.5$ from those with $\bar{\pi}_i \leq 0.5$. As one can see,

[17] Despite a mechanically larger degree of occupational mobility at the 2-digit level, these correlations are slightly higher at the more disaggregated level. This depends on the fact that the share of followers markedly diminishes at the 2-digit level, thus increasing the number of individuals for which the time-varying and the time-invariant definition of persistence coincide.

**Table II.** Summary statistics of occupational persistence measures

| Variable | Mean | SD | Min | Max | N |
|---|---|---|---|---|---|
| Father in same occupation ($\pi_{i,t}$), 1-digit | 0.18 | 0.38 | 0 | 1 | 95431 |
| Share of time in same occupation ($\bar{\pi}_i$), 1-digit | 0.18 | 0.27 | 0 | 1 | 95431 |
| Father in same most frequent occupation ($\phi_i$), 1-digit | 0.20 | 0.40 | 0 | 1 | 95431 |
| Father in same occupation ($\pi_{i,t}$), 2-digit | 0.07 | 0.26 | 0 | 1 | 95431 |
| Share of time in same occupation ($\bar{\pi}_i$), 2-digit | 0.07 | 0.19 | 0 | 1 | 95431 |
| Father in same most frequent occupation ($\phi_i$), 2-digit | 0.08 | 0.28 | 0 | 1 | 95431 |

*Source:* BHPS (1991–2008).

**Table III.** Correlation between the different measures of occupational persistence

| | **1-digit** | | | **2-digit** | | |
|---|---|---|---|---|---|---|
| **Variable** | $\pi_{i,t}$ | $\bar{\pi}_i$ | $\phi_i$ | $\pi_{i,t}$ | $\bar{\pi}_i$ | $\phi_i$ |
| Father in same occupation ($\pi_{i,t}$) | 1 | 0.70 | 0.53 | 1 | 0.72 | 0.56 |
| Share of time in same occ. ($\bar{\pi}_i$) | | 1 | 0.75 | | 1 | 0.77 |
| Father in same most frequent occupation ($\phi_i$) | | | 1 | | | 1 |

*Source:* BHPS (1991–2008).

occupational followers tend to do better at finding jobs, but they earn lower wages on average. The differences across the two groups are quite large: the job-finding premium is between 2 and 4 percentage points, whereas the wage discount is between 10 and 20 log points. Remarkably, the difference in job-finding probabilities appears to slowly fade out with age, while the one in wages seems to be constant over the life-cycle.[18]

These results may simply reflect the fact that workers in the two groups are different. In the next Section, we run regressions to investigate the extent to which these unconditional differences depend on observable heterogeneity.

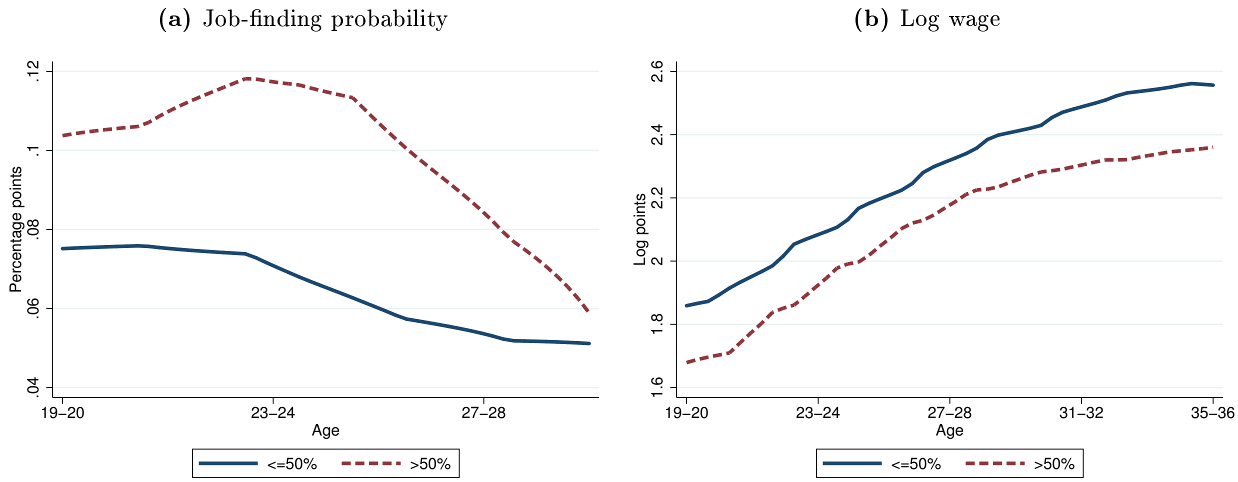
### 2.3.1 Job-finding probability regressions

We start with job-finding probabilities. We estimate the following model:

$$JF_{i,t} = \alpha + \beta p_{i,t} + \boldsymbol{\gamma} \boldsymbol{X}_{i,t} + \epsilon_{i,t}, \tag{1}$$

[18] We replicate Figure 2 at the 2-digit level, as well as for the time-varying definition of persistence (see Online Appendix D). Results on wages appear to be quite stable across definitions, whereas the ones on job-finding probabilities are less robust at the 2-digit level; this is most likely due to the limited number of followers at the 2-digit level and to our imputation of the occupation to the unemployed, which is likely to be less precise at the 2-digit level.

**Figure 2.** Labor market outcomes (followers vs. movers)




*Source:* BHPS (1991–2008). *Note:* Average labor market outcomes by proportion of employed worklife spent in the same occupation as the father. The occupation is defined at the 1-digit level.

where $JF_{i,t}$ is defined only for the unemployed and takes the value 1 if a job is found at time $t$ and 0 otherwise; $p_{i,t}$ is the variable capturing occupational persistence;[19] $\boldsymbol{X}_{i,t}$ include a third–degree age polynomial, dummies for educational categories and occupation (observed for the employed, imputed for the unemployed), marital status, ethnic group, smoking behavior (a proxy for health), the father's age, region of residence and quarter dummies; $\epsilon_{i,t}$ is an idiosyncratic error term.

We estimate Equation 1 with pooled OLS and fixed effects (FE), and present the estimates of $\beta$ in Table IV. We find that occupational followers have, on average, a substantially higher monthly job-finding probability relative to occupational movers; our baseline estimate is a difference of +5.5 percentage points (see Column 3, that includes all controls). Given that the in-sample probability of finding a job is estimated to be 12.5 percent, an individual whose father is in the same occupation increases his monthly probability of finding employment by about 44 percent. Importantly, the effect is robust to the inclusion of individual fixed effects (Column 4), which control for unobserved heterogeneity across individuals. The identification of individual fixed effects is made possible by the panel structure of the data. The coefficient presented in Column 4 of Table IV is estimated by exploiting the variation in $\pi_{i,t}$ (i.e. whether or not the father is in the same occupation) *within* the son's working life. In other words, we are using multiple unemployment spells for the same sons, exploiting the information on whether or not such spells terminate with a job in the same

[19] Recall that the occupation of an unemployed individual is assumed to be the one in which a job will be found at the end of the unemployment spell. Moreover, this variable is defined only for those with an employed father.

occupation as the father.[20] Importantly, the coefficient retains the same size - if anything, it is a little larger - when measuring occupational persistence with the intensity variable ($\bar{\pi}_i$). Instead, it is no longer statistically significant when we use the most frequent occupation ($\phi_i$). This may reflect the fact that, as far as job-finding probabilities are concerned, the contemporaneous presence of both the father and the son is key, whereas $\phi_i$ does not require that.[21] We also establish that our findings are robust to the exclusion of the self-employed from the sample (see Online Appendix B).

**Table IV.** Regressions of job-finding probability (transition from unemployed to employed)

| | (1) POLS | (2) POLS | (3) POLS | (4) FE | (5) POLS | (6) POLS |
|---|---|---|---|---|---|---|
| Father in same occupation ($\pi_{i,t}$) | 0.033 | 0.044 | 0.055 | 0.055 | | |
| | (0.015) | (0.016) | (0.016) | (0.026) | | |
| Share of time in same occupation ($\bar{\pi}_i$) | | | | | 0.058 | |
| | | | | | (0.025) | |
| Father in same most frequent occ. ($\phi_i$) | | | | | | 0.017 |
| | | | | | | (0.015) |
| Average in-sample JF | 0.125 | 0.125 | 0.125 | 0.125 | 0.125 | 0.125 |
| Controls for: | | | | | | |
| Age, education, occupation | | ✓ | ✓ | ✓ | ✓ | ✓ |
| All other controls | | | ✓ | ✓ | ✓ | ✓ |
| $N$ | 4142 | 4142 | 4142 | 4142 | 4142 | 4142 |
| $R^2$ | 0.001 | 0.013 | 0.057 | 0.046 | 0.056 | 0.055 |
| Number of pairs | - | - | - | 401 | - | - |

Standard errors in parentheses

*Source:* BHPS (1991–2008). *Note:* Models 1-3, 5 and 6 are pooled OLS regressions; model 4 is a fixed effects regression. Models 3-6 include a third-degree polynomial in age and dummies for education, region of residence, smoking behavior, marital status, ethnicity, father's age, quarter, and occupation of search/employment. The occupation is defined at the 1-digit level.

To the extent that social networks are slowly accumulated over time (as will be the case in our quantitative model), we also look at whether the impact of the father's occupation changes with his occupational tenure. Consistent with this hypothesis, we obtain a positive, though not statistically significant, coefficient for the interaction between $\pi_{i,t}$ and the father's tenure, as shown in Online

[20] A positive coefficient in the specification controlling for fixed effects is consistent with the results of Lo Bello & Morchio (2021): their model implies that even after controlling for occupation and the fixed type, the father's occupation is still a determinant of the individual's job-finding probability.

[21] The corresponding regression results with the 2-digit level aggregation can be found in Online Appendix B. Results are overall robust, with the notable exception of Column 4 (fixed effects), in which the estimated coefficient is smaller and no longer statistically significant. This is most likely due to the very limited number of followers at the 2-digit level that feature multiple unemployment spells.

Appendix B.

Moreover, we investigate whether these correlations vary by education or the age of the offspring and all related results can be found in Online Appendix B. As for education, we find a higher correlation for offspring holding a college degree, even though this difference is not statistically significant. As for age, we find that the correlations are particularly high (up to +9.3 percentage points) among the youngest workers and then monotonically decrease in age, see Figure 5 in Appendix A.[22] This piece of evidence lends support to our interpretation: young workers, who lack experience in the market, are expected to depend more heavily on their father's contacts. In a dynamic setting, like that to be developed in Section 3, workers accumulate contacts themselves, and therefore the influence of their father in relative terms will fade over time.

#### 2.3.2 Wage regressions

We now turn to study how wages differ by occupational following. To do so, we estimate the following regressions:

$$\log(w_{i,t}) = \alpha + \beta p_{i,t} + \boldsymbol{\gamma} \boldsymbol{X}_{i,t} + \epsilon_{i,t}, \tag{2}$$

where $\log(w_{i,t})$ is the natural logarithm of the hourly wage (observed at the annual frequency); $p_{i,t}$ is the variable capturing occupational persistence; $\boldsymbol{X}_{i,t}$ include a third-degree polynomial in age and dummies for education and occupation, second-order polynomials in occupational tenure and potential labor market experience, firm size, region of residence, smoking behavior, marital status, ethnicity, and year dummies; $\epsilon_{i,t}$ is an idiosyncratic error term.

We estimate Equation 2 by POLS and FE. The Columns 1–3 of Table V indicate that occupational followers tend to earn lower wages, even after adding all the controls; on average, being a follower is associated with a wage discount of about 8 log points (Column 3). However, the coefficient drops to zero when individual fixed effects are included in the regression (Column 4). Overall, these results are supportive of a model in which the wage discount is generated purely by selection.[23]

[22] We have also tried to run the regressions separately for the first job of each individual, but the sample is not large enough to allow us to do that: the reason is that, given our focus on unemployment, we do not include the individuals that move from inactivity straight to employment in our regressions.

[23] Indeed, the wage discount of our model in Section 3 will be driven by selection, as in Lo Bello & Morchio (2021) and Bentolila *et al.* (2010). Another natural test of our working hypothesis would be to look at the wages of occupational switchers. In fact, the fixed effects regression could identify the wage discount provided that enough individuals switched occupations to and from that of their father. Intuitively, our model predicts that wages should decline (increase) when individuals move to (from) their father's occupation. Unfortunately, due to the limited sample size, we cannot test this implication because we have a limited number of occupational switchers in our data.

Importantly, the wage discount is robust to the use of the alternative definitions of occupational following. We find that those who spend 10 percent more of their employed working life in the same occupation as their father earn wages that are lower by 13 log points, on average (Column 5).[24] In Online Appendix C, we show that these results are robust to trimming the bottom 1 percent or 5 percent of the wage observations from the sample.

**Table V.** Regressions of log hourly wage

| | (1) POLS | (2) POLS | (3) POLS | (4) FE | (5) POLS | (6) POLS |
|---|---|---|---|---|---|---|
| Father in same occupation ($\pi_{i,t}$) | -0.011 | -0.106 | -0.076 | -0.000 | | |
| | (0.021) | (0.016) | (0.014) | (0.014) | | |
| Share of time in same occupation ($\bar{\pi}_i$) | | | | | -0.133 | |
| | | | | | (0.021) | |
| Father in same most frequent occ. ($\phi_i$) | | | | | | -0.033 |
| | | | | | | (0.013) |
| Controls: | | | | | | |
| Age, education, occupation | | ✓ | ✓ | ✓ | ✓ | ✓ |
| All other controls | | | ✓ | ✓ | ✓ | ✓ |
| $N$ | 4776 | 4776 | 4776 | 4776 | 4776 | 4776 |
| $R^2$ | 0.000 | 0.458 | 0.604 | 0.624 | 0.604 | 0.602 |
| Number of pairs | | | | 850 | | |

Standard errors in parentheses

*Source:* BHPS (1991–2008). *Note:* All models are pooled OLS regressions except for model 4 which is a fixed effects regression. Models 3-6 include a third-degree polynomial in age, dummies for education and occupation, second-order polynomials in occupational tenure and potential labor market experience, firm size, region of residence, smoking behavior, marital status, ethnicity, and year. The occupation is defined at the 1-digit level.

### 2.3.3 Unemployment Risk and Wages: is there really a tradeoff?

We have so far established that occupational followers: i) tend to spend less time in unemployment; and ii) tend to earn lower wages. However suggestive, these two pieces of evidence *per se* do not imply that individuals actually face a tradeoff between employment prospects and wages in their occupational choice. For instance, it could be that these two findings refer to two different subsamples (the unemployed and the employed), which may differ in other characteristics as well. In order to address this issue, we construct new variables exploiting the entire working life of the workers

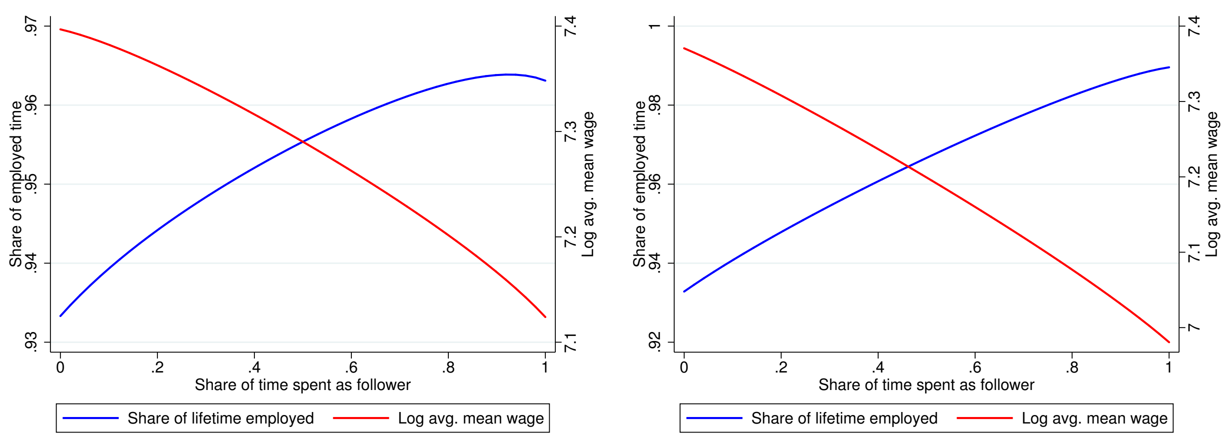
[24]The corresponding regression results with the 2-digit level aggregation can be found in Online Appendix C. Results are almost unchanged.

in the sample. For each worker $i$, we compute the share of time spent employed $\bar{E}_i = \frac{\sum_t E_{i,t}}{\sum_t E_{i,t}+U_{i,t}}$ (a measure of his employment prospects) and the average monthly wage earned throughout his working life $\bar{W}_i$ (a measure of lifetime labor earnings).

We find that $\bar{E}_i$ is positively related to $\bar{\pi}_i$, while the opposite is true for $\bar{W}_i$ (Figure 3). Occupational followers appear to be characterized by better employment prospects but lower wages. Interestingly, through regression analysis (see Online Appendix E) we find that employment prospects and wages are generally positively correlated, but their respective correlations with $\bar{\pi}_i$ have opposite signs. The sign of both of these correlations is robust to the introduction of the other as control variables. In other words, conditional on lifetime employment prospects, followers tend to have lower wages; and conditional on the average lifetime wage, they tend to spend more time employed. Taken together, the empirical evidence presented here is suggestive of a tradeoff between better employment prospects and higher wages faced in their occupational choice.

**Figure 3.** Average lifetime labor market outcomes (followers vs. movers)

**(a)** 1-digit classification **(b)** 2-digit classification




*Source:* BHPS (1991–2008). *Note:* Locally weighted linear polynomial regression (degree 1, bandwidth 0.5) of share of lifetime employed and log average mean wage against the share of time spent as a follower.

## 2.4 Absolute vs. Comparative Advantage

One of the key findings presented above, namely the wage discount of occupational followers, is consistent both with theories based on comparative advantage (Papageorgiou, 2014) and with theories of occupational sorting based on unobserved differences in absolute advantage (Groes *et al.*, 2014). According to the latter view, sons of high-wage fathers tend to be high-ability workers themselves and therefore they may be more prone to change occupation, perhaps because they face lower switching costs or because they have a higher level of talent to realize. If this were indeed the case, then the wage discount of occupational followers would be delivered by a mechanism that does not imply any occupational misallocation. We claim that it is possible to use the relationship between the father's wage and the son's likelihood of being a follower to discriminate between these two competing theories.

We argue that a theory based on selection along the comparative advantage margin implies that the sons of high-wage fathers are more likely to be occupational followers: the reason is that, if comparative advantage is persistent across generations, a high-wage father is likely to have a son with similar talents, who will then be following his comparative advantage if he works in the same occupation as the father. In other words, for these individuals there will be a lower chance of a trade-off between better employment prospects and higher wages, so they will be followers with a higher probability.[25] Instead, a view based on absolute advantage implies either no relationship or the *opposite* relationship with occupational following: according to the alternative view, a high-ability father is likely to have a high-ability son, who is going to choose a high-paying occupation regardless of his father's occupation. In other words, the son's type is the only determinant of his occupational choice.

Thus, the selection mechanism based on absolute advantage implies that, once we control for the individual's wage (a proxy for the individual's ability level), the father's wage does not have any residual predictive power for occupational persistence.[26] In contrast, according to a theory based on comparative advantage, the father's wage maintains its positive predictive power.[27]

We test the opposite predictions of the two theories by regressing the likelihood of being a follower on the father's wage, both unconditional and conditional on the individual's wage (Columns 1 and 2 of Table VI). In both cases, the strongly positive correlation between the two variables is supportive of a theory based on comparative advantage. To the extent that the level of productivity is better captured by the average (lifetime) log wage, we repeat the regressions using these average

[25]The simple model in Lo Bello & Morchio (2021), which is based on selection along the comparative advantage margin, implies exactly this relationship: there is a higher chance that sons of high-wage (and therefore well-matched according to our theory) fathers are occupational followers. This is due to the fact that sons of high-wage fathers face a tradeoff in their occupational choice with a smaller probability than those of low-wage fathers.

[26]Even if we were to consider measurement error in wages, the father's wage would still retain negative predictive power.

[27]The intuition behind this is straightforward: high-wage (i.e. well-sorted) sons are occupational followers to a larger extent if their father is also high-wage (i.e. well-sorted), given that productive types are positively correlated.

measures for both the father's and the son's wage. As shown in Columns 3 and 4 of the same table, results are nearly unchanged.[28]

**Table VI.** Regressions of intergenerational occupational persistence

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Father's log wage | 0.042 | 0.048 | | |
| | (0.016) | (0.016) | | |
| Log wage | | -0.078 | | |
| | | (0.017) | | |
| Father's average log wage | | | 0.036 | 0.050 |
| | | | (0.019) | (0.019) |
| Average log wage | | | | -0.094 |
| | | | | (0.020) |
| Average in–sample persistence rate | 0.172 | 0.172 | 0.172 | 0.172 |
| Controls: | | | | |
| All controls | ✓ | ✓ | ✓ | ✓ |
| $N$ | 3467 | 3467 | 3467 | 3467 |
| $R^2$ | 0.134 | 0.139 | 0.133 | 0.139 |

Standard errors in parentheses

*Source:* BHPS (1991–2008). *Note:* The dependent variable is $\pi_{i,t}$, being in the same occupation as the father. All models are pooled OLS regressions, and include a third-degree polynomial in age, dummies for education, region of residence, smoking behavior, marital status, ethnicity, father's age, father's occupation, quarter, and occupation of search/employment. The occupation is defined at the 1-digit level.

## 3 The Model

In this Section, we develop a quantitative model that we will use to decompose the sources of occupational persistence and to assess their welfare consequences. The model is a multi-occupation dynamic version of the standard search model à la Diamond-Mortensen-Pissarides with the OLG structure (individuals face a stochastic ageing process). Each young agent is connected to an old agent (his father); upon ageing, he loses the connection to his father and establishes a connection with a newly born young agent (his son). We assume that, at birth, workers differ in their comparative advantage and preferred occupation; that is, they draw an occupation in which they can achieve

[28]These results are also confirmed at the 2-digit level; see Online Appendix D.

high productivity and another occupation in which they achieve higher utility *ceteris paribus*, which we term the *preferred* occupation.[29] The two occupations may coincide or not.

As for intergenerational transmission and linkages, we allow for three different sources of occupational persistence: i) imperfect inheritance of comparative advantage; ii) imperfect inheritance of preferences; and iii) employed fathers help their offspring to find jobs (parental networks). The choice of the intergenerational channels is dictated by a large body of literature that emphasizes their importance, as well as by our empirical evidence.[30] We introduce differences in comparative advantage to account for lifetime wage heterogeneity and the existence of wage differentials between followers and movers; we need parental networks to account for the fact that workers find jobs faster in the occupation in which their father is employed; lastly, we add preferences to allow for a residual channel that can account for the remaining degree of occupational persistence.

Further, we also introduce occupation-specific human capital and networks, which accumulate and depreciate over time. Human capital increases productivity, while networks help to find jobs faster. The inclusion of human capital allows the model to produce realistic wage profiles, which is important to create plausible degrees of occupational attachment. Instead, the accumulation of networks has two main consequences: i) parental networks increase with the father's tenure; and ii) the relative importance of parental networks decreases with the offspring's experience, as offspring accumulate their own network. As reported in Section 2, both of these patterns are features of the data.

Finally, we introduce temporary shocks to non-pecuniary benefits, in order to allow the model to generate occupational mobility over the life-cycle. This is important in order to correctly account for occupational persistence, as occupational mobility interacts with the sources of persistence we introduce in the model. Accordingly, due to possible changes in the occupation delivering the highest utility, we also allow for endogenous job separations.

[29]This could also be interpreted as the effect of social pressure or, more generally, any other factor that shifts the utility level for a specific occupation.

[30]As for channel (i), see for instance Papageorgiou (2014); Hsieh *et al.* (2013) on the importance of comparative advantages in occupational choice, and Restuccia & Urrutia (2004); Abbott *et al.* (2013); Lee & Seshadri (2014); Gayle *et al.* (2015) on the transmission of productivity types across generations; for studies on the intergenerational transmission of preferences and work attitudes - our channel (ii) - see Dohmen *et al.* (2011); Paola (2013); Bisin & Verdier (2005), and Escriche (2007); Eberharter (2008); Doepke & Zilibotti (2008); Caner & Okten (2010); Doepke & Zilibotti (2017); finally, for channel (iii) see Magruder (2010); Corak & Piraino (2011); Kramarz & Skans (2014); Bamieh & Cintolesi (2021); Basso *et al.* (2021) on the intergenerational transmission of contacts or related advantages. Regarding this last channel, the previous Section of our paper provides some additional evidence that we will directly use in our calibration.

### 3.1 The Model Environment

Time is discrete ($t = 0, 1, 2, ...$) and goes on forever. The economy is divided into a discrete number of submarkets $O$, which represent the different occupations. A measure 2 of workers and a large outside measure of firms populate the economy. All agents are risk-neutral and discount the future at rate $\beta$. There are two phases of life: young and old. Every period young (old) individuals age (die) with probability $\zeta$. Old individuals who die are replaced by young unemployed workers. We assume that ageing shocks are perfectly correlated within a household (father-son pair). This is equivalent to assuming that individuals stop being connected to their parents when they have children, so that at each point in time only two generations are connected.[31] Let $a$ be the age of the worker. In what follows, we will refer to young workers as *sons* ($a = S$) and to old workers as *fathers* ($a = F$).

Workers are indexed by $i$ and differ along several dimensions: age $a^i \in \{S, F\}$, *preferred* occupation $o^i_\phi$, comparative advantage occupation $o^i_\tau$, occupation-specific human capital $h^i_{o,t}$, networks $n^i_{o,t}$ and preference shocks $\boldsymbol{\phi}^i_t$. Preferences are represented by a vector of size $O$, where the $o^{\text{th}}$ element is the level of the preference shock (i.e. temporary non-pecuniary benefits) associated with occupation $o$. We assume that the period $t$ non-pecuniary benefits are equal to the sum of two terms: a permanent component $\phi^P_o$ (which is normalized to zero in all occupations except for the *preferred* occupation $o^i_\phi$) and a transitory component $\phi^T_{o,t}$ (which is an element of the $\boldsymbol{\phi}^i_t$ vector). The permanent component and the comparative advantage occupation are drawn at birth (i.e. upon entry into the labor market) and do not change over time.[32] In contrast, the temporary component of preferences, as well as occupation-specific human and social capital, evolve over time according to laws of motion to be specified below. Each worker is either employed or unemployed ($e^i_t \in \{0, 1\}$), and works in some occupation $o^i_t$.[33] Unemployed workers receive an unemployment benefit equal to $b$ per period.

We denote a worker's father's variables using an F superscript, so that the occupation of individual $i$'s father will be denoted by $o^{i,F}_t$, the father's networks by $n^{i,F}_{o,t}$ and so on.

[31] This assumption is made for simplicity and does not affect our results.

[32] We do not allow for any investment in types, even though we do ackwnowledge that this may be important for the quantification of mismatch. Doing this in a credible way would require us to introduce assets and borrowing constraints, and to think seriously about occupation heterogeneity and its interaction with educational choice. We leave this to future research.

[33] Another way of modeling this would be to have the unemployed pool out of all occupations. We claim that this alternative model would yield exactly the same implications as our model, due to the CRS matching function and the fact that we focus on a symmetric equilibrium.

## 3.2 Search and Relocation across Occupations

We assume that search is costless and directed to a specific occupation. Unemployed workers decide in which occupation to look for jobs. Employed parents help their unemployed sons find a job, by letting them use part of their occupation-specific network. As a consequence, unemployed sons find jobs in their father's occupation with higher probability than anywhere else, *ceteris paribus*. We assume that unemployed fathers do not help their sons, since they are actively searching for a job themselves.[34]

Each occupation is a separate labor market, where the number of matches between unemployed workers and vacancies is governed by the following constant returns to scale technology:

$$M_{o,t} = (U_{o,t})^{\eta}(V_{o,t})^{1-\eta}, \tag{3}$$

where $M_{o,t}$ denotes the total number of matches produced, $U_{o,t}$ are the total efficiency units of search exerted, $V_{o,t}$ is the measure of vacancies posted at time $t$ in occupation $o$, and $\eta$ is the elasticity of the matching function with respect to $U_{o,t}$.

Search effort is exerted both by unemployed workers and employed fathers whose sons are currently unemployed. When searching for a job, workers exploit their social networks. Networks are assumed to operate such that information on vacancies can flow within them at zero cost and there is no competition among workers belonging to the same network. Thus, social networks can help workers find a job, and having a larger network represents an advantage for unemployed workers. This is represented in the model by an increase in the efficiency units of search that a worker can exert. In particular, it is assumed that a worker with network $n^i_{o,t}$ can exert $(1 + n^i_{o,t})$ efficiency units of search. We also assume that a worker can use either his own network or the one of his father, meaning that the two networks are substitutes. We make this choice because, in the data, we observe that individuals who have been longer in the labor market experience a substantially smaller job-finding premium of looking for a job in the same occupation as their father (see Figure 5 in Appendix A), which suggests a degree of substitutability between the worker's network and the

[34]This is a common assumption in the literature on networks; see for instance Calvó-Armengol & Jackson (2007). This assumption is also consistent with the empirical literature (Magruder, 2010; Cingano & Rosolia, 2012; Lo Bello & Morchio, 2020).

father's. Thus, a worker's units of search can be written as:

$$U^i_{o,t} = \begin{cases} (1+n^i_{o,t}) & \text{if father is unemployed or } o^{i,F}_t \neq o^i_t \\ \left[1+\max\left\{n^i_{o,t}, \xi(1+n^{i,F}_{o,t})\right\}\right] & \text{if father is employed and } o^{i,F}_t = o^i_t \end{cases}, \tag{4}$$

meaning that a worker will optimally choose to exploit the largest network between his own and the father's. The parameter $\xi$ represents the proportion of the father's network passed on to the son. Therefore, we define the aggregate units of search as

$$U_{o,t} = \int U^i_{o,t}\, di\,, \tag{5}$$

and the job-finding probability of individual workers in each occupation are as follows:

$$p^i_{o,t} = \begin{cases} \frac{M_{o,t}}{U_{o,t}}(1+n^i_{o,t}) & \text{if father is unemployed or } o^{i,F}_t \neq o^i_t \\ \frac{M_{o,t}}{U_{o,t}}\left[1+\max\left\{n^i_{o,t}, \xi(1+n^{i,F}_{o,t})\right\}\right] & \text{if father is employed and } o^{i,F}_t = o^i_t \end{cases}, \tag{6}$$

Thus, at each time $t$ workers face a single job-finding probability in their current occupation.

We assume free entry of firms, and that posting a vacancy costs $\kappa$ per period. Firms in occupation $o$ meet with a worker with probability $q_{o,t} = \frac{M_{o,t}}{V_{o,t}}$. Matches are exogenously destroyed with probability $\delta$ every period.

Workers (both employed and unemployed) can freely relocate across occupations.[35] It is assumed that when an employed worker decides to relocate, he is separated from his current match (i.e. the match is destroyed) and moves into the unemployment pool of his new occupation.

### 3.3 Intergenerational Transmission and Laws of Motion

We assume that upon entry into the labor market, both $o_\tau$ and $o_\phi$ are imperfectly correlated across generations, with $\rho_\tau$ and $\rho_\phi$ being the probabilities of drawing the same values as the father (with

[35] We abstract from direct costs of relocation, since these cannot be separately identified from the magnitude of the dispersion of preference shocks.

$\rho = 1$ representing perfect persistence):

$$o_\tau = \begin{cases} o_\tau^F & \text{w.p.} \quad \rho_\tau \\ o \neq o_\tau^F & \text{w.p.} \quad \frac{(1-\rho_\tau)}{O} \quad \forall\, o \neq o_\tau^F \end{cases} \tag{7}$$

$$o_\phi = \begin{cases} o_\phi^F & \text{w.p.} \quad \rho_\phi \\ o \neq o_\phi^F & \text{w.p.} \quad \frac{(1-\rho_\phi)}{O} \quad \forall\, o \neq o_\phi^F \end{cases} \tag{8}$$

The initial level of occupation-specific human and social capital is assumed to be zero in all occupations. We assume that both human and social capital are step functions, such that $h \in \{h_1, ..., h_{K^h}\}$, and $n \in \{n_1, ..., n_{K^n}\}$, where $h_1 = n_1 = 0$, $h_{k+1} \geq h_k$ and $n_{k+1} \geq n_k$ for all $k$.[36] Further, we assume that both human and social capital follow a Markov Chain. When employed (unemployed), human capital increases (decreases) with probability $p_h^+$ ($p_h^-$) and stays at the same level with the complementary probability. Social capital behaves in the same way but we denote the increase and decrease probabilities as $p_n^+$ and $p_n^-$ respectively.[37]

Furthermore, his occupation-specific human capital and social contacts stocks fully depreciate upon changing occupation:[38]

$$h_{o,t+1} = n_{o,t+1} = 0 \ \ \forall o \in \{1, ..., O\} \quad \text{if } o_{t+1} \neq o_t\,. \tag{9}$$

Finally, the temporary preference vector is drawn each period from the distribution $F_\phi$ (to be specified in the Calibration Section):

$$\boldsymbol{\phi}_t \sim F_\phi \tag{10}$$

### 3.4 Timing

The timing of the model is as follows:

1. Old (young) workers die (age) with probability $\zeta$. A young worker who has aged loses the connection to his father and gives birth to an unemployed son.

[36] The choice of having a finite grid allows us to avoid irrealistically high values of accumulated variables, that would otherwise arise due to the stochastic ageing assumption.

[37] We write down in detail the associated Markov Matrices in Online Appendix F.

[38] We assume this for computational reasons, even though in principle it would be interesting to track all occupation-specific variables and have them decay over time when the worker is no longer attached to that occupation.

2. Preference shocks are realized for fathers and sons simultaneously. In what follows, fathers always move before sons.

3. Unemployed and employed workers decide whether or not to relocate.

4. Wages and unemployment benefits are paid, and occupation-specific utility flows are realized.

5. Exogenous separations take place. Unemployed workers either find a job or remain unemployed.

6. The workers' state variables are updated according to the laws of motion.

### 3.5 The Worker's Problem

At the beginning of a worker's life, his problem consists of choosing the occupation in which to search. Besides this initial choice, workers have the option of relocating into a different occupation at the beginning of each period. In what follows, we suppress the $i$ superscript and the $t$ subscript for readability, although all variables (except for $o_\phi$ and $o_\tau$) change over time. We denote the next period's state variables with a prime. All functional equations are conditional on the worker's state variables.

Denote the state of a worker by $\mathit{\Gamma} = \{o_\phi, o_\tau, \boldsymbol{\phi}, h_o, n_o, o, e\}$, where for simplicity $o$ is set equal to zero for those workers who are choosing an occupation for the first time. A young worker's choices are influenced by his father who can help him find a job, so that his own state also includes his father's state $\mathit{\Gamma}^F = \{o^F_\phi, o^F_\tau, \boldsymbol{\phi}^F, h^F_o, n^F_o, o^F, e^F\}$. We must track all of the father's state variables because the son takes into account that: i) even if his father is unemployed today (and therefore does not affect the current job-finding probability), his father will help him find a job in the future once he becomes employed; and ii) fathers also change occupations over the life-cycle. Conversely, we make the father's problem independent of his son's; that is, a father optimizes his choices without taking into account the impact he has on his son's problem.[39] In the following, we make explicit the dependence of a worker's value functions on his employment status and occupation.

[39] From the model's standpoint, this is akin to assuming that fathers are not altruistic (i.e., they attach zero weight to their son's value function). We make this assumption for two reasons: first, we believe that this represents more faithfully actual occupational choices (due to the timing of fertility vs. occupational choices – that is, long-term career choices are usually made before becoming a parent). Second, this is unlikely to have a large quantitative effect, given that in the data more than 80 percent of workers are occupational movers; therefore fathers anticipate that, in expectation, their choices will matter little for their offspring. Third, we do this for simplicity, since allowing for an altruistic motive of fathers would create a complex dynamic game between fathers and sons (see for instance Barczyk & Kredler 2014).

Hence, conditional on employment status and occupation, we denote the state variable of workers by $\Omega = \{o_\phi, o_\tau, \boldsymbol{\phi}, h_o, n_o\} \cup \Gamma^F$. All Bellman equations are conditional on $\Xi$, the aggregate state variables, even though we omit this dependence for readability. We first write the value functions for old workers (denoted by a subscript $F$), with the understanding that they are characterized by $\Gamma^F = \varnothing$.

### 3.5.1 The Father's Problem

We denote by $W^R$ the value of relocation across occupations:

$$W_F^R(\Omega) = \max_{j \in \{1,\ldots,O\}} \left\{ W_{j,F}^U(\Omega) + \phi_{j,F}^T \right\}, \tag{11}$$

where $\phi_{j,F}^T$ represents the temporary preference shock for occupation $j$. Note that unemployed workers draw a vector of size $O$–by–1 of preference shocks each period.

The value of unemployment in occupation $o$ (net of the preference shock), $W_{o,F}^U$, includes the value of unemployment benefits for the current period and the expected discounted value of the future:[40]

$$W_{o,F}^U(\Omega) = b + \tilde{\beta}\Big[p_o(\Omega)\,\mathbb{E}\left[W_{o,F}^E(\Omega')\right] + (1 - p_o(\Omega))\,\mathbb{E}\left[W_F^R(\Omega')\right]\Big]. \tag{12}$$

An unemployed worker is matched with a vacancy in his occupation with probability $p_o(\Omega)$, and remains unemployed with probability $(1 - p_o(\Omega))$, in which case he can decide to relocate in the next period. The future is discounted at the rate $\tilde{\beta} = \beta(1-\zeta)$, in order to account for the risk of dying.

Employed workers face the relocation decision at the beginning of each period. If they decide to stay on the job, they receive the flow utility associated to their state, earn the corresponding wage and stay in the same job the next period, unless their match is exogenously destroyed, which happens with probability $\delta$. Define $\hat{W}_o^E(\Omega)$ to be the value of staying employed in occupation $o$ (that is, the value of being employed and choosing not to relocate):

$$\hat{W}_{o,F}^E(\Omega) = \phi_{o,F}^P + \phi_{o,F}^{T,E} + w(\Omega, o) + \tilde{\beta}\Big[(1-\delta)\,\mathbb{E}\left[W_{o,F}^E(\Omega')\right] + \delta\,\mathbb{E}\left[W_F^R(\Omega')\right]\Big]. \tag{13}$$

[40] In this case, the value function for unemployment has to be interpreted at the stage immediately *after* the relocation decision. That is, the worker has to spend the entire period unemployed in occupation $o$.

At the start of each period, a worker's value function is as follows:

$$W^E_{o,F}(\Omega) = \max\left\{\hat{W}^E_{o,F}(\Omega), W^R_F(\Omega)\right\}, \tag{14}$$

since this includes the possibility of leaving the job and relocating into a different occupation.

Notice that employed workers draw two sequences of preference shocks: the first determines whether or not they stay on the job, while the second determines their new occupation, in the case they wish to relocate.[41]

We denote by $j^*$ the preferred occupation in which to search, namely the occupation that maximizes the value of relocation:

$$j^*_F(\Omega) \in \mathrm{argmax}_{j\in\{1,\ldots,O\}}\left\{W^U_{j,F}(\Omega) + \phi^T_{j,F}\right\}. \tag{15}$$

When $j^*(\Omega)$ is different from the worker's current occupation, an unemployed worker will decide to relocate, while in the case of an employed worker the choice will depend on the difference between the value functions $\hat{W}^E_{o,F}(\Omega)$ and $W^R_F(\Omega)$.

We define $R^k_{o,F}(\Omega)$ (for $k \in \{E, U\}$) as the policy function with respect to the relocation decision. Thus, when $R^k_{o,F}(\Omega) = 1$, a worker of type $\Omega$ with employment status $k$ in occupation $o$ optimally decides to relocate:

$$R^U_{o,F}(\Omega) = \mathbb{1}\{j^*_F(\Omega) \neq o\}.$$

$$R^E_{o,F}(\Omega) = \mathbb{1}\{W^R_F(\Omega) > \hat{W}^E_{o,F}(\Omega)\}.$$

### 3.5.2 The Son's Problem

A son faces a very similar problem to that of a father. The main difference is that he takes into account his father's decisions. As a result, a young worker can decide to relocate as a consequence of a change in his own state variables (preferences) or because his father's state variables have changed, in which case he might want to follow his father in order to benefit from a higher probability of finding a job.

[41] This is done for computational convenience and does not alter our results.

The expression for the value of relocation remains identical:

$$W_S^R(\Omega) = \max_{j \in \{1,\ldots,O\}} \Big\{ W_{j,S}^U(\Omega) + \phi_{j,S}^T \Big\}. \tag{16}$$

The value of unemployment and employment are also reflecting the fact that the worker becomes a father in the next period with probability $\zeta$:

$$\begin{aligned} W_{o,S}^U(\Omega) = \quad & b + \beta \Big[ p_o(\Omega) \, \big( \zeta \, \mathbb{E}\left[W_{o,F}^E(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_{o,S}^E(\Omega')\right] \big) \\ & + (1 - p_o(\Omega)) \, \big( \zeta \, \mathbb{E}\left[W_F^R(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_S^R(\Omega')\right] \big) \Big]. \end{aligned} \tag{17}$$

$$\begin{aligned} \hat{W}_{o,S}^E(\Omega) = \quad & \phi_{o,S}^P + \phi_{o,S}^{T,E} + w(\Omega, o) \\ & + \beta \Big[ (1-\delta) \, \big( \zeta \, \mathbb{E}\left[W_{o,F}^E(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_{o,S}^E(\Omega')\right] \big) \\ & + \delta \, \big( \zeta \, \mathbb{E}\left[W_F^R(\Omega')\right] + (1-\zeta)\mathbb{E}\left[W_S^R(\Omega')\right] \big) \Big], \end{aligned} \tag{18}$$

$$W_{o,S}^E(\Omega) = \max \Big\{ \hat{W}_{o,S}^E(\Omega), W_S^R(\Omega) \Big\}. \tag{19}$$

The relocation decisions $R_{o,S}^U(\Omega)$ and $R_{o,S}^E(\Omega)$ are isomorphic to those of the father, and are defined according to the above-specified value functions.

### 3.6 Wages

Upon matching, the surplus generated is split according to a linear sharing rule, such that the wage is set to a share $\chi$ of the worker's output. Denote $y(o_\tau, h, o)$ as the output of a worker of type $(o_\tau, h)$ working in occupation $o$. We assume

$$y(o_\tau, h, o) = \begin{cases} (1+\hat{\tau})h & \text{if } o = o_\tau \\ h & \text{if } o \neq o_\tau \end{cases},$$

where $\hat{\tau}$ is the productivity premium of exploiting a worker's comparative advantage. Thus, wages are increasing in human capital $h$ and higher whenever $o_\tau = o$. The equilibrium wage is simply

$$w(o_\tau, h, o) = \chi \; y(o_\tau, h, o). \tag{20}$$

We assume that wages adjust every period, upon changes in the worker's level of human capital.[42]

### 3.7 The Firm's Problem

A firm is represented by a single job that is either filled or vacant. The value function for a job filled with a worker of type $\Omega$ is denoted by $J_{o,a}(\Omega)$, where $a \in \{F, S\}$ denotes the age of the worker. Provided that the worker does not choose to leave the firm, this value function includes the current profit (given by production net of the wage payment) and the continuation value of keeping the worker. The value of keeping an old worker is given by:

$$\begin{aligned} J_{o,F}(\Omega) = \quad & \big(1 - R^E_{o,F}(\Omega)\big)\Big[y(o_\tau, h_o, o) - w(\Omega, o) + \tilde{\beta}\big[(1-\delta)\mathbb{E}\left[J_{o,F}(\Omega')\right] + \delta V_o\big] + \beta\zeta V_o\Big] \\ & + R^E_{o,F}(\Omega) V_o. \end{aligned} \tag{21}$$

The match is exogenously destroyed with probability $\delta$ in the next period, in which case, as in the case of endogenous separation, the firm is left with the value of a vacancy $V_o$. With probability $(1-\delta)$ the match continues, and the state variables of the worker are updated.

The value of keeping a young worker is as follows:

$$\begin{aligned} J_{o,S}(\Omega) = \quad & \big(1 - R^E_{o,S}(\Omega)\big)\Big[y(o_\tau, h_o, o) - w(\Omega, o) + \beta\big[(1-\delta)\big(\zeta\,\mathbb{E}\left[J_{o,F}(\Omega')\right] \\ & + (1-\zeta)\mathbb{E}\left[J_{o,S}(\Omega')\right]\big) + \delta V_o\big]\Big] + R^E_{o,S}(\Omega) V_o. \end{aligned} \tag{22}$$

[42] An alternative assumption is that wages are set through some form of bargaining over the surplus of the match, e.g. Nash bargaining. We have tried calibrating the model under this assumption and we find that it has the counterfactual implication that wages of followers are *higher* than wages of movers, because their higher job-finding probability increases their outside option. Moreover, introducing Generalized Nash Bargaining in our setup requires the assumption that all networks, preferences and the productivity levels in *all other* occupations are common knowledge within the match. Given the richness of the state space, it seems unrealistic to assume that all of this is common information.

This equation has the same interpretation as the one for an old worker, except that it allows for the possibility of a worker becoming old (as a result of the $\zeta$ shock) and the match continuing.

The value of a vacancy $V_o$ is given by the expected value of profits less the posting cost $\kappa$.

$$V_o = -\kappa + \beta \left[ q_o \, \mathbb{E} \left[ J_o(\Omega') \right] + (1 - q_o) V_o \right], \tag{23}$$

where the expectation is taken over the distribution of unemployed workers in occupation $o$, which includes all possible types $\Omega$ and possible ages $\{F, S\}$.

### 3.8 Equilibrium Definition

We focus on a steady state equilibrium in which all value functions and relocation decisions are constant over time. As a result, worker flows are also constant over time.

**Definition:** A steady state equilibrium is a set of: value functions $W^U_{o,F}(\Omega)$, $W^U_{o,S}(\Omega)$, $W^E_{o,F}(\Omega)$, $W^E_{o,S}(\Omega)$, $V_o$; relocation decisions $R^U_{o,F}(\Omega)$, $R^U_{o,S}(\Omega)$, $R^E_{o,F}(\Omega)$, $R^E_{o,S}(\Omega)$, $j^*_F(\Omega)$, $j^*_S(\Omega)$; labor market tightness $\theta_o$; wages $w(\Omega, o)$; laws of motion for the individual state variables; and laws of motion of unemployed and employed workers for each occupation, such that:

- The value functions for workers and relocation decisions satisfy Equations (12) to (19).
- There is free entry into all occupations: $V_o = 0 \; \forall o \in \{1, .., O\}$.
- Labor market tightness satisfies Equation (23).
- Wages satisfy Equation (20).
- The individual fixed types are transmitted inter-generationally according to Equations (7) and (8).
- The individual state variables evolve according to the Markov matrices specified in Online Appendix F, and to Equations (10) and (9).
- The distributions of workers evolve according to the equations specified in Online Appendix G.
- The measures and flows of employed and unemployed workers of each type $\Omega$ are constant over time.

# 4 Quantitative Analysis

In this Section, we quantitatively assess the importance of each of the channels operating in the model (ability, preferences and networks transmission) in delivering occupational persistence. We first assign values to the structural parameters of our model, and then use the calibrated model to decompose occupational persistence and perform welfare analysis and policy experiments.

## 4.1 Calibration Strategy

Our strategy involves setting exogenously some of the parameters, and jointly calibrating all the rest to relevant moments of the UK data. First, we fix the number of occupations $O$ to 9 in order to be consistent with the 1-digit aggregation of the SOC. We calibrate an economy with no heterogeneity across occupations, so that a symmetric equilibrium arises, in which each occupation attracts the same measure of workers, with an identical composition of productivity, preferences and networks.[43] One period in the model corresponds to one month, and therefore the discount factor $\beta$ is set to 0.9966. The age shock $\zeta$ is set to 0.00416, to match an average working life of 40 years (20 as a young worker and 20 as an old one, on average). We also fix the surplus sharing rule parameter $\chi$ to 0.7 and the scale of the matching function $A$ to 0.1. Finally, we fix $\eta = 0.5$ following Petrongolo and Pissarides (2001).[44]

We calibrate the rest of the parameters in order to match relevant features of the data. In order to do so, we first need to choose the grid of possible values of the worker–specific state variables, as well as the functional forms describing their laws of motion. We let $h$ take three different values and $n$ take two different values, with $h_1 = n_1 = 0$. We allow for more flexibility in human capital accumulation in order to avoid obtaining an unrealistic flattening of the earnings-age profile over time, which has implications for later occupational mobility. The accumulation/depreciation of these occupation-specific variables is subject to a Markov-process characterized by the following parameters: $p_h^+$, $p_h^-$, $p_n^+$, $p_n^-$, where the $+$ and $-$ superscripts denote accumulation (when employed) and depreciation (when unemployed) probabilities, respectively. We calibrate $p_h^+ = 0.0166$, $\hat{h}_1 = 0.2$

[43] We have considered exploring and using the heterogeneity across occupations, but we came to the conclusion that the data currently at our disposal does not allow us to do so. We think that a credible analysis should allow the different intergenerational channels to have a different strength by occupation. Thus we would need to replicate the main empirical results (i.e. the job-finding premium and the wage discount of occupational followers, as well as the moment that identifies the transmission of productive types) by occupation, which requires a larger sample size. Nonetheless, we see this as a very interesting possibility for future work.

[44] We have also performed sensitivity checks with respect to these parameters and they do not alter our results significantly.

and $\hat{h}_2 = 0.2998$ to match the returns to 5-year and 10-year occupational tenure respectively.

We also assume that each worker has a productivity premium $\hat{\tau}$ in the occupation $o_\tau$. The minimum level of productivity is normalized to 1. In the same way, we assume that each worker has a non-pecuniary benefit premium ($\hat{\phi}$) in the occupation $o_\phi$, where he obtains a utility that is higher than elsewhere, and we normalize the baseline level of temporary preference shocks for an occupation to 0. As for integenerational transmission, recall that $\rho_\tau$ and $\rho_\phi$ represent the probabilities of drawing the same values as the father (with $\rho = 1$ representing perfect persistence, see Equations (7) and (8)). Finally, we assume that the idiosyncratic preference shocks are drawn from a type-1 extreme value distribution, with scale parameter $\sigma$.[45]

Together with $\kappa$ and $\xi$, we have a total of 12 parameters to be calibrated. We search for the parameter configuration that minimizes the following loss function:

$$\mathcal{L} = \frac{\sqrt{\sum_{n=1}^{K} \left( \frac{M_n(\Theta) - T_n}{T_n} \right)^2}}{K},$$

where $T$ is a $K \times 1$ vector containing our target statistics and $M$ is a $K \times 1$ vector containing the statistics generated by the model. We choose $K = 12$, so that the model is exactly identified. Table X in Appendix B reports the list of all parameters of the model, each of which is associated with the corresponding identifying moment in Column 4. While the calibration is joint, each parameter is mainly identified by one key moment.[46]

Given our focus on intergenerational persistence, the parameters $\xi$, $\rho_\tau$ and $\rho_\phi$ are of particular importance and we discuss their identification in greater detail than the rest of the calibration. We start with the transmission of networks $\xi$: a higher value of this parameter implies that a higher proportion of the father's network can be used by unemployed sons who choose to search in the father's occupation. Thus, a higher value of $\xi$ translates into a larger job-finding probability differential between followers and movers. For this reason, we calibrate $\xi$ to match the job-finding probability premium of occupational followers w.r.t. movers. We choose this target to be equal to 0.0546, which is the estimated coefficient with all controls (Column 3 of Table IV).[47] It is important to remark that, in the data, we define a "follower" as an individual who *finds* a job in the

[45] This is a standard assumption in the literature on occupational choice.

[46] See Online Appendix H for details.

[47] This estimate is also identical to that in Column 4 of Table IV, which accounts for individual fixed effects. This is important for our analysis because we want to control for other fixed heterogeneity that we do not include in the model as much as possible.

occupation of his father. We do this because we do not observe occupations of search throughout an unemployment spell. In order to correctly estimate this parameter, we adopt an indirect inference approach and we perform the same OLS regression in our model by simulating unemployment spells and dividing workers by the occupation in which they ultimately find a job in the model-generated data.

Turning to the transmission of comparative advantage, a higher value of $\rho_\tau$ increases the chances that the occupation of the father is also that in which the son finds his comparative advantage when the father is well-matched. Thus, higher values of $\rho_\tau$ increase persistence for those with a high-wage father, compared to persistence of those with a low-wage father. The intuition is that a father who displays a high wage is more likely to be well-matched, and higher persistence of comparative advantage $\rho_\tau$ makes it more likely that his son will follow him.[48] Therefore, we target the difference in probability of being an occupational follower if the father's wage is above the average, as observed in the BHPS data. To obtain this target, we regress $\pi_{i,t}$ on a dummy taking value 1 if the father's log wage is above the average and zero otherwise, controlling for covariates.[49] We find that there is a 2.3 percent difference in the probability of being a follower between high-wage and low-wage fathers. The details of the estimation are reported in Online Appendix H.[50]

Finally, the parameter governing the transmission of preferences $\rho_\phi$ is pinned down by asking the model to replicate the occupational persistence observed in the data, as measured by the weighted likelihood ratio of 1.72 at the 1-digit level, see Table I in Section 2. In other words, we are using the transmission of preferences as the residual channel to entirely match occupational persistence, above and beyond the persistence already generated by the other two channels.

We now turn to the rest of the calibration. The vacancy posting cost $\kappa$ is calibrated in order to match the average monthly unemployment-to-employment transition rate, which is 0.1251. A lower posting cost induces more firm entry, implying higher tightness and higher job-finding rates. The exogenous separation rate $\delta$ is set in order to match the average employment-to-unemployment transition rate, which is 0.0047.[51]

[48] The same argument was outlined more at length in Section 2.4.

[49] We do not use the estimates of Table VI, which were obtained treating the father's wage as a continuous variable, because our model features only six wage levels. Therefore, we believe that looking at fathers with relatively high and relatively low wage levels provides a better mapping to the data.

[50] We also run the same estimation dividing fathers in those above their occupation-specific average log wage and those below, and our results are substantially unchanged (see Online Appendix H).

[51] While this employment-to-unemployment transition rate may seem low compared to US data, it is well-known that labor market flows in the UK are substantially smaller. See for instance Elsby *et al.* (2013).

We use the comparative advantage premium $\hat{\tau}$ to match the level of within-occupation log wage variance. The rationale for this choice is that the more heterogeneous are the potential productivity levels of workers across occupations, the more dispersed wages will be. The network premium $\hat{n}$ is calibrated to match the proportion of jobs found through networks in the UK, which is 0.23 (Pellizzari, 2010). The higher $\hat{n}$ is, the more networks will be present in the economy and used for job search. While this parameter is relatively unimportant for our results, we want to discipline it to a data moment in order to obtain a realistic importance of networks for all workers, so that the father's influence is measured against a realistic backdrop. The preference premium $\hat{\phi}$ is chosen to replicate the average wage discount (of 7.6 log points) of occupational followers. High values of $\hat{\phi}$ imply that preferences are relatively more important than comparative advantage in occupational choice. The scale parameter of the preference shocks distribution ($\sigma$) is calibrated to the probability of switching occupation after an unemployment spell (0.3567). The larger the variance of the shocks, the more frequently occupational changes occur. The value of unemployment $b$ is calibrated to match the average replacement rate in the UK of 0.53 (OECD).

The probability of losing human capital $p_h^-$ is calibrated to match the average wage discount after unemployment of 7.6 percent (Arulampalam 2001). The probability of losing networks $p_n^-$ is set to match the slope of the job-finding probability–unemployment duration profile. In particular, we ask the model to replicate the drop in the job-finding probability that occurs between the first and second months of unemployment duration. Finally, we calibrate the probability of accumulating networks $p_n^+$ to the conditional correlation of the job-finding probability with months of past occupational tenure, which is 0.008.

### 4.2 Calibration Results

The full calibration results are presented in Table X of Appendix B. The model is able to precisely match all targets. Importantly for our analysis, it replicates the full extent of occupational persistence observed in the data by making both preferences and comparative advantage persistent across generations. The probability of inheriting the same comparative advantage (preference) is 0.141 (0.144), which implies an excess probability of 27 percent (30 percent). The proportion of parental networks exploited by the son is 0.344, which generates the same job-finding probability premium as in the data.

A large degree of heterogeneity is needed in order to match the data moments: the preference premium is 0.803, while the comparative advantage premium is even higher, at 0.994. The network premium is also substantial (1.21), whereas the human capital premium is 0.200 for five years of tenure and 0.299 for ten years (taken directly from the data). The monthly probability of human capital growing is 0.017, while for networks it is 0.004. In contrast, their depreciation during unemployment is substantially faster: the monthly probability of networks depreciating is 0.132, while for human capital it is 0.943.

We calculate that in this economy posting a vacancy costs around 4 times the average wage. Finally, the exogenous match destruction rate is 0.003, with the rest of the EU flows being accounted for by endogenous separations.

### 4.3 Occupational Persistence Decomposition and Welfare Analysis

The model allows us to study the factors behind occupational choice, and how they differ in importance between followers and movers. In Table VII, we calculate how often the occupational choice is aligned with the two fixed factors (comparative advantage and preferences) under the baseline calibration.

**Table VII.** Model-simulated sorting

| | All | Followers | Movers |
|---|---|---|---|
| Sorting along comparative advantage (fathers) | 0.648 | - | - |
| Sorting along preferences (fathers) | 0.463 | - | - |
| Sorting along comparative advantage (sons) | 0.708 | 0.623 | 0.728 |
| Sorting along preferences (sons) | 0.403 | 0.461 | 0.389 |
| Average log wage (sons) | 0.292 | 0.231 | 0.306 |
| Average unemployment rate (sons) | 0.061 | 0.045 | 0.065 |

*Note:* Model-simulated data under the baseline calibration. Sorting is defined as the fraction of workers whose occupation is aligned with their comparative advantage/preference.

For fathers, comparative advantage seems to be more important than preferences for occupational sorting: 65 percent (46 percent) of fathers choose the occupation in which they have a comparative advantage (preference). Among sons, the same holds true: about 71 percent of them pick the occupation in which they are most productive, whereas about 40 percent of them pick their preferred occupation. Substantial differences in sorting arise between followers and movers:

the former put more weight on preferences in their occupational decision (46 percent versus 39 percent of movers) and less on comparative advantage (62 percent versus 73 percent of movers). As a consequence, followers earn lower wages, as can be seen in Row 5 of Table VII. At the same time, followers have better employment prospects than movers, with an average unemployment rate of 4.5 percent, versus 6.5 percent for movers. Summing up, the model economy generates a clear sorting of workers in the two regions of high–employment/low–wages and low–employment/high–wages.

However suggestive, these correlations are not yet informative about the nature of occupational persistence. For this reason, we now sequentially shut down each of the three channels delivering occupational persistence. In this way, we are able to: i) quantify the contribution of each channel to overall persistence; and ii) evaluate welfare in each different scenario. To evaluate welfare in Steady State, we use the following function:

$$\mathcal{W} = O \int_{\Omega} \left[ (1 - u(\Omega)) \left[ y(\Omega) + \phi(\Omega) \right] + u(\Omega) b - \kappa \theta \right] \, dF\Omega, \tag{24}$$

where $u(\Omega)$, $y(\Omega)$ and $\phi(\Omega)$ represent the equilibrium unemployment rate, the productivity level and the preference component of a given type $\Omega$, respectively. Due to the symmetry of the equilibrium, the aggregation across occupations is achieved through a simple multiplication.

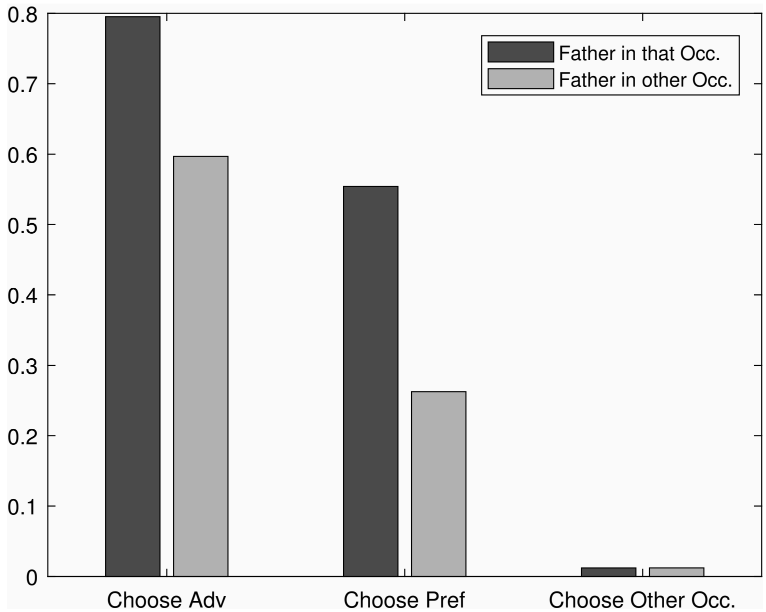
Table VIII shows the results of the experiments: Column 1 represents the baseline economy, while in Columns 2–8 we set $\xi = 0$, $\rho_\tau = 1/O$ and $\rho_\phi = 1/O$, along with all possible combinations of these parameter changes. First, all factors seem to matter for occupational persistence, though by differing degrees. Shutting down parental networks generates the largest drop in persistence, of about 79 percent (Column 2), while comparative advantage and preferences transmission respectively account for about 19 percent and 9 percent of persistence (Columns 3 and 4). Moreover, networks transmission appears to work in conjunction with the other sources of persistence, since shutting down these channels in pairs delivers less of a drop than the sum of the effects separately (Columns 5 and 6 versus 2–4). In contrast, comparative advantage and preferences work independently from one another: the drop in Column 7 is slightly larger than the combination of the effects reported in Columns 3 and 4.

The large importance of networks in explaining occupational persistence is not necessarily surprising, given that this channel encompasses several potential mechanisms that cause sons to find a job faster in their father's occupation (e.g. information provision, nepotism, alleviation of frictions). To better understand the mechanics behind the effect of networks, and how they interact with the other factors, in Figure 4 we plot the average policy function (occupational choice) of unemployed workers whose father is employed and whose comparative advantage and preferences are not aligned.[52] As one can see, the occupation of an employed father strongly impacts the occupational choice of his son. For instance, on average, individuals choose the occupation in which they have a comparative advantage with a probability of 80 percent if the father is also employed in that occupation. This probability drops to 60 percent if the father is employed in a different occupation (compare the first two bars in Figure 4). This effect is even larger for preferences: the occupation for which preference and parental networks are aligned is chosen in 55 percent of the cases, while the preferred occupation without parental networks is chosen in only 26 percent of the cases. It is significant that the benefits from the father's networks alone are not enough to attract the son. Indeed, by comparing the last two bars, one can easily see that choosing an occupation with neither comparative advantage nor preferences is almost never an attractive option, with or without the father's network. The reason for this stark difference is that the value of employment differs from the value of unemployment to a larger extent in occupations with either comparative advantage or preference than in other occupations. By improving the chances of employment, parental networks act as a multiplier of these differentials, therefore playing a much larger role in conjunction with these other fixed factors than by themselves.

Second, the welfare consequences of a reduction in persistence vary widely across the experiments. When we shut down parental networks (Column 2), welfare improves by 0.26 percent, due to the improved allocation of workers to occupations (sorting along the productivity dimension increases from 71 percent to 74 percent for sons, and from 65 percent to 67 percent for fathers) and despite a worsened sorting along the preferences dimension (which drops from 40 percent to 37 percent for sons, and from 46 percent to 45 percent for fathers). As a consequence of the increase in the productivity of the workforce, output per worker increases and the variance of wages decreases. Also, unemployment decreases by 1 percent – despite the fact that less efficiency units of search are now exerted in the market – since firms react to the change in average labor productivity by posting more vacancies. Overall, the welfare change is small because most of the improvement along the productivity dimension is undone by the worsened sorting along the preferences dimension. In

[52]The workers for which comparative advantage and preferences are not aligned represent the large majority of the population. In Online Appendix H, we show the same average policy function of workers for whom the two factors are aligned.

**Figure 4.** Probability of choosing occupations (average policy function)




*Source:* Author's calculations. *Note:* Model solution under baseline calibration: the bars show the probability of choosing different occupations (the policy function, averaged across model states), depending on whether the father works there, for unemployed workers with comparative advantage and preference in different occupations.

contrast, when we shut down the transmission of comparative advantage (Column 3), welfare decreases by 0.05 percent, while output per worker declines (sorting along the productivity dimension worsens, while sorting along the preferences dimension improves) and unemployment rises (by 0.25 percent). Finally, shutting down the transmission of preferences (Column 4) has a similar though smaller effect to that of shutting down parental networks. Thus, productivity becomes more dominant in an individual's choice, output per worker increases and unemployment decreases. The net effect of these changes, despite a worsened sorting along the preferences dimension, is an increase in welfare of 0.05 percent.

To gauge the importance of general equilibrium effects, we repeat our experiments while keeping labor market tightness constant. That is, we solve a partial equilibrium version of our counterfactuals in which firms are not allowed to react to the changes in the economy. Our results can be found in Table XI in Appendix B. We find that most of our results are accounted for by the partial equilibrium reaction of workers to the changes in the parametrization; for instance, even when labor market tightness is kept constant, shutting down parental networks still implies a large de-

**Table VIII.** Occupational persistence decomposition and welfare analysis

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|
| **No parental net.** | ($\xi = 0$) | - | ✓ | - | - | ✓ | ✓ | - | ✓ |
| **No comp. adv. trans.** | ($\rho_\tau = 1/O$) | - | - | ✓ | - | ✓ | - | ✓ | ✓ |
| **No pref. trans.** | ($\rho_\phi = 1/O$) | - | - | - | ✓ | - | ✓ | ✓ | ✓ |
| Occupational persistence | | 1.720 | 1.150 | 1.583 | 1.654 | 1.033 | 1.117 | 1.515 | 1.000 |
| ($\Delta$% from baseline) | | 0.000 | (-79.146) | (-19.006) | (-9.215) | (-95.423) | (-83.716) | (-28.493) | (-100.000) |
| Welfare ($\Delta$% from baseline) | | 0.000 | (0.264) | (-0.053) | (0.052) | (0.264) | (0.264) | (-0.001) | (0.264) |
| Output ($\Delta$% from baseline) | | 0.000 | (0.015) | (-0.002) | (0.003) | (0.015) | (0.015) | (0.000) | (0.015) |
| Sorting along comparative advantage (sons) | | 0.708 | 0.737 | 0.704 | 0.713 | 0.737 | 0.737 | 0.709 | 0.737 |
| Sorting along preferences (sons) | | 0.403 | 0.374 | 0.407 | 0.397 | 0.374 | 0.374 | 0.402 | 0.374 |
| Sorting along comparative advantage (fathers) | | 0.648 | 0.666 | 0.645 | 0.651 | 0.666 | 0.666 | 0.649 | 0.666 |
| Sorting along preferences (fathers) | | 0.463 | 0.445 | 0.466 | 0.460 | 0.445 | 0.445 | 0.463 | 0.445 |
| Output per worker (=1 in baseline) | | 1.000 | 1.014 | 0.998 | 1.003 | 1.014 | 1.014 | 1.000 | 1.014 |
| Variance of log wages ($\Delta$% from baseline) | | 0.166 | (-4.106) | (0.595) | (-0.695) | (-4.106) | (-4.106) | (-0.089) | (-4.106) |
| Welfare CV ($\Delta$% from baseline) | | 0.147 | (-0.135) | (0.027) | (-0.036) | (-0.135) | (-0.135) | (-0.010) | (-0.135) |
| Unemployment rate ($\Delta$% from baseline) | | 0.061 | (-0.991) | (0.248) | (-0.191) | (-0.991) | (-0.991) | (0.056) | (-0.991) |
| Average UE rate ($\Delta$% from baseline) | | 0.125 | (1.287) | (-0.201) | (0.213) | (1.287) | (1.287) | (0.013) | (1.287) |
| Average EU rate ($\Delta$% from baseline) | | 0.005 | (-0.122) | (0.046) | (0.032) | (-0.122) | (-0.122) | (0.079) | (-0.122) |
| Equilibrium tightness | | 1.565 | (2.591) | (-0.402) | (0.427) | (2.591) | (2.591) | (0.027) | (2.591) |

*Note:* Column (1) shows results under the baseline economy. In Columns (2), (5), (6) and (8), we shut down parental networks. In Columns (3), (5), (7) and (8), we shut down the transmission of comparative advantage. In Columns (4), (6), (7) and (8), we shut down the transmission of preferences.

crease in persistence. However, general equilibrium effects reinforce the partial equilibrium results: unemployment is lower and output is higher if optimal vacancy posting is accounted for.[53]

The cross-sectional distribution of fathers has intergenerational consequences, because types are persistent and a father who is mismatched will provide an incentive (through parental networks) to his son to be mismatched as well. Nonetheless, we find that the transmission of mismatch across generations is relatively weak. Table XII in Appendix B summarizes the results of an experiment in which we fix fathers to the baseline distribution, and solve the problem of sons as if they were born from the fathers of the baseline model. By comparing a simulation in which we keep fathers fixed to one in which we let them converge to the steady state, we can isolate the effect on the economy of the change in the distribution of sons that is induced by the change in the distribution of fathers. We find that the outcomes of sons are barely affected by the change in the distribution of fathers. The intuition behind this result is that too few fathers reallocate in our baseline experiments for the results to change significantly.

## 4.4 Other Counterfactual Experiments

### 4.4.1 What accounts for our results?

In order to understand what features of the data drive our results, we increase our parameters one at a time by 5 percent and analyse how our counterfactuals change with the model parametrization. We do this to simulate, in a time-efficient way, the effect of calibrating our parameters to different values of the moments. Our results are summarized in Table XIII in Appendix B.

Most parameters have a negligible impact on our counterfactual simulations. The only exceptions are $\hat{\tau}$, the parameter governing the size of the comparative advantage, and $\hat{\phi}$, the parameter governing the size of preferences. However, small changes in one of these parameters that are not accompanied by a recalibration of the other imply large reallocation of workers, so that this result is not necessarily surprising. Basically, an increase in the productive advantage by 5 percent increases lifetime utility in the most productive occupation by almost 5 percent while keeping all the rest constant. This is also reflected in the fact that the moment that identifies $\hat{\tau}$ reacts strongly to changes in this parameter (see Online Appendix H). The result is that, when we increase $\hat{\tau}$ by 5 percent, the vast majority of workers align their occupational choice with their comparative advantage and

[53]We find that welfare is slightly lower in general equilibrium, as the wage setting does not yield labor market efficiency: in particular, it turns out that the equilibrium tightness is above the optimal level; as a consequence, any futher increase is detrimental to aggregate welfare.

the trade-off with preferences stops being relevant in equilibrium, so most counterfactuals become muted, except that in which we shut down the transmission of comparative advantage. Similar considerations apply to an increase in the size of preferences $\hat{\phi}$, except that increasing this parameter increases the number of workers who decide to align their occupational choice with their preference instead.

For similar reasons, when we increase $\hat{\tau}$, the transmission of comparative advantage becomes so important to explain persistence that shutting it down removes occupational persistence from the economy almost altogether. Similarly, when we increase preferences $\hat{\phi}$, their importance in explaining occupational persistence is magnified. Another lesson that we can draw from this set of experiments is that, when occupational mobility is higher (when $\sigma$ or $\delta$ are larger), networks have less important allocative effects. This reflects the fact that due either to the lower degree of occupational attachment or to the shorter average employment duration, the importance of networks decreases.

#### 4.4.2 The Importance of Multiple Transmission Channels

In the model, intergenerational persistence is influenced by three different factors: comparative advantage, preferences and parental networks. An important question is whether we need all these features to account for the data. To answer this question, we shut down some of the aforementioned channels and recalibrate the model in an attempt to match the data with fewer degrees of freedom. We refer to this specification as the *restricted model.* This allows us to understand whether all model dimensions are really necessary in order to replicate the data patterns. We keep the transmission of productive abilities as the only transmission channel, since it can be seen as comprising genetic transmission, educational choices and human capital transmission in general, which are the channels most commonly emphasized in the literature on intergenerational persistence. Therefore, we set $\xi = 0$ and $\rho_\phi = 1/O$ and ask the model to match all data moments in Table X except for the job-finding premium and the wage discount. The rationale for our choice is that, with only one source of persistence, the model cannot replicate either of these two moments.

The calibration results of the restricted model can be found in Table XIV in Appendix B. While the model fits most of the targeted moments quite well, it can account only for a minor share of occupational persistence, generating a likelihood ratio of only 1.116. The value of $\rho_\tau$ remains similar to the previous calibration, as the model cannot match occupational persistence and the difference in persistence by high- and low-wage fathers at the same time. Another consequence is that the model completely fails to generate the wage discount (non-targeted) of followers relative to movers, and actually generates a wage premium. This reflects the fact that productivity transmission is the only channel producing persistence, and therefore occupational followers base their occupational choice on productivity to a larger extent than movers. By construction, the model also cannot replicate the job-finding rate premium of followers (non-targeted), since networks transmission is shut down.

When we shut down the persistence of comparative advantage in the restricted model (Table XV in Appendix B), we find that persistence is absolutely neutral in this economy. Shutting down the only source of persistence delivers an identical economy in all dimensions, except for occupational persistence, which vanishes completely. This is because, in the restricted model, persistence is not a sign of distortions in the occupational choice of individuals. In other words, persistence is generated only by the fact that father-son pairs tend to be more similar than two randomly picked workers. In this sense, occupational persistence is no longer a reflection of the fact that sons *care* about the occupational choices of their father and are affected by them. More precisely, a son's policy and value functions are now independent of his father's state variables.

#### 4.4.3 The Role of Search Frictions

Search frictions are an important determinant of productive mismatch in our framework. Therefore, it is interesting to investigate the extent to which the severity of frictions affects the importance of parental networks, the level of persistence and the overall allocation. To do so, we impose the degree of frictions implied by the monthly job-finding rates of different economies on the UK baseline calibration. We focus on two polar cases among OECD countries: the US and Spain. We target the average monthly job-finding rates estimated in Hobijn & Şahin (2009): 0.5630 for the US and 0.0389 for Spain. We recalibrate $\kappa$ in order to match these rates, keeping all other parameters constant; the implied new values of the vacancy posting cost are $\kappa = 1.19$ for the US and $\kappa = 12.43$ for Spain. We repeat the persistence decomposition exercises of Subsection 4.3 for the two counterfactual economies, with the results shown in Table XVI in Appendix B.

Two main results stand out: First, the importance of parental networks crucially depends on the size of the frictions. In the low-friction economy, removing parental networks barely affects persistence (which is reduced by only 2.4 percent), whereas the reduction in the high-friction economy is much more pronounced (80 percent). At the same time, the removal of networks is welfare-improving in the high-friction economy (because it raises average labor productivity) but is welfare-decreasing in the low-friction economy. The reason is that, in the low-friction economy, removing networks crowds out occupational choice along the preferences dimension, due to the fact that networks are not generating any occupational choice that is not based on productivity in the baseline equilibrium. Relatedly, we find that occupational persistence is much higher in the high-friction economy than in the low-friction economy, other things being equal (likelihood ratio of 1.69 vs. 1.26).

Second, by comparing Column 1 to Column 5, we can see that search frictions may be responsible for high unemployment and low productivity at the same time. This is a reflection of the fact that networks are more distortionary in environments with large frictions, where individuals are more willing to trade their productive advantage for better employment prospects.

#### 4.4.4 Policy Experiment: Unemployment Benefits

We now look at how changes in unemployment benefits affect the equilibrium of the economy. In order to assess the welfare consequences of such changes, we introduce a lump–sum tax $\nu$ on existing matches (which is split between workers and firms according to the same shares used in the wage setting mechanism, i.e. $\chi$ and $(1-\chi)$ respectively) and a government budget constraint. The new value functions for employed old workers and firms are as follows:

$$\begin{aligned} W^E_{o,F}(\Omega) = \quad & \max\Big\{\phi^P_{o,F} + \phi^{T,E}_{o,F} + w(\Omega,o) - \chi\nu \\ & + \tilde{\beta}\Big[(1-\delta)\,\mathbb{E}\left[W^E_{o,F}(\Omega')\right] + \delta\,\mathbb{E}\left[W^R_F(\Omega')\right]\Big], W^R_F(\Omega)\Big\}. \end{aligned} \tag{25}$$

$$\begin{aligned} J_{o,F}(\Omega) = \quad & \left(1 - R^E_{o,F}(\Omega)\right)\Big[y(\tau,h_o,o) - w(\Omega,o) - (1-\chi)\nu + \tilde{\beta}\big[(1-\delta)\mathbb{E}\left[J_{o,F}(\Omega')\right] \\ & + \delta V_{o,F}\big]\Big] + R^E_{o,F}(\Omega)V_{o,F}. \end{aligned} \tag{26}$$

and similarly for young workers.

The government balances its budget in each period. That is, the change in unemployment benefits from the baseline equilibrium must be financed by tax revenues:

$$\Delta b\, u = \nu(1-u), \tag{27}$$

where $u$ is the unemployment rate of the economy. The rest of the model remains unchanged.

Some of the channels through which unemployment benefits have an effect on the economy, such as the scope for redistribution (in the presence of risk aversion) or the disincentivizing effect on search intensity, are absent in our framework. At the same time, unemployment benefits interact strongly with the main tradeoff at work in our model. Thus, an increase (decrease) in the value of unemployment benefits decreases (increases) the distance between the value of employment and unemployment for workers. As a consequence, parental networks become less (more) important in the son's choice, since being employed becomes relatively less (more) valuable. This implies that workers sort more (less) according to productivity and preferences. To the extent that this increase in sorting is more prominent along the comparative advantage dimension, unemployment benefits can produce productivity gains.[54]

In the quantitative experiment (Table XVII in Appendix B), an increase of 10 percent (25 percent) in $b$ favours sorting along the preferences dimension, whereas it slightly dampens the sorting along the comparative advantage dimension. As a consequence, output per worker decreases by about 0.1 percent (0.3 percent). At the same time, occupational persistence decreases (since parental networks are less attractive) and unemployment increases (since unemployment is now a more attractive option). The overall net effect on welfare is negative (-0.2 percent and -0.6 percent), reflecting also the increase in the tax rate, driven by the higher equilibrium unemployment rate. Columns 4 and 5 show that decrease in $b$ have qualitatively opposite effects.

# 5 Conclusions

We investigated the determinants of occupational persistence across generations. When persistence is generated from multiple sources, it is crucial to assess their relative importance in order to understand the relationship between persistence and misallocation and to derive welfare implications. Exploiting micro data from the UK, we first documented novel facts on the extent of occupational persistence and on labor market outcomes of occupational followers. Importantly, we find that choosing the occupation where the father is employed is associated with better employment prospects, via higher job-finding rates, and lower wages.

Motivated by this evidence, we developed a dynamic model of occupational choice and search

[54]This mechanism has a very similar flavor to that in Acemoglu & Shimer (2000) and Golosov *et al.* (2013).

frictions, featuring multiple channels of intergenerational transmission and allowing for mobility over the life-cycle and accumulation/depreciation of human and social capital. We find that parental networks account for the bulk of occupational persistence and that a model based only on transmission of ability (the restricted model) would be at odds with important features of the data. A key result of our quantitative analysis is that only the portion of occupational persistence generated by parental networks and preferences transmission is detrimental to welfare. Furthermore, we show that search frictions interact with parental networks, amplifying their importance and their adverse effects on the aggregate equilibrium.

In the context of intergenerational persistence, interesting directions for future research include the study of cross-gender patterns of occupational persistence, the relationship between occupational choice and educational choice, and the heterogeneity across occupations. Analyzing the latter, possibly in connection with borrowing constraints and human capital investment, looks like a promising research avenue, but it would require a very rich dataset in order to reliably estimate the separate channels of persistence at a detailed occupational level.

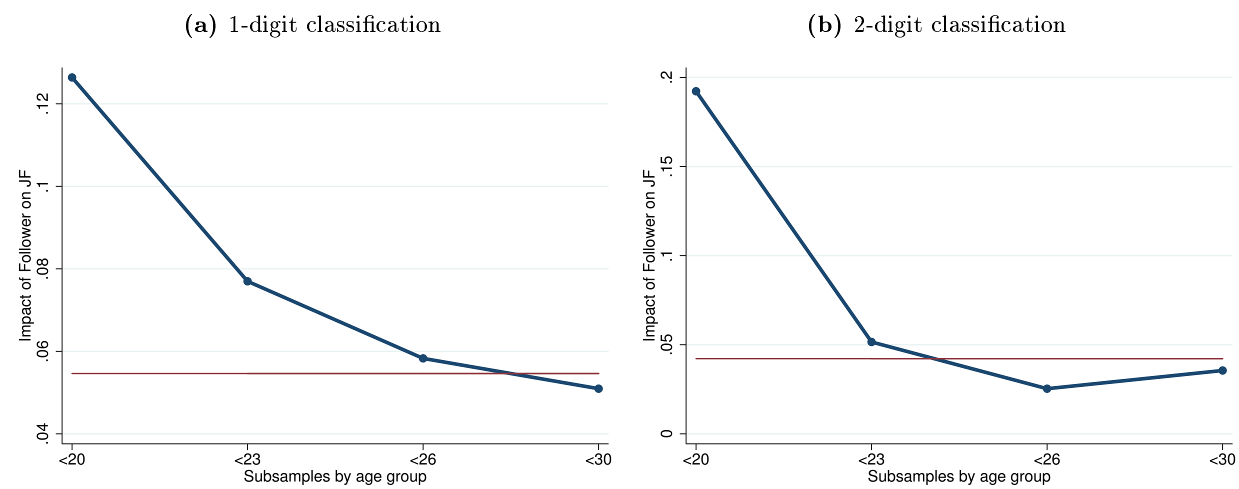
# Appendix A Further Empirical Evidence

**Table IX.** Occupational persistence at 1-digit level, without 2-digit

| Occ. code | Occupation (contemporaneous) | Likelihood Ratio | # of offspring | # of pairs |
|---|---|---|---|---|
| 1 | Managers & Administrators | 0.73 | 5330 | 880 |
| 2 | Professional | 1.83 | 2975 | 465 |
| 3 | Associate Professional & Technical | 1.30 | 7234 | 777 |
| 4 | Clerical & Secretarial | 0.89 | 7461 | 482 |
| 5 | Craft & Related | 1.14 | 13665 | 3024 |
| 6 | Personal & Protective Service | 0.52 | 2761 | 68 |
| 7 | Sales | 0.95 | 4847 | 207 |
| 8 | Plant & Machine | 1.26 | 5338 | 1358 |
| 9 | Agriculture & Elementary | 1.13 | 4526 | 230 |
| | Average (unweighted) | 1.08 | | |
| | Average (weighted) | 1.09 | | |

*Source:* BHPS (1991–2008). *Note:* The table presents the likelihood ratios at the 1-digit level discarding the cases of persistence at the 2-digit level. The occupation is defined at the 1-digit level (without 2-digit level persistence).

**Figure 5.** Occupational following and job-finding probability by age




*Source:* BHPS 1991–2008. *Note:* Partial correlation of $\pi_{i,t}$ by age group. The red line is the average partial correlation for the entire sample.

# Appendix B Other Quantitative Results

**Table X.** Calibration results.

| Parameter | Description | Value | Target/Source | Data | Model |
|---|---|---|---|---|---|
| **Intergenerational transmission** | | | | | |
| $\xi$ | Transmission of networks | 0.344 | Job-finding premium of followers (BHPS) | 0.055 | 0.055 |
| $\rho_\tau$ | Transmission of comparative advantage | 0.141 | Difference in proportion of followers by father's wage (BHPS) | 0.023 | 0.023 |
| $\rho_\phi$ | Transmission of preferences | 0.144 | Intergenerational occupational persistence (BHPS) | 1.720 | 1.720 |
| **Heterogeneity and laws of motion** | | | | | |
| $\hat{h}_1$ | Human capital grid point 1 | 0.200 | Average occupational tenure returns after 5 years (BHPS) | - | - |
| $\hat{h}_2$ | Human capital grid point 2 | 0.299 | Average occupational tenure returns after 10 years (BHPS) | - | - |
| $\hat{n}$ | Networks premium | 1.210 | Proportion of jobs found through contacts (Pellizzari, 2010) | 0.230 | 0.230 |
| $\hat{\tau}$ | Comparative advantage premium | 0.994 | Within-occupation log wage variance (BHPS) | 0.166 | 0.166 |
| $\bar{\phi}$ | Baseline preference for jobs | 0 | Normalization | - | - |
| $\hat{\phi}$ | Preference premium | 0.803 | Wage discount of followers (BHPS) | 0.076 | 0.076 |
| $p_h^+$ | Probability of accumulating HC (employed) | 0.017 | Average occupational tenure returns after 5 and 10 years | - | - |
| $p_h^-$ | Probability of losing HC (unemployed) | 0.943 | Average wage discount after unemp. (Arulampalam, 2001) | 0.076 | 0.076 |
| $p_n^+$ | Probability of accumulating networks (employed) | 0.004 | Regression of JF rate vs. past occupational tenure (BHPS) | 0.008 | 0.008 |
| $p_n^-$ | Probability of losing networks (unemployed) | 0.132 | JF rate–unemployment duration profile (BHPS) | 1.066 | 1.066 |
| $\sigma$ | Standard deviation of preference shocks | 0.246 | Occupational change rate after unemployment (monthly, BHPS) | 0.357 | 0.357 |
| **Environment** | | | | | |
| $O$ | Number of occupations | 9 | 1-digit SOC aggregation | - | - |
| $\kappa$ | Vacancy posting cost | 4.425 | Average UE rate (monthly, BHPS) | 0.125 | 0.125 |
| $\delta$ | Exogenous separation rate | 0.003 | Average EU rate (monthly, BHPS) | 0.005 | 0.005 |
| $\beta$ | Discount factor | 0.997 | From literature | - | - |
| $\zeta$ | Age shock | 0.004 | Average length of worklife: 20 (young) + 20 (old) years | 40 | 40 |
| $b$ | Unemployment benefit | 0.745 | Average replacement rate (OECD) | 0.530 | 0.530 |
| $\chi$ | Surplus sharing rule | 0.700 | Normalization | - | - |
| $A$ | TFP parameter of matching function | 0.100 | Normalization | - | - |
| $\gamma$ | Elasticity of matching function w.r.t. unemp. | 0.500 | Petrongolo & Pissarides (2001) | - | - |

**Table XI.** Partial equilibrium vs. general equilibrium simulations

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|---|
| **No parental net.** | ($\xi = 0$) | - | ✓ | ✓ | - | - | - | - |
| **No comp. adv. trans.** | ($\rho_\tau = 1/O$) | - | - | - | ✓ | ✓ | - | - |
| **No pref. trans.** | ($\rho_\phi = 1/O$) | - | - | - | - | - | ✓ | ✓ |
| **Partial or general equilibrium** | | GE | PE | GE | PE | GE | PE | GE |
| Occupational Persistence | | 1.720 | 1.150 | 1.150 | 1.583 | 1.583 | 1.654 | 1.654 |
| ($\Delta$% from baseline) | | 0.000 | (-79.193) | (-79.146) | (-19.027) | (-19.006) | (-9.210) | (-9.215) |
| Welfare ($\Delta$% from baseline) | | 0.000 | (0.389) | (0.264) | (-0.073) | (-0.053) | (0.074) | (0.052) |
| Output ($\Delta$% from baseline) | | 0.000 | (0.013) | (0.015) | (-0.002) | (-0.002) | (0.002) | (0.003) |
| Sorting along comparative advantage (sons) | | 0.708 | 0.735 | 0.737 | 0.704 | 0.704 | 0.713 | 0.713 |
| Sorting along preferences (sons) | | 0.403 | 0.376 | 0.374 | 0.407 | 0.407 | 0.398 | 0.397 |
| Sorting along comparative advantage (fathers) | | 0.648 | 0.664 | 0.666 | 0.645 | 0.645 | 0.651 | 0.651 |
| Sorting along preferences (fathers) | | 0.463 | 0.447 | 0.445 | 0.466 | 0.466 | 0.460 | 0.460 |
| Output per worker (=1 in baseline) | | 1.000 | 1.013 | 1.014 | 0.998 | 0.998 | 1.002 | 1.003 |
| Variance of log wages ($\Delta$% from baseline) | | 0.166 | (-3.771) | (-4.106) | (0.557) | (0.595) | (-0.654) | (-0.695) |
| Welfare CV ($\Delta$% from baseline) | | 0.147 | (-0.112) | (-0.135) | (0.024) | (0.027) | (-0.033) | (-0.036) |
| Unemployment rate ($\Delta$% from baseline) | | 0.061 | (0.310) | (-0.991) | (0.041) | (0.248) | (0.027) | (-0.191) |
| Average UE rate ($\Delta$% from baseline) | | 0.125 | (0.001) | (1.287) | (0.001) | (-0.201) | (0.001) | (0.213) |
| Average EU rate ($\Delta$% from baseline) | | 0.005 | (-0.101) | (-0.122) | (0.042) | (0.046) | (0.037) | (0.032) |
| Equilibrium tightness | | 1.565 | (0.000) | (2.591) | (0.000) | (-0.402) | (0.000) | (0.427) |

*Note:* Odd columns are general equilibrium counterfactuals. Even columns are in partial equilibrium, when labor market tightness does not change from the baseline economy. Column (1) shows results under the baseline economy. In Columns (2) and (3), we shut down parental networks. In Columns (4) and (5), we shut down the transmission of comparative advantage. In Columns (6) and (7), we shut down the transmission of preferences.

**Table XII.** The impact of fixing the father's distribution

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|---|
| **No parental net.** | ($\xi = 0$) | - | ✓ | ✓ | - | - | - | - |
| **No comp. adv. trans.** | ($\rho_\tau = 1/O$) | - | - | - | ✓ | ✓ | - | - |
| **No pref. trans.** | ($\rho_\phi = 1/O$) | - | - | - | - | - | ✓ | ✓ |
| **Fixed fathers** | | - | Fixed | - | Fixed | - | Fixed | - |
| Occupational Persistence | | 1.720 | 1.148 | 1.150 | 1.582 | 1.583 | 1.653 | 1.654 |
| ($\Delta$% from baseline) | | 0.000 | (-79.439) | (-79.193) | (-19.117) | (-19.027) | (-9.319) | (-9.210) |
| Welfare ($\Delta$% from baseline) | | 0.000 | (0.210) | (0.389) | (-0.044) | (-0.073) | (0.041) | (0.074) |
| Output ($\Delta$% from baseline) | | 0.000 | (0.008) | (0.013) | (-0.001) | (-0.002) | (0.001) | (0.002) |
| Sorting along comparative advantage (sons) | | 0.708 | 0.735 | 0.735 | 0.704 | 0.704 | 0.713 | 0.713 |
| Sorting along preferences (sons) | | 0.403 | 0.376 | 0.376 | 0.407 | 0.407 | 0.398 | 0.398 |
| Sorting along comparative advantage (fathers) | | 0.648 | 0.648 | 0.664 | 0.648 | 0.645 | 0.648 | 0.651 |
| Sorting along preferences (fathers) | | 0.463 | 0.463 | 0.447 | 0.463 | 0.466 | 0.463 | 0.460 |
| Output per worker (=1 in baseline) | | 1.000 | 1.008 | 1.013 | 0.999 | 0.998 | 1.001 | 1.002 |
| Variance of log wages ($\Delta$% from baseline) | | 0.166 | (-3.179) | (-3.771) | (0.463) | (0.557) | (-0.547) | (-0.654) |
| Welfare CV ($\Delta$% from baseline) | | 0.147 | (-0.048) | (-0.112) | (0.013) | (0.024) | (-0.021) | (-0.033) |
| Unemployment rate ($\Delta$% from baseline) | | 0.061 | (0.310) | (0.310) | (0.041) | (0.041) | (0.027) | (0.027) |
| Average UE rate ($\Delta$% from baseline) | | 0.125 | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Average EU rate ($\Delta$% from baseline) | | 0.005 | (-0.101) | (-0.101) | (0.043) | (0.042) | (0.037) | (0.037) |
| Equilibrium tightness | | 1.565 | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

*Note:* Odd columns are partial equilibrium as in Table XI with fixed tightness across simulations. Even columns are partial equilibrium simulations in which fathers are fixed to the baseline simulation of Column (1). Column (1) shows results under the baseline economy. In Columns (2) and (3), we shut down parental networks. In Columns (4) and (5), we shut down the transmission of comparative advantage. In Columns (6) and (7), we shut down the transmission of preferences.

**Table XIII.** Sensitivity of counterfactuals to changes in parameters

| | Baseline | $\kappa$ | $\delta$ | $\xi$ | $\rho_\phi$ | $\rho_\tau$ | $\sigma$ | $\hat{\phi}$ | $\hat{\tau}$ | $\hat{n}$ | $b$ | $p_h^-$ | $p_n^-$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shutting down parental networks: $\xi = 0$ | | | | | | | | | | | | | |
| Occupational persistence | -79.15 | -79.42 | -79.60 | -79.54 | -76.38 | -78.58 | -79.17 | -72.89 | -8.13 | -79.17 | -78.94 | -79.22 | -79.12 |
| Total output | 1.48 | 1.41 | 1.37 | 1.55 | 1.42 | 1.54 | 1.37 | -1.68 | 0.01 | 1.49 | 1.43 | 1.43 | 1.48 |
| Output per worker | 1.41 | 1.34 | 1.30 | 1.48 | 1.36 | 1.47 | 1.31 | -1.57 | 0.01 | 1.42 | 1.36 | 1.36 | 1.41 |
| Unemployment rate | -0.99 | -0.95 | -0.92 | -1.03 | -0.93 | -1.03 | -0.92 | 1.59 | 0.10 | -0.99 | -0.96 | -0.95 | -0.98 |
| Welfare | 0.26 | 0.25 | 0.24 | 0.27 | 0.25 | 0.28 | 0.24 | -0.28 | -0.03 | 0.26 | 0.25 | 0.25 | 0.26 |
| Shutting down transmission of comparative advantage: $\rho_\tau = 0$ | | | | | | | | | | | | | |
| Occupational persistence | -19.01 | -18.58 | -18.26 | -18.65 | -22.50 | -18.56 | -18.83 | -4.76 | -93.32 | -18.96 | -19.17 | -18.86 | -19.01 |
| Total output | -0.24 | -0.24 | -0.24 | -0.24 | -0.29 | -0.24 | -0.24 | -0.17 | -0.01 | -0.24 | -0.23 | -0.24 | -0.24 |
| Output per worker | -0.22 | -0.23 | -0.23 | -0.23 | -0.28 | -0.22 | -0.23 | -0.16 | -0.00 | -0.22 | -0.22 | -0.22 | -0.22 |
| Unemployment rate | 0.25 | 0.25 | 0.25 | 0.25 | 0.31 | 0.25 | 0.25 | 0.15 | 0.17 | 0.25 | 0.25 | 0.25 | 0.25 |
| Welfare | -0.05 | -0.05 | -0.05 | -0.05 | -0.07 | -0.05 | -0.05 | -0.03 | -0.01 | -0.05 | -0.05 | -0.05 | -0.05 |
| Shutting down transmission of preferences: $\rho_\phi = 0$ | | | | | | | | | | | | | |
| Occupational persistence | -9.22 | -9.51 | -9.74 | -9.20 | -8.76 | -11.04 | -9.48 | -28.05 | -0.01 | -9.24 | -9.27 | -9.35 | -9.24 |
| Total output | 0.26 | 0.27 | 0.27 | 0.27 | 0.26 | 0.32 | 0.26 | 0.21 | 0.00 | 0.27 | 0.26 | 0.26 | 0.26 |
| Output per worker | 0.25 | 0.26 | 0.26 | 0.26 | 0.25 | 0.31 | 0.25 | 0.20 | 0.00 | 0.25 | 0.25 | 0.25 | 0.25 |
| Unemployment rate | -0.19 | -0.19 | -0.20 | -0.20 | -0.19 | -0.23 | -0.19 | -0.10 | -0.00 | -0.19 | -0.18 | -0.19 | -0.19 |
| Welfare | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.06 | 0.05 | 0.03 | -0.00 | 0.05 | 0.05 | 0.05 | 0.05 |

*Note:* Each column corresponds to a counterfactual using a variation of the baseline calibration in which one parameter is increased by 5% of its calibrated value. We repeat the same counterfactual experiments starting from each perturbed calibration. The first column reports the result of the main counterfactuals under the baseline calibration. All numbers are percentage changes.

**Table XIV.** Calibration results: Restricted model.

| Parameter | Description | Value | Target/Source | Data | Model |
|---|---|---|---|---|---|
| **Intergenerational transmission** | | | | | |
| $\xi$ | Transmission of networks | $0^*$ | Job-finding premium of followers (BHPS) | [0.055] | 0.000 |
| $\rho_\tau$ | Transmission of comparative advantage | 0.141 | Difference in share of followers by father's wage (BHPS) | 0.023 | 0.024 |
| $\rho_\phi$ | Transmission of preferences | $0.111^*$ | Intergenerational occupational persistence (BHPS) | 1.720 | 1.116 |
| **Heterogeneity and laws of motion** | | | | | |
| $\hat{h}_1$ | Human capital grid point 1 | 0.200 | Average occupational tenure returns after 5 years (BHPS) | - | - |
| $\hat{h}_2$ | Human capital grid point 2 | 0.299 | Average occupational tenure returns after 10 years (BHPS) | - | - |
| $\hat{n}$ | Networks premium | 1.381 | Share of jobs found through contacts (Pellizzari, 2010) | 0.230 | 0.229 |
| $\hat{\tau}$ | Comparative Advantage premium | 1.005 | Within–occupation log wage variance (BHPS) | 0.166 | 0.163 |
| $\bar{\phi}$ | Baseline preference for jobs | 0 | Normalization | - | - |
| $\hat{\phi}$ | Preference premium | 0.812 | Wage discount of followers (BHPS) | [0.076] | -0.026 |
| $p_h^+$ | Probability of accumulating HC (employed) | 0.017 | Average occupational tenure returns after 5 and 10 years | - | - |
| $p_h^-$ | Probability of losing HC (unemployed) | 0.998 | Average wage discount after unemp. (Arulampalam, 2001) | 0.076 | 0.076 |
| $p_n^+$ | Probability of accumulating networks (employed) | 0.004 | Regression of JF rate vs. past occupational tenure (BHPS) | 0.008 | 0.008 |
| $p_n^-$ | Probability of losing networks (unemployed) | 0.102 | JF rate–unemployment duration profile (BHPS) | 1.066 | 1.078 |
| $\sigma$ | Standard deviation of preference shocks | 0.243 | Occupational change rate, after unemployment (monthly, BHPS) | 0.357 | 0.354 |
| **Environment** | | | | | |
| $O$ | Number of occupations | 9 | 1-digit SOC aggregation | - | - |
| $\kappa$ | Vacancy posting cost | 4.515 | Average UE rate (monthly, BHPS) | 0.125 | 0.125 |
| $\delta$ | Exogenous separation rate | 0.003 | Average EU rate (monthly, BHPS) | 0.005 | 0.005 |
| $\beta$ | Discount factor | 0.997 | From literature | - | - |
| $\zeta$ | Age shock | 0.004 | Average length of worklife: 20 (young) + 20 (old) years | 40 | 40 |
| $b$ | Unemployment benefit | 0.761 | Average replacement rate (OECD) | 0.530 | 0.533 |
| $\chi$ | Surplus sharing rule | 0.700 | Normalization | - | - |
| $A$ | TFP parameter of matching function | 0.100 | Normalization | - | - |
| $\gamma$ | Elasticity of matching function w.r.t. unemp. | 0.500 | Petrongolo & Pissarides (2001) | - | - |

*Note:* $^*$ = restricted parameters; [] = non-targeted moments.

**Table XV.** Occupational persistence decomposition and welfare analysis of the *restricted model*

| | | (1) | (2) |
|---|---|---|---|
| **No parental net.** | $(\xi = 0)$ | n.a. | n.a. |
| **No comp. adv. trans.** | $(\rho_\tau = 1/O)$ | - | ✓ |
| **No pref. trans.** | $(\rho_\phi = 1/O)$ | n.a. | n.a. |
| Occupational persistence | | 1.116 | 1.000 |
| ($\Delta$% from baseline) | | 0.000 | (-100.000) |
| Welfare ($\Delta$% from baseline) | | 0.000 | (0.000) |
| Output ($\Delta$% from baseline) | | 0.000 | (0.000) |
| Sorting along comparative advantage (sons) | | 0.732 | 0.732 |
| Sorting along preferences (sons) | | 0.379 | 0.379 |
| Sorting along comparative advantage (fathers) | | 0.664 | 0.664 |
| Sorting along preferences (fathers) | | 0.447 | 0.447 |
| Output per worker (=1 in baseline) | | 1.000 | 1.000 |
| Variance of log wages ($\Delta$% from baseline) | | 0.163 | (-0.000) |
| Welfare CV ($\Delta$% from baseline) | | 0.147 | (-0.000) |
| Unemployment rate ($\Delta$% from baseline) | | 0.062 | (-0.000) |
| Average UE Rate ($\Delta$% from baseline) | | 0.125 | (0.000) |
| Average EU Rate ($\Delta$% from baseline) | | 0.005 | (-0.000) |
| Equilibrium tightness | | 1.551 | (0.000) |

*Note:* In column (1) we show results under the *restricted* calibration. In column (2) we shut down the transmission of comparative advantage.

**Table XVI.** The impact of search frictions

| | | $(\kappa = 1.19)$ | | | | $(\kappa = 12.43)$ | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **No parental net.** | $(\xi = 0)$ | - | ✓ | - | - | - | ✓ | - | - |
| **No comp. adv. trans.** | $(\rho_\tau = 1/O)$ | - | - | ✓ | - | - | - | ✓ | - |
| **No pref. trans.** | $(\rho_\phi = 1/O)$ | - | - | - | ✓ | - | - | - | ✓ |
| Occupational Persistence | | 1.258 | 1.252 | 1.005 | 1.258 | 1.686 | 1.137 | 1.583 | 1.596 |
| ($\Delta$% from baseline) | | 0.000 | (-2.408) | (-97.999) | (-0.002) | (0.000) | (-80.057) | (-15.001) | (-13.218) |
| Welfare ($\Delta$% from baseline) | | 0.000 | (-0.284) | (-0.057) | (0.000) | (0.000) | (0.108) | (-0.059) | (0.056) |
| Output ($\Delta$% from baseline) | | 0.000 | (-0.000) | (-0.000) | (-0.000) | (0.000) | (0.005) | (-0.003) | (0.003) |
| Sorting along comparative advantage (sons) | | 0.999 | 0.999 | 0.999 | 0.999 | 0.601 | 0.609 | 0.596 | 0.606 |
| Sorting along preferences (sons) | | 0.112 | 0.111 | 0.112 | 0.112 | 0.510 | 0.503 | 0.515 | 0.505 |
| Sorting along comparative advantage (fathers) | | 0.936 | 0.936 | 0.936 | 0.936 | 0.579 | 0.583 | 0.576 | 0.582 |
| Sorting along preferences (fathers) | | 0.175 | 0.175 | 0.175 | 0.175 | 0.533 | 0.529 | 0.536 | 0.530 |
| Output per worker ($\Delta$% from baseline) | | 2.386 | (-0.013) | (-0.002) | (0.000) | (1.898) | (0.395) | (-0.220) | (0.246) |
| Log Wage Variance ($\Delta$% from baseline) | | 0.032 | (0.019) | (0.015) | (-0.000) | (0.169) | (-0.384) | (0.205) | (-0.251) |
| Welfare CV ($\Delta$% from baseline) | | 0.142 | (0.006) | (0.001) | (-0.001) | (0.154) | (0.023) | (0.027) | (-0.051) |
| Unemployment Rate ($\Delta$% from baseline) | | 0.010 | (2.573) | (0.467) | (0.000) | (0.183) | (-0.455) | (0.208) | (-0.161) |
| Average UE Rate ($\Delta$% from baseline) | | 0.563 | (-0.711) | (-0.132) | (-0.000) | (0.040) | (0.480) | (-0.211) | (0.210) |
| Average EU Rate ($\Delta$% from baseline) | | 0.005 | (-1.990) | (-0.199) | (0.002) | (0.005) | (-0.371) | (0.059) | (0.023) |
| Equilibrium Tightness | | 32.452 | (0.125) | (0.068) | (-0.000) | (0.158) | (0.963) | (-0.422) | (0.420) |

*Note:* Occupational persistence decomposition and welfare analysis. Numbers in parentheses are relative changes from baseline. Counterfactual experiments: Columns (1)-(4) are under the baseline calibration and the US level of labor market frictions; Columns (5)-(8) are under the baseline calibration and Spanish level of labor market frictions. In Columns (2) and (6) we shut down parental networks. In Columns (3) and (7) we shut down the transmission of comparative advantage. In Columns (4) and (8) we shut down the transmission of preferences.

**Table XVII.** Policy experiment: effect of changes in unemployment benefits

| **Change in $b$ ($\Delta$% from baseline)** | (1) - | (2) +10% | (3) +25% | (4) -10% | (5) -25% |
|---|---|---|---|---|---|
| Occupational Persistence | 1.720 | 1.702 | 1.673 | 1.737 | 1.762 |
| ($\Delta$% from baseline) | - | (-2.495) | (-6.461) | (2.392) | (5.804) |
| Welfare ($\Delta$% from baseline) | - | (-0.179) | (-0.560) | (0.134) | (0.270) |
| Output ($\Delta$% from baseline) | - | (-0.003) | (-0.010) | (0.002) | (0.005) |
| Sorting along comparative advantage (sons) | 0.708 | 0.707 | 0.703 | 0.709 | 0.710 |
| Sorting along preferences (sons) | 0.403 | 0.404 | 0.408 | 0.401 | 0.401 |
| Sorting along comparative advantage (fathers) | 0.648 | 0.647 | 0.644 | 0.649 | 0.650 |
| Sorting along preferences (fathers) | 0.463 | 0.464 | 0.467 | 0.462 | 0.461 |
| Output per worker (=1 in baseline) | 1.000 | 0.999 | 0.997 | 1.001 | 1.001 |
| Unemployment rate ($\Delta$% from baseline) | 0.061 | (3.695) | (11.430) | (-2.868) | (-6.021) |

*Note:* Column (1) reports baseline results. In Columns (2) to (5), we change the flow value of unemployment by +10 percent, +25 percent, -10 percent and -25 percent respectively.

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