Labour Market Effects of International Trade when Mobility is Costly *

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Abstract

I build and estimate a dynamic structural model of sectoral choices with heterogeneous workers accumulating imperfectly transferable human capital. Utility costs provide an additional barrier to mobility. Estimated by Simulated Minimum Distance on administrative data covering the population of Danish workers, costs are found to be in the range of 10% to 19% of average annual wages. Removing permanent unobserved heterogeneity increases the utility costs by an order of magnitude. I show that both the imperfect transferability of human capital and the utility costs are important in explaining the slow adjustment of the labour market following shocks to the economy.

Keywords: Globalisation, adjustment costs, worker heterogeneity
JEL: E24, F13, F16

The purpose of this paper is two-fold. First it is to estimate the reallocation costs facing Danish workers when switching between sectors of the economy. Second it is to investigate the role of worker heterogeneity for the reallocation cost estimates.

Developed countries have experienced increasing foreign competition, particularly from low wage countries, since the early 1990s. This has been coupled with a shift in production away from the manufacturing sector towards non-traded goods and services. The reallocation process has naturally involved a decline of some industries and the expansion of others. While the public debate on globalisation often focuses on the destruction of jobs rather than the gains, economists and policy makers insist that the gains from trade outweigh the losses, at least in the long run as resources are allocated towards comparative advantage industries. But focusing only on long term gains does not address questions on the sluggishness and costs of the reallocation process. As globalisation continues, this tension between workers concerned by short term outcomes and

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policy makers focused on aggregate long term outcomes is bound to increase, making estimation of the adjustment costs following globalisation an ever more present concern.

This paper estimates the reallocation costs for Denmark. Among Continental European countries Denmark is special as the flexibility of the Danish labour market is very high, comparable even to the United States.[1] With weak employment protection and high unemployment insurance (UI) benefits being two of three pillars of the 'flexicurity' system (active labour market policies is the third) firms are relatively free to hire and lay off workers as they desire. Workers, on the other hand, pay the price of this flexibility: They may experience spells of unemployment, they may find that their human capital is imperfectly transferable across sectors, or they may have a distaste for switching sectors for other reasons. The main purpose of this paper is to quantify these reallocation costs following globalisation.

To this end I build and estimate a dynamic structural model of the Danish economy, where heterogeneous workers of overlapping generations accumulate imperfectly transferable human capital. In every period of time, workers receive wage offers from all sectors of the economy after which they choose to work in the sector that maximises expected lifetime utility. Unemployment is endogenous and workers receive benefits according to whether they are members of UI funds or not. If a worker wishes to switch sectors from one year to the next, he faces different costs. First, he may not be able to offer the same amount of human capital to all sectors as human capital is only partially transferable. Second, the worker faces a utility cost of switching sectors that depends on characteristics such as gender, education and age. The production side of the model is characterised by perfect competition where sector-representative firms demand human and physical capital in order to produce output according to a Cobb-Douglas production function.

The structural parameters of the model are estimated using Simulated Minimum Distance (SMD) on a matched worker-firm dataset covering the population of Danish workers and the universe of firms from 1996 to 2008. Employing SMD on this dataset, I fit a set of Auxiliary Parameters (APs) that provide a detailed description of the data. The SMD estimator finds the set of structural parameters such that the distance between APs estimated on actual data and

[1] See Botero *et al.* (2004) for a cross country comparison of labour market flexibility.

APs estimated on data simulated from the model is minimised.

The main estimation results are (i) that the utility cost of switching sectors for the median worker is between 10% and 19% of average annual wages, providing an additional barrier to inter-sectoral mobility other than partially transferable human capital, (ii) the median utility cost covers substantial heterogeneity over the population of workers: female, less-educated, and in particular older workers face higher costs, (iii) between 88% and 98% of a worker's experience is transferable across sectors, and (iv) unobserved worker heterogeneity affects the utility cost of switching sectors by an order of magnitude.

Once the model parameters are estimated, I use it to explore the dynamic adjustment processes following a globalisation shock to the economy. While globalisation manifests itself in numerous ways, this paper focuses on trade liberalisation, which lowers the output prices of the liberalising sector. Since trade barriers are already low for Denmark, lower output prices can also be seen as a consequence of increased international competition. For example, it is well-established that, following its integration into the world economy, China exports products at lower unit values than other countries. In fact, Schott (2008) finds that, within product categories, Chinese unit values are 48% lower than unit values from countries at a similar level of development, and that this discount has increased over time. Although this type of shock is likely to be gradual, it remains relevant to treat it as a one-off episode for the purpose of studying labour market dynamics.

By affecting wages, trade liberalisation can increase the incidence of unemployment for workers in the contracting sectors, particularly if workers are unable to reallocate immediately. There is some evidence that globalisation increases unemployment: Working on similar data, Munch (2010) finds that outsourcing increases the unemployment risk of low-skilled Danish workers, albeit with modest quantitative effects.[2]

Consider increased globalisation of the manufacturing sector. The globalisation shock consists

[2] A growing body of theoretical papers studies the effect of international trade on unemployment. In Davidson *et al.* (1999), Helpman and Itskhoki (2010), Helpman *et al.* (2010), and Helpman *et al.* (2011), the equilibrium unemployment rate may rise following trade liberalisation.

of a trade liberalisation episode lowering the output price of the manufacturing sector. Lower output prices for manufacturing lowers the relative wages of workers employed there. This in turn leads some manufacturing workers to relocate towards other sectors. In the simulation exercise, I find that: (i) The labour market reallocation process is sluggish, so that only 91.1% is completed after 10 years following the globalisation shock; (ii) The utility costs provide an important barrier to mobility, and without these costs the reallocation process would be faster: After 10 years 97.6% of the reallocation would be completed.

Recent empirical papers have studied how international trade affects domestic labour markets. In an influential paper, Autor *et al.* (2013) find that increasing import competition from China increases unemployment in local labour markets: For every $1,000 increase in imports per worker, the share of employed manufacturing workers falls by 0.7 percentage points. Examples of other reduced form studies are the papers by Autor *et al.* (2014), and Ebenstein *et al.* (2014). In a recent study Dix-Carneiro and Kovak (2017) focus on regional outcomes in Brazil following trade liberalisation in the 1990s. They find that the impact of tariff changes on regional earnings 20 years after liberalisation was three times the size of the effect 10 years after liberalisation. The mechanism underlying this result involves imperfect interregional labour mobility and dynamics in labour demand, driven by slow capital adjustment and agglomeration economies. This slow adjustment of the Brazilian economy following trade liberalisation is in accordance with the results of the present paper.

In the past few years, efforts have been made to estimate the transition costs of labour reallocation in structural models, e.g. Artuç *et al.* (2010), Artuç and McLaren (2015), Coşar (2013), Coşar *et al.* (2016), and Dix-Carneiro (2014). In the important Artuç *et al.* (2010) paper, the authors set up a dynamic structural model of the US labour market where homogeneous workers (up to an i.i.d. shock) face costs when reallocating to a new sector. They find that the reallocation costs amount to about 6 times average annual wages. Dix-Carneiro (2014) builds a model where workers are allowed to be heterogeneous in several dimensions, e.g. in gender, education, and sectoral experience, and finds reallocation costs that are around 1.4 to 2.7 times annual average wages using Brazilian data. This suggests that worker heterogeneity plays an important role in the estimation of sectoral reallocation costs.[3]

This paper uses a slightly modified Dix-Carneiro (2014) model to estimate sectoral reallocation costs for Danish workers.[4] One benefit of this model is that it allows me to explore the role of worker heterogeneity for the reallocation cost estimates. I show that when the model is restricted so that there is no unobserved worker heterogeneity, the reallocation cost estimates increase by an order of magnitude.

Using similar data for Denmark, Utar (2017) analyses the effect of low-wage trade shock on manufacturing workers in a reduced form setup. Her paper captures the importance of industry-specific human capital in workers' adjustment to import shocks and she finds that trade-induced adjustment costs are substantial and heterogeneous across workers. Her reduced form results are corroborated by my findings using a dynamic structural approach.

The remainder of the paper is organised as follows. The next section presents a dynamic structural model of the labour market allowing for observed and unobserved heterogeneity on the worker side. Section 2 describes the matched worker-firm data and the aggregate data used for estimation. Section 3 gives an overview of the estimation procedure and presents the results. Section 4 examines the dynamic adjustments following a globalisation shock to the economy and conducts policy experiments. Finally, section 5 concludes.

1 Empirical Model

The objective is to design and estimate a general equilibrium model of the labour market that allows for an assessment of the transition costs of labour reallocation across sectors while allowing workers to be unemployed. Building on the framework developed in Keane and Wolpin (1994), Lee (2005), Lee and Wolpin (2006), and following Dix-Carneiro (2014) closely, the strategy is to estimate a dynamic Roy (1951) model.[5]

Each year, the economy is populated by overlapping generations of workers aged 30 to 65.

[3]Note that in Artuç and McLaren (2015) the estimated mobility costs are at about 1 times average annual wage, and thus lower than those found in Artuç *et al.* (2010).

[4]The model is modified to account for the institutional setting facing unemployed Danish workers.

[5]See Heckman and Sedlacek (1985, 1990), and Heckman and Honoré (1990).

Workers supply their human capital to one of five sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, or (5) Services.[6] A worker has different levels of human capital to offer the five sectors. Thus, a productive manufacturing worker may be a productive or unproductive construction worker. Changing sectors from one period to the next is costly for two reasons: First, not all experience is transferable across sectors, and second, the worker faces a utility cost of switching. In addition to the five productive sectors there is an unproductive unemployment sector (0) where workers sit idle, receiving UI benefits or welfare assistance. Unemployment is endogenous, and workers will only choose to be unemployed if that choice maximises lifetime utility.

The timing of the model is illustrated in Figure 1. Consider a worker who is initially in sector

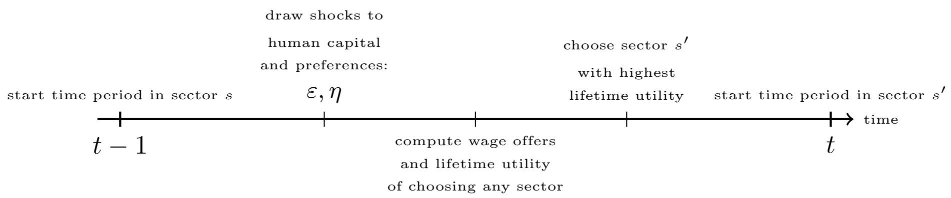


Figure 1: Model Timing

s in year $t-1$. In order to decide on a sector for year t he first draws shocks, ε, to the human capital he can supply each sector. For each, he also draws a preference shock, η. Once these shocks are realized, the worker is able to compute the wage or unemployment benefit he will receive in every single sector as well as the lifetime utility of choosing each. The lifetime utilities take into account all costs of switching sectors. Having computed these, the worker decides on the sector, s', that maximises lifetime utility. Then, in year t, the process is repeated.

In the following I describe the production and worker sides of the model before discussing how the model is solved and estimated.

[6]These sectors are chosen due to the availability of aggregate data for a number of variables from Statistics Denmark (see Section 2).

1.1 Sectoral Production

Representative firms in each sector demand the human capital supplied by workers in order to produce output. The production technology is assumed to be of a Cobb-Douglas form so that the value added of sector s becomes

$$Y_t^s = p_t^s A_t^s (H_t^s)^{\alpha_t^s} (K_t^s)^{1-\alpha_t^s}, \tag{1}$$

where p_t^s is the output price, A_t^s is productivity, H_t^s is the human capital employed in the sector, and K_t^s is physical capital. Notice that α_t^s is allowed to vary over time, and that the aggregate human capital, H_t^s, is not observed.

Given the production technology, the unit prices of human capital and physical capital are

$$\begin{aligned} r_t^s &= \alpha_t^s \frac{Y_t^s}{H_t^s}, \\ r_t^{s,K} &= (1-\alpha_t^s)\, \frac{Y_t^s}{K_t^s}. \end{aligned} \tag{2}$$

1.2 Workers

Each year, workers choose the sector that maximises the present value of lifetime utility, taking into account the costs of switching sectors. The mobility costs are comprised of imperfectly transferable work experience, and of a utility cost of switching. Consider worker i with a set of characteristics, Ω_{it}, in year t. The characteristics are specified below. Let $\mathbf{V}(\Omega_{it})$ denote the value function of this worker. The value function represents the maximum expected present value of lifetime utility over the choice alternatives. The Bellman equations are then

$$\mathbf{V}\left(\Omega_{it}\right) = \max_s \left\{\mathbf{V}^s\left(\Omega_{it}\right)\right\}, \tag{3}$$

with alternative-specific value functions

$$\mathbf{V}^s\left(\Omega_{it}\right) = \begin{cases} w^s(\Omega_{it}) + \rho \mathbb{E}_{\boldsymbol{\varepsilon},\boldsymbol{\eta}} \mathbf{V}(\Omega_{i,t+1}|\Omega_{it}, d_{it}=s) + \eta_{it}^s - \mathbf{C}^{s_{t-1},s}(\Omega_{it}) & \text{if age} < 65 \\ w^s(\Omega_{it}) + \eta_{it}^s - \mathbf{C}^{s_{t-1},s}(\Omega_{it}) & \text{if age} = 65 \end{cases} \tag{4}$$

where $w^s(\Omega_{it})$ is the real wage offer (or unemployment benefit) in sector s, η_{it}^s is a zero mean random sectoral preference shock, $\mathbf{C}^{s_{t-1},s}(\Omega_{it})$ is the utility cost incurred by a worker switching from sector s_{t-1} to sector s, and ρ is the discount factor. The variable d_{it} records the sectoral choice of worker i in year t. Note that workers aged 65 retire at the end of year t and therefore have no future expected values.

In the following I describe each of the components of the value function.

1.2.1 Wages

As is common in the literature, the wage offer a worker receives in a sector is the product of the unit price of human capital in that sector and the amount of sector-specific human capital that the worker possesses.[7] The wage offer in sector s is given by

$$w^s(\Omega_{it}) = r_t^s \cdot H^s(\Omega_{it}), \tag{5}$$

where r_t^s is the unit price of human capital, and $H^s(\Omega_{it})$ is the amount of human capital worker i can offer to sector s. The sector-specific human capital production function can be decomposed into a deterministic part and an idiosyncratic shock. The deterministic part depends on worker characteristics such as gender, education, and experience

$$H^s(\Omega_{it}) = \exp\left[\beta_1^s \text{Female}_i + \beta_2^s \text{Educ}_i + \beta_3^s \text{Exper}_{it} + \beta_4^s (\text{Exper}_{it})^2 + \lambda_i^s + \varepsilon_{it}^s\right], \tag{6}$$

where Female_i is a gender indicator, Educ_i indicates if the worker has completed college education, and ε_{it}^s is the mean zero idiosyncratic human capital shock. The λ_i^s parameter captures permanent unobserved (by the econometrician) heterogeneity in the human capital supplied to sector s.

Work experience, Exper_{it}, is gained for each year of employment. However, when a worker switches from one sector to another, part of his human capital is lost. Specifically, I assume that labour market experience depreciates at the sector-specific rate of $1 - \gamma^s$ when switching, such that only the fraction γ^s is transferable:

$$\text{Exper}_{it} = \begin{cases} \text{Exper}_{i,t-1} + 1 & \text{if } s = s_{t-1} \\ \gamma^s \text{Exper}_{i,t-1} & \text{else} \end{cases} \tag{7}$$

[7] See e.g. Dix-Carneiro (2014), Heckman and Sedlacek (1985), Lee (2005), and Lee and Wolpin (2006).

Suppose a manufacturing worker has Exper_t years of experience. Then he switches to, say, the service sector for one year, which depreciates his experience to $\text{Exper}_{t+1} = \gamma^{\text{service}}\text{Exper}_t$. If he then continues in the service sector, his experience will be $\text{Exper}_{t+2} = \text{Exper}_{t+1} + 1$. However, if he chooses to return to manufacturing the following year, then instead of depreciating his experience once more, I add the experience that was depreciated when he moved to the service sector and only depreciate the one year of service sector experience he has accrued. Thus, he re-enters manufacturing with

$$\begin{aligned}\text{Exper}_{t+2} &= \text{Exper}_{t+1} + (1-\gamma^{\text{service}})\text{Exper}_t + \gamma^{\text{manufacturing}} \times 1 \\ &= \text{Exper}_t + \gamma^{\text{manufacturing}} \times 1\end{aligned}$$

years of experience, where Exper_t was his experience when he left manufacturing and $\gamma^{\text{manufacturing}} \times 1$ is the depreciated value of the one year of service sector experience he brings back to the manufacturing sector. Had he remained in the service sector for two years before returning, his return experience would be $\text{Exper}_{t+3} = \text{Exper}_t + \gamma^{\text{manufacturing}} \times 2$, and so forth.

The wage offers in Equations (5) and (6) differ from those in the literature in one important way.[8] Rather than accumulating sector-specific experience, workers accumulate general work experience that is then transferred across sectors only at sector-specific discounts of γ^s. The benefit of the current modelling strategy is that it reduces the number of state variables from 5 sector-specific experience variables to one general work experience term. My dataset comes with a variable on total lifetime work experience that I use as a proxy to generate initial values for the experience variable of this model.

Figure 2 shows what these assumptions imply in terms of wage dynamics. The solid lines in the figure show hypothetical wage profiles for different levels of experience, while the markers indicate a possible wage dynamic for a worker aged 44 to 65. Initially the worker is employed in Sector 1. Then at age 50, he decides to switch to Sector 2. This depreciates his work experience so that he enters Sector 1 with less experience than he had the year before. In this particular case, however, his wage increases in spite of the experience depreciation.

[8] See Dix-Carneiro (2014) or Neal (1995).

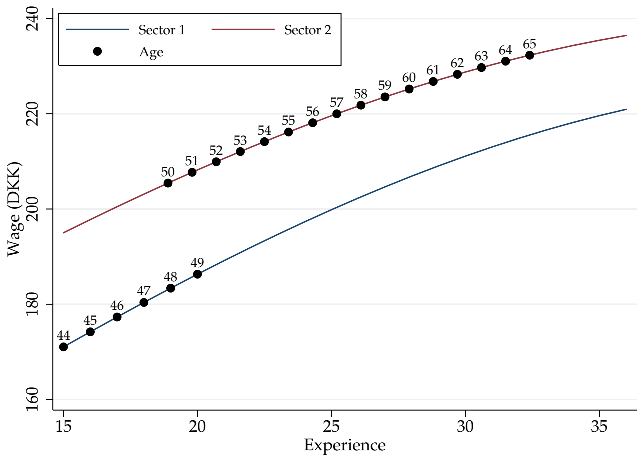


Figure 2: Wage Dynamics

1.2.2 Unemployment

Here, I build a model of the institutional setting that unemployed workers face in Denmark. During spells of unemployment, the worker receives unemployment benefits, the size of which depends on whether he is eligible for UI benefits or has to rely on welfare assistance:

$$w^0(\Omega_{it}) = \begin{cases} \min\left\{k \cdot w_{i,t-\mathcal{T}}, \overline{\mathrm{UI}}\right\} + \exp(\lambda_i^0) + \varepsilon_{it}^0 & \text{if } \mathrm{Elig}_{it} = 1, \\ \mathrm{WA} + \exp(\lambda_i^0) + \varepsilon_{it}^0 & \text{if } \mathrm{Elig}_{it} = 0, \end{cases} \tag{8}$$

where k is the degree of compensation for the insured, $w_{i,t-\mathcal{T}}$ is the wage received in the most recent employment (so that $\mathcal{T}$ denotes the year of last employment), $\overline{\mathrm{UI}}$ is the maximum UI benefit, Elig_{it} is an indicator of whether the worker is eligible for UI benefits, WA is the welfare assistance, λ_i^0 is permanent unobserved heterogeneity, and ε_{it}^0 is a shock to the value of being unemployed. $\overline{\mathrm{UI}}$, WA, and k are set to values that matches what unemployed Danish workers are facing. Eligibility for UI benefits depends on two criteria. First, the worker must be member of a UI fund. Second, the worker must not have received UI benefits for more than 4 years. This is why it is necessary to keep track of the year of last employment: A worker is only eligible for UI benefits if $t - \mathcal{T}$ is less than or equal to 4 years.

Work experience is discounted with every year of unemployment at a rate of γ^0. Thus, if a worker with experience Exper_i is unemployed for one year before he finds work in sector s, he enters with experience $\gamma^s \cdot (\gamma^0 \cdot \text{Exper}_i)$, where the term in parenthesis is the human capital cost of one year of unemployment and γ^s is the human capital cost of switching to sector s.

Note that unemployment is modelled as an endogenous choice for the worker. In that sense, all unemployment is voluntary. In practice, however, UI insurance and welfare benefits are of a magnitude that workers in this model would never choose to be unemployed absent a combination of negative shocks to human capital and positive shocks to the value of being unemployed. Online Appendix B describes the institutional setting facing unemployed Danish workers in some detail.

1.2.3 Utility Costs

The utility cost that a worker incurs when switching sectors is a function of gender, education and age, and is given by

$$\mathbf{C}^{s_{t-1},s}(\Omega_{it}) = \exp\left[\xi^s + \xi^{s_{t-1}} + \kappa_1 \text{Female}_i + \kappa_2 \text{Educ}_i + \kappa_3(\text{age} - 30) + \kappa_4(\text{age} - 30)^2\right], \quad (9)$$

where ξ^s and $\xi^{s_{t-1}}$ are parameters depending on the chosen and previous sectors, respectively. The costs are only incurred if the worker switches sectors from one year to the next, meaning that $\mathbf{C}^{s_{t-1},s}(\Omega_{it}) = 0$ if $s_{t-1} = s$. The utility costs represent workers' distaste for switching to a new sector. It may arise for a number of reasons, e.g. due to the existence of search costs. This paper remains agnostic as to the exact source of the utility costs, and leaves exploring this important issue to future research.

1.2.4 Expectations of Future Human Capital Prices

For a worker to be able to decide in which sector to work in any given year, he must compute what wage offers he expects to receive in the future. These wage offers depend not only on the idiosyncratic sector specific shocks to his human capital $\boldsymbol{\varepsilon}_{i\tau}$, which is unknown to him in year $t < \tau$, but also on the unit price of human capital in all sectors, $\mathbf{r}_\tau$. The bold symbols are vectors over the five productive sectors in the economy such that the first entry of $\boldsymbol{\varepsilon}_{i\tau}$ is $\varepsilon^1_{i\tau}$ and so forth. Following Lee (2005), it is assumed that workers have perfect foresight with respect to the future sequence of human capital prices, a sequence that is computed endogenously when the model is solved.

1.2.5 Idiosyncratic Shocks and Distribution of Types

The vectors of idiosyncratic shocks, $\boldsymbol{\varepsilon}_{it}$ and $\boldsymbol{\eta}_{it}$, comprise the components of the state space that are unobserved by the researcher. In order to solve the model, assumptions on their distributions are necessary. It is assumed that they are independent and drawn from a mean zero normal distribution and a mean zero Extreme Value Type I distribution[9], respectively:

$$\begin{aligned} \varepsilon_{it}^{s} &\overset{\text{iid}}{\sim} \mathcal{N}\left(0, \sigma^{s}\right), \\ \eta_{it}^{s} &\overset{\text{iid}}{\sim} \text{EV}(-0.5772\nu, \nu). \end{aligned} \tag{10}$$

The i.i.d. extreme value assumption on the preference shocks yields a convenient closed form solution when taking the expectation, contributing to computational tractability.

In order to identify the permanent unobserved heterogeneity in the wage offers it is assumed that there are two types of workers, so that the vector (over sectors) of unobserved heterogeneity, $\boldsymbol{\lambda}_i$, has two points of support.

$$\boldsymbol{\lambda}_i \sim \left\{ \left(\boldsymbol{\lambda}_1, \mathcal{P}_1\right), \left(\boldsymbol{\lambda}_2, \mathcal{P}_2\right) \right\}, \tag{11}$$

where $\mathcal{P}_1$ and $\mathcal{P}_2$ are the probabilities of being a type 1 and type 2 worker, respectively. The type probabilities are assumed to depend on gender, level of education and initial general work experience

$$\begin{aligned} \mathcal{P}_1 &= \frac{1}{1 + \exp\left[\phi_0 + \phi_1 \text{Female}_i + \phi_2 \text{Educ}_i + \phi_3 \text{Exper}_i\right]}, \\ \mathcal{P}_2 &= 1 - \mathcal{P}_1, \end{aligned} \tag{12}$$

and the parameters in these equations are estimated along with the other structural parameters of the model.

1.2.6 State Space

Finally, having specified all the variables necessary for workers' decision making, it is possible to define the state space, Ω_{it}. It is given by all variables that are relevant for the determination

[9] The parametrization of the Extreme Value Type I distribution is chosen to ensure that the mean is zero. 0.5772 is Euler's constant.

of the real wage the worker would get in any sector and any other variables relevant for the formation of expectations.

$$\Omega_{it} = \left\{ \text{age}_i, \text{Female}_i, \text{Educ}_i, \text{Elig}_{it}, \text{Exper}_{it}, \{\mathbf{r}_{t+\tau}\}_{\tau=0}^{65-\text{age}_i}, s_{t-1}, w_{i,t-\mathcal{T}}, \boldsymbol{\lambda}_i, \boldsymbol{\eta}_{it}, \boldsymbol{\varepsilon}_{it} \right\}. \tag{13}$$

These include age, gender, level of education, eligibility for UI benefits, experience, the sequence of future human capital prices, previous sector including unemployment, wage in last employment, and current idiosyncratic shocks.

Again, the bold symbols for $\mathbf{r}$, $\boldsymbol{\lambda}$, $\boldsymbol{\eta}$ and $\boldsymbol{\varepsilon}$ indicate vectors over the five productive sectors. Note that $\{\mathbf{r}_{t+\tau}\}_{\tau=0}^{65-\text{age}}$ is the sequence of human capital returns that workers of any ages face from the current year until retirement. Thus, for a worker of age 60 in year t, what matters for the current sectoral choice are the current human capital prices, $\mathbf{r}_t$, and those of the following five years until year $t+5$.

1.3 Model Equilibrium

In year t, each worker solves his optimisation problem given by Equations (3) and (4) in order to decide what sector to work in. Once all workers have made their choices, the total supply of human capital to sector s is

$$H_t^{s,sup}\left(\{\mathbf{r}_{t+\tau}\}_{\tau=0}^{35}\right) = \sum_{a=30}^{65}\sum_{i=1}^{n_{at}} H^s\left(\Omega_{it}\right) \cdot \mathbf{1}\left\{d_{it} = s\right\}, \tag{14}$$

where $H^s(\Omega_{it})$ is the individual sector specific human capital of worker i, $\mathbf{1}\{d_{it} = s\}$ is an indicator function for sectoral choice s, and n_{at} is the number of workers of age a in year t. The current aggregate supply of human capital in sector s, $H_t^{s,sup}$, is a function of the entire sequence of human capital prices in all sectors, $\{\mathbf{r}_{t+\tau}\}_{\tau=0}^{35}$.

In equilibrium, sectoral supply of human capital, from Equation (14), equals sectoral demand, which is found from Equation (2) to be

$$H_t^{s,dem} = \alpha_t^s \frac{Y_t^s}{r_t^s}.$$

Combining the aggregate supply and demand for human capital yields the equilibrium condition for sector s

$$H_t^{s,sup}\left(\left\{\mathbf{r}_{t+\tau}^{*}\right\}_{\tau=0}^{35}\right)=\alpha_t^s\frac{Y_t^s}{r_t^{s,*}}, \tag{15}$$

whose solution determines the equilibrium human capital prices. As my sample period is finite, I am able to impose perfect foresight only between the initial and final sample years. Therefore it is assumed that workers have static expectations from the final year onwards. Thus, when deciding where to work in, say, the final sample year, a worker of age 30, who forms expectations on the future sequence of human capital prices from now until he retires at age 65, assumes that future human capital prices remain at their contemporaneous levels.

Online Appendix A describes how the model is solved.

2 Data

Estimating the empirical model puts certain requirements on the data. It necessitates the use of panel data on the worker side, including observations of outcomes for the unemployed. It also requires panel data on sectoral real value added and income shares for the factors of production. Both such datasets are available from Statistics Denmark for the period 1996 to 2008. This section documents each of the sources of these data, and gives some descriptive statistics.

2.1 Worker Data

For each year in the sample period, the worker data is taken from the administrative register "Integrated Database for Labour Market Research" (IDA), which covers the entire Danish population aged 15-74. At birth, or when becoming a permanent resident, every individual is given a unique personal identification number, used by the local and central government to record a variety of individual level information. Likewise, the universe of Danish firms, each with a unique identifier, are recorded in the "Firm Statistics Register" (FirmStat), whose information allows me to assign each firm to the five productive sectors that are defined in accordance with the NACE Rev. 2 statistical classification of economic activities in the European Union. Workers and firms can then be matched using the "Firm-Integrated Database for Labour Market Research" (FIDA) database.

From this matched worker-firm dataset I extract data on age, gender, labour market status (employed or unemployed), UI fund membership, total work experience, and hourly wages for workers aged 30 to 65. The entry age of 30 is chosen since almost all workers have completed their education at this age. For workers who are employed I observe hourly wage rates, while for the unemployed I observe unemployment benefits, which can be decomposed into UI benefits for those eligible and welfare assistance for others. It is possible to match workers with firms only from 1995 onwards, so I use the 1995 data to construct initial conditions for estimating the model.

The dataset allows me to track individual workers over the sample period, which makes it possible to construct sectoral transition rates as well as transitions to and from unemployment. Table 1 shows average yearly transition rates between the five productive sectors as well as the unemployment sector. Several features are worth noting. First, a key feature of the data that

Table 1: Average Yearly Transition Rates

From ↓ , To →	(0)	(1)	(2)	(3)	(4)	(5)
(0)	0.4794	0.0141	0.1053	0.0436	0.1046	0.2531
(1)	0.0409	0.8447	0.0281	0.0228	0.0265	0.0370
(2)	0.0294	0.0017	0.9090	0.0080	0.0249	0.0271
(3)	0.0290	0.0042	0.0208	0.9009	0.0191	0.0261
(4)	0.0227	0.0016	0.0226	0.0063	0.9144	0.0324
(5)	0.0182	0.0009	0.0075	0.0026	0.0111	0.9596

Sectors: (0) Unemployment, (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

the model must be able to replicate is the high degree of persistence in sectoral choices: The diagonal elements of the transition matrix are all much larger than the off-diagonals, which may be the result of workers being unable to arbitrage wage differentials. Second, although there is persistence in unemployment, the persistence is smaller than that of the productive sectors. Third, workers initially unemployed are less likely to find a job in the Agriculture/Mining sector and the Construction sector than they are of finding a job in the other sectors, with the service sector being the most likely employer. Moreover, workers initially employed in Agriculture/Mining are those most likely to become unemployed, while those from the Service sector are least likely.

2.2 Aggregate Series

The aggregate series used for estimation and simulation are taken from the online databases of Statistics Denmark.[10] From the PRIS8 database I extract the Consumer Price Index (CPI) and set the base year to 2000. Gross value added series on the sectoral level are obtained from NATE101, while income shares for human capital and physical capital, also on the sectoral level, are constructed from data from NATE102 as

$$\alpha_t^s = \frac{(\text{Wage bill})_t^s}{(\text{Gross value added})_t^s - (\text{Production taxes})_t^s},$$

with the physical capital share being $1 - \alpha_t^s$. Figure 3 shows the evolution of human capital income shares.

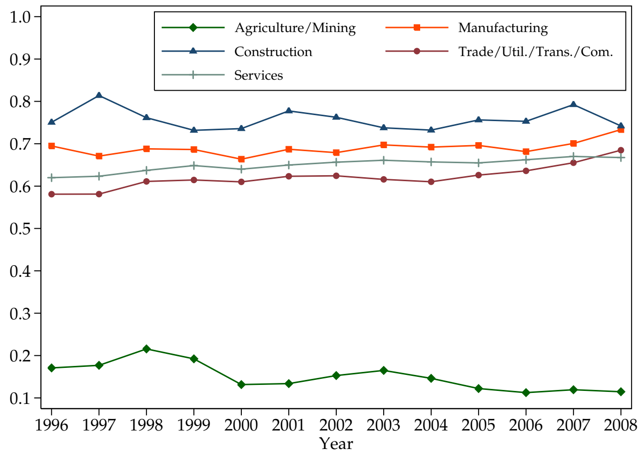


Figure 3: Evolution of Labour Income Shares

From NAT09N I extract data on sectoral capital stocks, which together with income shares of capital allows me to compute the return to capital in sector s as

$$r_t^{s,K} = (1 - \alpha_t^s)\,\frac{Y_t^s}{K_t^s} = \frac{(\text{Gross surplus from production})_t^s}{(\text{Capital stock})_t^s}.$$

[10]Statistikbanken (http://statistikbanken.dk)

Finally, using Input-Output tables for the Danish economy in 2008, I construct economy-wide expenditure shares as

$$\mu^s = \frac{(\text{Total uses})^s}{\sum_{k=1}^{5} (\text{Total uses})^k},$$

where $(\text{Total uses})^s$ is the share of income that is spent on the output of sector s for any use, including purchases from other sectors. The expenditure shares are shown in Table 2.

Table 2: Expenditure Shares

	μ^s
Agriculture/Mining	0.0114
Manufacturing	0.1757
Construction	0.0610
Trade/Util./Trans./Com.	0.2748
Services	0.4770

In order to reduce the choice set, the sectors have been aggregated to the five productive sectors of (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/ Utilities/Transportation/Communication, (5) Services. The exact composition of each sector is specified in Online Appendix C. Aggregate data series for these sectors are readily available from the sources indicated above.

3 Estimation Strategy and Results

The model has 69 structural parameters. The three unemployment benefit parameters are chosen to replicate the institutional setting in Denmark. The discount factor is set to 0.95. This leaves 65 parameters. These are further reduced by assuming that the unobserved permanent heterogeneity parameters of Type 1 workers is zero. This assumption aids in the identification of the remaining unobserved heterogeneity parameters and is common in the literature.[11] Finally, the fixed utility cost parameter for leaving the Agriculture/Mining sector, $\xi^{s_{t-1}=1}$, is set to zero so that the remaining ξ parameters are interpreted in terms relative to switching away from this sector. That leaves 58 structural parameters, denoted by θ, to be estimated.

[11] See e.g. Dix-Carneiro (2014).

These are estimated using Simulated Minimum Distance (SMD), also known as Indirect Inference (see Hall and Rust (2002) and Gourieroux and Monfort (1996) for details). As the name suggests, this is a simulation based estimation technique that minimises the distance between a set of simulated and sample moments, known as Auxiliary Parameters (APs). The sample APs are calculated once and for all, and stored in a vector, $\mathbf{a}^D$. Then, for a trial value of θ, the APs are calculated on data from one or more simulations of the model, and stored in $\mathbf{a}^S(\theta)$. The SMD estimator of θ is the vector that minimises a quadratic form of distance between the two sets of APs:

$$\widehat{\theta}_{SMD} = \arg\min_{\theta} \left[\mathbf{a}^S(\theta) - \mathbf{a}^D\right]' \mathbf{A} \left[\mathbf{a}^S(\theta) - \mathbf{a}^D\right],$$

where $\mathbf{A}$ is a positive definite matrix. So long as the APs are well enough specified, $\widehat{\theta}_{SMD}$ is a consistent estimator (asymptotically) of the true structural parameters, even when computing $\mathbf{a}^S(\theta)$ using a single simulation. As shown in Online Appendix D, using a single simulation effectively doubles the asymptotic variance of the SMD estimator compared to a situation where the number of simulations approaches infinity. In the present context, this is a fairly small price to pay when compared to the significant computational gain of simulating data from the model only once.

3.1 Auxiliary Parameters

The purpose of the APs is to capture statistical relationships that allows for identification of the structural parameters of the model. Therefore, although the researcher's choice of APs may seem rather *ad hoc*, the choice should be motivated by identification reasons. As the parameters to be estimated here relate to the wage offer functions and the utility costs of switching, the APs are simply chosen to be the coefficients of OLS regressions of the form

$$Y_{it} = X_{it}'\zeta + \delta_t + \eta_{it},$$

where Y_{it} is the outcome, X_{it} is a vector of regressors excluding a constant, ζ is a parameter vector, and δ_t are year fixed effects for each of the years from 1996 to 2008.

In order to identify the parameters of the wage offer functions in Equations (5) and (6), the first set of regressions are chosen to be log wage regressions for each of the five productive sectors. In addition to recording the coefficients, I also record the standard error of the regressions to help in the identification of the standard error of the shock to human capital. For these regressions, the regressors X_{it} are a female dummy, a college education dummy, age, age squared, and experience. The AP-coefficients on gender and education are directly relevant for the identification of their corresponding structural parameters (β_1^s and β_2^s), while the age and experience coefficients help identify both the experience coefficients (β_3^s and β_4^s) and the fraction of experience that is transferable (γ^s) in Equation (7). The time dimension aids in the identification of the unobserved permanent heterogeneity parameters and the corresponding type probability parameters (λ_i^s and ϕ_0–ϕ_3) in Equation (12). However, identification of the latter is also aided by the AP-coefficients on the female dummy, the education dummy, and the age and experience terms.

The next set of regressions are linear probability models (LPMs) for sectoral choices (six regressions) where the left-hand side variable for each regression is an indicator for working in a particular sector or being unemployed. Finally I have LPMs for transitions between any pair of sectors (36 regressions). For all LPMs, I also include log wages as an additional regressor to get sectoral choices and transitions conditional on wages. These regressions are crucial for identifying the utility cost parameters in Equation (9). The idea is that, for a given wage, the LPMs are informative on the characteristics of those who are likely to switch sectors and the characteristics of those who are not. The transition regressions are also important for identifying the scale parameter on the preference shock (ν). Note that these APs also aid in the identification of the fraction of experience that is transferable across sectors and the unobserved permanent heterogeneity parameters: Consider a situation where experience is untransferable across sectors, i.e. where the γ's are zero. In this case, the experience variables in the auxiliary LPMs would not be very informative on simulated sectoral transitions, and the resulting distance between the simulated APs and the APs from the data would increase, lowering the fit of the model.

The APs are comprised of the ζ's and δ's from the regressions, as well as the root mean squared error of the log wage regressions, making a total of 893 APs. Online Appendix E shows the results of their estimation on the sample data. The efficient choice of the weighting matrix, $\mathbf{A}$, is the inverse covariance matrix of the APs, which I bootstrap also using the matched worker-firm data.

The structural parameters are identified when changing them leads to changes in the simulated APs, $\mathbf{a}^S(\theta)$. Consider identification of the ξ^s parameter in the equation for the utility cost of switching. If this structural parameter is too high, the utility cost of switching to sector s will be very high and few if any workers will switch to this sector from the others when data is simulated. This in turn will affect the simulated APs for the LPMs of transition to sector s from the other sectors in such a way that the distance between $\mathbf{a}^S(\theta)$ and $\mathbf{a}^D$ will grow. In the limiting case where ξ^s is so high that no simulated worker chooses sector s, the APs for the transitional LPMs to this sector are not identified at all. The SMD estimation procedure then lowers the value ξ^s to line up the simulated transitional LPMs with the actual transitional LPMs. It is in this sense that the structural parameters are identified.

3.2 Estimation Procedure

The estimation procedure involves searching for a minimum over the 58 structural parameters. As already mentioned, the remaining parameters are calibrated. The parameters concerning

Table 3: Calibrated Parameters

Parameter		Equation	Value	USD
Discount factor,	ρ	(4)	0.95	
Compensation rate,	k	(8)	0.90	
Maximum benefit,	$\overline{\text{UI}}$	(8)	101	\$22.47
Welfare assistance,	WA	(8)	75	\$16.69

The values for $\overline{\text{UI}}$ and WA are hourly real benefits in 2000 DKK, calculated by dividing deflated annual figures by 1,702 work hours per year. The last column shows the benefits in current US dollars using Danish CPI of 1.288 to convert to 2012 DKK and then the exchange rate of 5.79 DKK/\$.

unemployment benefits are set to mimic the institutional setting faced by Danish workers (see Online Appendix B).

The estimation procedure follows the steps:

1. From the data, obtain series for real value added, Y_t^s, and human capital income shares, α_t^s. These are imposed throughout the estimation procedure.

2. Obtain the 665 sample auxiliary parameters, $\mathbf{a}^D$, and get their covariance matrix by a bootstrap procedure.

3. Solve the structural model and simulate sectoral choice paths that resembles those observed in the data with respect to e.g. age, gender and education profiles. Obtain simulated auxiliary parameters, $\mathbf{a}^S(\theta)$, using the simulated data.

4. Search for the structural parameter vector, $\widehat{\theta}_{SMD}$, that minimises the quadratic distance between the simulated and sample auxiliary parameters using the bootstrapped covariance matrix as the weighting matrix.[12]

Once the structural model parameters are estimated, the covariance matrix is computed at their optimised values. As shown in Online Appendix D, the covariance matrix for the estimated parameters is computed using the bootstrapped covariance matrix of the sample auxiliary parameters. Thus, the precision of the structural estimates are a function of the precision of the auxiliary estimates.

3.3 Estimation Results

Panels A to F of Table 4 present estimates for the 58 structural parameters of the model. The human capital production functions for the five productive sectors are shown in Panel A. They show that, on average, women earn less than men, higher educated workers have higher wages, and wages increase at a decreasing rate in work experience. Panel B reports estimates for the standard deviation of the human capital shocks, the shock to the value of being unemployed, and the scale parameter for the preference shocks. For the productive sectors the smallest and largest values of σ are found for sectors 3 and 4, respectively. The estimates suggest that a one standard deviation idiosyncratic shock to human capital raises wages by 20% to 22%. The standard error

[12] I use the Nelder-Mead simplex search algorithm. Only the diagonal elements of the bootstrapped covariance matrix is used.

for the shock to the value of being unemployed, σ^0, is higher: For unemployment to be a viable choice large shocks are needed.

The unobserved permanent heterogeneity parameters in Panel C are all positive. Having restricted these to be zero for type 1 workers, these results can be interpreted as indicating that type 2 workers are more productive. Panel D shows the estimates of the parameters determining type probabilities. These are interpreted in Table 5, which presents the distribution of type probabilities for type 1 workers (the corresponding type 2 probabilities are 1 minus the type 1 probabilities). The probability of being a type 1 worker decreases in education and experience, with women being more likely to be type 1 than men.

Panel E shows estimates of the fraction of work experience that is transferable when switching sectors. Work experience is most transferable to the Service sector and least transferable to the Trade/Utilities/Transportation/Communication sector. The panel also shows that each year of unemployment depreciates 5.6% of previous experience. Consider an unemployed worker who has to decide which sector to re-enter. Table 6 shows the fraction of previous experience that he is able to retain as a function of the number of years he has been unemployed and the return sector, if the return sector is not the same as his previous sector of employment. One year of unemployment depreciates experience between 7% and 17%. These numbers increase in the number of years he has been unemployed. As illustrated in Figure 2, depreciation of work experience does not necessarily equal lower wages as wages depend both on the parameters of the human capital functions and on the prices of human capital.

Finally, Panel F shows parameter estimates for the utility costs of switching. These are higher for women, lower for higher educated workers, and increasing at a decreasing rate in age. They differ across sectors due to the sector specific fixed parameters, ξ^s and $\xi^{s_{t-1}}$. To interpret these, Table 7 shows the median costs of entering the indicated sector in terms of average annual wages and in terms of the discounted value of all expected future earnings. The median cost of entering the Service sector is 19% of average annual wages while the corresponding number for the Construction sector is 10%. However, in terms of future earnings, these drop to 1.0% and 0.5%, respectively. Note that when computing the costs in terms of future earnings that the

Table 4: Parameter Estimates

Panel A: Human Capital Production Functions, Equation (6)						
		(1)	(2)	(3)	(4)	(5)
β_1, Female		-0.269834	-0.163248	-0.282349	-0.214545	-0.139674
		(0.000205)	(0.000152)	(0.000387)	(0.000092)	(0.000124)
β_2, Educ		0.132389	0.298727	0.259822	0.210376	0.237521
		(0.000092)	(0.000311)	(0.000125)	(0.000153)	(0.000177)
β_3, Exper		0.043462	0.025382	0.031882	0.029734	0.024721
		(0.000003)	(0.000002)	(0.000003)	(0.000002)	(0.000001)
β_4, Exper^2		-0.000492	-0.000386	-0.000417	-0.000308	-0.000212
		(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Panel B: Standard Errors and Scale Parameter of Shocks, Equation (10)						
	(0)	(1)	(2)	(3)	(4)	(5)
σ	0.394753	0.180472	0.192742	0.178229	0.201856	0.192825
	(0.001338)	(0.000114)	(0.000107)	(0.000089)	(0.000093)	(0.000127)
ν	2.308736					
	(0.014083)					
Panel C: Unobserved Permanent Heterogeneity, Equations (6) and (8)						
	(0)	(1)	(2)	(3)	(4)	(5)
λ	3.524116	1.286352	1.002471	1.148352	1.097452	0.867373
	(0.062482)	(0.002784)	(0.001856)	(0.003866)	(0.002037)	(0.001386)
Panel D: Type Probabilities, Equation (12)						
	Constant	Female	Educ	Exper		
ϕ	0.744541	-0.199827	0.301341	0.089263		
	(0.001107)	(0.000374)	(0.000784)	(0.000026)		
Panel E: Transferability of Experience, Equation (7)						
	(0)	(1)	(2)	(3)	(4)	(5)
γ	0.943783	0.936489	0.960352	0.928462	0.879235	0.982639
	(0.000953)	(0.000238)	(0.000174)	(0.000216)	(0.000263)	(0.000089)
Panel F: Utility Costs of Switching, Equation (9)						
	(0)	(1)	(2)	(3)	(4)	(5)
ξ^s	2.081485	2.135732	2.101564	1.727461	2.201656	2.989263
	(0.012259)	(0.009146)	(0.012672)	(0.011345)	(0.015124)	(0.022087)
$\xi^{s_{t-1}}$	0.847652		0.592673	0.730572	1.169831	1.974467
	(0.005514)		(0.001701)	(0.001592)	(0.005356)	(0.012575)
	Female	Educ	Age	Age^2		
κ	0.257254	-0.439273	0.037639	-0.000406		
	(0.000592)	(0.000652)	(0.000017)	(0.000000)		

Standard errors in parenthesis. Sectors: (0) Unemployment, (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 5: Distribution of Type 1 Probabilities

	Experience						
	1	5	10	15	20	25	30
Panel A: Male							
Educ = 0	0.3028	0.2331	0.1629	0.1107	0.0738	0.0485	0.0316
Educ = 1	0.2432	0.1836	0.1258	0.0843	0.0557	0.0364	0.0236
Panel B: Female							
Educ = 0	0.3466	0.2707	0.1920	0.1320	0.0887	0.0586	0.0383
Educ = 1	0.2818	0.2155	0.1495	0.1011	0.0672	0.0440	0.0286

The table shows the distribution of Type 1 probabilities, $\mathcal{P}_1$ from Equation (12), for workers with 1 to 30 years of work experience, conditional on college education and gender. Type 2 probabilities are $\mathcal{P}_2 = 1 - \mathcal{P}_1$.

Table 6: Retainment of Experience Following Unemployment

	Years Unemployed				
	1	2	3	4	5
Return Sector					
(1)	0.8838	0.8342	0.7873	0.7430	0.7012
(2)	0.9064	0.8554	0.8073	0.7619	0.7191
(3)	0.8763	0.8270	0.7805	0.7366	0.6952
(4)	0.8298	0.7832	0.7391	0.6976	0.6584
(5)	0.9274	0.8753	0.8261	0.7796	0.7358

The table shows the fraction of initial work experience that is retained following an unemployment spell of 1 to 5 years when returning to a new sector. Return sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

future earnings vary greatly over workers of different ages: The future earnings of a 64 year old worker is lower than for a 35 year old as the older worker only has one year left on the labour market prior to retirement.

Table 7: Median Utility Costs of Switching

	Entry costs in terms of	
	Annual Wages	Future Earnings
Unemployment	0.1345	0.0070
Agriculture/Mining	0.1387	0.0076
Manufacturing	0.1587	0.0087
Construction	0.0979	0.0053
Trade/Util./Tran./Com.	0.1718	0.0091
Services	0.1886	0.0097

Median costs of entry to the indicated sector is computed as $\mathbf{C}^{ss'}(X_i)/\hat{w}(X_i)$ in the first column, where $\hat{w}(X_i)$ is an estimate of the average annual wage of a worker with characteristics X_i. In the second column the utility cost is computed as $\mathbf{C}^{ss'}(X_i)/\mathbb{E}\mathbf{V}(X_i)$, where $\mathbb{E}\mathbf{V}(X_i)$ is the present value of expected future earnings.

3.4 Goodness of Fit

To asses the goodness of fit of my model, I plot the auxiliary parameters from the data against auxiliary parameters simulated from the model. A perfect fit would result in all point lying on the plotted 45 degree line. Though all points are not on the 45 degree line, the estimated

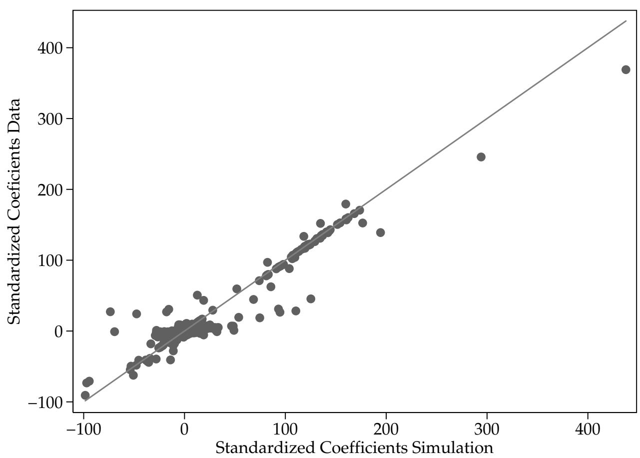


Figure 4: Goodness of Fit – Scatter over 45 degree line

model does a sensible job of matching the moments from the observed data. The parameters that are most off the diagonal are related to the LPMs for sectoral transitions out of the Trade/Utilities/Transportation/Communication sector. This is corroborated in Table 8. Panel A replicates the sectoral transition matrix from Table 1 while Panel B shows the transition matrix in the data simulated by the model. Though the model generally does a reasonable job of replication the transitions present in the data, it does less well in replicating the transitions away from the Trade/Utilities/Transportation/Communication sector as shown in row (4) of Panel B.

Table 8: Sectoral Transition Matrix

Panel A: Actual Data						
From ↓ , To →	(0)	(1)	(2)	(3)	(4)	(5)
(0)	0.4794	0.0141	0.1053	0.0436	0.1046	0.2531
(1)	0.0409	0.8447	0.0281	0.0228	0.0265	0.0370
(2)	0.0294	0.0017	0.9090	0.0080	0.0249	0.0271
(3)	0.0290	0.0042	0.0208	0.9009	0.0191	0.0261
(4)	0.0227	0.0016	0.0226	0.0063	0.9144	0.0324
(5)	0.0182	0.0009	0.0075	0.0026	0.0111	0.9596
Panel B: Simulated Data						
(0)	0.4913	0.0168	0.0917	0.0442	0.1132	0.2428
(1)	0.0415	0.8206	0.0338	0.0156	0.0319	0.0566
(2)	0.0302	0.0030	0.9114	0.0069	0.0135	0.0350
(3)	0.0302	0.0032	0.0158	0.9136	0.0184	0.0188
(4)	0.0238	0.0011	0.0092	0.0088	0.9537	0.0034
(5)	0.0207	0.0004	0.0054	0.0037	0.0075	0.9623

Sectors: (0) Unemployment, (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 9 shows average sectoral choices in actual and simulated data. The model somewhat underestimates the fraction of workers choosing the Service sector while it overestimates the fraction of Trade/Utilities/Transportation/Communication workers.

Table 9: Average Sectoral Choices

	Actual Data	Simulated Data
Unemployment	0.0397	0.0371
Agriculture/Mining	0.0132	0.0122
Manufacturing	0.1861	0.1712
Construction	0.0591	0.0629
Trade/Util./Tran./Com.	0.1948	0.2267
Services	0.5071	0.4899

3.5 The Role of Worker Heterogeneity

The recent literature attempting to structurally estimate worker reallocation costs in dynamic programming models have found costs that vary greatly. Artuç *et al.* (2010) estimated costs to be about 6 times average annual wages for U.S. workers, while estimates based on Dix-Carneiro (2014)-type models, such as this paper, find much lower cost estimates.

One of the main differences between the two modelling approaches is the degree to which workers are allowed to be heterogeneous. As shown in Section 1, workers in this paper are heterogeneous along many observable dimensions, such as gender, education and experience levels. Furthermore the model allows for permanent unobserved heterogeneity in human capital. In contrast to this, the Artuç *et al.* (2010)-model features homogeneous workers, up to an i.i.d. shock.

To illustrate the importance of worker heterogeneity for the reallocation cost estimates, I re-estimate a version of my model, where I turn off the permanent unobserved heterogeneity parameters, i.e. the $\lambda_i^s = 0$ for all workers and sectors. Accordingly, there is now only one type of worker in the model, and therefore no type probability parameters (ϕ's) to estimate.

Table 10 reports the estimated structural parameters for the restricted model. The ξ^s and $\xi^{s_{t-1}}$ parameter estimates in Panel F are much larger than was the case for the unrestricted model in Table 4, indicating higher reallocation costs.

In fact, the median utility cost of switching sectors is an order of magnitude larger in the restricted model when compared to the unrestricted model. Table 11 illustrates that, in terms of annual wages, the cost of entering the manufacturing sector is 2.95 times average annual wages for the median worker. For the unrestricted model, the corresponding cost was 0.16 times average annual wages.

Thus, removing permanent unobserved heterogeneity from the model dramatically increases the estimated reallocation costs. One possible explanation is offered by considering the role of the λ_i^s parameters: Permanent unobserved heterogeneity creates comparative advantage over sectors for workers. Some sectors are therefore relatively more attractive than others. This comparative advantage creates an additional barrier to sectoral worker mobility other than the reallocation

Table 10: Parameter Estimates for Restricted Model

Panel A: Human Capital Production Functions, Equation (6)						
		(1)	(2)	(3)	(4)	(5)
β_1, Female		-0.257341	-0.172348	-0.269243	-0.227461	-0.149572
		(0.000211)	(0.000142)	(0.000309)	(0.000127)	(0.000097)
β_2, Educ		0.148261	0.279371	0.267124	0.227457	0.216448
		(0.000185)	(0.000331)	(0.000109)	(0.000231)	(0.000137)
β_3, Exper		0.042951	0.027931	0.030013	0.031934	0.026318
		(0.000002)	(0.000003)	(0.000003)	(0.000002)	(0.000002)
β_4, Exper^2		-0.000391	-0.000376	-0.000429	-0.000351	-0.000226
		(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
Panel B: Standard Errors and Scale Parameter of Shocks, Equation (10)						
	(0)	(1)	(2)	(3)	(4)	(5)
σ	0.506231	0.281464	0.289353	0.279034	0.302946	0.290182
	(0.001591)	(0.000152)	(0.000174)	(0.000096)	(0.000134)	(0.000127)
ν	2.298961					
	(0.015912)					
Panel C: Unobserved Permanent Heterogeneity, Equations (6) and (8)						
	(0)	(1)	(2)	(3)	(4)	(5)
λ	–	–	–	–	–	–
Panel D: Type Probabilities, Equation (12)						
	Constant	Female	Educ	Exper		
ϕ	–	–	–	–		
Panel E: Transferability of Experience, Equation (7)						
	(0)	(1)	(2)	(3)	(4)	(5)
γ	0.957121	0.939815	0.925982	0.948159	0.895491	0.971093
	(0.001104)	(0.000325)	(0.000294)	(0.000271)	(0.000319)	(0.000163)
Panel F: Utility Costs of Switching, Equation (9)						
	(0)	(1)	(2)	(3)	(4)	(5)
ξ^s	4.904661	4.831880	4.622037	3.853608	4.752799	4.830172
	(0.040262)	(0.011275)	(0.017390)	(0.013281)	(0.018104)	(0.029017)
$\xi^{s_{t-1}}$	1.387031		0.810469	1.074714	1.709137	2.069311
	(0.006147)		(0.002504)	(0.001933)	(0.005542)	(0.013901)
	Female	Educ	Age	Age^2		
κ	0.248651	-0.457815	0.048955	-0.000392		
	(0.000744)	(0.000681)	(0.000029)	(0.000000)		

Standard errors in parenthesis. Sectors: (0) Unemployment, (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

Table 11: Median Utility Costs of Switching for Restricted Model

	Entry costs in terms of	
	Annual Wages	Future Earnings
Unemployment	3.4362	0.1743
Agriculture/Mining	3.2002	0.1695
Manufacturing	2.9540	0.1607
Construction	1.2489	0.0659
Trade/Util./Tran./Com.	2.8770	0.1583
Services	2.1069	0.1073

Median costs of entry to the indicated sector is computed as $\mathbf{C}^{ss'}(X_i)/\hat{w}(X_i)$ in the first column, where $\hat{w}(X_i)$ is an estimate of the average annual wage of a worker with characteristics X_i. In the second column the utility cost is computed as $\mathbf{C}^{ss'}(X_i)/\mathbb{E}\mathbf{V}(X_i)$, where $\mathbb{E}\mathbf{V}(X_i)$ is the present value of expected future earnings.

costs. When the λ_i^s are restricted to be zero, then the utility cost parameters increase to capture this additional barrier to mobility.

This exercise has shown that the degree to which workers are allowed to be heterogeneous can be an important ingredient in determining the magnitude of the reallocation cost estimates.

4 Simulations

Now that the parameters of the model are estimated, it can be used to evaluate the effects of counter-factual structural changes in the model economy. The focus here is to study the dynamics following a shock to the manufacturing sector that reduces its output price. Such a counter-factual experiment mirrors those of Artuç *et al.* (2010) and Dix-Carneiro (2014) who consider the shock to be due to a trade liberalisation episode. A maintained assumption through the simulation is that only the outputs of the agriculture/mining sector and the manufacturing sector are traded globally at exogenous world market prices. The output prices of the remaining non-traded sectors are endogenously determined by the model. The price shock is modelled as a permanent 10% decline in the output price of the manufacturing sector.

4.1 Additional Assumptions

In estimating the model in Section 3, no assumptions were made on the accumulation of physical capital. All that was needed was the sectoral real value added series and income shares, both of which were observed.[13] When simulating the model this no longer suffices: Further assumptions are necessary in order to endogenise output prices for the non-traded sectors. I assume that the sectoral returns to physical capital, which are observed in the sample period (see Section 2), remain fixed at their 2008 level. This has two consequences: (i) Physical capital cannot flow across sectors, so physical capital is sector specific, and (ii) Sectoral physical capital levels adjust freely in order for physical capital returns to remain constant. This has the consequence that, for the traded-goods sectors, the marginal product of human capital will only be affected by changes to the exogenous prices or to productivity. It is important to note that the assumptions I make on physical capital mobility have important implications for the dynamics of the model. The assumptions made here are motivated by the fact that, as a very small, very open economy, Denmark has little influence on the prices at which capital is available and therefore takes these as given by the world market.[14]

The instantaneous utility from consumption is given by the Cobb-Douglas function

$$u(\mathbf{C}) = \prod_{s=1}^{5} C_s^{\mu^s},$$

where the expenditure shares, $\boldsymbol{\mu}$, are those from Table 2. The indirect utility of a worker with nominal wage w_t is then $w_t / \prod_{s=1}^{5} (p_t^s)^{\mu^s}$. The real income of capital owners is $\sum_{s=1}^{5} r_t^{s,K} K_t^s$.

All output from the non-traded sectors must be consumed domestically, which identifies the output prices of these sectors:

$$\begin{aligned} \mu^s \sum_{k=1}^{5} Y_t^k = Y_t^s \quad &\iff \\ p_t^s = \frac{\mu^s}{1-\mu^s} \left[\frac{\left(\sum_{k=1}^{5} Y_t^k\right) - Y_t^s}{A_t^s \left(H_t^s\right)^{\alpha_t^s} \left(K_t^s\right)^{1-\alpha_t^s}} \right] \quad &\text{for } s = 3,4,5. \end{aligned}$$

[13]This is an implicit assumption that capital is allocated efficiently during the estimation procedure.

[14]Readers interested in the impact of different assumptions on physical capital mobility in this type of model are referred to Dix-Carneiro (2014).

Finally, the unemployed are compensated by lump-sum transfers from employed workers and capital owners. With these assumptions, the dynamics following counter-factual shocks to the economy can now be examined.

4.2 Price Shock

Consider the effects of a 10% decrease in the output price of the manufacturing sector due to e.g. trade liberalisation. The output price of the Agriculture/Mining sector remains constant as it is assumed that its output is traded internationally. The output prices of the remaining non-traded sectors adjust endogenously.

Human capital prices in the manufacturing sector drop with the output price shock for two reasons. First, lowering output prices reduces the marginal product of human capital, putting downward pressure on human capital prices. Second, in order to keep the physical capital return fixed, the ratio of physical to human capital drops, further lowering human capital prices. Whereas human capital prices drop in the manufacturing sector, they rise in the remaining sectors as the price index falls.

The manufacturing sector employment falls from 14.3% to 4.7% as workers reallocate towards the other sectors. The adjustment process is sluggish: 25.3% of the reallocation is complete after 1 year, while 91.1% is completed in 10 years. The unemployment rate remains at an average level of about 4.3% throughout the simulation: Only those workers with quite large shocks to human capital and preferences find that lifetime utility is maximised by choosing to be unemployed.

As human capital reallocates to the sectors that are unaffected by the shock, physical capital flows freely into these to keep physical capital returns constant. This in turn increases the real output of the economy after the initial jump at year zero due to the falling price index. When the economy reaches the new steady state, real value added has increased by 12.9%. Note that given the preference shocks and the costs involved when switching sectors, workers do not necessarily move to the sector where they will earn the highest wage. Rather, they consider both the wage effects, the costs, and other welfare effects in deciding whether to move or not. The equilibrium distribution of workers over sectors does therefore not generally maximise the economy-wide value added. When the shock dislocates some workers, it raises value added by moving the economy closer to the output-maximising allocation.

Aggregate welfare is comprised not only of workers' wages and the return to capital owners. It also includes the preference shocks, η^s_{it}, and the utility costs of reallocating workers, $\mathbf{C}^{s_{t-1},s}$. It also takes into account the lump-sum transfers from the employed to the unemployed workers in terms of unemployment benefits. The long run welfare gains are 2.8%.

The new steady-state yearly welfare gain of 2.8% is net of both the reallocation costs and the unemployment benefits. However, focusing only on the steady-state welfare gains is problematic since, as is evident from Figure 5, the steady-state gains take more than 15 years to materialize. This suggests that the present value of the yearly stream is a more appropriate measure of aggregate welfare gains. The present value of the percentage gain in aggregate welfare is computed as

$$\text{pvWelfareGain} = \frac{\sum_{t=0}^{\infty} \rho^t \left(\text{Welfare}_t - \text{Welfare}_{-1}\right)}{\sum_{t=0}^{\infty} \rho^t \text{Welfare}_{-1}},$$

where Welfare_{-1} is the initial equilibrium welfare level. Computed this way, the present value of the aggregate welfare gains is found to be 2.33%. In terms of the lower right diagram, this is the area below the line showing the evolution of aggregate welfare, but above a horizontal line (that is not shown) representing the equilibrium level of welfare prior to the shock.

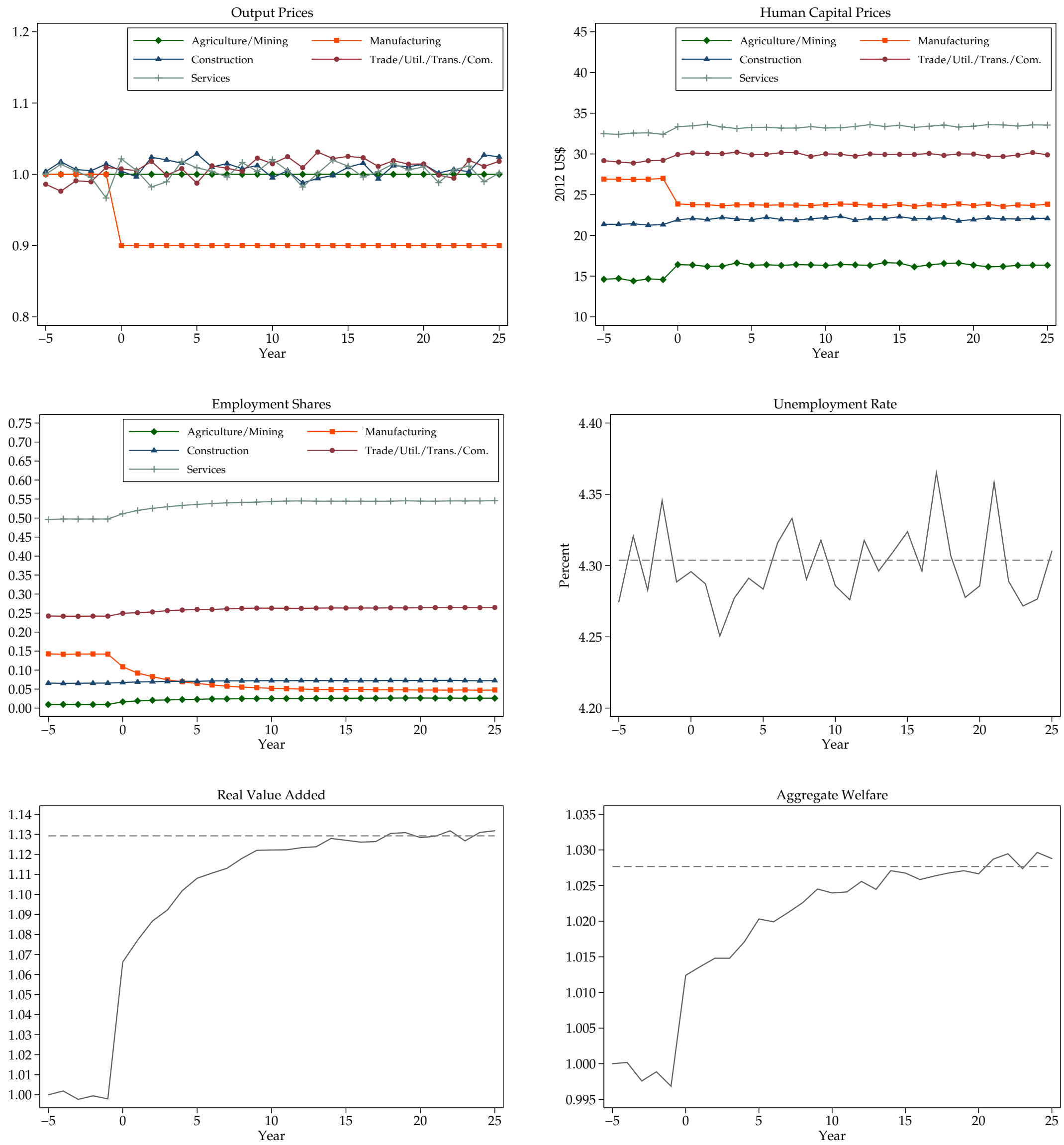
The gradual realisation of the aggregate welfare gains is due to the adjustment costs. If the transition had been immediate, welfare would have reached its new steady-state level in the year of the shock. This implies that the difference between the welfare levels of a hypothetical immediate adjustment process and the actual adjustment process is a measure of the total adjustment costs. In present value terms, the potential welfare gain with an immediate transition is

$$\text{Gain} = \frac{1}{1-\rho} \left(\text{Welfare}_\infty - \text{Welfare}_{-1}\right),$$

where Welfare_∞ and Welfare_{-1} are the post and pre shock steady-state welfare levels, respectively. The welfare costs of adjustment is then the difference between potential and actual welfare

$$\text{AC} = \frac{1}{1-\rho} \text{Welfare}_\infty - \sum_{t=0}^{\infty} \rho^t \text{Welfare}_t.$$

Figure 5: Simulation – Price Shock



Top left: output prices relative to year $t = -5$. Top right: real human capital prices. Middle left: shares of total employment. Middle right: unemployment rate as a percent of the workforce. Bottom left: total real value added relative to year $t = -5$. Bottom right: total welfare relative to year $t = -5$. All real variables have been divided with the price index.

I find the ratio of the adjustment costs (AC) to potential welfare gains (Gain) to be 23.2%, implying that the adjustment costs dissipate 23.2% of the increase in welfare.

It is worth noting that the preceding analysis of aggregate welfare masks a great deal of heterogeneity over the population of workers, some of whom are affected adversely by the shocks to unemployment and prices. In particular, older workers are less capable of responding to the shocks by switching to a new sector; indeed, workers who are 65 in the year of the shock cannot respond at all, as they retire the following year.

Table 12: Welfare Effects (%) Across Sectors and Ages

Initial age	30–39	40–49	50–59	60–65
(1)	4.35	5.01	5.02	5.27
(2)	−1.97	−2.73	−3.48	−4.65
(3)	2.80	2.79	2.77	2.41
(4)	3.83	3.52	3.71	2.81
(5)	2.74	2.71	2.67	2.15
Average welfare change (%): 2.29				

The table shows present value welfare effects in percent for workers initially employed in the indicated sector. Workers are divided into groups based on ages at the year of the shock. The bottom row shows the welfare effect averaged over workers of all ages. Sectors: (1) Agriculture/Mining, (2) Manufacturing, (3) Construction, (4) Trade/Utilities/Transportation/Communication, (5) Services.

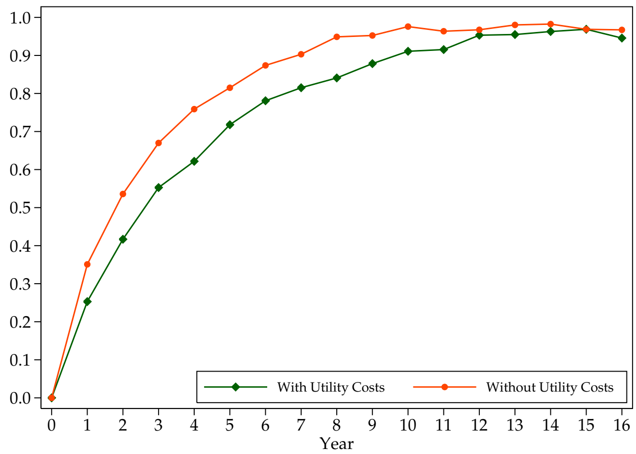
Table 12 shows average welfare effects for workers employed in each sector in the year of the shock. The sample is split into age groups to capture heterogeneous welfare effects. On average, the present value of welfare for manufacturing workers initially aged 30 to 39 is 1.97% less than it would have been had the shocks not occurred. As expected, this figure increases to a welfare loss of 4.65% for workers aged 60 to 65. Workers in the other sectors experience welfare gains. Generally, these gains are lower for older workers who remain on the labour market for fewer years after the shock. The average welfare effect is a gain of 2.29% as reported in the bottom row. This table makes it very clear that the older manufacturing workers are the losers from the shock.

In interpreting the results shown in Table 12 it is important to remember that the assumption of free capital mobility made in this section implies that there is little scope for manufacturing wages to increase in response to workers leaving the sector, nor for the wages of other sectors to drop. Hence, the cost of the shock must be borne by the manufacturing workers. Also note that the welfare loss for older manufacturing workers would be less if the model included retirement savings. In that case, the fall in the price level would increase the real value of the retirement funds, and thereby mitigate the direct loss.

4.3 The Role of the Utility Costs

In order to examine how the reallocation costs affect the dynamic adjustment process, it is useful to consider a situation in which the utility cost of switching sectors is zero. Figure 6 plots the

Figure 6: Speed of Labour Reallocation Following an Unemployment and Price Shock



cumulated labour market reallocation as a percent of the final year for the globalisation shock. This is done for two scenarios: One where the utility cost is set to zero for all workers, and one where the utility cost is the one estimated above.

The green line in the figure shows the reallocation process described in the simulation above where utility costs are estimated. The reallocation process is sluggish and takes several years to complete: One year after the shock 25.3% of the reallocation process is completed and 91.1% completion is reached only after 10 years. In absence of the utility costs, the reallocation is much faster: 35.1% of the reallocation is completed by the end of the first year and 97.6% after ten years. The reallocation is not immediate when the utility costs are zero for two reasons: (i) depreciation of sector specific human capital makes it costly to switch sectors even when utility costs are zero, and (ii) a worker's draw of sector-specific idiosyncratic shocks, ε_{it}^s and η_{it}^s may be such that that the worker is better off remaining in the adversely affected sector, even as human capital prices fall.

This would suggest that, policy makers wishing to minimise the length of the reallocation period could focus on policies that minimise the utility costs and increases the cross-sectoral transferability of human capital. One such policy may be educating workers through job training programs.

5 Conclusion

This paper built and estimated a dynamic structural model of the Danish labour market in order to quantify the reallocation costs involved when the economy transitions from one steady-state equilibrium to another. The reallocation costs consist of imperfectly transferable experience and a utility cost of switching sectors. The degree of transferability ranges from 88% to 98% over the sectors. Unemployment is found to depreciate experience by 5.6% per year. Median utility costs are found to be between 10% and 19% of average annual wages, though this number is higher for workers that are female, have less education, and older workers.

A restricted version of the model where permanent unobserved heterogeneity was removed was estimated. This increased the utility cost parameters by an order of magnitude, showing that worker heterogeneity plays an important role when estimating reallocation costs. In particular, permanent unobserved heterogeneity creates comparative advantage for workers across sectors, which provides an additional barrier to mobility. Ignoring this barrier biased the utility cost estimates upwards.

The estimated model was used to trace out the dynamic adjustment of the economy when the manufacturing sector is hit by a shock to output prices, lowering these by 10%. In this exercise, manufacturing employment fell from 14.3% of total employment to 4.7%. The labour market adjustment process is sluggish: After 1 year, only 25.3% of the reallocation is completed. In the new post-shock steady state, the yearly welfare gain is 2.8%. The present value of the welfare gain is 46.8% higher than it would have been in the absence of the shocks. However, this welfare gain would have been higher had it not been for the adjustment costs: These are shown to dissipate 22.9% of the potential welfare gains. Although aggregate welfare has increased, some workers lose welfare. Specifically, workers who are employed in the manufacturing sector in the year of the shock lose on average 3.2% of their remaining lifetime utility. This number increases in the initial age of the worker such that those who are initially between 30 and 39 face a welfare loss of 1.97% while those initially aged 60 to 65 lose 4.65%.

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