Occupational Mobility over the Business Cycle

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Abstract:

This paper proposes a job search model of occupational mobility in which a worker can change occupations not only when unemployed (as in the existing literature), but also when employed. This extension of the existing literature is motivated by observations from the 2004 and 2008 panels of the SIPP, as well as by existing empirical stylized facts in the literature. Simulations of the calibrated model show that this proposed extended model can replicate a mildly countercyclical occupational mobility rate as well as a countercyclical fraction of occupational switchers going through an unemployment spell, a feature not generated by existing models.

JEL Classifications: E24, E30, J21, J24, J62, J64

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1 Introduction

In recent decades, the increased use of outsourcing by large businesses is one indication of the ongoing process of globalization. This trend, together with an accelerating rate of technological change, causes rapid changes in the demand for certain occupations that are particularly sensitive to these factors.[1] These fluctuations in demand have caused some workers to change occupations, while others remained, even with a rapidly decreasing demand for their occupation. Understanding why some workers decide to move and other workers do not is important in order to make accurate predictions about a worker's behaviour as the process continues. Thus, one needs to gain a deeper understanding of occupational mobility, broadly defined as the fraction of employed workers whose occupation is different from their occupation one year ago (resembling the definition in Kambourov and Manovskii, 2009b).[2] Understanding why workers decide to move occupations is important not only in this specific context, but also in the context of general labour markets. After all, understanding occupational mobility may be an important factor in understanding increasing wage inequality over the last few decades (see Kambourov and Manovskii, 2009a). Furthermore, earlier research finds that the links between occupational experience and wages may even be much more important than the link between either employer-specific or industry-specific experience and wages (Kambourov and Manovskii, 2009b).[3] This finding raises the question of why workers change occupations when there is such a strong link between wages and occupational tenure. In this paper, I contribute to the existing research on this question by proposing a model of occupational mobility in which I explicitly separate occupational switches through unemployment from those made on the job,

[1] A large literature on the influence of technological change argues that technological change is biased towards certain occupations. For an overview of this discussion, see for example Acemoglu and Autor (2011).

[2] Most empirical investigations of occupational mobility focus on the one-year rate but it is possible to change the time period under consideration, for example focusing on a 4-month rate instead.

[3] Note the difference between an occupation and an industry: An occupation (e.g. postmaster) is defined using the tasks performed by a worker, whereas an industry (e.g. hospitals) is defined using the products produced by the firm.

being motivated to do so by observations I make from the Survey of Income and Program Participation (SIPP).

The topic of occupational mobility has not been studied extensively in the economic literature until recent years. This apparent lack of research is due largely to the potential impact of measurement errors when trying to obtain empirical estimates of the occupational mobility rate. These measurement errors are caused by the fact that the occupational categories are not always clearly separated, and certain job descriptions may not clearly correspond to a single occupational category. Therefore, the same job description may be coded as a different occupation in different years, thus falsely suggesting an occupational switch. In order to prevent this measurement error from contaminating the results, the general approach taken in the literature, as suggested in Kambourov and Manovskii (2009b), is to identify true occupational switches by looking at simultaneous labour market changes of the kind that often occur together with occupational switches, such as a switch of employer. In my data section (Section 2) I will use a similar set of conditions to prevent the aforementioned measurement error to contaminate my results.

My first observation when looking at the data concerns the level and cyclicality of the total occupational mobility rate. Not surprisingly, occupational mobility rate itself is widely documented. For example, using the method above, Kambourov and Manovskii (2008) measure occupational mobility rates in the US between 1968 and 1996, finding an average (gross[4]) mobility rate of 18% at the 3-digit occupation level, which declines to approximately 13% at the 1-digit occupation level.[5]. This observation is roughly consistent with the 4-month rate of 3-4% I find in Section 2. When it comes to the cyclicality of the occupational mobility

[4]Gross mobility rates do not take into account that worker flows may go in both directions (e.g. from occupation A to occupation B but also the other way), whereas net mobility rates take these directions into account by cancelling out worker flows going in opposite directions.

[5]The 3-digit occupation code is generally the most disaggregated occupation code available. These 3-digit codes can easily be aggregated to 2- and 1-digit levels. Aggregating to higher levels necessarily decreases the resulting occupational mobility rate, but will also decrease the likelihood of measurement errors of the earlier-described kind affecting the results.

rates, a mild procyclical pattern is generally found in the literature (Kambourov and Manovskii, 2008). After I take into account the downward trend in occupational mobility rates over the observed time period, as observed in (among others) Xu (2017) and Lalé (2017), I find a mild countercyclical pattern. However, changing the time span of my data set or focusing only on a subset of occupational switchers recovers the mild procyclicality found in the literature.

When differentiating occupational switches by whether or not workers go through unemployment, some interesting patterns arise. First of all, I find that the majority of occupational switches do not involve unemployment. This result is consistent with the findings in Xiong (2008), who reaches a similar conclusion using the same dataset as I use in this paper (the SIPP), but for a different time period. Similarly, when focusing only on those workers who did not go through unemployment, I find that a large fraction of them also stay with the same employer, a conclusion that was reached earlier in Papageorgiou (2016).[6]

Finally, I find that the switches through unemployment exhibit a different pattern than the direct job-to-job switches. In particular, I find that the fraction of occupational switchers going through unemployment is countercyclical, which contradicts results from Carrillo-Tudela et al. (2014) and Carrillo-Tudela et al. (2016) (both of whom find no differences in these groups' cyclical patterns), although this result seems consistent with the combination of jobless recoveries and job polarization observed in Jaimovich and Siu (2014). I also find that job-to-job occupational switchers tend to experience a higher initial increase in their wage, which persists over time. This result is consistent with the results obtained in Longhi and Taylor (2013), who do a similar exercise using UK data.

There are also a number of recent papers that provide a theoretical model of occupational mobility. Many of these models are in the spirit of the Islands model from Lucas and Prescott (1974), and interpret these "islands" as occupations. In

[6] To be specific, Papageorgiou (2016) uses the 1996 SIPP panel to find that, annually, 8% of employed workers switch occupations within the firm. I do not find a rate this large, which is not necessarily surprising given my focus on the 3-digit level.

particular, Kambourov and Manovskii (2009a) take into account occupational human capital (as suggested in Kambourov and Manovskii (2009b)) to set up a model of occupational mobility that performs very well in explaining increasing wage inequality. A similar model is used in Lalé (2017), who uses his model to explicitly estimate mobility costs. He finds a substantial increase in mobility costs in the last decades, an observation that was linked to the decreasing trend in occupational mobility in Xu (2017).

Though models of occupational mobility often use the Lucas Islands model, there are also other types of models. The model I present in this paper uses a DMP-style search model, which makes a very explicit distinction between unemployed and employed workers while also incorporating search frictions on the labour market. In particular, the model in this paper is based on Carrillo-Tudela and Visschers (2014). They extend the standard DMP model (see for example Pissarides, 2000) to analyze how the (unemployed) worker's decision to switch occupations (reallocate) changes with individual and aggregate occupations. Their model generates productivity cutoffs for both separation and reallocation, and the relative positioning of these cutoff functions imply that workers may be unwilling to reallocate even though they face a zero job-finding probability. Such a worker is referred to as rest unemployed, a concept that appears earlier in Alvarez and Shimer (2011), Shimer (2007), and Coles and Smith (1998), although the latter of these three is a model not specific to the labour market.

The model in Carrillo-Tudela and Visschers (2014) fits the data on unemployment and occupational mobility of unemployed workers, but does not allow workers to switch occupations on the job. However, my observations from the data (along with those already made in the literature mentioned above) suggest that job-to-job occupational switches are an important element of occupational mobility, thereby motivating me to extend Carrillo-Tudela and Visschers (2014) to include these types of switches as well, while not destroying the computational tractability of their model. In my extensions, I make a distinction between switches (of occupation, but not employer) as a consequence of an exogenous shock and voluntary switches (of both occupation and employer) as a result of either on-the-job search (in the spirit of Menzio and Shi, 2011) or changing labour market conditions while the worker is unemployed. With this model, I can explain how unemployed and employed workers' reallocation decisions are affected by individual and aggregate productivity levels, which is the main purpose of this paper. The main contribution to the literature thus lies in the distinction between occupational changes by unemployed and employed workers. By separating these two types of mobility, I can explain the dependence of the experience of a worker who switches occupations on the type of switch, as found in the empirical literature.

Simulations of the calibrated model indicate that the extensions enable the model to replicate the cyclicality of both the total occupational mobility rate as well as the fraction of occupational switchers going through an unemployment spell. These indications show that the extra layer of complexity added by the extension may help explain the dependence of consequences (including subsequent wage paths) for a worker who switches occupations on the type of switch.

The rest of this paper is organized as follows: Section 2 describes some of the patterns found in the data, using the 2004 and 2008 panels of the Survey for Income and Program Participation (SIPP). Section 3 then presents the model. The quantitative analysis of the model is split into two sections: Section 4 focuses on the calibration of the model and the resulting parameter values; Section 5 on the implications of the model for the question of interest. Finally, Section 6 concludes and provides some directions for potential future research.

2 Observations from the Data

In this section I present some observations from the data that motivate the model and its extensions in the next section. The results presented in this section are obtained using data from the Survey of Income and Program Participation (SIPP). The SIPP is one of three datasets that are often used in the existing literature to empirically investigate occupational mobility. The other two datasets are the Current Population Survey (CPS) and the Panel Study of Income Dynamics (PSID). For my purposes, the SIPP is the most appropriate given its design as a sequence of rotating panels.[7] Specifically, each panel of the SIPP tracks a representative (multistage stratified) sample of the civilian non-institutionalized population of the United States.[8] This sample is divided into four "rotation groups". In every four-month period (called a "wave"), these rotation groups are then interviewed in their corresponding month.[9] As every interview asks the respondent about the prior four months, the resulting panel contains monthly information for every respondent.[10] For these months, the SIPP contains information on income, labour market participation, program participation and general demographics.[11] Most importantly, the SIPP contains monthly data on the respondent's occupation on a 3-digit level, which allows me to calculate occupational mobility rates on a 3-digit level or higher.

For the purpose of this section, I restrict the sample to respondents between the age of 23 and 61, who participated in the first interview of the panel, are not self- or dual-employed, and do not work for the government. These restrictions largely follow Xiong (2008), although he also restricts respondents to be male.

[7]The way the CPS is structured makes that dataset more appropriate when one is interested in cross-sections given that each respondent is only interviewed twice with an 8-month gap in between, whereas the SIPP allows me to track the same individual over an extended period of time. Furthermore, the SIPP tracks a larger sample than the PSID does (although the subjects of the PSID are tracked for a longer period), which makes the observations more reliable. The SIPP also interviews the subjects more frequently than the PSID does (every four months instead of annually).

[8]Generally, respondents are not paid for their participation in the survey. However, there are exceptions to this rule. For example, in the first wave of the 1996 panel, a random selection of the respondents were given a small incentive payment of \$10 or \$20, in order to assess the effect of these payments on the response rate and the consistency of responses. A further discussion of this experiment can be found in James (1997) and Davern et al. (2003), among others.

[9]The first rotation group is interviewed in the first month, the second rotation group is interviewed in the second month, and so on.

[10]The nature of the data collection implies that the first month of data from the fourth rotation group coincides with the fourth month of data from the first rotation group so that the monthly information is not complete for the first three and last three months in the data.

[11]These collected variables are collected to serve the main purpose of the SIPP, which is "to provide accurate and comprehensive information about the income and program participation of individuals and households in the United States, and about the principal determinants of income and program participation" (U.S. Census Bureau, 2001).

Furthermore, I follow Kambourov and Manovskii (2008) and define occupational mobility as the fraction of employed individuals who report an occupation different from their most recent previous reported occupation. Here I use the reported occupation in the same month of the previous wave as the previous report, thus avoiding the seam bias that occurs in the SIPP due to respondents often reporting the same value for many variables for all months they are asked about (which creates a disproportionate amount of changes between the last month of a certain wave and the first month of the next wave). More information on the construction of the dataset used to obtain the observations below, and in particular the measures of occupational mobility, can be found in Appendix A.1. All results below are obtained using the 2004 and 2008 panels of the SIPP. I use only these two panels because they are the most recent complete panels, and all earlier panels are using alternative occupational coding systems. To provide a comparison with earlier panels, however, Appendix A.3 repeats the analysis below using the 1996 and 2001 panels instead.

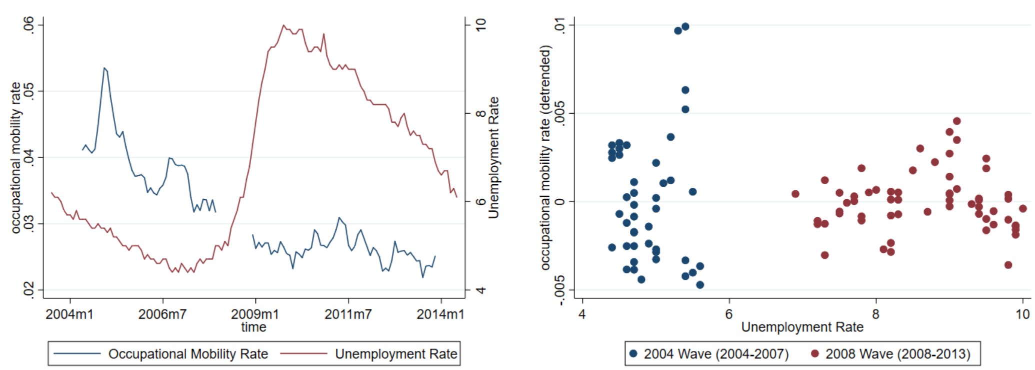

Figure 1: *The 1-digit occupational mobility rate and the corresponding month's unemployment rate from the BLS, plotted over time (left) and against each other in a scatter plot (right).*

As the model in Section 3 focuses on the 1-digit occupational mobility rate rather than its 3-digit counterpart, this section focuses on the occupational mobility on a 1-digit level.[12] First, the left panel of figure 1 plots the 1-digit (4

[12]Appendix A.2 provides a figure similar to the left panel of Figure 1 for the 3-digit level to

month) occupational mobility rate over time. As can be seen in the figure, rates range from 2% to 5.5%, with an average rate of approximately 3.5%. This observation is roughly consistent with the results in Kambourov and Manovskii (2008), who find a 1-digit (yearly) occupational mobility rate of approximately 13%. Both panels also compare the occupational mobility rate to the unemployment rate, in order to provide an indication of the cyclical behaviour of the mobility rate. After all, the cyclical behaviour of the occupational mobility rate is one of the things I try to replicate with the model in this paper. However, in order to properly assess the cyclicality of the occupational mobility rate, the trend should first be removed. In the left panel of Figure 1, a clear negative trend is visible, one that was observed in the existing literature as well (see e.g. Xu, 2017). The right panel therefore uses the detrended data instead.[13] From the right panel of Figure 1, there is no clear cyclical pattern visible. However, a naive regression reveals a slope of 0.0003 for the 2004 panel and 0.0001 for the 2008 panel (both insignificant), thus leading me to the conclusion that the occupational mobility rate is (if anything) mildly countercyclical. This conclusion seems at odds with the existing literature discussed in Section 1. However, for the 1996 and 2001 panels I do find a mildly procyclical pattern (again insignificant), as shown in Appendix A.2 and as found in Kambourov and Manovskii (2008), and similarly I do find the mildly procyclical pattern when only considering occupational mobility through unemployment, as done in Carrillo-Tudela and Visschers (2014).[14]

Figure 1 focuses on the gross occupational mobility rate. However, one might expect that there may be net flows of workers into or out of specific occupations, thus leading to a substantial net occupational mobility rate as well.[15] In order

enhance comparability with the existing literature.

[13] In order to detrend the occupational mobility rates, I apply a HP filter with smoothing parameter 14,400.

[14] If I only consider reallocation through unemployment, the naive regression coefficients on the unemployment rate become -0.0003 for the 2004 panel and -0.0001 for the 2008 panel.

[15] Recall that in calculating the net occupational mobility rate, flows between two occupations are cancelled out against each other. So, a switch from occupation A to occupation B cancels out a switch from occupation B to occupation A, whereas in the gross occupational mobility rate these two switches would both add to the total.

Occupation	1	2	3	4	5	6	7	8
Observations	230339	301609	44396	12870	67938	51349	35294	163160
Inflow	6347	6473	1962	734	3337	2563	2131	6532
Outflow	5918	6485	1874	690	3774	2364	1906	6879
Net Inflow	429	-12	88	44	-437	199	225	-347

Occupation	9	10	11	12	13	14	15
Observations	233244	10595	74641	62352	139794	94670	92
Inflow	8103	509	2736	1937	4403	4351	11
Outflow	7936	608	2683	2036	4666	4300	10
Net Inflow	167	-99	53	-99	-263	51	1

Table 1: *Total number of incoming and outgoing switches found in the data for every 1-digit occupations, and number of times I observe a worker in each of these occupations in the data. For a list of the occupations corresponding to these codes, see Appendix A.1.*

to investigate this net rate, Table 1 lists the total inflow and outflow for each occupation, as well as the total number of times I observe a worker in these occupation.[16] As can be seen in Table 1, the net inflow for each occupation is fairly low compared to the gross worker flows. Thus, I infer that there does not seem to be a specific occupation that expels or attracts workers. This observation is be confirmed by Table A.2 in Appendix A.2, which repeats the analysis but is specific to the occupation of origin and destination for all observed flows. As there is no specific occupation that expels or attracts workers, I assume in the model in Section 3 that workers who change occupations are assigned a random new occupation.

Since the focus of this paper is on the distinction between those who change occupations with and without going through an unemployment spell (which I refer to as U-switchers and E-switchers), it is important to confirm whether these two groups follow different cyclical patterns. As can be seen in both panels of

[16]Note that all numbers in Tables 1 and A.2 are totals over the entire sample period. As such, one cannot easily convert the totals in these tables into fractions of workers in these occupations, as the number of workers in these occupations is fluctuating over time. Nevertheless, to give an idea of what this fraction would look like, I include the number of times I observe a worker in each occupation. Furthermore, Table 1 and A.2 do not use the sample weights. If the tables are tabulated using sample weights, the table is more difficult to read but the conclusions remain unchanged.

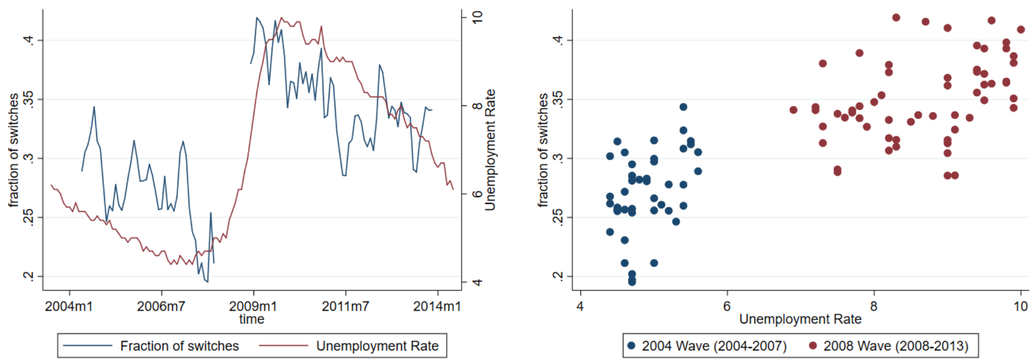

Figure 2: *The fraction of occupational switchers (1-digit) going through unemployment and the corresponding month's unemployment rate from the BLS, over time (left) and plotted against each other in a scatter plot (right).*

Figure 2, the fraction of switches that goes through unemployment shows a clear countercyclical pattern. This result continues to hold when looking at the state level instead of the national level, as shown in Appendix A.2. Given that the two groups of occupational switchers show very different cyclical patterns, it is important to model the two groups separately. This separation is an extension to the existing models of occupational mobility, which I make in Section 3.

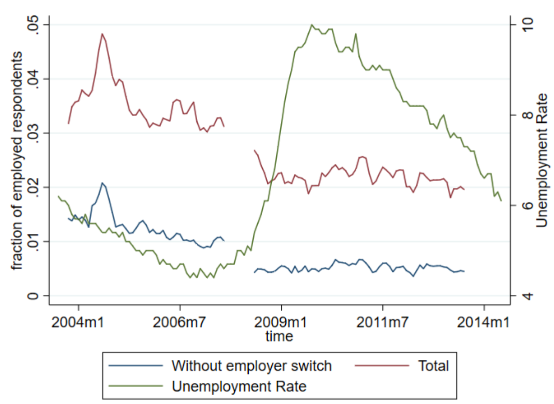

Figure 3: *The fraction of employed workers switching occupations in the next 4 months, the fraction of employed workers doing so without switching employer, plotted over time together with the corresponding month's unemployment rate from the BLS.*

While most of the above discussion focuses on a mobility rate defined as the fraction of all respondents, it may also be informative to look at the fraction of employed respondents who switch occupations. In Figure 3, I plot this fraction instead.[17] Inspecting the graph, it can be seen that approximately a third of the employed workers who switch occupations do so without changing employers. This observation is especially surprising given that an employer switch is one of the events I use to verify an occupational switch, but it is nevertheless consistent with the findings in Papageorgiou (2016). Thus, job-to-job occupational mobility is not just a result of on-the-job search for a better match with a new employer. Therefore, when I model job-to-job occupational mobility in Section 3, I make an explicit distinction between job-to-job occupational mobility with and without an employer change.

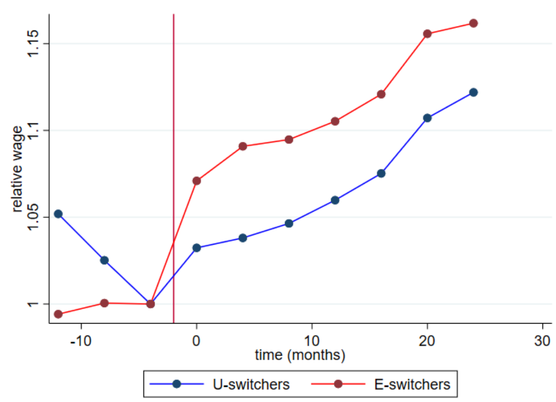

Figure 4: *Wage paths over time for occupational U-switchers and E-switchers. The switch takes place between time -4 and 0, as represented by the vertical line at -2.*

Finally, to stress the point made above that workers who switch occupations while unemployed follow different patterns than job-to-job occupational switchers, Figure 4 plots the average wage for these two groups, from 12 months before I observe the switch until 24 months after I observe the switch and relative to

[17]Note that the rate shown in Figure 3 looks at the next 4 months instead of the previous 4 months. This restriction is necessary as I am interested in the fraction of previously employed workers rather than the fraction of currently employed workers.

the last observed wage before the switch takes place.[18] The only restriction I make in creating this figure is that I only use respondents for which I observe the wage in every single month in this time frame. As can be seen in the figure, the jump in the average wage is much larger for E-switchers, and this difference is persistent over time, although it becomes insignificant (as shown in the corresponding Figure A.5 in Appendix A.2). As these two groups furthermore differ substantially in their age and education, as demonstrated in Appendix A.2, an explicit separation of E-switchers (both within and across firms) and U-switchers in a model of occupational mobility is clearly needed. In the next section, in present a model that implements this separation.

3 The Model

Motivated by the observations made in Section 2, this section presents the model used for obtaining the results in Sections 4 and 5. The model extends Carrillo-Tudela and Visschers (2014), henceforth referred to as the CTV model. Given the similarity of the two models, it is natural that the presentation in this section is in many ways very similar. In particular, to enhance the comparability of the two models, I choose to use the same notation wherever possible, and point out differences when they arise. Furthermore, note that while most variables (but not the parameters) change over time, I drop the time subscript in the equations to enhance readability. To nevertheless stress the fact that these variables change over time, I do use the time subscripts when discussing these variables in the text.

3.1 Firms

The model economy is divided into O occupations, each of which is home to a continuum (of measure one) of risk-neutral workers and firms. Each firm

[18]For U-switchers, the wages before the switch refer to the wages earned in their previous job(s), thus implying that these wages are further back than 4, 8, and 12 months before the switch.

has room for only one worker, which it can hire on a frictional labour market. As labour is the only input in production, and it is equal to 1 if the firm is producing, the production of the firm (y_t) depends only on productivity variables. Throughout this paper, the production function is assumed to take the following simple constant returns to scale form:

$$y = pxz \tag{1}$$

The three elements in this production function (p_t, x_t, and z_t) are three different types of productivity. The first productivity type, p_t, is aggregate productivity. This productivity, which takes the same value for all workers (regardless of occupation), can take a value between $\underline{p} > 0$ and $\bar{p} < \infty$ and follows a first-order stationary Markov process. It can be interpreted as the state of the economy as a whole: a low value for p_t corresponds to the economy being in a recession, and a high value corresponds to the economy experiencing a boom. The other two types of productivity are idiosyncratic productivity z_t and occupational human capital of the worker x_t. As both of these are specific to the worker (and occupation), I postpone the discussion of these productivity types to the next subsection.

It is assumed in the model that when the firm is not currently matched with a worker, it will post a vacancy at a (time-invariant) cost k. In principle, the firm chooses which occupation to operate in, but since the value of posting a vacancy will in equilibrium be zero in all markets this choice is not explicitly modeled. When being matched with a worker, the firm also generally does not switch occupations, unless the match is hit with an exogenous occupational transfer shock (which is further discussed in the subsection on occupational transfers). However, even when matched with a worker, the firm always has the possibility to end the match at the start of each period. This separation decision is the choice variable for the firm, and it will be influenced by the three worker productivity variables p_t, z_t and x_t. Generally, this decision will be denoted by $\sigma(p, z, x) \in \{\delta, 1\}$, reflecting that regardless of its decision the firm will always face an exogenous probability $\delta \in [0, 1]$ of being separated from the worker.[19]

[19]It is assumed here that when the firm is indifferent between separating and not separate, she will

3.2 Workers

From the previous subsection, it can be deduced that a firm can be in one of two states: it can be producing or it can be posting a vacancy. Similarly, the worker can also be in two states: she can either be employed or unemployed. In either state, the worker faces a probability of death ϕ. However, this probability is not important when it comes to the decisions of the worker, and can be though of as embedded in the discount rate β.[20] When the worker is unemployed, she receives b every period, and has the choice of either searching in her current occupation or switching to a different occupation (this alternative is further discussed in Subsection 3.4).

If the worker is matched with a firm, she receives a wage $w(p, z, x)$ from the firm every period. Just like the firm, the worker also always has the choice of terminating the match[21], a decision which is denoted by $d(p, z, x) \in \{\delta, 1\}$. Furthermore, unlike in the CTV model, the worker also has the choice to search for a match in a different occupation, a choice that will be further discussed in Subsection 3.4. As stressed by the notation, these two decisions both depend on all three types of productivity. As mentioned earlier, two of these productivities are specific to the worker-occupation pair. The idiosyncratic productivity z_t is in many ways similar to p_t: It can take values between $\underline{z} > 0$ and $\bar{z} < \infty$, and follows the same first-order stationary Markov process for all workers, represented by $F(z_{t+1}|z_t)$, the probability of having idiosyncratic productivity z_{t+1} or lower next period conditional on having z_t this period.

The third and last type of productivity, x_t, is (just like z_t) worker- and occupation-specific. As mentioned earlier, x_t is interpreted as occupational human

always decide not to separate. Thus, the firm will never decide to follow a mixed strategy.

[20]Throughout the model, I use the same β for workers and firms, even though the firm does not face this probability of death. However, for the producing firm the death of its worker is identical to separation, thus justifying using β for these firms as well. For the firms that have a vacancy, this inconsistency will not influence the solution, as β will be multiplying a term with value zero.

[21]Mirroring the assumption made for firms, it is assumed that a worker never follows a mixed strategy. Thus, if the worker is indifferent between separating and not separating, she will decide not to separate.

capital. It can take H values, ranging from $x_1 > 0$ to $x_H < \infty$. When a worker starts working in a new occupation, she starts with the lowest value x_1. After that, the occupational human capital increases to the next level with probability $\chi(x_{h+1}|x_h)$ as long as the worker is employed in the occupation. While this occupational human capital does not depreciate over time (not even when the worker is unemployed), the worker can still lose her accumulated human capital. This loss occurs when a worker chooses to change occupations. Whenever a worker changes occupations, all the accumulated human capital in her former occupation is completely destroyed, and she starts over in her new occupation with $x_t = x_1$.[22] Arguably, a complete loss of human capital is not necessarily a realistic assumption to make, but the assumption greatly simplifies the model as there is no need to keep track of human capital in occupations other than the worker's current occupation.

3.3 Labour Markets

As mentioned earlier, it is assumed in this model that there is a separate labour market for each combination of occupation and the two worker-occupation specific productivities. In other words, it is assumed that the firm can observe the productivity values of the worker, and can thus aim a vacancy at a specific level of productivities x_t and z_t. In each of these labour markets, matches are formed according to a matching function. Letting $\theta(p, z, x)$ be the labour market tightness, this matching function can be rewritten such that $q(\theta(\cdot))$ is the matching probability for the firm and $\lambda(\theta(\cdot)) = \theta(\cdot)q(\theta(\cdot))$ is the matching probability for the worker.

When a worker and a firm match, the wage for the worker is determined as a solution to a standard Nash bargaining problem, where the bargaining power of the firm is denoted by η. The wage thus depends on both the value of being

[22] Note that this loss also occurs in situations in which an unemployed worker chooses to switch from occupation A to occupation B while unemployed, and decides to switch back one period later (without having been employed in occupation B). In this situation, the worker will have $x_t = x_1$ in occupation A after she returns, regardless of how much human capital she had accumulated before switching to occupation B.

employed $W^E(p,z,x)$ for the worker and the value of producing $J(p,z,x)$ for the firm, as well as the outside options for both parties: the value of being unemployed $W^U(p,z,x)$ for the worker and the value of setting a vacancy $V(p,z,x)$ for the firm. The explicit expressions for these value functions are presented in Subsection 3.6. In short, the wage rate solves the following equation:

$$\eta\left(W^E(p,z,x) - W^U(p,z,x)\right) = (1-\eta)\left(J(p,z,x) - V(p,z,x)\right) \qquad (2)$$

Finally, note since the elements of this equation change over time, it follows that the wage rate earned by the worker also changes over time. Thus, rebargaining takes place every period.

3.4 Occupational Transfers

Up to this point, the model described has been almost identical to the CTV model. The extension made in this paper is that in this model there are three ways in which a worker could switch occupations, instead of the one way in the CTV model. In short, the CTV model includes only a possibility for an unemployed worker to switch occupations. In the extended model in this paper, however, it is also possible to switch occupations without going through unemployment. This switch can occur either as a result of an exogenous shock, or through on-the-job search. In this subsection, I will discuss all three possible ways of switching occupations.

The first way in which a worker can switch occupations is identical to the only method included in the CTV model. When a worker is unemployed, she has the option of choosing to switch occupations every period (before the matching takes place), at a constant cost c^u.[23] This decision is captured by the variable $\rho^u(p,z,x)$, which can thus take a value of either 0 or 1.[24] If the worker decides not

[23]This cost is denoted by c in Carrillo-Tudela and Visschers (2014)

[24]This decision was denoted by $\rho(p,z,x)$ in Carrillo-Tudela and Visschers (2014). It is assumed here that when the worker is indifferent between switching and not switching, she will always decide not to switch. Thus, the worker will never decide on a mixed strategy.

to switch ($\rho^u(p, z, x) = 0$), she will search for a match in her current occupation this period. If the worker decides to switch occupations ($\rho^u(p, z, x) = 1$), she will randomly select one of the $O - 1$ other occupations.[25] In that occupation, she will start with occupational human capital of the lowest level (x_1). She will also have a new value for the idiosyncratic productivity z_t, drawn from the stationary distribution $F(z)$ associated with the first-order Markov process that z_t follows. Finally, the worker will have to sit out one period unemployed. Thus, she will not be allowed to search for a match until the next period.

The second method through which a worker can switch occupations (and the first extension of the CTV model) is similar to the first, with the exception that it concerns workers who are already in a match. A worker who is matched to a firm at the beginning of a period has the option to search in a different occupation, a decision which is denoted by $\rho^e(p, z, x)$, which can take a value of 0 or 1.[26] If she decides to do so, she pays a cost c^e, after which she searches in her new (randomly drawn) occupation. If she matches with a firm in that new occupation, which occurs with probability $\lambda(\theta(p, \tilde{z}, x_1))$ (where $\tilde{z}$ is the level of z_t drawn in the new occupation), she quits her current job and switches to that new occupation.[27] If she does not match with a firm in the new occupation, she remains in her current occupation without losing her accumulated human capital x_h.

Finally, it is possible for a worker (and firm) to switch occupations as the consequence of an exogenous shock. This shock, which hits with probability ψ, forces the worker to switch occupations, while not switching employers or losing

[25] The assumption of random search instead of directed search when it comes to changing occupations is motivated by the observation made in Section 2 that there do not seem to be specific occupations that are the target or source of occupational mobility flows.

[26] It is once again assumed that when the worker is indifferent between switching and not switching, she will decide not to switch.

[27] Specifically, it is assumed that the worker does not know her value of $\tilde{z}$ until she enters the bargaining process with a new firm. As a worker needs to quit her current job before entering a bargaining process with a new firm, a worker will always decide to do so (after all, this decision will be the same as the decision captured by ρ^e, without the switching cost c^e). Note that this order of events also implies that the outside option of the worker when bargaining with the new firm will be the value of being unemployed.

any human capital. This type of switch corresponds to workers switching occupations without leaving the firm. In principle, it is not always a beneficial switch for the worker, as she will draw a new value for z which may be lower than her value at the start of the period. Thus, interpreting this exogenous shock as a promotion shock does not fully capture the effect of this shock. Rather, one might interpret the shock as a reorganization of the firm. After all, if the worker switches occupations without switching employers, it is implied that the firm switched occupation as well. As it was shown in Section 2 that these types of switches are quite common among job-to-job occupational switches, it is important to include these types of switches in the model explicitly. After all, while the other two reallocation decisions are a choice of the worker, these switches are imposed on the worker, without the worker having any say in it. As such, the consequences for the worker may be very different.

3.5 Timing

Having described all the elements of the model, it may be worth reviewing the order of events and decisions in a single period. After all, the order in which these take place has a substantial influence on the value functions in the next subsection. In short, a model period can be divided in 6 subperiods. In the first of these subperiods, the new values for p_t, z_t, and x_t are revealed to all surviving workers and firms (the death shock occurs before the start of the period), and a value of z_t is drawn from $F(z)$ for all newborn workers.[28] Thus, when making decisions later in the period, the firm (and worker) is assumed to know the value of production (and wages) if the match remains intact.

In the second subperiod, the occupational transfer shock ψ is realized, after which the workers and firms who are currently in a match make their separation decisions (and thus set $d(p, z, x)$ and $\sigma(p, z, x)$) in the third subperiod. It

[28] It is assumed here that a new worker is born whenever a worker dies. This newborn worker is allocated to a random occupation where they will be unemployed with occupational human capital at its lowest level x_1.

should be noted that workers and firms who are hit by the occupational transfer shock and workers decide to destroy their match do not make any of the decisions in the remaining subperiods. Firms decide to set their vacancy after this subperiod, and can thus set a vacancy in the same period as the one in which their match was destroyed.

Next, in the fourth subperiod, the occupational transfer decisions are made by workers who were unemployed in the first subperiod and workers who are employed and were not hit by the occupational transfer shock in the second subperiod. Thus, in the fourth subperiod, these workers set $\rho^u(p, z, x)$ or $\rho^e(p, z, x)$ (whichever applies to them) and pay the associated cost.

In the fifth subperiod, the search and matching process takes place, conditional on the workers and firms being allowed to search in this period.[29] Finally, production takes place in the sixth and last subperiod.

3.6 Value Functions

Following the above description of the model and its corresponding timing of events and decisions, one can now provide an expression for the value functions of the worker and firm. First, the value of being unemployed at the start of the last (production) subperiod, $W^U(p, z, x)$, can be expressed as follows:

$$
\begin{aligned}
W^U(p, z, x_h) = b + \beta \mathbb{E}_{p',z'} \Bigg[\max_{\rho^u(\cdot)} \Bigg\{ \rho^u(p', z', x_h) \left[\int_{\underline{z}}^{\bar{z}} W^U(p', \tilde{z}, x_1) dF(\tilde{z}) - c^u \right] \\
+ (1 - \rho^u(p', z', x_h)) \Big[\lambda(\theta(p', z', x_h)) W^E(p', z', x_h) \\
+ (1 - \lambda(\theta(p', z', x_h))) W^U(p', z', x_h) \Big] \Bigg\} \Bigg]
\end{aligned} \tag{3}
$$

This value function reflects that an unemployed worker only has one decision to make: the decision of whether or not to change occupations. If she

[29]As mentioned earlier, workers are not allowed to search in a period if they have destroyed their previous match in the same period, or if they have decided to (or were forced to) switch occupations while unemployed in the same period.

decides to change occupations ($\rho^u(p, z, x_h) = 1$), she pays the cost c^u and will be unemployed next period at the new values for p_t (p') and z_t ($\tilde{z}$), and the lowest level of occupational human capital x_1. If she decides not to change occupations, she will be searching for a job, and she will match with a firm with probability $\lambda(\theta(p', z', x_h))$.[30]

An employed worker has two decisions to make: her occupational transfer decisions $\rho^e(p, z, x)$ and her separation decision $d(p, z, x)$. Denoting the value of searching in a different occupation by $R^E(p, z, x)$, the value of being employed at the start of the last (production) subperiod, $W^E(p, z, x)$ can be expressed as follows:

$$
\begin{aligned}
W^E(p, z, x_h) &= w(p, z, x_h) + \beta \mathbb{E}_{p', z', x'} \Bigg[\max_{d(\cdot), \rho^e(\cdot)} \Bigg\{ \psi \int_{\underline{z}}^{\bar{z}} W^E(p', \tilde{z}, x') dF(\tilde{z}) \\
&\quad + (1-\psi) \Bigg[d(p', z', x')(W^U)' + (1 - d(p', z', x')) \Bigg[(1 - \rho^e(p', z', x'))(W^E)' \\
&\quad + \rho^e(p', z', x')(-c^e + R^E(p', z', x')) \Bigg] \Bigg] \Bigg\} \Bigg] \qquad (4) \\
R^E(p', z', x') &= \int_{\underline{z}}^{\bar{z}} \left[(1 - \lambda(\theta(p', \tilde{z}, x_1))) W^E(p', z', x') \right. \\
&\quad \left. + \lambda(\theta(p', \tilde{z}, x_1)) W^E(p', \tilde{z}, x_1) \right] dF(\tilde{z}) \qquad (5)
\end{aligned}
$$

This value functions has become considerably more complicated (compared to its counterpart in (Carrillo-Tudela and Visschers, 2014)) as a result of the two extensions. The inclusion of the exogenous occupational transfer shock has caused the inclusion of ψ and the integral on the first line of equation (4), the latter of which reflects the expected value for the worker who receives the occupational transfer shock (next period). The inclusion of the occupational transfer decision has in turn caused the inclusion of $\rho^e(\cdot)$ as well as the term $R^E(\cdot)$.

Firms that are currently not matched to a worker are not making an explicit decision in this model, as they are assumed to be posting a vacancy. Therefore,

[30]Note that the value of her occupational human capital in the next period is the same as in the current period (x_h), reflecting that the occupational human capital does not depreciate when the worker is unemployed.

the value of posting a vacancy in a market with productivity pair (z, x_h) at the start of the fifth (matching) subperiod is rather simple[31]:

$$V(p,z,x) = -k + q(\theta(p,z,x))J(p,z,x) + (1 - q(\theta(p,z,x)))\beta\mathbb{E}_{p'}\left[V(p',z,x)\right] \tag{6}$$

Finally, firms that are currently in a match with a worker only make the separation decision $\sigma(p,z,x)$. However, since they are also subject to the occupational transfer shock, their value function includes an additional term similar to the one seen earlier in equation (4), the value function for employed workers. As a consequence, the value function for producing firms at the start of the last (production) subperiod can be expressed as follows:

$$\begin{aligned} J(p,z,x_h) &= y(p,z,x_h) - w(p,z,x_h) + \beta\mathbb{E}_{p',z',x'}\left[\max_{\sigma(\cdot)}\left\{\psi\int_{\underline{z}}^{\bar{z}} J(p',\tilde{z},x')dF(\tilde{z})\right.\right. \\ &+\ (1-\psi)\left[(1-\sigma(\cdot))(1-\hat{\rho}(p',z',x'))J(p',z',x')\right. \\ &+\ \left.\left.\left.(1-\sigma(\cdot))\hat{\rho}(p',z',x')\beta\mathbb{E}_{p''}[V(p'',z',x')] + \sigma(\cdot)V(p',z',x')\right]\right\}\right] \end{aligned} \tag{7}$$

Here, $\hat{\rho}(p',z',x') = \rho^e(p',z',x')\int_{\underline{z}}^{\bar{z}}\lambda(p',\tilde{z},x_1)dF(\tilde{z})$ represents the probability that the worker will decide to search in a different occupation and match there (and thus destroy her current match). As these are both events outside of the control of the firm, the firm will take the function $\hat{\rho}(p',z',x')$ as given. Furthermore, as the vacancies are set before $\hat{\rho}$ is realized, the firm will have to wait until the next period to set a vacancy in this case.

3.7 Transition Equations

So far, the model description has mostly focused on the agent's decisions within a single period. However, it will also be important to keep track of the

[31]Note that the timing of this value function is slightly different than the others. This inconsistency follows Carrillo-Tudela and Visschers (2014) and is mainly implemented to avoid expectations in this value function, as firms decide on vacancies after separation subperiod. The β and the expectation that are currently still in equation (6) do not appear in the original model, but since this expectation (as well as the realized value) is zero this inconsistency with the original model does not influence the solution.

mass of workers flowing in and out of unemployment across periods. These transitions can be summarized with two equations: one for the mass of unemployed and one for the mass of employed workers, both specific to a combination of productivities $(z_t, x_t) = (z, x_h)$ as well as the occupation o. The first equation provides an expression for the mass of unemployed workers next period in occupation o, with idiosyncratic productivity $z_t = z$ and occupational human capital $x_t = x_h$:

$$\begin{aligned} u'_o(z, x_h) = &\int_{\underline{z}}^{\bar{z}} (1 - \lambda(\theta(p, \tilde{z}, x_h)))(1 - \rho^u(p, \tilde{z}, x_h))(1 - \phi)u_o(\tilde{z}, x_h)dF(z|\tilde{z})d\tilde{z} \\ &+ \int_{\underline{z}}^{\bar{z}} d(p, \tilde{z}, x_h)(1 - \psi)(1 - \phi)e_o(\tilde{z}, x_h)dF(z|\tilde{z})d\tilde{z} \\ &+ (\mathbb{1}_{h=1}) \left[\sum_{\tilde{o} \neq o} \sum_{h=1}^{H} \left[\int_{\underline{z}}^{\bar{z}} \rho^u(p, \tilde{z}, \tilde{x}_h)(1 - \phi)u_{\tilde{o}}(\tilde{z}, \tilde{x}_h)d\tilde{z} \right] \right] \frac{dF(z)}{O - 1} \\ &+ (\mathbb{1}_{h=1}) \frac{\phi}{O} dF(z) \end{aligned} \tag{8}$$

From the equation, it can be seen that unemployed workers with this combination of o, $z_t = z$, and $x_t = x_h$ (next period) can be divided into four categories. The first term corresponds to surviving workers currently unemployed in the same occupation o with occupational human capital $x_t = x_h$, who decide not to change occupations. The second term in equation (8) corresponds to surviving workers who were employed in the same occupation o with occupational human capital x and did not receive the occupational transfer shock, but had their match destroyed. Finally, the third term corresponds to those who are unemployed in a different occupation ($\tilde{o} \neq o$) and decide to switch, and the fourth term corresponds to newborn workers. As these workers move to a random occupation, they will go to occupation o with probability $1/(O-1)$ if they came from a different occupation and with probability $1/O$ if they are newborn. Furthermore, as these workers will have the lowest level of occupational human capital (x_1) in their new occupation, these terms only apply if $x_h = x_1$.

For employed workers, there are five ways in which a worker can end up employed next period in occupation o, with idiosyncratic productivity $z_t = z$

and occupational human capital $x_t = x_h$. These five ways are reflected by the five different terms in equation (9):

$$\begin{aligned}
\frac{e'_o(z, x_h)dz}{1-\phi} &= \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p, \tilde{z}, x_h))(1-\rho^u(p, \tilde{z}, x_h))u_o(\tilde{z}, x_h)dF(z|\tilde{z})d\tilde{z} \\
&+ \chi(x_h|x_h)\int_{\underline{z}}^{\bar{z}} (1-\hat{\rho}(p, \tilde{z}, x_h))(1-d(p, \tilde{z}, x_h))(1-\psi)e_o(\tilde{z}, x_h)dF(z|\tilde{z})d\tilde{z} \\
&+ \mathbb{1}_{h>1}\left[\chi(x_h|x_{\tilde{h}})\int_{\underline{z}}^{\bar{z}} (1-\hat{\rho}(p, \tilde{z}, x_{\tilde{h}}))(1-d(p, \tilde{z}, x_{\tilde{h}}))(1-\psi)e_o(\tilde{z}, x_{\tilde{h}})dF(z|\tilde{z})d\tilde{z}\right] \\
&+ \Bigg[(\mathbb{1}_{h=1})\sum_{\tilde{o}\neq o}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} [1-d(p, \tilde{z}, \tilde{x}_h)]\rho^e(p, \tilde{z}, \tilde{x}_h)\lambda(\theta(p, z, x_1))(1-\psi)e_{\tilde{o}}(\tilde{z}, \tilde{x}_h)d\tilde{z} \\
&\quad + \sum_{\tilde{o}\neq o}\left[\int_{\underline{z}}^{\bar{z}} \psi e_{\tilde{o}}(\tilde{z}, x_h)d\tilde{z}\right]\Bigg]\frac{dF(z)}{O-1} \qquad (9)
\end{aligned}$$

Here, the first term corresponds to workers who are currently unemployed in the occupation of interest o, did not decide to change occupations, and subsequently matched with a firm. Similarly, the second and third term in equation (9) correspond to workers who are currently employed in this occupation, did not match with a firm in a different occupation, and either remained in the occupational human capital level of interest x_h (second term) or moved up to x_h from the previous level $x_{\tilde{h}} = x_{h-1}$ (third term). The fourth term corresponds to workers who are employed in a different occupation, but switched occupations by searching while on the job (and matching with a firm in occupation o), and the fifth term corresponds to those who are employed in a different occupation and switched occupations due to the occupational transfer shock. As before, I define $\hat{\rho}(p', z', x')$ to equal $\rho^e(p', z', x')\int_{\underline{z}}^{\bar{z}} \lambda(p', \tilde{z}, x_1)dF(\tilde{z})$. Finally, note that the entire expression is divided by $1-\phi$ (the probability of staying alive) to account for the fact that newborn workers always start unemployed.

3.8 Equilibrium

In this paper, the equilibrium of interest will be a block-recursive equilibrium (BRE). This type of equilibrium has the advantage of allowing me to solve for the agents' decisions without taking into account the distribution of workers and firms across occupations, and productivity levels. This feature greatly reduces the computational costs of solving (and simulating) the model. The BRE is defined as follows:

Definition 1. *A block-recursive equilibrium (BRE) consist of a set of value functions* $W^U(p,z,x)$, $W^E(p,z,x)$, $J(p,z,x)$, $V(p,z,x)$, *policy functions* $d(p,z,x)$, $\rho^u(p,z,x)$, $\rho^e(p,z,x)$, $\sigma(p,z,x)$, *labour market tightness function* $\theta(p,z,x)$, *wage function* $w(p,z,x)$, *and laws of motion for* p, z, x, u_o, *and* e_o *such that:*

1. *The value functions and policy functions solve the worker's and firm's problems as described by equations* (3)*,* (4)*,* (6)*, and* (7)
2. *Free entry in labour markets:* $V(p,z,x) \leq 0$*, and* $\theta(p,z,x) = 0$ *if* $V(p,z,x) < 0$*.*
3. *Wages* $w(p,z,x)$ *solve the Nash bargaining problem in equation* (2)
4. *The laws of motion for* u_o *and* e_o *satisfy equations* (8) *and* (9)

Proposition 1. *The block-recursive equilibrium exists and it is the unique equilibrium of the model.*

Proof. See appendix B.1 □

The proposition justifies a complete focus on block-recursive equilibria when it comes to solving the model in order to obtain the quantitative results in Section 5. However, when comparing the resulting equilibrium functions with those obtained by solving the social planner's problem, it can be noticed that the two sets of functions do not (necessarily) coincide, as stated in the following proposition:

Proposition 2. *Unless c^e is prohibitively high or $\lambda(p, z, x_1) = 0$ for all (p, z), the block-recursive equilibrium is not constrained efficient.*

Proof. See appendix B.2 □

As can be seen in the proof, the inefficiency of the decentralized solution is caused by the reallocation decision of the employed worker, ρ^e. When deciding whether to search in a new occupation, the worker takes into account only her own value of the current match when considering the value lost upon reallocation. Thus, the worker fails to take into account that if she reallocates to another occupation, the firm that currently employs her will also lose its value of the match, J. Thus, it can be expected that the worker will decide to search in another occupation more often than the social planner would allow her to. Note that this result deviates from the efficiency results obtained in other papers, such as Carrillo-Tudela and Visschers (2014) and Menzio and Shi (2011). In the case of Carrillo-Tudela and Visschers (2014), this deviation does not surprise me as the element of my model that causes the departure from constrained efficiency is not present in their model. On the other hand, the model in Menzio and Shi (2011) does include on-the-job search, and would thus be subject to the same issue. The difference between my model and the model in Menzio and Shi (2011) is that in the latter model it is (unrealistically) assumed that the contract between the worker and firm specifies when exactly the worker is allowed to search (and where she would search in that case). In that case, as the contract is negotiated between the worker and the firm, the decision to search does take into account the lost value for the firm when the worker reallocates, thus getting around the issue that leads to the departure from constrained efficiency in my model. In principle, my result implies that one cannot use the social planner's problem to solve the model instead of solving the worker and firm problem. However, the result does provide me with the opportunity to evaluate how important this inefficiency is, by solving the social planner's problem and comparing the solution to the solution of the worker and firm problems.

4 Calibration

The model presented in the previous section is characterized by a total of $17 + H$ parameters[32], where the distribution of each of the productivity variables p and z is characterized by three parameters, which govern the mean value, persistence, and volatility of the corresponding variable. As I follow Carrillo-Tudela and Visschers (2014) in setting $H = 3$, there will be 20 parameters to calibrate. For the purpose of the simulation, I divide these parameters into two groups. One of these groups contains the parameters whose values are determined in the calibration, and the parameters in the other group are set directly.

The set of parameters that are determined outside of the calibration is $\{O, x_1, \mu_p, \phi, \chi, \beta, \psi, b, \delta, \eta\}$. The number of occupations O is set to 18, in order to enhance the comparability with Carrillo-Tudela and Visschers (2014). Both parameters x_1 (the lowest level of occupational human capital) and μ_p (the mean value of aggregate productivity p) are furthermore normalized to 1. The probability of death, ϕ, is set such that an individual "lives" for 40 years on average. Given that the model period corresponds to approximately a week (so that four periods correspond to a month), this average survival rate yields a value of $\phi = 1/1920 \approx 0.00052$. Similarly, χ (the probability of moving to the next level of occupational human capital) is set so that employed workers on average reach the next level after 5 year, as in Carrillo-Tudela and Visschers (2014), so that the associated level of $\chi = 1/240 \approx 0.0042$. In order to set the discount rate β, I then use the value of ϕ, together with a yearly interest rate of 4% (so that $r = 1.04^{1/48}$), to set the discount rate $\beta = (1 - \phi)/(1 + r) \approx 0.9987$. Next, the exogenous job destruction rate δ is set to 0.003, corresponding to the monthly rate of 0.012 found in Menzio and Shi (2011). Similarly, the value of unemployment benefit b is set to 0.716, again corresponding to the value found in Menzio and Shi (2011), while the firm's bargaining weight η is set to 0.5, corresponding to symmetric bargaining. Finally, the value for

[32]Recall that H stands for the number of values the occupational human capital variable x_h can take.

ψ is set to match the average rate at which employed workers switch occupations without switching employers. Since the numbers corresponding to Figure 3 suggest that this rate is approximately 0.008 on a 4-month basis, and my model period is one week, I set $\psi = 0.0005$.

Given the above parameter levels, there remain 10 parameters $\{\sigma_p, \sigma_z, \rho_p, \rho_z, \mu_z, k, c^u, c^e, x_2, x_3\}$ that are estimated in the calibration to match a set of 17 moments as close as possible.[33] Most of these moments are taken from Carrillo-Tudela and Visschers (2014), but I re-estimate the target values whenever possible. As the model is overidentified, it is not surprising that I am unable to match these moment exactly. The model values for these moments (which are discussed briefly below) and their data counterparts can be found in Table 2. The calculation method for these moments can be found in appendix C.

While the calibration does not restrict certain moments to inform a specific parameter (rather, the calibration minimizes the sum of squared distances to all targets), most of the moments are chosen with a certain parameter in mind.

The only calibrated parameter that does not appear in the original model is c^e (the cost of searching in a different occupation if the worker is employed). Its corresponding moment is the occupational mobility rate specific to employed workers. This rate comes from the SIPP dataset and is displayed in Figure 3.

A number of parameters also appear in the basic search and matching model, and one of these parameters appears in the calibration exercise as well.[35] Specifically, the moment corresponding to this parameter k (vacancy cost) is the average job-finding rate.

Some of the productivity parameters have a clear counterpart in the data.

[33]To be specific, I set the parameters to minimize the sum of square differences between model and data moments.

[34]In particular, the data I use to calculate the persistence and volatility of aggregate productivity is the “Real Output per Hour of All Persons” time series for the Nonfarm Business Sector. I use only the time period corresponding to the sample period of the SIPP.

[35]For an overview of the basic search and matching model, see for example Pissarides (2000).

Moment	Source	Data	Model
Average job-finding rate	SIPP	0.378	0.5988
Average aggregate productivity	Normalization	1	1.0540
Persistence of aggregate productivity	BLS	0.7713	0.9640
Volatility of aggregate productivity	BLS	0.0087	0.0144
Returns to occupational experience (5 years)	CTV14/KM09	0.154	0.1309
Returns to occupational experience (10 years)	CTV14/KM09	0.232	0.2789
Unemployment survival rate (4 months)	SIPP	0.517	0.4012
Unemployment survival rate (8 months)	SIPP	0.284	0.1905
Unemployment survival rate (12 months)	SIPP	0.181	0.1066
Occupational mobility rate for workers unemployed for at least 1 month	SIPP	0.572	0.1352
Occupational mobility rate for workers unemployed for at least 3 months	SIPP	0.611	0.2287
Occupational mobility rate for workers unemployed for at least 6 months	SIPP	0.613	0.3899
Occupational mobility rate for workers unemployed for at least 9 months	SIPP	0.611	0.5477
Occupational mobility rate for workers unemployed for at least 12 months	SIPP	0.624	0.6649
Subsequent mobility rate	SIPP	0.516	0.9185
Relative occupational mobility rate of unexperienced workers	SIPP	1.100	1.0768
Occupational mobility rate for employed workers	SIPP	0.028	0.0027

Table 2: *The moments targeted in the calibration. The second column names the source of the data counterpart of the moment. CTV14 refers to Carrillo-Tudela and Visschers (2014), KM09 refers to Kambourov and Manovskii (2009b), and "SIPP"/"BLS" means that the data counterpart of the moment was calculated using the dataset created from the SIPP or using data on productivity from BLS.*[34]

For example, the data counterparts parameters σ_p and ρ_p (the standard deviation and persistence of aggregate productivity) are the persistence and volatility of aggregate productivity. To obtain the corresponding persistence and volatility of aggregate productivity in the data, I apply an HP filter with smoothing parameter on the quarterly "Real Output Per Person" data from the Bureau of Labor Statistics (BLS). Similarly, since the parameters x_2 and x_3 are related to the additional wage that an individual might receive if his occupational human capital is higher, these parameters can be calibrated to match the returns to occupational experience. Specifically, the moments used here are the returns to 5 and 10 years of occupational experience since the parameter χ is set so that an individual reaches the next level after 5 years (on average). The data counterparts of these moments are taken from Carrillo-Tudela and Visschers (2014), who base their numbers on the results in Kambourov and Manovskii (2009b). Finally, the average value of the idiosyncratic productivity is set such that the average productivity equals 1. This normalization is made so that it is easier to interpret the parameters and equilibrium objects that have a monetary interpretation, such as c^e and the wage $w(p, z, x)$.

The remaining moments correspond to the standard deviation and persistence of idiosyncratic productivity (σ_z and ρ_z) and the cost of reallocation for an unemployed worker (c^u). These moments include the 4-, 8-, and 12-month unemployment survival rate, the occupational mobility rate for workers who are unemployed either 1, 3, 6, 9, or 12 months, the subsequent mobility rate, and the relative occupational mobility rate of unexperienced workers.[36] The data counterpart for these moments are calculated using the dataset created for the observations in Section 2. The procedure used to calculate these data counterparts mimics that used to calculate the model counterparts, which is discussed in Appendix C.

O	x_1	μ_p	ϕ	χ	β	ψ	b	δ	η
15	1	1	0.0005	0.0042	0.9987	0.0005	0.716	0.0030	0.500

σ_p	σ_z	ρ_p	ρ_z	μ_z	k	c^u	c^e	x_2	x_3
0.003	0.0078	0.981	0.9992	0.621	3.578	0.072	0.035	1.129	1.500

Table 3: *Values of parameters used to obtain the results in Section 5. Parameters are either planned to be determined by calibration (bottom table) or set outside of the calibration (top table).*

Table 3 lists the parameter values for both groups of parameters. Given that the average production in a model period is approximately 1, the parameter

[36]As I do not observe experience in my data, I define an individual to be experienced if he is aged between 35 and 55 and I define an individual to be unexperienced if he is aged between 20 and 30. Of course, the worker's age does not map directly into the worker's experience in his occupation, especially if the worker changes occupation relatively late in his working life. However, it is not unreasonable to expect age and experience to be strongly correlated, thus making age a good proxy for experience.

value that stands out here is the vacancy cost k, which is calibrated to equal almost a month (4 model periods) worth of production. This large value reflects that the matching probability for a firm is generally very high (if not equal to zero), while the low volatility of the aggregate and idiosyncratic productivity p and z cause matches to last for a considerable number of periods (in expectation). Table 3 also shows that the calibrated values for c^u and c^e are very low. This low value signals that besides the consequences included in the model (most notably the loss of occupational human capital) the (net) cost of reallocating is rather small.

The model counterparts of the moments used in the calibration exercise can be found in the fourth column of Table 2. As can be seen by comparing these moments generated by the model with those generated by the data (in the third column of Table 2), the model has trouble matching several features of the data. While the model matches the unemployment survival rates, the returns to occupational experience, and the relative occupational mobility rate for unexperienced workers relatively well, it does generate too much persistence in the aggregate output. More importantly, the model is unable to generate enough occupational mobility. This inability holds for both the occupational switches made during short-term unemployment (although the model does generate the increasing pattern over the length of the unemployment spell) and the occupational switches made on the job. Once again, this result can be related to the matching probabilities, which are quite low for workers. Therefore, as the chance of matching with an employer is low in any occupation, workers will generally not find it desirable to switch occupations as it destroys their occupational human capital while not improving their chances of finding a job by much.

From the discussion above it can be concluded that the fit of the model is not perfect. However, despite not matching the levels of the occupational mobility rate, the model does seem to be able to match patterns over time. Thus, it is interesting to see whether this conclusion still holds when looking at patterns over time that were not targeted in the calibration, such as wage paths and cyclical patterns. The analysis of these patterns will be the focus of the next section.

5 Results

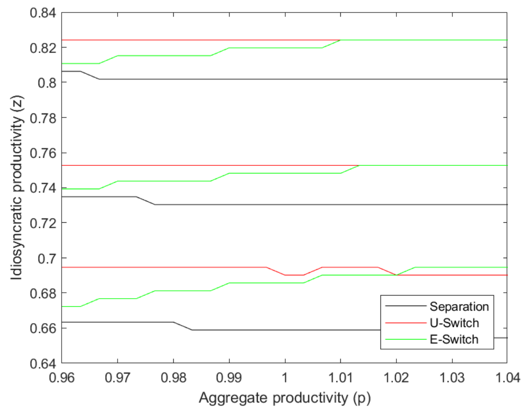

Figure 5: *Threshold values of z below which a worker chooses to separate, reallocate when unemployed, or reallocate when employed, for different values of p. For each threshold type (colour), the highest threshold corresponds to $x = x_1$ and the lowest threshold corresponds to $x = x_3$.*

In this section I analyze the implications of the model for labour market behaviour of workers, in particular focusing on reallocation decisions of workers. In general, there are three decisions made in the model (the separation decision and the reallocation decision for both unemployed and employed workers). Essentially, all three of these decisions are binary decisions: either the worker decides to separate/reallocate or she decides not to. In fact, the structure of the model is such that for every combination of p and x, one can find a threshold value of z below which the worker decides to separate/reallocate, and above which the worker decides not to do so. These threshold functions are plotted in Figure 5. As can be seen in the figure, the thresholds generally are higher for lower levels of occupational human capital x. For the reallocation decisions this pattern makes sense because if the worker decides to reallocate, his occupational human capital will be destroyed. As generally the value functions for the worker are increasing in x, the value of reallocation will be lower relative to the value the worker would expect to obtain when not reallocating. Similarly, because the value of producing for a firm is also increasing in x, the separation threshold is also decreasing in x. The relative positions of the thresholds in Figure 5 have consequences for both the distribution of workers over productivity pairs (p, z) and for the decomposition of the unemployment rate into three different types.[37]. These patterns are shown in Appendix D.

Shifting the focus to cyclical patterns, it can be observed in Figure 5 that the thresholds for on-the-job reallocation are generally increasing in aggregate productivity, while the thresholds for separation and reallocation during unemployment are (mildly) decreasing in aggregate productivity. Keeping everything else constant, these patterns would cause a countercyclical E-mobility rate, a countercyclical unemployment rate, and a procyclical U-mobility rate. However, this pattern does not arise when looking at the correlations between the unemployment rate and either the occupational mobility rate or the fraction of switches going through unemployment in the simulated data (mirroring Figures 1 and 2). While the pattern, displayed in a scatter plot in Figure D.4 in Appendix D, is rather noisy, the resulting correlations give a clear conclusion. In particular, I find a correlation of 0.1544 between the unemployment rate and the (total) occupational mobility rate, leading to the conclusion that the model produces a countercyclical occupational mobility rate like observed in the data in Section 2. Similarly, I find a correlation of 0.1483 between the unemployment rate and the fraction of occupational switches going through unemployment, which reveals a countercyclical pattern similar to the one found in the data.

Figure 6 shows the wage patterns for U-switchers and E-switchers, resulting from the simulation. As can be seen in the figure, the E-switchers are generally better off than the U-switchers in terms of their wages (relative to their wages before the switch). However, it can also be observed that both groups experience a decrease in their wage. This decrease is a consequence of one of the simplifying assumptions of the model. In particular, I assume that workers who switch occupations lose all of their occupational human capital, while in reality workers likely

[37]Specifically, I decompose the unemployment rate into rest, search and reallocation unemployment, following Carrillo-Tudela and Visschers (2014)

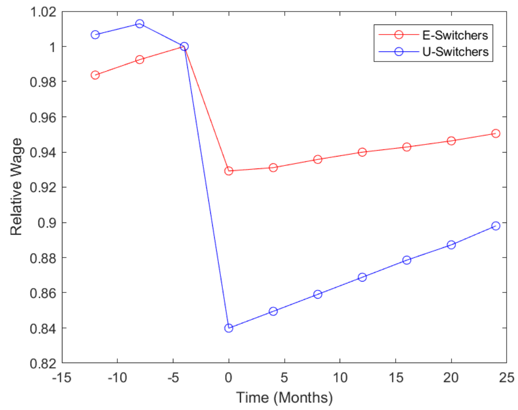

Figure 6: *Simulated wage paths over time for occupational U-switchers and E-switchers. As in Figure 4, the switch takes place between time -4 and 0.*

only lose part of their human capital. As a consequence, workers in the simulation are forced to start over in the lowest wage bracket (the wage range for the lowest level of occupational human capital), as shown in Appendix D. Nevertheless, as the model matches the other wage patterns observed in Section 2 (Figure 4), I conclude that the model generally performs well in replicating the wage patterns of the two types of occupational switchers.

	(1)	(2)	(3)
	corr(URate, OccmobRate)	corr(URate, Uswitch frac)	Occ E-Mob Rate
Baseline	0.1544	0.1483	0.0027
$\psi = 0$	0.2253	0.2461	0.00002
$c^e = 0$	0.1070	0.1956	0.007
$c^e \to \infty$	0.1593	0.1476	0.0025

Table 4: *Robustness of main results to alternative specifications of the model. Results include (1) the correlation between the unemployment rate and the (total) occupational mobility rate, (2) the correlation between the unemployment rate and the fraction of occupational switchers going through unemployment, and (3) the job-to-job occupational mobility rate.*

Finally, Table 4 shows how the most important results of this section, the results on cyclicality and job-to-job occupational mobility, change when some of the key parameters are changed. Here, the "Baseline" refers to the calibrated model used to generate the results above. From the table, it can be seen that a large fraction of the occupational E-mobility in the baseline model is driven by the exogenous reallocation shock. After all, taking out the exogenous reallocation shock (by setting $\psi = 0$) reduces the occupational E-mobility rate to a value close to zero, whereas changing the cost of searching in a different occupation c^e does not influence this rate a lot. Again, this pattern is likely a consequence of the low job-finding probabilities which make it unlikely for a worker to switch on-the-job, even if she decides to search in a different occupation.

When comparing columns (1) and (2) of Table 4 across different specifications in the table, it can be observed that removing the exogenous reallocation shock strengthens the cyclical patterns. This conclusion should not be surprising, as the probability of facing the exogenous reallocation shock does not change over the business cycle, and thus the amount of occupational switches within the firm does not vary much over the business cycle either. Therefore, it can be concluded that the exogenous reallocation shock dampens the total cyclicality of both the total occupational mobility rate and the fraction of occupational switchers going through unemployment.

Removing on-the-job reallocation does not have a large effect on the correlations reported in Table 4, which is not surprising as the incidence of on-the-job reallocation is already very low in the baseline model. On the other hand, if I remove the cost of searching on-the-job in a different occupation (c^e), there is a substantial increase in the occupational E-mobility rate. At the same time, the countercyclicality of the total occupational mobility rate becomes weaker, whereas the countercyclicality of the fraction of occupational switchers going through unemployment becomes stronger. Intuitively, this pattern is the consequence of the procyclical pattern in the on-the-job reallocation threshold, shown in Figure 5, becoming more relevant.

In conclusion, it can be stated that changes in key parameters do not influence the ability of the model to generate the cyclical patterns observed in Section 2. As particularly the countercyclical pattern in the fraction of switchers going through unemployment cannot be explained in the model without the extension (i.e. without the possibility of reallocating without going through unemployment), this observation leads me to the conclusion that the model proposed in this paper has an added value over the models already existing in the literature.

6 Conclusion

In this paper, I propose a DMP-style job search model of occupational mobility in which it is possible for workers to change occupations not only when unemployed (as in the existing literature), but also when still employed in their former occupation. This extension of the existing literature is motivated by observations from the 2004 and 2008 panels of the Survey of Income and Program Participation (SIPP). These two panel data sets suggest that the occupational mobility rate is mildly countercyclical. However, the fraction of occupational switchers who switch during unemployment exhibits a much stronger (counter)cyclical pattern, which is a pattern that has not been documented before. The previous literature further argues that those who switch occupations while employed tend to have wage patterns that differ from those who switch while unemployed, a pattern which I see in my dataset as well. My observations in the data, combined with the arguments in the literature, provide the motivation for an explicit distinction between the two types of mobility in my model. I also add an exogenous shock that forces the employed worker to change occupations without leaving their firm, in order to take into account that a large proportion of on-the-job switches I observe in the data do not involve a change of employer.

Simulations of the calibrated model show that the extensions made to the model enable it to replicate the cyclical direction of both the total occupational mobility rate and the fraction of occupational switchers that experiences an unemployment spell in between the two jobs. Thus, the extensions made to the model in this paper may be worth the extra layer of complexity, keeping in mind the observed differences between occupational switchers who do or do not go through unemployment. However, in the current version the model does not fit the calibration targets very well. In a future version of this paper, I plan to further investigate this poor fit.

Even though this paper extends the existing theoretical literature in a promising way, the model in this paper still has a number of limitations that can be addressed in future work. For example, in the model presented in this paper it is possible to search on-the-job in other occupations, but not in the worker's current occupation, which seems unrealistic. Furthermore, while the assumption of random reallocation to a new occupation seems supported by the data, it may be interesting to see whether results change when workers can direct their reallocation to a specific occupation, for example based on the average wage obtained in that occupation. Especially when one is interested in a more detailed occupational classification system (such as the 3-digit classification), directed search seems more realistic. Finally, the reallocation within the firm is currently taken as an exogenous shock. It would be interesting to further explore the within-firm occupational mobility of workers.

Other limitations come from the assumptions that are made in the model. Most of these assumptions are common in the theoretical literature, but have been questioned or rejected in the empirical literature. The main example is the assumption that wage determination takes place through Nash bargaining, where the value of unemployment is used by the worker as the outside option. This assumption is rejected by several empirical papers, such as Moscarini and Postel-Vinay (2017), whose results suggest that rather than using the value of unemployment, the workers use a credible threat to quit once an alternative offer has arrived. Another simplifying assumption made in my paper is that everyone who searches for a job searches with the same intensity. However, several empirical papers have already indicated otherwise. In fact, Faberman and Kudlyak (2017) find that it seems to be those with a lower search intensity who find a job in a shorter time, suggesting that the matching probability depends on more than just the search intensity and labour market tightness. Finally, my model does not allow a worker to become inactive. However, when investigating the explanatory power of a search model for labour market outcomes during and after the Great Recession, Kroft et al. (2016) find an important role for transitions from inactivity to unemployed and back, while also suggesting a role for duration dependence in job-finding rates.

All of the possible extensions mentioned above present a significant complication to the model, which is why I chose not to include them in this paper. However, given the empirical importance of several of these channels, these are interesting extensions that should be explored in future work.

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A Data Appendix

A.1 Data Construction

In this section, I will provide some more details on the construction of the dataset I use to generate the figures and tables in Sections 2, A.2, and A.3, and to obtain the data counterparts of the moments in Section 4. While the discussion of the details in this section is aimed towards using the 2004 and 2008 panels, the process to obtain the comparable dataset using the 1996 and 2001 panels is identical.

The dataset of the Survey of Income and Program Participation contains many more variables than the occupation and employment status variables that I use, and because of the size of the dataset the data is usually delivered separately by wave (thus meaning that each panel will consist of more than 10 separate datasets). The first step is thus to combine all these files and clean all the relevant variables. For this purpose, the Center for Economic and Policy Research (CEPR) has made a number of programs available, separating the cleaning process according to theme.[38] After running these programs, one can start using the data to create the dataset of interest. It is at this point where I impose the sample restrictions, thus dropping any observations belonging to individuals who did not participate in the first wave (interview) of the panel, who are not male, who are aged below 23 or over 61, who are self- or dual-employed, or who work for the government.

In order to create the measure for occupational mobility, I compare the respondent's occupation in a certain month to his reported occupation 4 months ago (which is the same reference month one interview earlier). Of course, this previous occupation is not always available. For example, the occupation variable is not always filled when the respondent is unemployed. In those cases, I look further back up to a maximum of 8 months. As these occupation variables are

[38]For Stata, these programs are available at http://ceprdata.org/sipp-uniform-data-extracts/sipp-recoding-programs/

the 3-digit occupations, it is easy to track the 1-digit occupation as well. To do so, I first assign all respondents to their 1-digit occupation group, after which I follow the same procedure as described above. As the 1996 and 2001 panels of the SIPP use a different occupation classification system than the 2004 and 2008 panels (SOC 1990 instead of SOC 2000), the procedure to create the measure for occupational mobility creates a discontinuity between the end of the 2001 panel and the start of the 2004 panel. This discontinuity occurs at the 1-digit level too, as the classification system used in the 1996 and 2001 panel has 15 1-digit occupations, whereas the classification system used in the 2004 and 2008 panel has 14 1-digit occupations. It is for this reason that I decided to separate the two sets of panels and focus only on the most recent ones in the main text. Table A.1 lists all the 1-digit occupational codes that the tables in the main text and in the next sections refer to.

Of course, the procedure above will also pick up the occupation changes in the data that were caused by measurement errors, as discussed in Section 1. Therefore, I check whether the respondent also changed either his employer, industry, working hours, or hourly wage. If either of these changes occur, I conclude that the respondent genuinely changed occupations and record it accordingly. If none of these changes occur, I conclude that the occupation change in the data may be caused by a measurement error. If that is the case, I set the occupational change variable to missing, essentially deleting this observation for the purpose of measuring the mobility rate.

In order to identify whether the respondent went through an unemployment spell, I use the SIPP's employment status recode variable, which can take 8 different values. I define the respondent to be unemployed if he is reported to be "3. With a job all month, absent from work without pay 1+ weeks, absence due to layoff", "5. With a job at least 1 but not all weeks, some weeks on layoff or looking for work", "6. No job all month, on layoff or looking for work all weeks", "7. No job all month, at least one but not all weeks on layoff or looking for work", or "8. No job all month, no time on layoff and no time looking for work".

	SOC 1990 1-digit occupations (1996, 2001 SIPP)	**SOC 2000 1-digit occupations** (2004, 2008 SIPP)
1	Executive, Administrative, and Managerial Occupations	Management, Business, and Financial Occupations
2	Professional Specialty Occupations	Professional and Related Occupations
3	Technicians and Related Support Occupations	Healthcare Support Occupations
4	Sales Occupations	Protective Service Occupations
5	Administrative Support Occupations, Including Clerical Occupations	Food Preparation and Serving Related Occupations
6	Private Household Services Occupations	Building and Grounds Cleaning and Maintenance Occupations
7	Protective Services Occupations	Personal Care and Service Occupations
8	Services, except Household and Protective Occupations	Sales and Related Occupations
9	Farming, Forestry, and Fishing Occupations	Office and Administrative Support Occupations
10	Precision Production, Craft, and Repair Occupations	Farming, Fishing, and Forestry Occupations
11	Machine Operators, Assemblers, and Inspectors	Construction and Extraction Occupations
12	Transportation and Material Moving Occupations	Installation, Maintenance, and Repair Occupations
13	Handlers, Equipment Cleaners, Helpers, and Laborers	Production Occupations
14	Armed Forces	Transportation and Material Moving Occupations
15		Military

Table A.1: *1-digit occupation codes according to the SOC 1990 system (left) and according to the SOC 2000 system (right).*

As a result, I say a respondent is employed if he is reported to be “1. With a job entire month, worked all weeks”, “2. With a job all month, absent from work without pay 1+ weeks, absence not due to layoff”, or “4. With a job at least 1 but not all weeks, no time of layoff and no time looking for work”.

For the construction of the data counterparts of the moments in Section 4 of the main text, I also need to keep track of the length of an unemployment spell. In general, I can keep track of unemployment spells immediately once I have defined a respondent to be employed or unemployed. However, some respondents have missing information for a month or for one or multiple interviews. For these respondents, I assume that during these months their employment status remains the same. For example, if a respondent was unemployed when he last gave information, and five months later (after missing 4 months) he reports being employed, I assume this person was unemployed for all 4 months. In order to find previous reports of employment status, I look back up to a maximum of 13 months. Then, using the same constructed variable of occupational changes, I identify the data counterparts of the moments using the same procedure as used on the simulated data from the model. This specific procedure is outlined for each moment separately in Appendix C. Using the measure created for the occupational mobility rate for employed workers, I then create the Figure 3 in the main text (and Figure A.10 in Section A.3), where I define a worker to not have changed occupations if he did not change industry and did not report an employer change.[39]

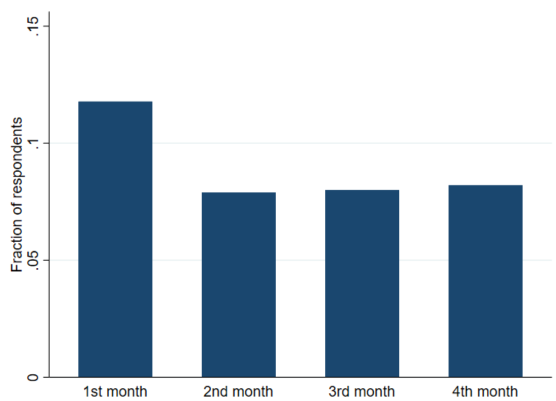

Figure A.1: *The fraction of respondents who change employment status compared to the previous month, by interview reference month.*

In the main text I explained that I use occupational changes at a 4 month rate rather than a 1 month rate because of so-called seam bias. This bias occurs because respondents will often report the same value 4 months in a row (those 4 months being the months the respondent is interviewed about in a single interview). One way to see how severe this seam bias might be is to look at the months in

[39]I require both of these to be true because the variable indicating employer change is often not filled.

which respondents change their employment status. Figure A.1 reports the fraction of respondents who changed employment status compared to the previous month, by reference month.[40] As can be seen in the figure, the fraction of employment status changes is substantially higher in the first reference month. This observation indicates that there may be seam bias arising, and while the rotating panel design makes sure that each month is a first reference month for one group of respondents, the observation makes me conclude that in order to avoid biased estimates it is better to assess the data on a 4 month basis.

A.2 Additional Observations (2004 and 2008 SIPP)

In this section, I present some additional observations made from the 2004 and 2008 panels of the SIPP. These observations mainly serve to strengthen the points made in Section 2, although the observations in this section are not critical to the conclusions made there.

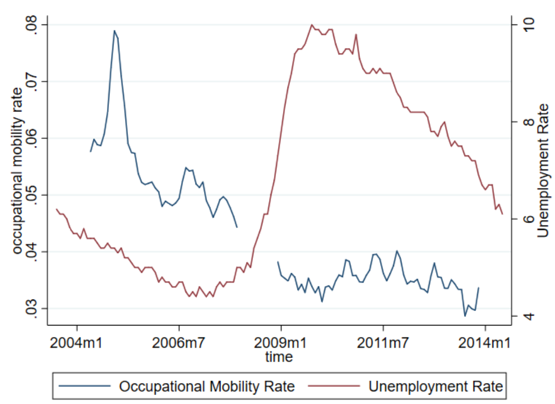

Figure A.2: *The 3-digit occupational mobility rate, plotted over time together with the corresponding month's unemployment rate from the BLS.*

To first provide a clearer comparison between the occupational mobility rates I find in the data and results from the previous literature, Figure A.2 plots the 3-

[40]Recall that the reference months are the months the respondent is asked about in an interview. For example, if the interview asks about the months of May, June, July, and August, then the month of May would be the first reference month.

digit occupational mobility rate, which is the rate that is most commonly reported. Not surprisingly, the 3-digit mobility rate is substantially higher than the 1-digit rate reported in Section 2. As can be seen in the figure, the occupational mobility rates found in the data range from 3 to 8% with an average rate of approximately 5%. Keeping in mind that the rates in the figures are 4-month rates instead of yearly rates, this rate seems roughly consistent with (though slightly smaller than) the 18% yearly rate found in Kambourov and Manovskii (2008).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	1286	115	67	335	134	188	1175	1575	25	210	150	385	273	0
2	1525	0	574	82	304	174	390	812	1437	16	256	255	365	287	8
3	119	566	0	24	138	107	256	148	346	19	12	4	73	62	0
4	48	88	20	0	55	24	52	99	92	0	32	44	43	93	0
5	393	377	177	30	0	287	194	742	617	35	194	98	305	325	0
6	166	144	96	24	286	0	82	294	284	83	222	103	258	322	0
7	183	445	224	37	154	102	0	291	308	4	40	23	48	47	0
8	1221	911	216	91	672	276	327	0	1748	26	203	203	502	483	0
9	1641	1456	349	120	549	268	378	1542	0	41	189	133	609	658	3
10	21	32	8	8	32	84	22	43	24	0	72	24	116	122	0
11	231	182	16	67	136	268	14	199	225	39	0	310	509	487	0
12	158	229	16	12	101	150	16	218	157	30	323	0	354	272	0
13	378	464	87	63	309	325	86	492	631	64	493	354	0	920	0
14	263	289	64	107	266	364	126	477	655	127	490	236	836	0	0
15	0	4	0	2	0	0	0	0	4	0	0	0	0	0	0

Table A.2: *Number of switches found in the data for every combination of 1-digit occupations. Rows correspond to the previous occupations, and columns correspond to new occupations. For a list of the occupations corresponding to these codes, see Appendix A.1.*

In order to further investigate the net occupational mobility, Table A.2 lists the number of occupational changes observed in the data for every possible combination of 1-digit occupations.[41] At first sight, the table looks fairly symmetric: for every pair (A,B) of occupations, the number of workers switching from A to B is roughly similar to that who switch from B to A. This symmetry confirms the

[41] Note that Table 1 and A.2 do not use the sample weights. If the tables are tabulated using sample weights, the table is more difficult to read but the conclusions remain unchanged.

observation made in Section 2, where I observed that there does not seem to be a specific occupation that expels or attracts workers.

The analysis of Tables A.2 and 1 is repeated in Tables A.3 to A.10 for subsets of the data. In particular, Tables A.3 and A.4 look at the 2004 panel only, and Tables A.5 and A.6 look at the 2008 panel only, while Tables A.7 and A.8 count only U-switches, and Tables A.9 and A.10 count only E-switches. Looking at these tables, it seems clear that the conclusions drawn from Tables A.2 and 1 regarding the direction of occupational changes continues to hold. There is only one example for which it does not seem to hold, namely occupational E-switches in and out of occupation 1 (Management, Business, and Financial Occupations). For this occupation, the inflow seems much larger than the outflow, which makes sense as one could imagine many within-firm promotions going into managerial positions.[42]

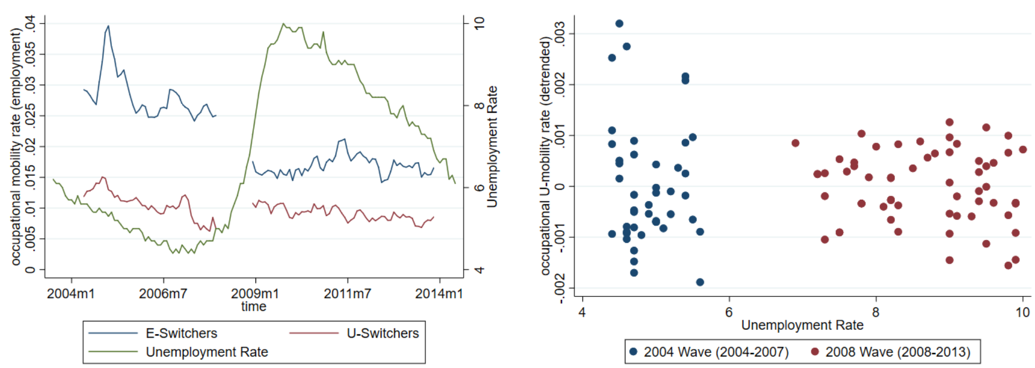

Figure A.3: *The 1-digit occupational mobility rate, counting only U-switchers or E-switchers, and the corresponding month's unemployment rate from the BLS (left). The detrended 1-digit occupational U-mobility rate (counting only U-switchers) plotted against the corresponding month's unemployment rate (right)*

Figure A.3 plots the unemployment rate as well as the occupational mobility rate separately for workers who change occupations with and without going

[42]It should be noted while that occupation code 1 includes many managerial occupations, most of the supervisory occupations are included in the occupation codes that are closest to the type of work (of their team).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	721	64	31	210	67	97	709	940	20	123	84	256	136	0
2	884	0	279	55	150	81	225	396	709	8	148	119	204	106	8
3	52	303	0	20	83	63	147	87	203	15	8	0	57	20	0
4	36	44	16	0	16	8	28	36	51	0	20	24	23	49	0
5	235	206	73	12	0	136	89	358	343	19	99	32	152	178	0
6	80	68	56	20	151	0	42	131	187	48	132	55	146	144	0
7	95	247	104	25	90	47	0	131	163	4	24	19	24	31	0
8	795	507	94	36	352	158	168	0	1010	20	115	118	321	243	0
9	1002	756	177	80	260	163	170	946	0	21	106	97	361	345	0
10	16	20	8	8	8	44	4	20	8	0	44	12	52	75	0
11	105	80	8	52	94	131	6	103	119	16	0	184	315	274	0
12	106	112	4	4	32	70	4	112	83	20	217	0	209	124	0
13	238	266	67	43	165	216	36	299	339	28	298	248	0	545	0
14	150	141	40	67	132	161	61	243	369	87	252	133	473	0	0
15	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0

Table A.3: *Number of switches found in the data for every combination of 1-digit occupations, for the 2004 panel only. Rows correspond to the previous occupations, and columns correspond to new occupations. For a list of the occupations corresponding to these codes, see Appendix A.1.*

Occupation	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Observations	99128	125701	18254	5421	28963	20764	14131	72538	104953	4663	36233	27218	69788	42765	36
Inflow	3794	3471	990	455	1743	1345	1077	3571	4524	306	1586	1125	2593	2270	8
Outflow	3458	3372	1058	351	1932	1260	1004	3937	4484	319	1487	1097	2788	2309	2
Net Inflow	336	99	-68	104	-189	85	73	-366	40	-13	99	28	-195	-39	6

Table A.4: *Total number of incoming and outgoing switches found in the data for every 1-digit occupations, and number of times I observe a worker in each of these occupations in the data, for the 2004 panel only. For a list of the occupations corresponding to these codes, see Appendix A.1.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	565	51	36	125	67	91	466	635	5	87	66	129	137	0
2	641	0	295	27	154	93	165	416	728	8	108	136	161	181	0
3	67	263	0	4	55	44	109	61	143	4	4	4	16	42	0
4	12	44	4	0	39	16	24	63	41	0	12	20	20	44	0
5	158	171	104	18	0	151	105	384	274	16	95	66	153	147	0
6	86	76	40	4	135	0	40	163	97	35	90	48	112	178	0
7	88	198	120	12	64	55	0	160	145	0	16	4	24	16	0
8	426	404	122	55	320	118	159	0	738	6	88	85	181	240	0
9	639	700	172	40	289	105	208	596	0	20	83	36	248	313	3
10	5	12	0	0	24	40	18	23	16	0	28	12	64	47	0
11	126	102	8	15	42	137	8	96	106	23	0	126	194	213	0
12	52	117	12	8	69	80	12	106	74	10	106	0	145	148	0
13	140	198	20	20	144	109	50	193	292	36	195	106	0	375	0
14	113	148	24	40	134	203	65	234	286	40	238	103	363	0	0
15	0	4	0	0	0	0	0	0	4	0	0	0	0	0	0

Table A.5: *Number of switches found in the data for every combination of 1-digit occupations, for the 2008 panel only. Rows correspond to the previous occupations, and columns correspond to new occupations. For a list of the occupations corresponding to these codes, see Appendix A.1.*

Occupation	1	2	3	4	5	6	7	8
Observations	131211	175908	26142	7449	38975	30585	21163	90622
Inflow	2553	3002	972	279	1594	1218	1054	2961
Outflow	2460	3113	816	339	1842	1104	902	2942
Net Inflow	93	-111	156	-60	-248	114	152	19

Occupation	9	10	11	12	13	14	15
Observations	128291	5932	38408	35134	70006	51905	56
Inflow	3579	203	1150	812	1810	2081	3
Outflow	3452	289	1196	939	1878	1991	8
Net Inflow	127	-86	-46	-127	-68	90	-5

Table A.6: *Total number of incoming and outgoing switches found in the data for every 1-digit occupations, and number of times I observe a worker in each of these occupations in the data, for the 2008 panel only. For a list of the occupations corresponding to these codes, see Appendix A.1.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	283	27	15	120	41	62	319	477	16	48	41	78	82	0
2	291	0	132	5	77	56	103	250	429	6	90	54	85	101	0
3	40	103	0	9	41	26	80	60	77	10	4	0	16	24	0
4	15	32	4	0	23	8	20	36	37	0	15	12	21	29	0
5	71	94	54	8	0	93	70	310	253	19	99	31	134	150	0
6	36	23	27	4	99	0	23	99	73	54	88	28	90	149	0
7	39	147	58	19	60	42	0	88	121	4	10	1	19	18	0
8	281	197	94	36	271	102	111	0	536	8	83	61	159	201	0
9	378	405	114	24	255	114	111	506	0	14	91	31	164	216	3
10	7	20	4	4	13	53	14	5	16	0	49	8	64	44	0
11	41	68	8	43	68	111	8	73	83	24	0	127	240	174	0
12	15	42	4	1	38	49	8	77	44	18	138	0	117	82	0
13	81	107	23	27	116	111	15	152	246	21	217	78	0	363	0
14	55	77	22	41	133	165	45	179	208	55	234	115	338	0	0
15	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0

Table A.7: *Number of switches found in the data for every combination of 1-digit occupations, for U-switchers only. Rows correspond to the previous occupations, and columns correspond to new occupations. For a list of the occupations corresponding to these codes, see Appendix A.1.*

Occupation	1	2	3	4	5	6	7	8
Observations	230339	301609	44396	12870	67938	51349	35294	163160
Inflow	1350	1598	571	236	1314	971	670	2154
Outflow	1609	1679	490	252	1386	793	626	2140
Net Inflow	-259	-81	81	-16	-72	178	44	14

Occupation	9	10	11	12	13	14	15
Observations	233244	10595	74641	62352	139794	94670	92
Inflow	2604	249	1166	587	1525	1633	3
Outflow	2426	301	1068	633	1557	1667	4
Net Inflow	178	-52	98	-46	-32	-34	-1

Table A.8: *Total number of incoming and outgoing switches found in the data for every 1-digit occupations, and number of times I observe a worker in each of these occupations in the data, for U-switchers only. For a list of the occupations corresponding to these codes, see Appendix A.1.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	1003	88	52	215	93	126	856	1098	9	162	109	307	191	0
2	1234	0	442	77	227	118	287	562	1008	10	166	201	280	186	8
3	79	463	0	15	97	81	176	88	269	9	8	4	57	38	0
4	33	56	16	0	32	16	32	63	55	0	17	32	22	64	0
5	322	283	123	22	0	194	124	432	364	16	95	67	171	175	0
6	130	121	69	20	187	0	59	195	211	29	134	75	168	173	0
7	144	298	166	18	94	60	0	203	187	0	30	22	29	29	0
8	940	714	122	55	401	174	216	0	1212	18	120	142	343	282	0
9	1263	1051	235	96	294	154	267	1036	0	27	98	102	445	442	0
10	14	12	4	4	19	31	8	38	8	0	23	16	52	78	0
11	190	114	8	24	68	157	6	126	142	15	0	183	269	313	0
12	143	187	12	11	63	101	8	141	113	12	185	0	237	190	0
13	297	357	64	36	193	214	71	340	385	43	276	276	0	557	0
14	208	212	42	66	133	199	81	298	447	72	256	121	498	0	0
15	0	4	0	2	0	0	0	0	0	0	0	0	0	0	0

Table A.9: *Number of switches found in the data for every combination of 1-digit occupations, for E-switchers only. Rows correspond to the previous occupations, and columns correspond to new occupations. For a list of the occupations corresponding to these codes, see Appendix A.1.*

Occupation	1	2	3	4	5	6	7	8
Observations	230339	301609	44396	12870	67938	51349	35294	163160
Inflow	4997	4875	1391	498	2023	1592	1461	4378
Outflow	4309	4806	1384	438	2388	1571	1280	4739
Net Inflow	688	69	7	60	-365	21	181	-361

Occupation	9	10	11	12	13	14	15
Observations	233244	10595	74641	62352	139794	94670	92
Inflow	5499	260	1570	1350	2878	2718	8
Outflow	5510	307	1615	1403	3109	2633	6
Net Inflow	-11	-47	-45	-53	-231	85	2

Table A.10: *Total number of incoming and outgoing switches found in the data for every 1-digit occupations, and number of times I observe a worker in each of these occupations in the data, for E-switchers only. For a list of the occupations corresponding to these codes, see Appendix A.1.*

through an unemployment spell (U-switchers and E-switchers). As can be seen in the left panel of Figure A.3, the occupational mobility rate that counts only those going through unemployment is consistently lower than the one that counts only those not going through unemployment. Furthermore, the latter seems much more volatile. In terms of cyclicality, the right panel does not seem to provide any conclusive evidence on whether the mobility rate is still countercyclical if one only counts those who change occupations while going through an unemployment spell. A simple (naive) OLS regression (of this rate on the unemployment rate) however gives a coefficient of -0.0003 for the 2004 panel and -0.0001 for the 2008 panel, thus revealing this rate to be mildly procyclical.

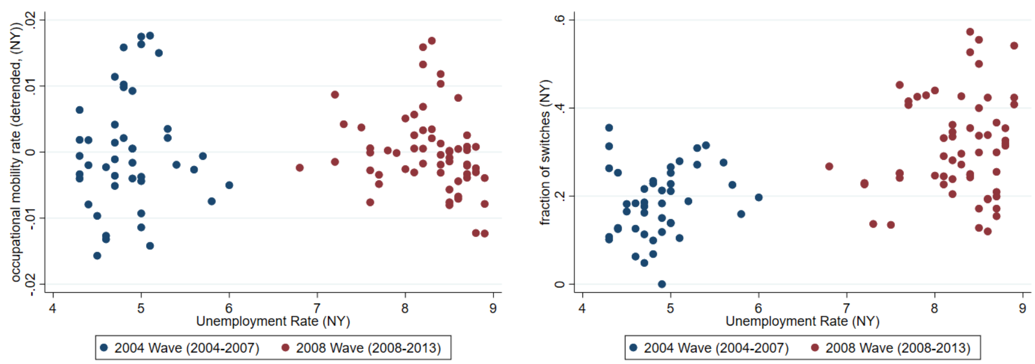

Figure A.4: *The total 1-digit occupational mobility rate (left) and the fraction of occupational switchers (1-digit) going through unemployment (right) for New York, plotted against the unemployment rate in a scatter plot.*

To show that the results discussed in Section 2 still hold on a state-level, Figure A.4 re-plots the right panel of Figures 1 and 2 for the state of New York only. As can be seen in the figures, the cyclicality of the total occupational mobility rate is still weak but countercyclical (left), and the fraction of the switches that goes through unemployment still shows a strong countercyclical pattern, although the pattern becomes substantially noisier.

Finally, to stress the point made that workers who switch occupations while unemployed (U-switchers) follow different patterns than job-to-job occupational switchers (E-switchers), Table A.11 provides some descriptive statistics on

	Non-Switchers	U-Switchers	E-Switchers	t
Age	42.031 (0.009)	36.725 (0.089)	38.922 (0.058)	20.587
Education	2.978 (0.001)	2.626 (0.008)	2.815 (0.005)	18.926
Gender (Female)	0.489 (0.000)	0.496 (0.004)	0.498 (0.003)	0.295
Wage (Before)	-	13.653 (0.208)	16.343 (0.090)	13.888
Wage (After)	-	12.924 (0.126)	16.949 (0.105)	21.939
Wage	21.677 (0.019)	-	-	-
Observations	1454355	13895	34222	

Table A.11: *Descriptive statistics for Non-switchers, U-switchers, and E-switchers, with standard errors in parentheses. The t-statistic reported in the last column refers to a t-test testing for equality of means between U-switchers and E-switchers.*

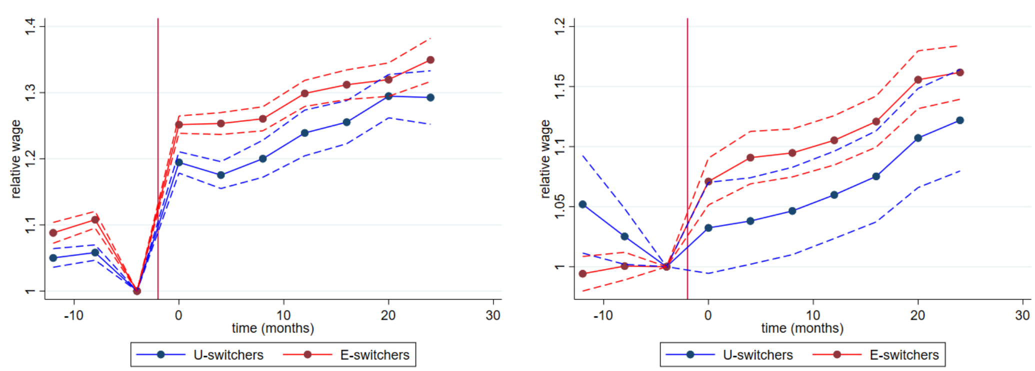

Figure A.5: *Wage paths over time for occupational U-switchers and E-switchers. The switch takes place between time -4 and 0, as represented by the vertical line at -2.*

a number of parameters of interest, separately for the two groups of occupational switchers as well as for non-switchers. As can be seen in the table, non-switchers, U-switchers and E-switchers differ substantially in especially their age and education. This difference points towards low-educated young workers mainly switching through unemployment and highly educated older (but still younger than average) workers switching on the job. Furthermore, it is true for both groups that their wage tends to be lower than the average, and for U-switchers the wage both before and after the switch is lower than that of E-switchers. Most importantly, the table stresses the point that U-switchers and E-switchers are different. Additionally, Figure A.5 plots the average wage for these two groups, from 12 months before I observe the switch until 24 months after I observe the switch and relative to the last observed wage before the switch takes place (thus not taking into account the wage difference shown in Table A.11).[43] In the left panel, I remove unrealistic wages[44], whereas in the right panel (which corresponds to Figure 4 in the main text) I furthermore restrict the respondents to have observations in all periods in the time frame.[45] As can be seen in the figure, the jump in the average wage is much larger for E-switchers, and this difference is persistent over time, although it becomes insignificant with the additional restriction in the right panel, due to the low number of remaining observations.

A.3 Additional Observations (1996 and 2001 SIPP)

In this section, I repeat the analysis of the data from Section 2 and parts of Section A.2 using the 1996 and 2001 panels of the SIPP instead. To avoid a tedious repetition of the same discussion as in the main text, I will keep the discussion of the figures rather brief. It suffices to note that all tables and figures can be interpreted in exactly the same way as the corresponding tables and figures in the

[43] Again, for U-switchers the wages before the switch refer to the wages in their previous job.

[44] Specifically, I remove observations that suggest a wage far below the minimum wage and observations with very high wages even though all other observed wages for the respondent are modest.

[45] Note that these restrictions are not made in creating Table A.11. Rather, the numbers reported in that table are raw averages.

main text (which are identified in the caption of each table and figure below).

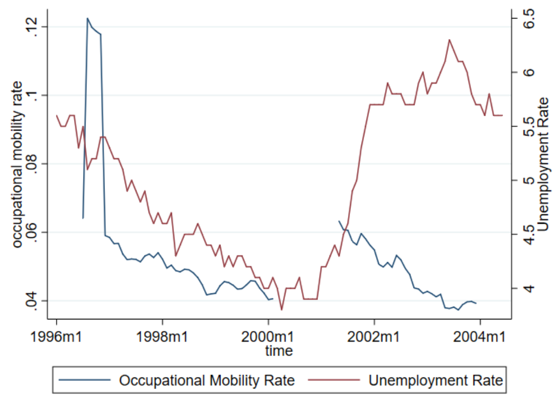

Figure A.6: *The 3-digit occupational mobility rate, plotted over time together with the corresponding month's unemployment rate from the BLS. This corresponds to Figure A.2 in the previous section.*

First, Figure A.6 plots the 3-digit occupational mobility rate. While most of the observed rate is consistent with the observed rates in the main text, the peaks in 1996 seem strange and inconsistent with the rest of the data. This peak is also observed in Xiong (2008), who notes that a potential reason for this observation is that "the occupation affiliation data are relatively inaccurate for Rotation Group 1's first 2 waves". Not taking into account this peak, it seems like the occupational mobility rate averages around 5%, consistent with my observations in Section A.2. The 1-digit occupational mobility rate, shown in the left panel of Figure A.7, averages around 4%. This rate is higher than the average rate I observed in Section 2 but is nevertheless consistent with the existing literature, which observes a decreasing trend (Xu, 2017). After detrending the mobility rates in the left panel, the right panel shows a clear (mild) procyclical pattern, again consistent with the existing literature.

Tables A.12 and A.13 list the number of occupational changes observed in the data for every possible combination of 1-digit occupations in the 1996 and 2001 SIPP panels, and the corresponding total in- and outflow for each occupation. The observations that can be drawn from these tables are identical to those made in

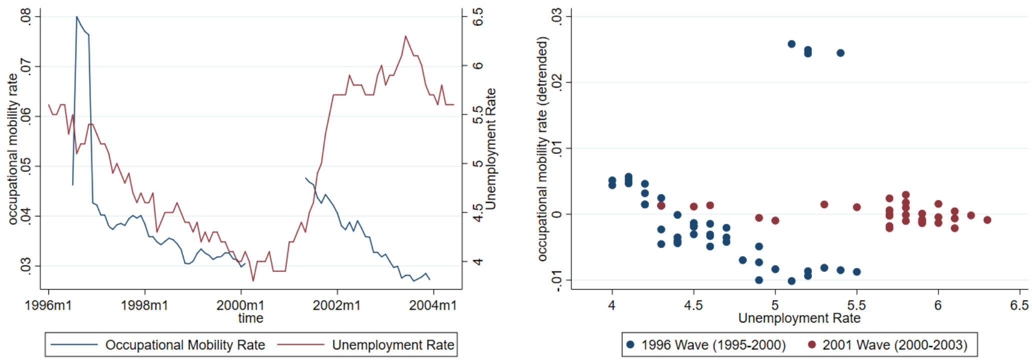

Figure A.7: *The 1-digit occupational mobility rate and the corresponding month's unemployment rate from the BLS, plotted over time (left) and against each other in a scatter plot (right). This figure corresponds to Figure 1 in the main text.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	0	1144	276	1415	1636	16	42	551	52	411	170	216	194	4
2	1221	0	413	542	799	24	32	656	86	300	179	56	138	0
3	274	530	0	167	384	6	5	252	12	240	96	36	50	0
4	1401	616	177	0	1722	55	58	1082	100	524	280	228	417	0
5	1882	885	337	1531	0	45	107	996	86	435	426	277	383	4
6	12	59	0	61	40	0	3	221	24	11	28	8	16	0
7	44	26	5	75	43	4	0	62	17	52	48	12	76	0
8	727	696	235	1154	1005	239	80	0	185	449	522	229	461	0
9	93	55	36	106	90	12	12	251	0	290	157	142	191	0
10	592	294	173	465	464	14	44	498	171	0	928	413	804	0
11	246	144	109	369	478	51	32	601	187	1060	0	323	763	0
12	166	107	36	246	259	4	20	226	122	440	255	0	352	0
13	261	146	52	416	431	12	55	496	266	849	627	478	0	0
14	0	0	0	0	0	0	0	0	0	0	0	4	0	0

Table A.12: *Number of switches found in the data for every combination of 1-digit occupations. Rows correspond to the previous occupations, and columns correspond to new occupations. For a list of the occupations corresponding to these codes, see Section A.1. This table corresponds to Table A.2 in the previous section (and thus also does not take into account sample weights)*

Occupation	1	2	3	4	5	6	7
Observations	194889	170977	52720	150005	191936	5740	8459
Inflow	6919	4702	1849	6547	7351	482	490
Outflow	6127	4446	2052	6660	7394	483	464
Net Inflow	792	256	-203	-113	-43	-1	26

Occupation	8	9	10	11	12	13	14
Observations	135035	24954	155532	106863	60880	55388	24
Inflow	5892	1308	5061	3716	2422	3845	8
Outflow	5982	1435	4860	4363	2233	4089	4
Net Inflow	-90	-127	201	-647	189	-244	4

Table A.13: *Total number of incoming and outgoing switches found in the data for every 1-digit occupations, and number of times I observe a worker in each of these occupations in the data. For a list of the occupations corresponding to these codes, see Section A.1. This table corresponds to Table 1 in the main text (and thus also does not take into account sample weights)*

the main text: it does not seem like there is specific occupation from which workers are changing or a specific occupation that workers are changing to.

Figures A.8 and A.9 analyze the differences in occupational mobility rates when counting only those switchers who went through an unemployment spell or counting only those who did not. The observations regarding level and volatility of these rates made in the main text hold here. However, it does seem like the occupational mobility rate for U-switchers and E-switchers are much closer together than observed in the main text. Similarly, the cyclical pattern of the fraction of switches going through unemployment is still countercyclical, but the relation seems weaker than it was in the main text (although that may simply be a consequence of the smaller range of unemployment rates in Figure A.9).

Finally, Figure A.10 plots the fraction of employed respondents who switch occupations in the next 4 months, and the fraction of employed respondents who do so without switching employers. As can be seen in this figure, the observation that a third of the employed workers who switch occupations do so without changing employers still holds when using the 1996 and 2001 SIPP panels instead

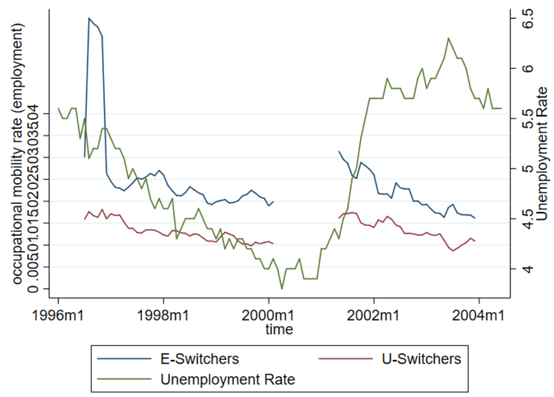

Figure A.8: *The 1-digit occupational mobility rate, counting only U-switchers or E-switchers, plotted over time together with the corresponding month's unemployment rate from the BLS. This figure corresponds to Figure A.3 in the previous section.*

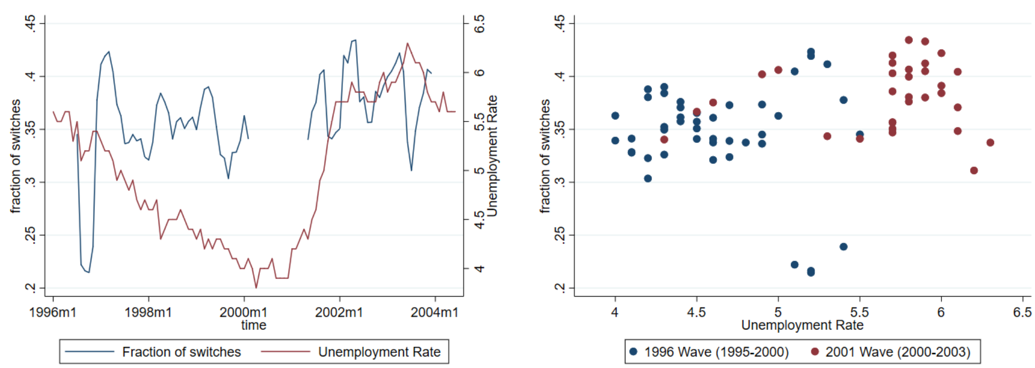

Figure A.9: *The fraction of occupational switchers (1-digit) going through unemployment and the corresponding month's unemployment rate from the BLS, over time (left) and plotted against each other in a scatter plot (right). This figure corresponds to Figure 2 in the main text.*

Figure A.10: *The fraction of employed workers switching occupations in the next 4 months, the fraction of employed workers doing so without switching employer, plotted over time together with the corresponding month's unemployment rate from the BLS. This figure corresponds to Figure 3 in the main text.*

of the 2004 and 2008 panels.

B Omitted Proofs

B.1 Proposition 1

Proposition 1: The block-recursive equilibrium exists and it is the unique equilibrium of the model.

Proof. Let $M(p,z,x_h) = W^E(p,z,x_h) + J(p,z,x_h)$ be the value of a match, and let T be an operator that maps $M(p,z,x_h)$ and $W^U(p,z,x_h)$ into the same function space. In order to do so, define Γ such that $\Gamma(p,z,x_h,0) = W^E(p,z,x_h) + J(p,z,x_h)$ and $\Gamma(p,z,x_h,1) = W^U(p,z,x_h)$. Using $\sigma(p,z,x_h) = d(p,z,x_h) = \hat{\sigma}(p,z,x_h)$, equations (4) and (7), and the free entry condition, one can rewrite $T(\Gamma(p,z,x_h,0))$ as follows (dropping the subscript h from x_h throughout, and using $(\cdot)$ instead of (p',z',x')):

$$
\begin{aligned}
T(\Gamma(p,z,x,0)) &= w(p,z,x) + \beta\mathbb{E}_{p',z',x'}\left[\max_{\hat{\sigma}(\cdot),\rho^e(\cdot)}\left\{\psi\int_{\underline{z}}^{\bar{z}} W^E(p',\tilde{z},x')dF(\tilde{z})\right.\right. \\
&\quad +(1-\psi)\left[\hat{\sigma}(\cdot)W^U(\cdot) + (1-\hat{\sigma}(\cdot))\left[(1-\rho^e(\cdot))W^E(\cdot)\right.\right. \\
&\quad \left.\left.\left.\left. +\rho^e(\cdot)\left(-c^e + R^E(\cdot)\right)\right]\right]\right\}\right] + y(p,z,x) - w(p,z,x) \\
&\quad + \beta\mathbb{E}_{p',z',x'}\left[\max_{\hat{\sigma}(\cdot)}\left\{\psi\int_{\underline{z}}^{\bar{z}} J(p',\tilde{z},x')dF(\tilde{z})\right.\right. \\
&\quad \left.\left. +(1-\psi)\left((1-\hat{\sigma}(\cdot))\left(1-\rho^e(\cdot)\int_{\underline{z}}^{\bar{z}}\lambda(\theta(p',\tilde{z},x_1))dF(\tilde{z})\right)J(\cdot)\right)\right\}\right] \\
&= y(p,z,x) + \beta\mathbb{E}_{p',z',x'}\left[\max_{\hat{\sigma}(\cdot)}\left\{\psi\int_{\underline{z}}^{\bar{z}} M(p',\tilde{z},x')dF(\tilde{z})\right.\right. \\
&\quad +(1-\psi)\left[\hat{\sigma}(\cdot)W^U(\cdot) + (1-\hat{\sigma}(\cdot))\left[\max_{\rho^e(\cdot)}\left\{(1-\rho^e(\cdot))W^E(\cdot) + \rho^e(\cdot)\left(-c^e\right.\right.\right.\right. \\
&\quad \left.\left. + \int_{\underline{z}}^{\bar{z}}[(1-\lambda(\theta(p',\tilde{z},x_1)))W^E(\cdot) + \lambda(\theta(p',\tilde{z},x_1))W^E(p',\tilde{z},x_1)]dF(\tilde{z})\right)\right\} \\
&\quad \left.\left.\left.\left. + \left(1-\rho^e(\cdot)\int_{\underline{z}}^{\bar{z}}\lambda(\theta(p',\tilde{z},x_1))dF(\tilde{z})\right)J(\cdot)\right]\right]\right\}\right]
\end{aligned}
$$

$$
\begin{aligned}
&= y(p,z,x) + \beta \mathbb{E}_{p',z',x'} \Bigg[\max_{\hat{\sigma}(\cdot)} \Bigg\{ \psi \int_{\underline{z}}^{\bar{z}} M(p',\tilde{z},x') dF(\tilde{z}) + (1-\psi) \Bigg[\hat{\sigma}(\cdot) W^U(\cdot) \\
&\quad + (1-\hat{\sigma}(\cdot)) \Bigg[\max_{\rho^e(\cdot)} \Bigg\{ \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) W^E(\cdot) \\
&\quad + \rho^e(\cdot) \left(-c^e + \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) W^E(p',\tilde{z},x_1) dF(\tilde{z}) \right) \Bigg\} \\
&\quad + \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) J(\cdot) \Bigg] \Bigg] \Bigg\} \Bigg] \\
&= y(p,z,x) + \beta \mathbb{E}_{p',z',x'} \Bigg[\max_{\hat{\sigma}(\cdot)} \Bigg\{ \psi \int_{\underline{z}}^{\bar{z}} M(p',\tilde{z},x') dF(\tilde{z}) + (1-\psi) \Bigg[\hat{\sigma}(\cdot) W^U(\cdot) \\
&\quad + (1-\hat{\sigma}(\cdot)) \Bigg[\max_{\rho^e(\cdot)} \Bigg\{ \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) \left[M(\cdot) - \frac{k\theta(\cdot)}{\lambda(\theta(\cdot))} \right] \\
&\quad + \rho^e(\cdot) \left(-c^e + \int_{\underline{z}}^{\bar{z}} [\lambda(\theta(p',\tilde{z},x_1)) M(p',\tilde{z},x_1) - k\theta(p',\tilde{z},x_1)] dF(\tilde{z}) \right) \Bigg\} \\
&\quad + \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) \frac{k\theta(\cdot)}{\lambda(\theta(\cdot))} \Bigg] \Bigg] \Bigg\} \Bigg] \qquad (10)
\end{aligned}
$$

Here, the last equality uses that (using the free entry condition and the definition of M) $J(p,z,x) = k\theta(p,z,x)/\lambda(\theta(p,z,x))$ and $W^E(p,z,x) = M(p,z,x) - k\theta(p,z,x)/\lambda(\theta(p,z,x))$.

Similarly, one can rewrite $T(\Gamma(p,z,x_h,1))$ as follows (dropping the subscript h from x_h throughout, and using $(\cdot)$ instead of (p',z',x_h)):

$$
\begin{aligned}
T(\Gamma(p,z,x,1)) &= b + \beta \mathbb{E}_{p',z'} \Bigg[\max_{\rho^u(\cdot)} \Bigg\{ \rho^u(\cdot) \left[-c^u + \int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1) dF(\tilde{z}) \right] \\
&\quad + (1-\rho^u(\cdot)) \left[\lambda(\theta(\cdot)) W^E(\cdot) + (1-\lambda(\theta(\cdot))) W^U(\cdot) \right] \Bigg\} \Bigg] \\
&= b + \beta \mathbb{E}_{p',z'} \Bigg[\max_{\rho^u(\cdot)} \Bigg\{ \rho^u(\cdot) \left[-c^u + \int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1) dF(\tilde{z}) \right] \\
&\quad + (1-\rho^u(\cdot)) \left[\lambda(\theta(\cdot)) M(\cdot) - k\theta(\cdot) + (1-\lambda(\theta(\cdot))) W^U(\cdot) \right] \Bigg\} \Bigg] \qquad (11)
\end{aligned}
$$

Throughout the rest of this proof, I will further simplify notation by not acknowledging the arguments of functions. However, in order to still acknowledge that arguments of the function differ throughout the equation, I introduce some additional notation. So, if f is a function (e.g. θ), then $f = f(p',z',x')$ (noting that

$x' = x$ if the worker is unemployed), $\bar{f} = f(p, z, x)$, and $\tilde{f} = f(p', \tilde{z}, x')$. Applying this notation, equations (10) and (11) reduce to equations (12) and (13) below:

$$
\begin{aligned}
T(\Gamma(p,z,x,0)) = \bar{y} + \beta\mathbb{E}\Bigg[\max_{\hat{\sigma}}\Bigg\{\psi \int_{\underline{z}}^{\bar{z}} \tilde{M} dF(\tilde{z}) + (1-\psi)\Bigg[\hat{\sigma} W^U \\
+(1-\hat{\sigma})\Bigg[\max_{\rho^e}\Bigg\{\rho^e\left(-c^e + \int_{\underline{z}}^{\bar{z}} [\tilde{\lambda}\tilde{M} - k\tilde{\theta}] dF(\tilde{z})\right) \\
+\left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)[M - k\theta/\lambda]\Bigg\} + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)\frac{k\theta}{\lambda}\Bigg]\Bigg]\Bigg\}\Bigg] \qquad (12)
\end{aligned}
$$

$$
\begin{aligned}
T(\Gamma(p,z,x,1)) = b + \beta\mathbb{E}\Bigg[\max_{\rho^u}\Bigg\{\rho^u\left[-c^u + \int_{\underline{z}}^{\bar{z}} \tilde{W^U} dF(\tilde{z})\right] \\
+(1-\rho^u)\left[\lambda M - k\theta + (1-\lambda)W^U\right]\Bigg\}\Bigg] \qquad (13)
\end{aligned}
$$

It can be shown that T maps continuous functions into continuous functions: After all, W^E, J, W^U, λ and y are all continuous. Because the choice ρ^u comes down to selecting $\max\{-c^u + \int_{\underline{z}}^{\bar{z}} \tilde{W^U} dF(\tilde{z}),\, \lambda M - k\theta + (1-\lambda)W^U\}$, and both these elements are continuous, so is $T(\Gamma(p,z,x,1))$. A similar argument holds for ρ^e, which comes down to selecting $\max\{W^E, \int_{\underline{z}}^{\bar{z}}[(1-\tilde{\lambda})W^E + \tilde{\lambda}\tilde{W^E}]dF(\tilde{z})\}$ and $\hat{\sigma}$, which comes down to selecting
$\max\left\{W^U, \rho^e\left(-c^e + \int_{\underline{z}}^{\bar{z}}[\tilde{\lambda}\tilde{M} - k\tilde{\theta}]dF(\tilde{z})\right) + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right) M\right\}$ (using the optimal ρ^e from the previous max operator). Therefore, $T(\Gamma(p,z,x,0))$ is also continuous. As a result, it can be concluded that T maps bounded continuous functions into bounded continuous functions, where the boundedness follows from the boundedness of p, z, and x.

To show that in fact T is a contraction mapping, one can use Blackwell's sufficiency conditions (see Stokey et al. (1989), Theorem 3.3). The monotonicity condition requires that for all $f, g \in \Gamma$ for which $f(p,z,x,n) \leq g(p,z,x,n)\ \forall p,z,x$ (on the grid) and $n = 0, 1$, it must be that $T(f(p,z,x,n)) \leq T(g(p,z,x,n))$. In this case, checking this condition entails assuming $W^U(p,z,x) \leq \hat{W^U}(p,z,x)$ and $M(p,z,x) \leq \hat{M}(p,z,x)$, and showing that this assumption implies
$T(\Gamma(p,z,x,n)) \leq T(\hat{\Gamma}(p,z,x,n))$ for both $n = 0$ and $n = 1$ (and for all p, z, x on the grid). For $n = 1$, this implication follows immediately: If $W^U(p,z,x) \leq$

$\hat{W}^U(p,z,x)$ for all (p,z,x), then it must be that $\int_{\underline{z}}^{\bar{z}} W^U dF(z) \leq \int_{\underline{z}}^{\bar{z}} \hat{W}^U dF(z)$. As it furthermore holds that $\beta \in (0,1)$, $\rho^u \in [0,1]$, and $\lambda \in [0,1]$, it follows from equation (13) that $T(\Gamma(p,z,x,1)) \leq T(\hat{\Gamma}(p,z,x,1))$. To show that $T(\Gamma(p,z,x,0)) \leq T(\hat{\Gamma}(p,z,x,0))$, a similar reasoning can be used, which leads to the conclusion that this condition will also hold if $\psi \in [0,1]$, $\hat{\sigma} \in [0,1]$, $\rho^e \in [0,1]$, and $\lambda \in [0,1]$, all of which hold by assumption. Therefore, it can be concluded that the monotonicity condition is satisfied.

The discounting condition requires that $\exists \beta \in (0,1)$ such that $T(f+a) \leq T(f) + \beta a \;\forall f \in \Gamma$, $\forall a \geq 0$, and $\forall (p,z,x)$. To show that this condition also holds, one can replace all M and W^U in equations (12) and (13) by $M+a$ and W^U+a:

$$
\begin{aligned}
T(\Gamma(p,z,x,0)+a) &= \bar{y} + \beta \mathbb{E}\left[\max_{\hat{\sigma}}\left\{\psi \int_{\underline{z}}^{\bar{z}} (\tilde{M}+a) dF(\tilde{z}) + (1-\psi)\left[\hat{\sigma}(W^U+a)\right.\right.\right. \\
&\quad + (1-\hat{\sigma})\left[\max_{\rho^e}\left\{\rho^e\left(-c^e + \int_{\underline{z}}^{\bar{z}} [\tilde{\lambda}(\tilde{M}+a) - k\tilde{\theta}] dF(\tilde{z})\right)\right.\right. \\
&\quad \left.\left.\left.\left.\left. + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)[M+a-k\theta/\lambda]\right\} + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)\frac{k\theta}{\lambda}\right]\right]\right\}\right] \\
T(\Gamma(p,z,x,0)+a) &= \bar{y} + \beta \mathbb{E}\left[\max_{\hat{\sigma}}\left\{\psi \int_{\underline{z}}^{\bar{z}} \tilde{M} dF(\tilde{z}) + \psi \int_{\underline{z}}^{\bar{z}} a dF(\tilde{z})\right.\right. \\
&\quad + (1-\psi)\left[\hat{\sigma}W^U + \hat{\sigma}a + (1-\hat{\sigma})\left[\max_{\rho^e}\left\{\left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)\left[M - \frac{k\theta}{\lambda}\right]\right.\right.\right. \\
&\quad \left. + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right) a + \rho^e\left(-c^e + \int_{\underline{z}}^{\bar{z}} [\tilde{\lambda}\tilde{M} - k\tilde{\theta}] dF(\tilde{z}) + \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} a dF(\tilde{z})\right)\right\} \\
&\quad \left.\left.\left.\left. + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)\frac{k\theta}{\lambda}\right]\right]\right\}\right] \\
T(\Gamma(p,z,x,0)+a) &= \bar{y} + \beta \mathbb{E}\left[\max_{\hat{\sigma}}\left\{\psi \int_{\underline{z}}^{\bar{z}} \tilde{M} dF(\tilde{z}) + \psi a + (1-\psi)\left[\hat{\sigma}W^U + \hat{\sigma}a\right.\right.\right. \\
&\quad + (1-\hat{\sigma})\left[a + \max_{\rho^e}\left\{\rho^e\left(-c^e + \int_{\underline{z}}^{\bar{z}} [\tilde{\lambda}\tilde{M} - k\tilde{\theta}] dF(\tilde{z})\right)\right.\right. \\
&\quad \left.\left.\left.\left.\left. + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)\left[M - \frac{k\theta}{\lambda}\right]\right\} + \left(1-\rho^e \int_{\underline{z}}^{\bar{z}} \tilde{\lambda} dF(\tilde{z})\right)\frac{k\theta}{\lambda}\right]\right]\right\}\right]
\end{aligned}
$$

$$
\begin{aligned}
&T(\Gamma(p,z,x,0)+a) = \bar{y} + \beta\mathbb{E}\left[\max_{\hat{\sigma}}\left\{\psi\int_{\underline{z}}^{\bar{z}}\tilde{M}dF(\tilde{z}) + (1-\psi)\left[\hat{\sigma}W^U\right.\right.\right. \\
&\quad +(1-\hat{\sigma})\left[\max_{\rho^e}\left\{\rho^e\left(-c^e+\int_{\underline{z}}^{\bar{z}}[\tilde{\lambda}\tilde{M}-k\tilde{\theta}]dF(\tilde{z})\right)\right.\right. \\
&\quad \left.\left.\left.\left.\left. +\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)[M-k\theta/\lambda]\right\} + \left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)\frac{k\theta}{\lambda}\right]\right]\right\}\right] + \beta a \\
&T(\Gamma(p,z,x,0)+a) = T(\Gamma(p,z,x,0)) + \beta a \qquad (14) \\
&T(\Gamma(p,z,x,1)) = b + \beta\mathbb{E}\left[\max_{\rho^u}\left\{\rho^u\left[-c^u+\int_{\underline{z}}^{\bar{z}}(\tilde{W^U}+a)dF(\tilde{z})\right]\right.\right. \\
&\quad \left.\left. +(1-\rho^u)\left[\lambda(M+a)-k\theta+(1-\lambda)(W^U+a)\right]\right\}\right] \\
&T(\Gamma(p,z,x,1)) = b + \beta\mathbb{E}\left[\max_{\rho^u}\left\{\rho^u\left[-c^u+\int_{\underline{z}}^{\bar{z}}\tilde{W^U}dF(\tilde{z})+\int_{\underline{z}}^{\bar{z}}adF(\tilde{z})\right]\right.\right. \\
&\quad \left.\left. +(1-\rho^u)\left[\lambda M-k\theta+(1-\lambda)W^U+a\right]\right\}\right] \\
&T(\Gamma(p,z,x,1)) = b + \beta\mathbb{E}\left[\max_{\rho^u}\left\{\rho^u a+\rho^u\left[-c^u+\int_{\underline{z}}^{\bar{z}}\tilde{W^U}dF(\tilde{z})\right]\right.\right. \\
&\quad \left.\left. +(1-\rho^u)a+(1-\rho^u)\left[\lambda M-k\theta+(1-\lambda)W^U\right]\right\}\right] \\
&T(\Gamma(p,z,x,1)) = b + \beta\mathbb{E}\left[\max_{\rho^u}\left\{\rho^u\left[-c^u+\int_{\underline{z}}^{\bar{z}}\tilde{W^U}dF(\tilde{z})\right]\right.\right. \\
&\quad \left.\left. +(1-\rho^u)\left[\lambda M-k\theta+(1-\lambda)W^U\right]\right\}\right] + \beta a \\
&T(\Gamma(p,z,x,1)) = T(\Gamma(p,z,x,1)) + \beta a \qquad (15)
\end{aligned}
$$

From equations (14) and (15) it can be concluded that for both $n = 0$ and $n = 1$ it holds that $T(\Gamma(p,z,x,n)+a) \leq T(\hat{\Gamma}(p,z,x,n)) + \beta a$. As the derivation above does not rely on the actual value taken by W^U, M or a, and since $\beta \in (0,1)$ by assumption, it can thus be concluded that the discounting condition is also satisfied. Therefore, it can be stated that T is a contraction mapping, which by the contraction mapping theorem (see Stokey et al. (1989), Theorem 3.2) has a unique fixed point. This fixed point is a candidate for a BRE.

The fixed point of contraction mapping T contains functions $M(p,z,x)$ and $W^U(p,z,x)$. As W^E can be calculated using these two objects using

$W^E(p,z,x) = (1-\eta)M(p,z,x)+\eta W^U(p,z,x)$, which follows from the Nash bargaining condition (equation 2), and $V(p,z,x)$ follows from the free entry condition, it can be concluded that all value functions can be obtained from the fixed point. One can then use the free entry condition to calculate $\theta(p,z,x)$, after which functions d, σ, ρ^u, and ρ^e follows from the inequality conditions above (in the paragraph following equation 13), and $w(p,z,x)$ can be calculated from the expression for $J(p,z,x)$ (equation 7). Finally, the expression for $W^E(p,z,x)$ (equation 4) is satisfied by construction, given that the expression for $J(p,z,x)$ holds and $M(p,z,x)$ is a combination of the expressions for $J(p,z,x)$ and $W^E(p,z,x)$. Therefore, it can be concluded that this fixed point of T satisfies all the equilibrium conditions, thus completing the proof of existence of the BRE.

In order to prove uniqueness, first suppose that the BRE constructed above is not the unique BRE as a function of p, z, and x. Then, there must be a second set of functions $W^U, W^E, J, V, \theta, w, d, \sigma, \rho^u, \rho^e$ that satisfies the equilibrium conditions. Using W^U, W^E, and J from that second set of functions, one can then construct a corresponding $\Gamma(p,z,x,0)$ and $\Gamma(p,z,x,1)$, which must be a fixed point of T. After all, if this set $\Gamma(p,z,x,0)$ and $\Gamma(p,z,x,1)$ would not be a fixed point of T, the equilibrium conditions (specifically at least one of equations 3, 4, and 7) are not satisfied. However, this conclusion contradicts the uniqueness of the fixed point of T, thus contradicting the existence of this second set of equilibrium functions. As there is no reason to believe the equilibrium functions depend on anything other than the three productivity variables p, z, and x, given that no other variables enter in any of the equilibrium conditions, this contradiction completes the proof of uniqueness.

$\square$

B.2 Proposition 2

Proposition (Proposition 2)**.** *Unless c^e is prohibitively high or $\lambda(p,z,x_1) = 0$ for all (p,z), the block-recursive equilibrium is not constrained efficient.*

Proof. Throughout this proof, denote by $\mathcal{E}_t^j$ the distribution of unemployed and employed workers over all occupations at the start of subperiod j or period t. Similarly, let $\Omega_t^j = \{es_t, o_t, p_t, z_t, x_h, \mathcal{E}_t^j\}$ be the state space for a worker at the start of subperiod j of period t. Here, es_t denotes the worker's employment status, and o_t denotes the worker's current occupation. In order to evaluate the (constrained) efficiency of the BRE, I will compare the social planner's problem (in recursive form) with the operator T defined in the proof of Proposition 1 (Section B.1).In general, one can write down the social planner's problem as follows:

$$\max_{d(\cdot),\rho^u(\cdot),\rho^e(\cdot),v(\cdot)} \mathbb{E}\left[\sum_{t=0}^{\infty}\beta^t\sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}\Big[u_{o,t}(z,x_h)b + e_{o,t}(z,x_h)y(p_t,z,x_h)\right.$$
$$\left. - \Big(c^u\rho^u(\cdot)u_{o,t}(z,x_h) + c^e\rho^e(\cdot)(1-\psi)(1-d(\cdot))e_{o,t}(z,x_h) + kv_{o,t}(\cdot)\Big)\Big]\, dz\right]$$

s.t. equations (8) and (9), and initial p_0 and $\mathcal{E}_0$ (16)

Note that the functions d, ρ^u, and ρ^e represent the same decision as in the decentralized economy, but now are also a function of $\mathcal{E}_t^j$. Specifically, as these decisions are made at different subperiods, they are functions of $\mathcal{E}_t^{sep}$, $\mathcal{E}_t^{re}$, and $\mathcal{E}_t^{re}$ respectively (where "sep" stands for the third (separation) subperiod, and "re" stands for the fourth (reallocation) subperiod). The function $v_{o,t}(p_t, z_t, x_h, \mathcal{E}_t^{mat})$ denotes the number of vacancies posted at time t in a market for occupation o that is characterized by productivity parameters z_t and x_h. As the decision to set a vacancy is made in the matching (fifth) subperiod, the relevant distribution is $\mathcal{E}_t^{mat}$.

The social planner's problem can be written in recursive form. To do so, define operator T^{SP} as follows:

$$
\begin{aligned}
T^{SP}W^{SP}(\Omega^{prod}) = & \max_{d(\cdot),\rho^u(\cdot),\rho^e(\cdot),v(\cdot)} \Bigg\{ \sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} \Big(e_{o,t}(z,x_h) y(p_t,z,x_h) \\
& + u_{o,t}(z,x_h) b \Big) dz + \beta \mathbb{E}_{p',z',x'} \Bigg[- \Bigg(k \sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} v_o(p',z',x'_h,\mathcal{E}^{mat\prime}) dz' \\
& + c^e \sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} \rho^e(p',z',x'_h,\mathcal{E}^{re\prime})(1-\psi)(1-d(p',z',x'_h,\mathcal{E}^{sep\prime}))e_o(z',x'_h)dz' \\
& + c^u \sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} \rho^u(p',z',x'_h,\mathcal{E}^{re\prime}) u_o(z',x'_h)dz' \Bigg) + W^{SP}(\Omega^{prod\prime}) \Bigg] \Bigg\} \qquad (17)
\end{aligned}
$$

Note that the maximization here is still subject to the flow equations (8) and (9) and the initial conditions for p and $\mathcal{E}$. Furthermore, note that the problem is defined in the last (production) subperiod. As at that point all the reallocation for the period has already taken place, the terms in the expectation refer to u_o and e_o rather than u'_o and e'_o. Finally, it should be noted that one could replace the maximization with respect to $v_o(p,z,x_h,\mathcal{E}^{mat})$ with a maximization with respect to labour market tightness $\theta_o(p,z,x_h,\mathcal{E}^{mat})$, with:

$$
\begin{aligned}
& v(\cdot) = \theta(\cdot)(1-\rho^u(p,z,x_h,\mathcal{E}^{re}))u_o(z,x_h) = \Psi \text{ for } h \neq 1 \\
& v(\cdot) = \theta(\cdot)\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}(1-d(p,\tilde{z},x_h,\mathcal{E}^{sep}))\rho^e(p,\tilde{z},x_h,\mathcal{E}^{re})(1-\psi)e_o(\tilde{z},x_h)d\tilde{z}dF(z) \\
& \qquad + \Psi \text{ for } h = 1
\end{aligned}
$$

Defining $u(z,x_h) = \sum_{o=1}^{O} u_o(z,x_h)$ and $e(z,x_h) = \sum_{o=1}^{O} e_o(z,x_h)$, one can now use the fact that the social planner's problem in equation (17) is linear in both $u_o(z,x_h)$ and $e_o(z,x_h)$ to argue that then the functions $d(\cdot)$, $\rho^u(\cdot)$, $\rho^e(\cdot)$ and $\theta(\cdot)$ should be independent of $\mathcal{E}^j_t$. The linearity of W^{SP} (and therefore of $T^{SP}W^{SP}$) furthermore implies that the problem can be separated into two parts: one relevant to unemployed workers and one relevant to employed workers. Defining the corresponding values $W^U(p, z, x_h)$ and $M(p, z, x_h)$, one could thus write

$$W^{SP}(\Omega^{prod}) = \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \left[W^U(p, z, x_h) u(z, x_h) + M(p, z, x_h) e(z, x_h) \right] dz \tag{18}$$

Plugging this equation into the recursive formulation of the social planner's problem, equation (17), then gives:

$$\begin{aligned}
T^{SP}W^{SP}(\Omega^{prod}) = \max_{d(\cdot), \rho^u(\cdot), \rho^e(\cdot), \theta(\cdot)} & \left\{ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \left(u(z, x_h) b + e(z, x_h) y(p, z, x_h) \right) dz \right. \\
& + \beta \mathbb{E}_{p', z', x'} \left[-c^u \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \rho^u(p', \tilde{z}, x'_h) u(\tilde{z}, x_h) d\tilde{z} \right. \\
& - c^e \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \rho^e(p', \tilde{z}, x'_h)(1 - \psi)(1 - d(p', \tilde{z}, x'_h)) e(\tilde{z}, x'_h) d\tilde{z} \\
& - k \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \theta(p', \tilde{z}, x'_h) \left[(1 - \rho^u(p', \tilde{z}, x'_h)) u(\tilde{z}, x'_h) \right. \\
& \left. + \mathbb{1}_{h=1} \sum_{\tilde{h}=1}^{H} \int_{\underline{z}}^{\bar{z}} (1 - d(p', \ddot{z}, x'_{\tilde{h}})) \rho^e(p', \ddot{z}, x'_{\tilde{h}})(1 - \psi) e(\ddot{z}, x'_{\tilde{h}}) d\ddot{z} dF(\tilde{z}) \right] d\tilde{z} \\
& \left. \left. + \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} W^U(p', \tilde{z}, x'_h) u(\tilde{z}, x'_h) d\tilde{z} + \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} M(p', \tilde{z}, x'_h) e(\tilde{z}, x'_h) d\tilde{z} \right] \right\}
\end{aligned} \tag{19}$$

Again, the maximization here is still subject to the flow equations (8) and (9) and the initial conditions for p and $\mathcal{E}$. However, I can now use these flow equations so that the equation is only in terms of current values $u(z, x_h)$ and $e(z, x_h)$. Then, and with some further rearrangement, the equation can be rewritten as the following recursive problem, only subject to initial conditions for p and $\mathcal{E}$:

$$
\begin{aligned}
T^{SP}W^{SP}(\Omega^{prod}) = &\max_{d(\cdot),\rho^u(\cdot),\rho^e(\cdot),\theta(\cdot)} \Bigg\{ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} bu(z,x_h)dz \\
&+ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \beta \mathbb{E}_{p',z'} u(z,x_h) \Big[-k\theta(p',z',x_h)(1-\rho^u(p',z',x_h)) \\
&-c^u\rho^u(p',z',x_h) \Big] dz + \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} y(p,z,x_h)e(z,x_h)dz \\
&+ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \beta \mathbb{E}_{p',z',x'} \Big[-c^e\rho^e(p',z',x'_h)(1-d(p',z',x'_h)) \Big] (1-\psi)e(z,x_h)dz \\
&+ \int_{\underline{z}}^{\bar{z}} \beta \mathbb{E}_{p',z'} \Bigg[-k\theta(p',z',x_1) \sum_{\tilde{h}=1}^{H} \int_{\underline{z}}^{\bar{z}} (1-d(p',\tilde{z},x'_{\tilde{h}}))\rho^e(p',\tilde{z},x'_{\tilde{h}})(1-\psi) \\
&\times e(\tilde{z},x'_{\tilde{h}})d\tilde{z}dF(z) \Bigg] dz + \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \beta \mathbb{E}_{p',z'} \Bigg[\rho^u(p',z',x_h) \int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1)dF(\tilde{z}) \\
&+(1-\rho^u(p',z',x_h)) \Big[\lambda(\theta(p',z',x_h))M(p',z',x_h) \\
&+(1-\lambda(\theta(p',z',x_h)))W^U(p',z',x_h) \Big] \Bigg] u(z,x_h)dz \\
&+ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \beta \mathbb{E}_{p',z',x'} \Bigg[\psi \int_{\underline{z}}^{\bar{z}} M(p',\tilde{z},x'_h)dF(\tilde{z}) \\
&+(1-\psi) \bigg(d(p',z',x'_h)W^U(p',z',x'_h) \\
&+(1-d(p',z',x'_h)) \Big[\rho^e(p',z',x') \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1))M(p',\tilde{z},x_1)dF(\tilde{z}) \\
&+ \bigg(1-\rho^e(p',z',x') \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1))dF(\tilde{z}) \bigg) M(p',z',x') \Big] \bigg) \Bigg] e(z,x)dz \Bigg\}
\end{aligned} \tag{20}
$$

Once again using $(\cdot)$ instead of (p', z', x'_h) (where $x'_h = x_h$ for unemployed workers), this equation simplifies as follows:

$$
\begin{aligned}
T^{SP}W^{SP}(\Omega^{prod}) = & \max_{d(\cdot),\rho^u(\cdot),\rho^e(\cdot),\theta(\cdot)} \left\{ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} u(z,x_h) \, (b \right. \\
& + \beta \mathbb{E}_{p',z'} \left[\left(\int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1) dF(\tilde{z}) - c^u \right) \rho^u(\cdot) \right. \\
& \left. \left. + (1-\rho^u(\cdot)) \left(\lambda(\theta(\cdot)) M(\cdot) + (1-\lambda(\cdot)) W^U(\cdot) - k\theta(\cdot) \right) \right] \right) dz \\
& + \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} e(z,x_h) \left(y(p,z,x_h) + \beta \mathbb{E}_{p',z',x'} \left[\psi \int_{\underline{z}}^{\bar{z}} M(p',\tilde{z},x') dF(\tilde{z}) \right. \right. \\
& + (1-\psi) \left[d(\cdot) W^U(\cdot) + (1-d(\cdot)) \left[\left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) M(\cdot) \right. \right. \\
& \left. \left. \left. \left. \left. + \rho^e(\cdot) \left(\int_{\underline{z}}^{\bar{z}} \left[\lambda(\theta(p',\tilde{z},x_1)) M(p',\tilde{z},x_1) - k\theta(p',\tilde{z},x_1) \right] dF(\tilde{z}) - c^e \right) \right] \right] \right] \right) dz \right\}
\end{aligned} \tag{21}
$$

Given that most functions that are being chosen in this problem only appear in part of the rewritten problem in equation (21), this equation can be rewritten as follows:

$$
\begin{aligned}
& T^{SP}W^{SP}(\Omega^{prod}) = \\
& \qquad \max_{\theta(\cdot)} \left\{ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \left[W^U_{\max}(p,z,x_h) u(z,x_h) + M_{\max}(p,z,x_h) e(z,x_h) \right] dz \right\}
\end{aligned} \tag{22}
$$

Here, $W^U_{\max}(p,z,x_h)$ and $M_{\max}(p,z,x_h)$ are defined as follows:

$$
\begin{aligned}
W^U_{\max}(p,z,x_h) = & \max_{d(\cdot),\rho^e(\cdot)} \left\{ b + \beta \mathbb{E}_{p',z'} \left[\left(\int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1) dF(\tilde{z}) - c^u \right) \rho^u(\cdot) \right. \right. \\
& \left. \left. + (1-\rho^u(\cdot)) \left(\lambda(\theta(\cdot)) M(\cdot) + (1-\lambda(\cdot)) W^U(\cdot) - k\theta(\cdot) \right) \right] \right\}
\end{aligned} \tag{23}
$$

$$
\begin{aligned}
M_{\max}(p,z,x_h) = & \max_{\rho^u(\cdot)} \left\{ y(p,z,x_h) + \beta \mathbb{E}_{p',z',x'} \left[\psi \int_{\underline{z}}^{\bar{z}} M(p',\tilde{z},x') dF(\tilde{z}) \right. \right. \\
& + (1-\psi) \left[d(\cdot) W^U(\cdot) + (1-d(\cdot)) \left[\left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) M(\cdot) \right. \right. \\
& \left. \left. \left. \left. + \rho^e(\cdot) \left(\int_{\underline{z}}^{\bar{z}} \left[\lambda(\theta(p',\tilde{z},x_1)) M(p',\tilde{z},x_1) - k\theta(p',\tilde{z},x_1) \right] dF(\tilde{z}) - c^e \right) \right] \right] \right] \right\}
\end{aligned} \tag{24}
$$

Note the resemblance between $M_{\max}(p, z, x_h)$ and $T(\Gamma(p, z, x_h, 0))$ (in equation 10) and between $W^U_{\max}(p, z, x_h)$ and $T(\Gamma(p, z, x_h, 1))$ (in equation 11), taking $\hat{\sigma}(\cdot) = d(\cdot)$. Nevertheless, if one looks closely at $M_{\max}(p, z, x_h)$ in equation (24) and $T(\Gamma(p, z, x_h, 0))$ in equation (10), it can be seen that the two are not exactly identical. After all, in equation (10), the maximization for function $\rho^e(\cdot)$ does not take into account all terms in which this function enters. Specifically, this difference means that in a competitive market, the term that is not taken into account when the employed worker makes his reallocation decision is as follows:

$$\left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p', \tilde{z}, x_1)) dF(\tilde{z})\right) \frac{k\theta(\cdot)}{\lambda(\theta(\cdot))}$$

This term specifically represents the value lost by the current employer if the worker decides to quit his job and change occupations. Looking at equation (10), a similar term appears negatively inside the maximization, meaning that if one were to expand the maximization to cover this extra term at the end, it would cancel out and reduce equation (10) to equation (24). Therefore, the only way to ensure that the social planner's problem (which takes this term into account) and the decentralized problem give the same solution (thus implying that the decentralized problem's solution is contrained efficient) is to place restrictions on the parameters in the extra term that will make it cancel out. Specifically, the extra term can be cancelled out by setting $\lambda(\theta(p', \tilde{z}, x_1))$ for all p and $\tilde{z}$, so that the integral evaluates to zero, or by setting reallocation cost c^e prohibitively high, so that the worker would always set $\rho^e(p, z, x_h) = 0$. $\square$

C Simulation Method

C.1 Solution Method

Due to its size and structure, the model presented in Section 3 is not analytically solvable. Instead, in order to obtain the results in Section 5, I solve the model numerically. The step-by-step procedure followed to obtain the model solution in this paper is described below. It takes as given the values for the parameters $(\beta, O, \chi, \psi, \phi, b, c^u, c^e, \eta, \delta, k, \rho_p, \sigma_p, \sigma_z, z_0, x_2, x_3)$, and results in the equilibrium values for all equilibrium objects (W^U,W^E,J,V,d,ρ^u,ρ^e,σ,θ,w, all functions of p,z, and x). Below, I refer to the number of grid points for p_t, z_t, and x_t as N_p, N_z and N_x. The algorithm closely follows the proof of Proposition 1:

1. In order to obtain the grid for (x, p, z), the process for p_t and z_t needs to be discretized. I do so using Tauchen method, which requires (besides the number of desired grid points for each of these two productivity variables) a value for σ_p (σ_z for z_t), ρ_p (ρ_z for z_t), μ_p (μ_z for z_t), and an upper and lower limit to the grid. Of these parameters, μ_p is set equal to 1, and all the others are parameters set in the calibration (with $\mu_z = z_0$), just like the values for x_h ($h \neq 1$). The upper and lower limits for p_t are set to 1.04 and 0.96 respectively, whereas the upper and lower limits for z_t depend on the value of z_0. These limits for z_t are set at a symmetric distance from μ_z, with the distance determined by the maximum of the absolute distance between μ_z and 0.7 or 0.4 respectively.

2. Defining $M \equiv J + W^E$, guess a value for M and W^U, for every triple (p, z, x) on the grid.

3. Using equation (2) and the guess for $M(p, z, x)$ and $W^U(p, z, x)$, calculate the value of $J(p, z, x) = \eta M(p, z, x) - \eta W^U(p, z, x)$ and $W^E(p, z, x) = M(p, z, x) - J(p, z, x)$

4. Using the expression for the value function V (equation (6)), and using that by the free entry condition $\mathbb{E}_{p'}\left[V(p', z, x_h)\right] = 0$, solve for $q(\theta(p, x, z))$, $\theta(p, z, x)$, and $\lambda(\theta(p, z, x)$, using the value of $J(p, x, z)$. Specifically, using the value for $J(p, z, x)$, calculate $q(\theta(p, z, x))$ that will make equation (6) equal to zero if $J(p, z, x) > k$, or set $q(\theta(p, z, x)) = 0$ if $J(p, z, x) \leq k$ (Using k instead of 0 as a value for J in between would imply $q(\theta) > 1$). Then, use the matching function $q(\theta(p, z, x)) = \frac{1}{1+\theta(p,z,x)}$ to back out $\theta(p, z, x)$

and calculate $\lambda(\theta(p,z,x)) = \frac{\theta(p,z,x)}{1+\theta(p,z,x)}$, or set both of these equal to zero (if $J(p,z,x) < k$).

5. Using equation (3), and using the obtained values for $W^E(p,z,x)$, $W^U(p,z,x)$ and $\lambda(\theta(p,z,x))$, solve for $\rho^u(p,z,x)$: From equation (3), it can be concluded that $\rho^u(p,z,x) = 1$ if $W^U(p,z,x_h) + \lambda(\theta(p,z,x_h))(W^E(p,z,x_h) - W^U(p,z,x_h)) < -c^u + \int_{\underline{z}}^{\bar{z}} W^U(p,\tilde{z},x_1)dF(\tilde{z})$ and $\rho^u(p,z,x) = 0$ otherwise.

6. Use the expression for the value function W^E (equation (4)) to solve for $\rho^e(p,z,x)$. From the equation, it can be concluded that $\rho^e(p,z,x) = 1$ if $-c^e + R^E(p,z,x) > W^E(p,z,x)$ (where $R^E(p,z,x)$ is evaluated using equation (5)) and $\rho^e(p,z,x) = 0$ otherwise. Simply evaluating this condition will give the desired solution.

7. Using the expression for the value function for J (equation (7)) and the values obtained above, solve for $d(p,z,x)$ and $\sigma(p,z,x)$: From equation (7), it can be concluded that $\sigma(p,z,x) = 1$ if $J(p,z,x) < V(p,z,x)$ and $\sigma(p,z,x) = \delta$ otherwise. Using this condition (and the free entry condition), conclude that $\sigma(p,z,x)$ in the equation will equal $\delta + (1-\delta)\cdot \mathbb{1}\{J(p,z,x) < 0\}$, which can be calculated given the current guess of $J(p,z,x)$. As it can be argued that the firm will always decide to separate if the worker does (but not necessarily the other way around), set $d(p,z,x) = \sigma(p,z,x)$.[46]

8. Now update $M(p,z,x)$ and $W^U(p,z,x)$ for all triples (p,z,x), using equations (10) and (11) (from Appendix B.1). Unless convergence has been reached, return to step 4.

9. Once convergence is reached, one can obtain the wage $w(p,z,x)$ implied by the solution through either equation (4) or (7). As the solutions will differ

[46]This argument holds because the separation decision of the firm is based on the inequality $J(p,z,x) < 0$, while the worker's separation decision is is based on the inequality $W^U > (1-\rho^e(p,z,x))W^E + \rho^e(p,z,x)(-c^e + R^E(p,z,x)) \geq W^E$, where the last inequality is strict if $\rho^e(p,z,x) = 1$. This statement implies that there can be a situation where $J(p,z,x) < 0$ and thus (by Nash bargaining) $W^E(p,z,x) - W^U(p,z,x) < 0$, and yet the worker decides not to separate.

very slightly, I take the average of the two wages for the purpose of the simulation. One can also simplify the laws of motion of u_o and e_o (if desired), by using all the values obtained for the other equilibrium objects and plugging them into the corresponding equations (8) and (9).

C.2 Calibration Method

As mentioned in the main text, the calibration of most parameters involves the estimation of the model counterparts of a set of 17 moments. These parameters are then set to minimize the distance between these moments and the corresponding moments from the data. In this section, I will describe how the model counterparts of the moments are estimated.

The model counterparts of the targeted moments are all estimated from the simulation that is obtained after solving the model (the steps for which were described in the previous subsection). Specifically, I use the equilibrium solutions for all the relevant equilibrium objects ($d, \rho^u, \rho^e, \sigma, \theta, w$), as well as parameters ($O, \chi, \psi, \phi, \delta, x_2, x_3$) and transition matrices (for z and p) to create multiple time series that mimic the SIPP in terms of their age and employment distribution in the first period[47] and in terms of their length (which is set to 5 years). In each of these simulations, I follow the timing of the model (described in Section 3) in recording the decisions.

As I create a total of $N_{sim} = 250$ such time series, each with a length of $T_{sim} = 240$ periods and $I_{sim} = 1000$ individuals, and each period corresponds to approximately one week[48], I end up with a panel of 250000 individuals, followed over 5 years. This panel will contain information on each individual's age, wage,

[47]The initial distribution used here is that of the fourth month of the combined SIPP of 2004 and 2008 (so that each rotation group of the original SIPP is included). Furthermore, I base the initial distribution of agents over x_1, x_2 and x_3 on age, setting $x = x_1$ if the agent is 35 years old or younger and setting $x = x_3$ if the agent is 49 years old or older.

[48]To be precize, the model period is set to one quarter of a month, so that it is easy to generate monthly statistics, while still keeping the relatively short periods. Furthermore, the simulation used to generate is actually substantially longer than T_{sim} periods, in order to account for differences caused by the initial distribution I impose.

employment status, occupation, production (if employed), labour market tightness (if unemployed), as well as information on the individual's employment (and occupation) history. Most of the tracked variables follow directly from the model variables, combined with the specific values for p, z, and x that an individual is faced with in a certain period. The only variable that does not immediately follow from variables in the model is the age of the worker, which is tracked starting from the initial age by simply adding on a year every 48 periods, assuming that the group of individuals of a certain age in the first period was spread evenly among weeks (for example, the number of agents aged 23 years and 4 weeks is roughly the same as the number of agents aged 23 years and 32 weeks). Similarly, whenever an agent dies, the newborn agent is assumed to be exactly 23 years old (which was the minimum age in the SIPP). Once an agent turns 62 the simulation of the remainder of her life is no longer relevant to the estimation of the moments (as the estimation from the SIPP had a maximum age of 61). However, the simulation is continued as it is used to determine when a new agent enters the sample.

After obtaining the simulation data, the model counterparts of all 17 moments are estimated. The procedure for each of these moments is described below:

- Average job-finding rate: This particular moment is rather straightforward to estimate from the simulated data. For each month in the simulation (so once every four periods), I take all workers who are unemployed. The proportion of those workers who are employed again 4 months later is the job-finding rate for that particular period, thus mimicking the procedure followed with the SIPP data, where I compare employment status across waves. The average job-finding rate is then simply the average of all the job-finding rates. Note that this moment thus ignores workers who are employed but decided to search for a job in another occupation. I ignore these workers because this search pattern would not have been observed in the SIPP data either.
- Persistence and volatility of aggregate productivity: In order to estimate the

model counterpart of this moment, I follow the exact same procedure as the one used to obtain this moment from the data. First, I calculate the total output in the economy by summing up the value of $y = pxz$ for all employed workers. Then, the aggregate productivity will be this total, divided by the number of employed workers. Then, to mimic the quarterly data structure of the BLS data, I average this number for every quarter. The persistence and volatility is then obtained by estimating an AR(1) process from the resulting time series.

- Returns to occupational experience (5 and 10 years): In order to estimate the model counterpart, I use a simple OLS regression of the log of the wage of all employed agents in the simulation on their years of occupational experience (counting only years of employment as attributing to experience), thereby mimicking the OLS regressions in Kambourov and Manovskii (2009b) without the additional variables that were included there (such as marital status and age).

- Unemployment survival rates (for 4, 8, and 12 months): The model counterpart of these moments are estimated by taking all workers in the model simulation that are newly unemployed at the start of a certain month of the simulation. The moment of interest is then the proportion of these workers that is still unemployed after the specified time (4, 8, or 12 months) has passed.

- Occupational mobility rate for unemployed workers (at durations of 1, 3, 6, 9, and 12 months): For these moments, I define a switch to take place once the worker matched with a firm in a different occupation than the one she worked in last. Thus, while switching back and forth between occupations while being unemployed will destroy the agent's human capital in the model, it will not count as an occupational switch for the purpose of this moment. After all, I would not have observed this switch in the data either. Specifically, the model counterpart of these moments will be the proportion of workers who were unemployed for at least the specified number of months (1, 3, 6, 9, and 12) and eventually found a job in a different occupation than her previous occupation of employment.

- Subsequent mobility rate: The model counterpart of this model is the reason why I need to keep track of the occupational mobility in the previous (complete) unemployment spell. Following Carrillo-Tudela and Visschers (2014), I estimate the model counterpart directly as the proportion of occupational stayers who again do not switch occupations in their next unemployment spell. Here, "occupational stayers" thus refers to agents who did not switch occupations while being unemployed. Thus, the estimation of the model counterpart of this moment does not take into account any switches that the worker may have made while being employed.

- Relative occupational mobility rate of unexperienced workers (relative to experienced workers): As this moment is one of the moments that were also used in Carrillo-Tudela and Visschers (2014), the occupational mobility here is defined as the proportion of unemployed workers who eventually find a job in a different occupation, thus ignoring occupational transitions without an unemployment spell. Mimicking the structure of the SIPP, the observations of interest will be the first period of a certain month and the period 4 months (16 periods) later.

- Occupational mobility rate for employed workers: Finally, the model counterpart of this moment is estimated by determining the proportion of employed workers who are still employed, but in a different occupation, 4 months later (thus again mimicking the wave structure of the SIPP). Note that the estimation of the value for ψ is done similarly, but with the additional criterion that the worker is still working for the same employer.[49]

[49]This estimation method is also part of the reason why I choose to set ψ exogenously. After all, in my simulation I do not keep track of the firm in which the worker is working.

D Additional Simulation Results

In this section, I show some further results arising from the simulation of the calibrated model. While these results provide some additional insight into the patterns generated by the model, discussed in Section 5, the results presented in this section are not critical for the conclusions reached in that section.

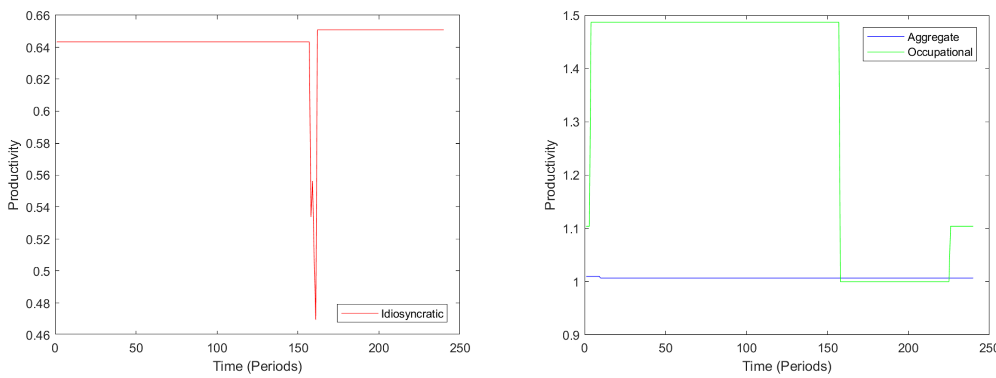

Figure D.1: *The evolution of idiosyncratic productivity z as well as aggregate productivity p and occupational human capital x for a single panel ID number over the entire panel duration.*

As there are a number of variables and decisions to keep track of for every individual, it might be useful to consider a single individual's path throughout the panel. Figure D.1 plots one individual's values for aggregate productivity p, idiosyncratic productivity z, and occupational human capital x, over the entire duration of the panel. This particular individual is employed at the start of the panel[50], and soon sees her occupational human capital increase from the second to the third level. She then remains employed for a number of periods until period 158, where she dies. At that point, the individual is replaced by a newborn individual in the same occupation, but with the lowest level of occupational human capital, a randomly drawn value of idiosyncratic productivity z, and without a job. In this case, the newborn individual drew a value of z below the reallocation threshold and

[50]Note that this observation is not necessarily implied by the graph. Rather, this information is taken from this individual's data on other variables (not displayed in the figures).

switched occupations. She switches occupations a number of times, as reflected by the multiple large changes in z in those periods. Eventually, she draws a high enough value of z to make her decide not to reallocate. Indeed, one period later the newborn individual finds a job, and a number of periods later she sees her occupational human capital increase from the lowest level to the second level.

As in Carrillo-Tudela and Visschers (2014), it is possible to decompose the unemployment rate generated by the model into three types: rest, search and reallocation unemployment. Rest unemployment would occur if the worker decides to separate but not reallocate. As the separation decision coincides with the threshold below which the probability of obtaining a job is zero, such a worker will remain unemployed until shocks in either p or z push him either to a combination with a positive job-finding probability (above the separation threshold)[51] or to a combination which leads the worker to reallocate. However, Figure 5 in the main text reveals that there are no combinations of p, z and x for which the worker decides to separate but not reallocate, and thus one should not expect to see any rest unemployment in the simulation. There is also the possibility for workers to be unemployed with a combination of p, z and x above the separation threshold. These workers will have a positive job-finding probability and they are referred to as search unemployed. Finally, the workers who changed occupations because their combination of p, z and x lead them below the reallocation threshold are by assumption not allowed to search for a job in the same period as their reallocation. Regardless of their new value of z, these workers are referred to as reallocation unemployed.[52]

[51] The separation threshold coincides with the threshold below which job-finding probability is zero, because the separation decision made by the firm is based on whether the value of producing is positive. If it is not positive (and thus the firm decides to separate), the firm would also not want to post a vacancy for this productivity combination, as finding a match would lead to negative profits as opposed to the zero expected profits of posting a vacancy anywhere with a positive value of producing. Thus, there will be no vacancies in these markets, implying a job-finding probability of zero.

[52] Note that it is possible for an unemployed worker to locate below the (unemployed) reallocation and separation thresholds for one period, as a consequence of not being able to immediately reallocate when the match is destroyed. As these workers will reallocate in the next period, I will consider these workers to be reallocation unemployed. Therefore, these workers will be reallocation unemployed for (at least) two periods in a row.

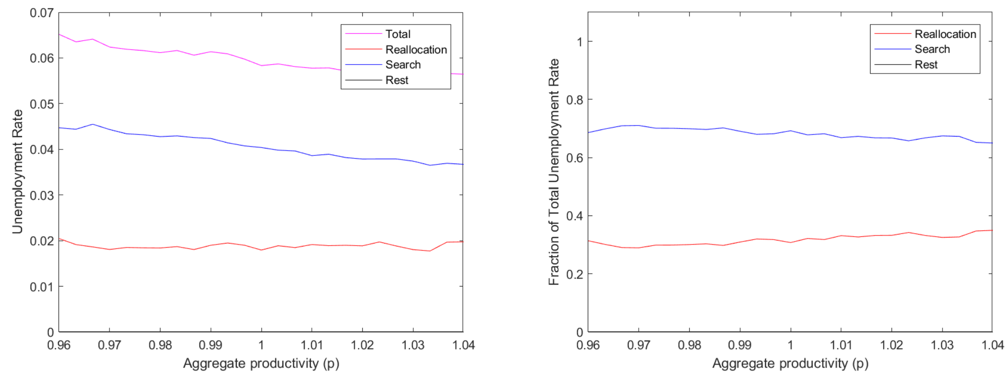

Figure D.2: *The decomposition of the unemployment rate into search, rest, and reallocation unemployment, for different values of aggregate productivity p. Different types of unemployment are plotted either as a fraction of the total population (left) or as a fraction of unemployed workers (right).*

As all unemployed workers are either rest, search, or reallocation unemployed, it is possible to split out the (total) unemployment rate into an unemployment rate specific to these types of unemployment. This decomposition is shown in Figure D.2. As can be seen in this figure (in the right panel), no unemployed workers are rest unemployed any value of aggregate productivity p. Furthermore, the fraction of unemployed workers classified as reallocation unemployed slightly increases in aggregate productivity. As can be deduced from the left panel, however, this increase is largely caused by a decrease in the number of search unemployed workers as p increases, which in turn is a consequence of the fact that the separation thresholds in Figure 5 are decreasing in p.

The fact that the decision thresholds shown in Figure 5 of the main text are not all constant in aggregate productivity p is also clearly visible in Figure D.3, which shows the distribution of unemployed (left) and employed (right) workers over different values of idiosyncratic productivity z, for each value of aggregate productivity p. Looking at the left panel, for unemployed workers, the threshold for reallocation (while unemployed at the highest level of occupational human capital) is clearly visible. The high concentration above this threshold also indicates that a majority of the workers in the simulation have the lowest level of occupational

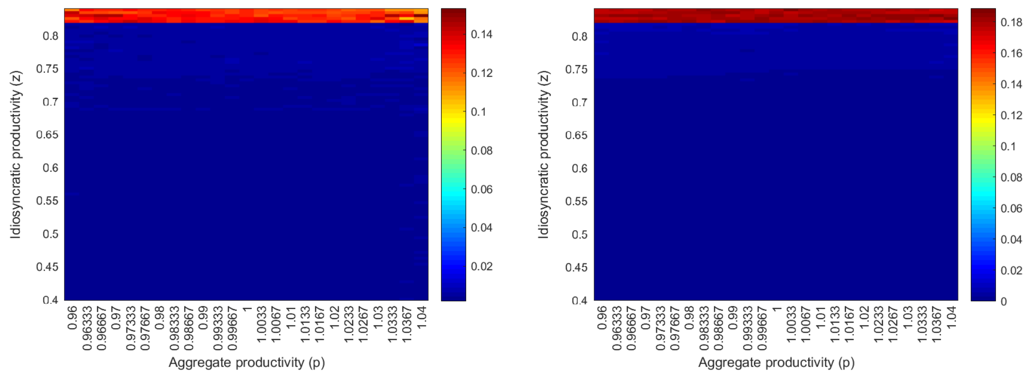

Figure D.3: *The distribution of unemployed (left) or employed (right) workers over different combinations of aggregate productivity p and idiosyncratic productivity z, generated from the model simulation. The heatmaps are generated separately for each value of p, so the values are relative to the total number of (un)employed workers with the same value of p.*

human capital. Looking more closely at the figure, one can also identify the reallocation thresholds for the other levels of occupational human capital x, but as these thresholds are irrelevant for workers with the lowest level of x and most workers have the lowest value for x, these thresholds are less pronounced in the figure.

For employed workers, the distribution of workers across different combinations is shown in the right panel of Figure D.3. Generally, employed workers are also located above the highest threshold displayed in Figure 5, which was the reallocation threshold for unemployed workers with the lowest possible level of occupational human capital. However, for higher levels of occupational human capital it is possible for workers to be located below this threshold, which is reflected by the positive (but low) mass of employed workers located at slightly lower values of z. Furthermore, a closer inspection of the figure also clearly reveals the threshold for on-the-job reallocation at the second occupational human capital level x_2.

While it is certainly interesting to see at which productivity values employed and unemployed workers are located, the main question of this paper involves occupational mobility. In order to provide an indication of the model's capability to replicate this pattern beyond that already provided in the main text, Figure

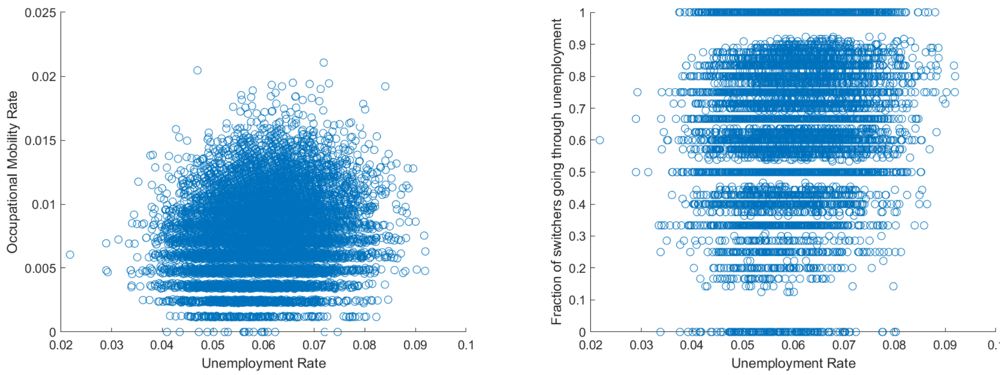

Figure D.4: *The unemployment rates generated from the model simulation, plotted against the total occupational mobility rate (left) and the fraction of occupational switchers going through unemployment (right) in a scatter plot.*

D.4 plots combinations of unemployment rates and either occupational mobility rates (left) or the fraction of switchers going through unemployment (right). The figures contain a lot of noise, which reflects that unemployment rates do not immediately jump up or down in reaction to a shock to the value of aggregate productivity p, but rather take a number of periods to adjust. In general, however, both figures seem to exhibit a countercyclical pattern, as confirmed by the positive correlation coefficients reported in the main text[53], which is consistent with the observations presented in Section 2.

Finally, Figures D.5 and D.6 show the distribution of U-switchers (Figure D.5) and E-switchers (Figure D.6) over wages, both before their switch (left panel) and after their switch (right panel). These histograms confirm the explanation offered in Section 5 for the decrease in wages for both types of switches. For both types of workers, the distribution of workers over different wages is rather spread out before the switch takes place. After the switch, all U-switchers are located at the relatively low wages, reflecting that all of them destroyed their occupational human capital when switching occupations. For E-switchers, this pattern is less pronounced, which is because within-firm job-to-job switchers (who switch as

[53]This correlation coefficient is computed not taking into account observations where only one switch occurred, therefore making the observation 100% or 0% through unemployment.

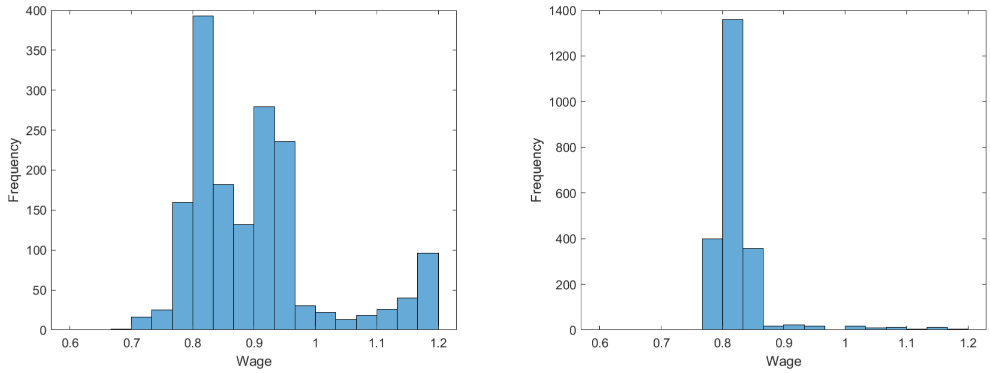

Figure D.5: *The distribution of occupational U-switchers over wages, before (left) and after (right) their switch.*

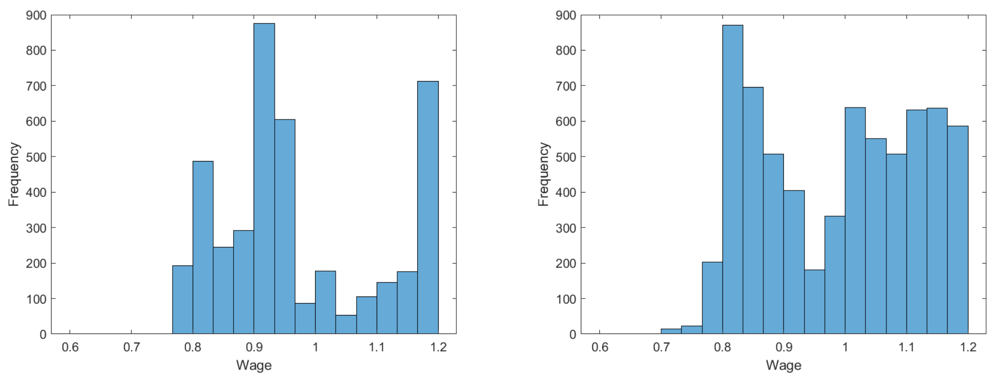

Figure D.6: *The distribution of occupational E-switchers over wages, before (left) and after (right) their switch.*

a consequence of the exogenous reallocation shock) do not lose their occupational human capital when switching. As it was already identified in Section 5 that the majority of job-to-job switches in the simulation are switches within the firm, it is not surprising that the pattern is much less pronounced for job-to-job switchers.