Business Cycle Patterns of Occupational Mobility and Subsequent Earnings

Frank Leenders*

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July 5, 2022

Abstract:

This paper investigates the cyclicality of occupational mobility and its consequences for subsequent earnings and wages, distinguishing between workers who switch occupations through unemployment and workers who switch as part of a job-to-job transition. Using data from the Survey of Income and Program Participation, I find that the fraction of occupational switchers who switch through unemployment is countercyclical, and while these workers generally do worse in terms of earnings than workers who make a job-to-job transition, their earnings and wage patterns may slightly improve in recessions. I then propose a job search model of occupational mobility in which I incorporate both types of occupational switches and show that the overall deterioration of earnings and wage outcomes for occupational switchers in recessions is largely driven by a composition change towards switching through unemployment, dampened by the outcomes experienced by workers who switch occupations without switching employers.

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

Keywords: Occupational Mobility, Productivity, Job Search

*frank.leenders@mail.utoronto.ca, Department of Economics, University of Toronto, Canada. I thank Ronald Wolthoff for his excellent supervision throughout this project, and Gueorgui Kambourov and Jessica Wagner for their comments and discussions. The paper has also benefited from numerous suggestions from Kevin Fawcett, Carolyn Pitchik, and participants of the ECO4060 Graduate Seminar and the Macroeconomics Brown Bag Seminar. This research was enabled in part by support provided by Calcul Québec (www.calculquebec.ca) and Compute Canada (www.computecanada.ca).

1 Introduction

In recent decades, the increased use of outsourcing by large businesses is an 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.

When thinking about the switchers' labour market outcomes after the occupational switch has been made, earlier research finds that the links between occupational experience and wages may be more important than the link between either employer-specific or industry-specific experience and wages (Kambourov and Manovskii, 2009b).[2] This finding raises the question of why workers change occupations when there is such a strong link between wages and occupational tenure. Therefore, understanding why some workers decide to move and other workers do not, especially given that workers on average suffer from substantial wage and earnings losses when making such a move (see e.g. Forsythe, 2020), is important in order to make accurate predictions about a worker's behaviour as the process continues. Furthermore, gaining 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), is also important in the context of general labour markets.[3] 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), lifetime wage inequality (see Gyetvai, 2021), and cyclicality of earnings changes in the tails of the earnings change distribution (see Carrillo-Tudela et al., 2021). In this paper, I contribute to the literature on this topic by explicitly distinguishing between workers who switch occupations through unemployment and workers who switch as part of a job-to-job transition, arguing that this distinction helps to explain a substantial share of the cyclicality in the estimated earnings and wage losses experienced by occupational switchers after making the switch.

[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] 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.

[3] 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 like I do in this paper.

The topic of occupational mobility has not been studied extensively in the economic literature until fairly recently. 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 at times very close to each other, and certain job descriptions may therefore not clearly correspond to a single occupational category, especially if the survey respondent's description of their job changes slightly between interviews. 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 from contaminating my results.

My first set of observations from the data focuses on the level and cyclicality of the occupational mobility rate. The total 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 4% I find in Section 2. When it comes to the cyclicality of the occupational mobility 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 confirm such a mild procyclical pattern.

When differentiating occupational switches by whether or not workers go through unemployment, some interesting patterns arise. First of all, I find that 60-70% of occupational switches do not involve unemployment. This result is consistent with the findings in Xiong (2008), who uses the same dataset as I use in this paper (the Survey of Income and Program Participation),

[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.

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 consistent with Papageorgiou (2018).[6] 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 seemingly 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).

The second set of observations from the data focuses on earnings and wage paths experienced by occupational switchers after their switch is complete. Generally, I find that job-to-job occupational switchers tend to do better both in terms of earnings and wages. This result is consistent with the results obtained in Longhi and Taylor (2013), who use UK data to stress that occupational switches do not necessarily have negative consequences on earnings and wages. Indeed, while focusing on all switchers simultaneously reveals a wage and earnings loss, consistent with results from Forsythe (2020), these averages mask large differences between switchers through unemployment and job-to-job switchers, the latter of which do not necessarily face any losses in earnings and wages.

The main empirical contribution of this paper lies in distinguishing between the cyclical patterns of post-switch earnings and wage paths of job-to-job switchers and occupational switchers who experienced an intervening unemployment spell. The result above (on job-to-job switchers generally doing better) continues to hold regardless of the economic conditions at the time of the switch. However, when focusing on the cyclicality of earnings and wage losses for job-to-job occupational switchers and switchers going through unemployment I find that the two groups experience different patterns. In particular, while job-to-job switchers generally tend to do worse in recessions (compared to job-to-job switchers in booms), this is not necessarily true for switchers going through unemployment. For switchers who go through unemployment, I instead find that they do slightly better in recessions than in booms. This result, combined with the aforementioned result that in a recession more switchers make their change through unemployment, leads me to hypothesize that the cyclical patterns in overall earnings and wage patterns after occupational mobility are largely shaped by offsetting composition effects and cyclicality of the outcomes themselves. In particular, it may be the case that the cyclicality of average earnings changes after occupational

[6] To be specific, Papageorgiou (2018) 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 1-digit level.

mobility is primarily due to more workers switching through unemployment, and therefore experiencing worse outcomes than they would have in a boom (as their transition may have been a job-to-job transition in a boom). However, this is not something I can directly confirm in the data, and therefore I turn to a model instead.

There are 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 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 an explicit distinction between unemployed and employed workers while also incorporating search frictions on the labour market. In particular, the model in this paper is fairly closely related to the model in Carrillo-Tudela and Visschers (2021). They extend the standard DMP model (see for example Pissarides, 2000) to analyze how the (unemployed) worker's decision to switch occupations 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 workers are 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. This type of unemployment also appears in the model I propose in this paper, where similar productivity cutoffs appear (with an additional cutoff for job-to-job switches).

Generally, the existing models of occupational mobility do not allow for occupation switching as part of a job-to-job transition. One exception to this is the model in Carrillo-Tudela et al. (2021), who use a model that allows for both types of occupational switches in order to explain cyclicality in the tails of the earnings change distribution. My model is fairly similar to theirs in that it allows for both on-the-job search in different occupations and occupational switches through unemployment. Additionally, my model allows for workers to switch occupations without switching employers. Furthermore, as I focus on gross occupational mobility patterns, which I find to be fairly symmetric in the data, I abstract from occupation-specific elements that would lead a worker to target specific occupations in their search, such as in Carrillo-Tudela and Visschers (2021), Carrillo-Tudela et al. (2021), and Pilossoph (2022). Instead, I make the simplifying assumption that workers move to a randomly drawn new occupation, thereby essentially interpreting occupations as "islands", which are ex-ante identical.

Following the discussion above, the main contribution of this paper to the theoretical literature lies in the distinction between occupational changes by unemployed and employed workers, and further between job-to-job switches with and without an accompanying employer change. By separating these types of mobility, I can explain the cyclical patterns in the incidence of occupational mobility as well as its consequences that I found in the empirical section of the paper. Indeed, I find that the overall cyclicality of the earnings and wage consequences of occupational mobility are dampened by two opposing forces. On the one hand, there are the earnings and wage consequences conditional on the type of switch, which worsen in recessions for job-to-job switchers especially. Furthermore, the fraction of switchers through unemployment increases in recessions, which further increases the procyclicality of the average earnings profile since switchers through unemployment generally do worse than job-to-job switchers. On the other hand, however, the job-to-job switching rate within the same employer is constant across the business cycle, and this dampens the procyclicality induces by the first force. This is because while the productivities drawn by these within-employer job-to-job switchers do not change over the business cycle, the aggregate productivity at the time of bargaining does still affect the wages obtained by these workers in their new job. Therefore, the cyclicality of the endogenous separation threshold still plays a role, leading to more workers rejecting this within-employer job-to-job switch and the resulting average effect being better than in a boom.

The rest of this paper is organized as follows: Section 2 describes some of the patterns found in the data, using the 1996 to 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 order to motivate the setup of the model in the next section, this section presents some observations from the data. These results are obtained using data from the Survey of Income and Program Participation (SIPP). The SIPP is one of three U.S. 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 up to the 3-digit level.

All results below are obtained using the 1996, 2001, 2004 and 2008 panels of the SIPP. I use only these panels because they are fairly consistent in terms of how variables are measured

[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 when it comes to fairly low-frequency events such as an occupational switch at the 1-digit level. 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).

across individuals and across time. 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.[12] 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. In order to obtain consistency between the 1996 and 2001 panels on the one hand (which use the SOC 1990 system), and the 2004 and 2008 panels on the other hand (which use the SOC 2000 system), I convert the reported occupational codes using the occupation system from Dorn (2009). Throughout, 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.

2.1 The Cyclicality of Occupational Mobility Rates

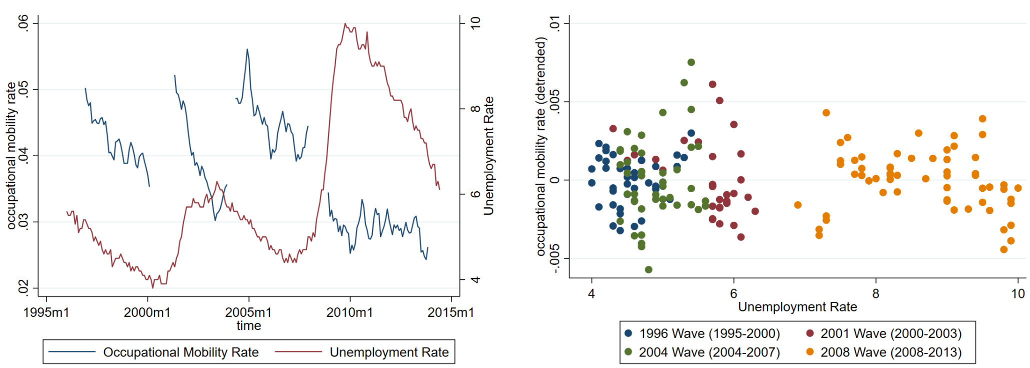

Figure 1: *The 1-digit occupational mobility rate and the corresponding month's unemployment rate from the BLS, plotted over time (left) and against each other in a scatter plot (right).*

As the model in Section 3 focuses on the 1-digit occupational mobility rate rather than its 2- or 3-digit counterpart, this section focuses on the occupational mobility on a 1-digit level.[13] First,

[12]In appendix A.2 I show how this restriction influences the results obtained in this section.

[13]In appendix A.3, I show how results in this section change when considering the 2-digit counterpart, while also providing the equivalent of figure 1 for the 3-digit counterpart.

the left panel of figure 1 plots the 1-digit (4 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 4%. 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. 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 for each SIPP panel, one that was observed in the existing literature as well (see e.g. Xu, 2017).[14] The right panel therefore uses the detrended data instead.[15] From the right panel of Figure 1, there is no clear cyclical pattern visible. However, a naive regression reveals a slope of -0.00004, albeit not statistically significant.[16] This leads me to the conclusion that the occupational mobility rate is (if anything) mildly procyclical. This conclusion is in line with the existing literature discussed in Section 1. Similarly, I find a mildly procyclical (but not statistically significant) pattern when only considering occupational mobility through unemployment, in line with Carrillo-Tudela and Visschers (2021).[17]

Occupation	1	2	3	4	5	6
Observations	1238030	735782	439620	111905	233481	564869
Inflow	32968	33147	22128	5640	11627	22527
Outflow	30934	33770	23344	5887	12258	21844
Net Inflow	2034	-623	-1216	-247	-631	683

Table 1: *Total number of incoming and outgoing switches found in the data for every 1-digit occupation, and number of times I observe a worker in each of these occupations in the data.*[18]

Figure 1 focuses on the gross occupational mobility rate. However, one might expect

[14]It is worth noting that this visible negative trend for each panel is not observed when I omit the validation exercise for occupation switches described in appendix A.1, thus implying that it is likely to be a consequence of the validation I impose to check for "true" occupational switches.

[15]In order to detrend the occupational mobility rates, I apply a HP filter with smoothing parameter 14,400 for each SIPP panel separately.

[16]Naive regressions by SIPP panel reveal a slope of 0.0006 for the 1996 panel, -0.0020 for the 2001 panel, 0.0012 for the 2004 panel, and -0.0004 for the 2008 panel, with only the coefficient for the 2001 panel being statistically significant at the 5% level.

[17]If I only consider reallocation through unemployment, the naive regression coefficient on the unemployment rate becomes -0.00003, with the SIPP panel-specific coefficients being 0.0005 for the 1996 panel, -0.0004 for the 2001 panel, -0.0004 for the 2004 panel, and -0.0003 for the 2008 panel.

[18]The 1-digit occupations listed are "(1) Management, Professional, Technical, Financial Sales, and Public Security Occupations", "(2) Administrative Support and Retail Sales Occupations", "(3) Low-skill Services", "(4) Precision Production and Craft Occupations", "(5) Machine Operators, Assemblers and Inspectors", and "(6) Transportation, Construction, Mechanics, Mining, and Agricultural Occupations".

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.[19] In order to investigate this net rate, Table 1 lists the total inflow and outflow for each 1-digit occupation, as well as the total number of times I observe a worker in these occupation.[20] 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 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.

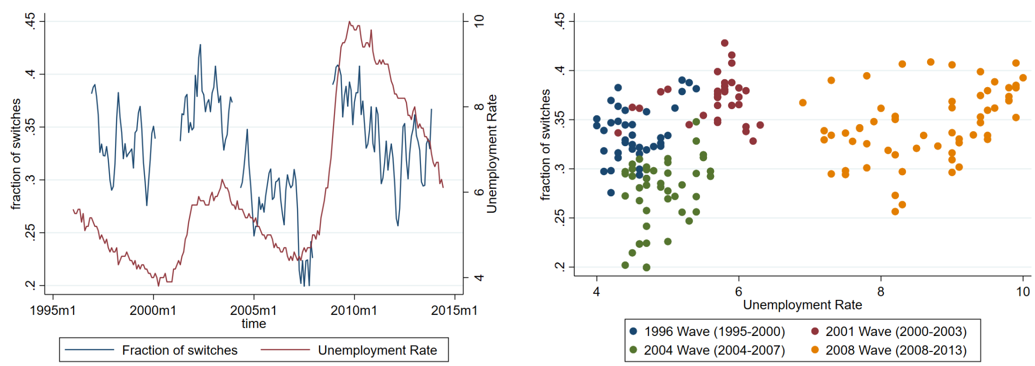

Figure 2: *The fraction of occupational switchers (1-digit) going through unemployment and the corresponding month's unemployment rate from the BLS, over time (left) and plotted against each other in a scatter plot (right).*

Since the focus of this paper is on the distinction between those who change occupations with and without going through an unemployment spell (referred to as U-switchers and E-switchers respectively), it is important to confirm whether these two groups follow different cyclical patterns. As can be seen in both panels of Figure 2, the fraction of switches that goes through unemployment shows a clear countercyclical pattern. This result continues to hold when

[19]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.

[20]Note that all numbers in Tables 1 and A.2 are totals over the entire sample period (and do not use the sample weights). 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, in Appendix A.2, when I show panel-specific equivalents on table 1, I include the number of times a worker is observed in the occupation in the first complete month of the panel.

looking at the state level instead of the national level, as shown in Appendix A.2. Note that this result holds despite the occupational mobility rate through unemployment (as well as its counterpart through employment) being mildly procyclical, as shown in Appendix A.2, thus suggesting that it is primarily a mechanical result, driven by the base number (of unemployed workers) being highly countercyclical, and therefore the procyclicality of the occupational mobility rate through unemployment being slightly weaker. However, given that the two types of occupational mobility show very different cyclical patterns in terms of their subsequent earnings, as stressed in the next subsection, it is important to model the two groups separately, as I do in Section 3.

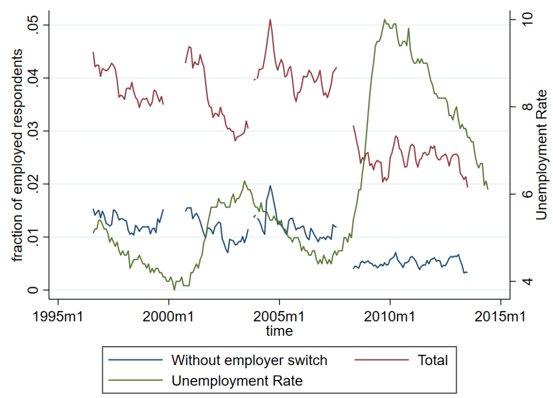

Figure 3: *The fraction of employed workers switching occupations in the next 4 months and the fraction of employed workers doing so without switching employer, plotted over time together with the corresponding month's unemployment rate from the BLS.*

Before moving to the earnings pattern experienced by occupational switchers, it is worth taking a closer look at the occupational switches that occur without an intervening unemployment spell. In Figure 3, I plot the occupational mobility rate considering only switches through employment.[21] Inspecting the graph, it can be seen that approximately a quarter to a third of the employed workers who switch occupations do so without changing employers. This observation is noteworthy 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 (2018). Thus, job-to-job occupational mobility is not always a result of on-the-job search for a better match with a new employer. Therefore, I make an explicit distinction between job-to-job occupational mobility with and without an employer change when modeling job-to-job occupational mobility in Section 3.

[21] 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.

2.2 The Cyclicality of Earnings and Wage Gains after Occupational Mobility

Having established the cyclical patterns of (1-digit) occupational mobility, both overall and specific to switches with and without intervening unemployment spells (U-switchers and E-switchers), I now proceed to examine patterns in the affected workers' real wages and real earnings after such switches.

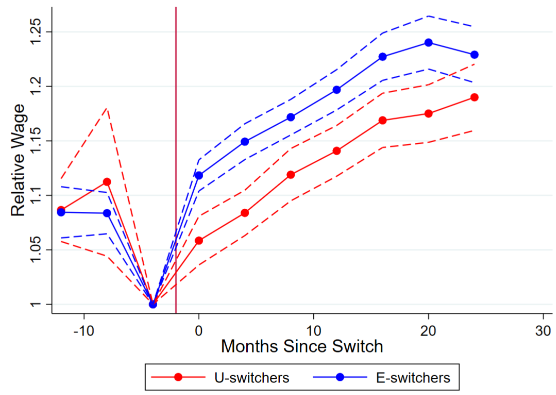

Figure 4: *Real wage paths over time for occupational U-switchers and E-switchers. The switch takes place between time -4 and 0, as represented by the vertical line at -2. The dashed lines correspond to the (pointwise) 95% confidence interval.*

In Figure 4, I plot the average wage for U-switchers and E-switchers, 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.[22] The main restriction I make in creating this figure is that I only use respondents for whom I observe the wage in at least 5 of the relevant 4-month periods, including times 0 and 4, at least one of times 8 and 12, at least one of times 16, 20, or 24, and at least one of the pre-event periods.[23] Furthermore, I remove observations where the ratio of wages between two successive waves is more than 2 or less than 0.5. 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.

One way to investigate how the pattern from Figure 4 changes over the business cycle

[22]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.

[23]In Appendix A.2, I show that the result is not substantially affected if I remove this restriction. Furthermore, I show where the relative wages of non-switchers would appear in this graph.

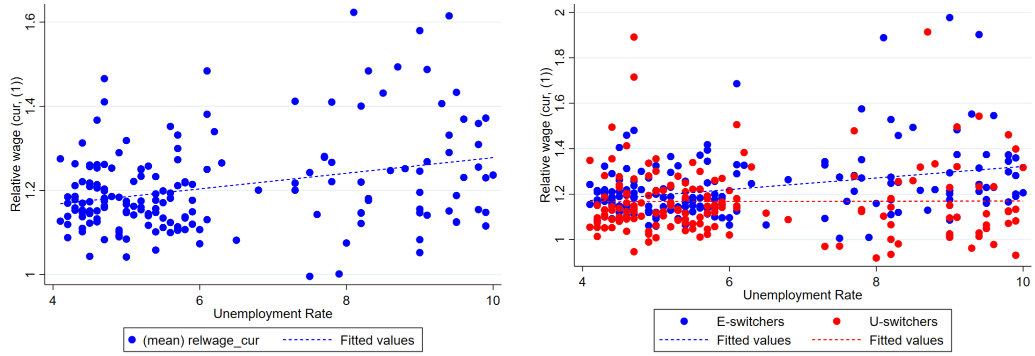

Figure 5: *Real wages immediately after the occupational switch, relative to the real wage before the switch, for all occupational switchers (left) or for occupational U-switchers and E-switchers (right), plotted against the unemployment rate at the time of the switch. Dashed lines show fitted values corresponding to a simple OLS regression.*

is to calculate these relative wages separately for each wave and rotation group, and plot the resulting numbers against the unemployment rate at the time of observation. In Figure 5, I do this for the wages observed immediately after the occupational switch (corresponding to month 0 in Figure 4), conditioning on each data point in the graph summarizing the wage differential of at least 20 individuals.[24] As can be seen in the left panel of Figure 5, the overall wage differentials for occupational switchers are mildly countercyclical. However, this primarily reflects the countercyclicality of the wage differentials for E-switchers, as shown in the right panel of Figure 5. The wage differentials for U-switchers, on the other hand, appear to be acyclical. In Appendix A.2, I show that this conclusion is robust to removing validation checks on occupational switches and to removing all female workers from the sample.

While the analysis above is based on raw wage differentials, one can imagine that the groups of occupational U-switchers and E-switchers are not necessarily comparable in terms of their pre-switch wage (against which the relative wage above is measured), and may be different in terms of other characteristics as well.[25] Therefore, I now proceed to estimate the wage and earnings patterns experienced by occupational switchers in regression frameworks. The first of these frameworks is an event study setup, where I define the event of interest to be the occupational switch, with the time of the event corresponding to the time at which the worker starts their job

[24]Similar figures for different points in time (e.g. 4 months after the switch) are available upon request. Note that I no longer impose Figure 4's restriction on having observed the individual in at least 5 periods when creating Figure 5, as now only the wages in period -4 and 0 are relevant.

[25]Indeed, as demonstrated in Appendix A.2, these two groups differ substantially in their age and education

in their new occupation. In practice, the estimation is set up as a two-way fixed effects (TWFE) estimation, estimating equation (1) below:

$$w_{it} = \alpha_i^C + \gamma_t^C + \bar{e}_i^C \lambda_t^C + \beta^C X_{it} + \sum_{\substack{k=-3 \\ k \neq -2}}^{K} \delta_k^C D_{it}^{C,k} + \varepsilon_{it}^C \tag{1}$$

Equation (1) is estimated separately for each sample wave C. Within each such estimation, only occupational switches that took place in wave C are considered to be treatments. In equation (1), i refers to the individual and t refers to the wave. The dependent variable in this specification, w_{it} refers to the wage (or earnings) of individual i in period t. The explanatory variables include an individual fixed effect α_i^C and a time fixed effect γ_t^C (both of which are allowed to differ between estimations, as denoted by superscript C), as well as a quadratic polynomial in age X_{it} and an (estimation-specific) error term ε_{it}^C. The variable $\bar{e}_i^C$ denotes the average earnings of individual i between waves $C-5$ and $C-1$, and I will generally refer to this as recent earnings. When deriving these recent earnings, I condition on the individual having earnings available in the data for at least three of the waves between $C-5$ and $C-1$, one of which should be wave $C-1$. The coefficients of interest are a series of coefficients on dummy variables $D_{it}^{C,k}$. These variables equal 1 if individual i was displaced in period $t-k$ (where the dummy variable for $k=-1$ is omitted), and where period $t-k$ corresponds to wave C. As these dummy variables always equal 0 for workers who did not switch occupations (in wave C), the coefficients represent the effect of switching occupations on wages (relative to the wage of non-switching workers), k periods after the occupational switch. The maximum number of future periods equals $K=5$, reflecting the relatively short panels of the SIPP. As the estimation is done separately for each sample wave C, only observations that correspond to waves $C-3$ to $C+5$ are used for the estimation. To enhance the interpretation of the estimated value, I then divide the estimated coefficient δ_k^C by the control group's average wage in wave $C+k$, obtaining relative coefficient $\tilde{\delta}_k^C$. The graphs below then plot the resulting relative coefficient $\tilde{\delta}_k$ over k (where $\tilde{\delta}_k$ is the average of $\tilde{\delta}_k^C$ over base waves C), thus revealing a wage (or earnings) path from 3 periods before to 5 periods after the occupational switch event.

In Figure 6, I plot the results of an estimation of equation (1) where I do not distinguish between E-switchers and U-switchers. As can be seen in the figure, the subsequent wage and earnings patterns of occupational switchers are subject to some degree of cyclicality. In particular, the figure suggests that the wage and earnings outlook is worse for workers who switch occupations

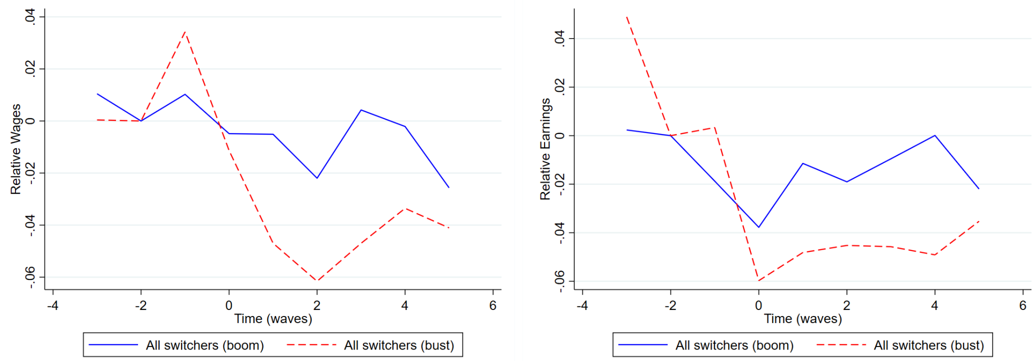

Figure 6: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the control group of never-switched workers, using estimated coefficients from equation* (1),*specific to switches that materialized in booms or busts.*

during a recession.

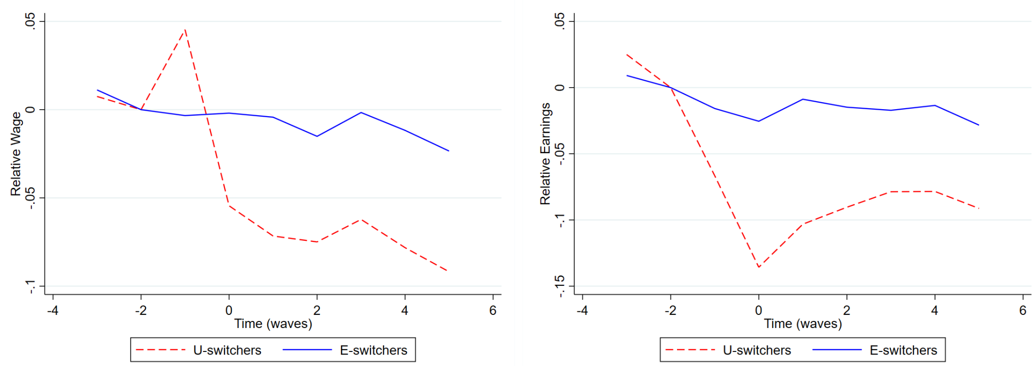

Figure 7: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the control group of never-switched workers, by type of switch, using estimated coefficients from equation* (1).

Since the conclusions drawn from figure 6 abstract from the distinction between E-switchers and U-switchers, they do not consider my earlier observation that during recessions a larger fraction of occupational switchers goes through an intervening unemployment spell. In Figure 7, I estimate equation (1) while allowing for the treatment effect to be different for the two types of switches.[26] As can be seen in Figure 7, workers who switch through unemployment are generally worse off than workers who switch occupations without going through unemployment

[26]Note that I do not estimate the effects for the two groups separately. Rather, I allow for two types of (mutually exclusive) treatments, such that the fifth term in equation (1) becomes $\sum_{U=0}^{1}\sum_{\substack{k=-3\\k\neq-2}}^{K}\delta_k^{C,U}D_{it}^{C,U,k}$ instead of $\sum_{\substack{k=-3\\k\neq-2}}^{K}\delta_k^{C}D_{it}^{C,k}$, where U corresponds to the type of switch.

(both in terms of wages and earnings), which is consistent with the observations from the raw data in figures 4 and 5.

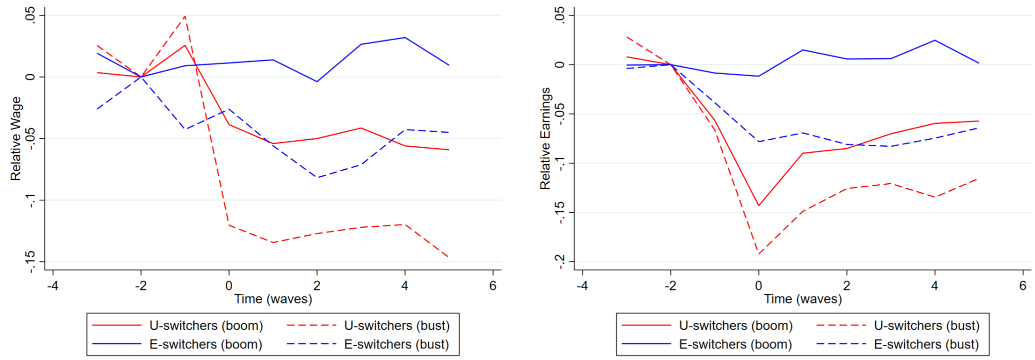

Figure 8: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the control group of never-switched workers, by type of switch, using estimated coefficients from equation* (1)*, specific to switches that materialized in booms or busts (right panel).*

In Figure 8, I show how the wage and earnings patterns of E-switchers and U-switchers change over the business cycle. Contrary to Figure 7, Figure 8 is not consistent with the observations from the raw data, as it suggests that wage (and earnings) differentials are procyclical for both U-switchers and E-switchers. One potential explanation for this inconsistency could be that the workers who switch occupations in booms or busts are different in more dimensions than just the type of switch they make. Such differences would not be accounted for in the figures generated using raw data, but in a two-way fixed effects specification some of those differences would be accounted for through the individual fixed effect.

Recently, a number of papers have stressed the shortcomings of event study settings such as the used above, in particular stressing that the estimates of δ_k^C in equation (1) may be contaminated by effects from earlier and later periods, as well as by subsequent and prior treatments that are ignored in this specification.[27] In the specification above, this occurs because individuals who switch in waves $C + 1$ and later, as well as individuals who switched before wave C who are re-employed again (and satisfy other sample requirements) are likely to be placed in the control group when estimating the effect for workers switching in wave C. In order to take into account potential contamination of the estimate of δ_k^C (and consequentially of the average $\tilde{\delta}_k$), I use the three-step estimation method from Borusyak et al. (2022).

The method proposed in Borusyak et al. (2022) proceeds in three steps. In the first

[27] See, for example, Callaway and Sant'Anna (2021), Sun and Abraham (2021), and Borusyak et al. (2022).

step, the method aims to directly estimate the counterfactual implicitly used in a difference-in-differences estimation procedure. This is done by estimating a standard two-way fixed effects model (without the leads and lags for treatment) on all not-yet-treated and never-treated workers in the sample. Following the notation in equation (1) , this means that I estimate the following equation:

$$w_{it} = \alpha_i + \gamma_t + u_{it} \tag{2}$$

Note that specification (2) no longer includes control variables $\bar{e}_{it}$ (recent earnings) and X_{it} (the quadratic polynomial in age). The estimates of the individual and time fixed effects in equation (2) are then used to estimate the untreated (counterfactual) outcome for all treated observations as well. In other words, the estimated counterfactual outcome combines the estimated individual fixed effect (estimated using the individual's observations before treatment) and the estimated time fixed effect (estimated using other individuals, who were not treated at the time period of interest).

In the second step, these counterfactual untreated outcomes are compared to the (observed) treated outcome to form an estimate of the individual- and time-specific treatment effect (which is thus the difference between the estimated untreated outcome from step 1 and the observed outcome). In the third and final step, the target aggregation is then estimated using a weighted average of the individual and time-specific estimated treatment effects from step 2.

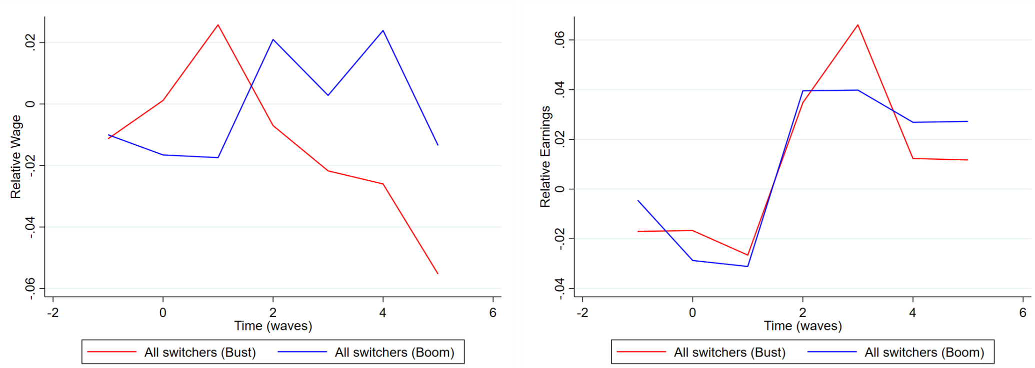

Figure 9: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

In Figure 9, I show the results of an estimation using the three-step estimation method, where I do not distinguish between E-switchers and U-switchers. Compared to Figure 6, it can be concluded from this figure that the cyclicality of the wage and earnings paths after occupational switches may be milder than initially thought. While the cyclicality of the post-switch wage path remains, the differences are much smaller than those observed in Figure 6. When it comes to earnings, the cyclicality observed in Figure 6 is no longer visible in the right panel of 9, thus suggesting that the aforementioned conclusion on procyclicality of the estimated earnings path may be a result of the contamination discussed in the recent literature (and in the text above).

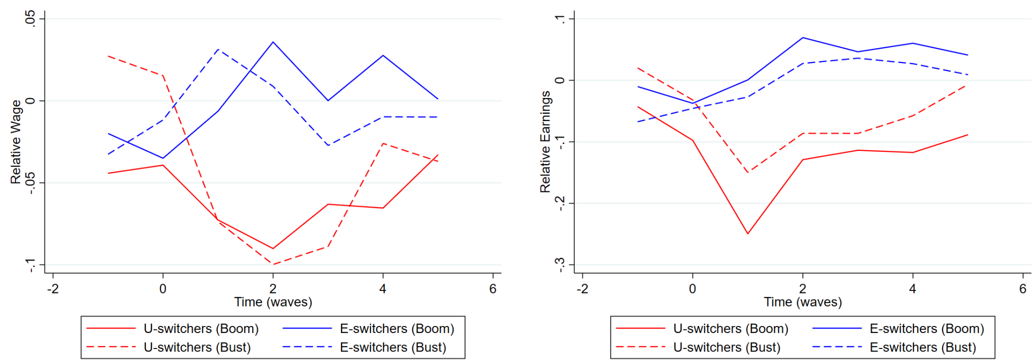

Figure 10: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, by type of switch, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

Figure 10 displays the results of repeating this estimation while allowing for the treatment effect to be different for the two types of switches. As can be seen in the left panel, the difference between E-switchers and U-switchers observed earlier (in Figure 7) remains intact, and even strengthens slightly for earnings. However, when it comes to the cyclicality of these wage paths, Figure 10 suggests a milder cyclical pattern for wage. For earnings, the cyclical pattern for U-switches even clearly reverses: the right panel of Figure 10 suggests that post-switch earnings paths are countercyclical for U-switchers, whereas the post-switch earnings paths for E-switchers are procyclical.

Having investigated the cyclicality of the post-switch real wage and real earnings patterns experienced by occupational switchers in three different ways, it can be said that the overall conclusion is not particularly clear. Generally, all methods agree that U-switchers tend to do worse than E-switchers, and the regression-based methods agree that subsequent real wage and real earnings pats of E-switchers are procyclical. However,when it comes to the cyclicality of these paths for U-switchers, the methods disagree. Unfortunately, while one could argue that regression-based methods should be expected to provide a more accurate picture than raw numbers, it is not necessarily clear that one of the two regression-based methods dominates. In particular, one could argue that the estimates obtained using three-step estimation method may dominate because they should avoid some of the bias stressed in the recent event study literature. However, one also has to keep in mind a second impactful difference between the two specifications, namely the fact that the three-step estimation method requires me to take a stance on when the impact of the switch starts. In the estimation results above, I allow for the effects to start in the wave before the switch materializes, but one could argue that this may not be far enough back for U-switchers, who may be switching at the end of an unemployment spell of several months. This is especially true when considering that U-switchers in recessions may take longer to find a new job and are therefore more likely to be unemployed in the second wave prior to the switch materializing. The conclusion would therefore be that the true effect is likely to fall in between the two estimated effects, thus suggesting procyclicality in the real wage and real earnings patterns for E-switchers, whereas the real wage and real earnings patterns for U-switchers are ambiguous (acyclical or mildly countercyclical).

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 is heavily based on the model Carrillo-Tudela and Visschers (2021). In particular, I use a version of their model where workers cannot direct their search to an occupation of their choice, and add the possibility of switching while staying employed. 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. 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 Environment

3.1.1 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 has room for only one worker, hired 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 exhibit constant returns to scale and depend on three types of productivity (p_t, x_t, and z_t), so that $y = f(p, x, z)$. 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 $k > 0$. In principle, the firm chooses which occupation to operate in, but since the value of posting a vacancy will be zero in all markets in equilibrium, this choice is not explicitly modeled. When being matched with a worker, the firm 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.[28]

[28]It is assumed here that when the firm is indifferent between separating and not separate, the firm will always decide not to separate. Thus, the firm will never decide to follow a mixed strategy.

3.1.2 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.[29] 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 3.1.4).

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, a decision which is denoted by $d(p, z, x) \in \{\delta, 1\}$.[30] Furthermore, the worker also has the choice to search for a match in a different occupation, a choice that will be further discussed in subsection 3.1.4. 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 the idiosyncratic productivity being at most z_{t+1} next period conditional on the current value being z_t.

The third and last type of productivity, x_t, is interpreted as occupational human 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 $\chi(x_{h+1}|x_h)$ in every period in which 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

[29] 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.

[30] 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.

over in her new occupation with $x_t = x_1$.[31] 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.

3.1.3 Labour Markets

In this model, 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 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 3.2. In short, the wage rate solves the following equation:

$$\eta \left(W^E(p, z, x) - W^U(p, z, x)\right) = (1 - \eta) \left(J(p, z, x) - V(p, z, x)\right) \tag{3}$$

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.

[31] 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.

3.1.4 Occupational Transfers

There are three ways in which a worker could switch occupations. The first opportunity for a worker to switch occupations occurs when the worker is unemployed. When a worker is unemployed, she has the option of choosing to switch occupations every period (before the matching takes place), at a cost $c^u(p)$, which is allowed to vary over the business cycle. This decision is captured by the variable $\rho^u(p, z, x) \in \{0, 1\}$.[32] If the worker decides not 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.[33] 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 the rest of the period unemployed. Thus, she will not be allowed to search for a match until the next period.

The second channel through which a worker can switch occupations 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 $\rho^e(p, z, x) \in \{0, 1\}$.[34] If she decides to do so, she pays a cost $c^e(p)$, which is allowed to vary over the business cycle, 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.[35] 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

[32] 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.

[33] 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 occupational mobility flows seem to be fairly symmetric.

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

[35] 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.

occupations, while not switching employers or losing 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, and a firm and worker may decide to subsequently destroy their match if the new value of z is sufficiently low. 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, the model implies 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.

3.1.5 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.[36] 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 should be noted that workers and firms who are hit by the occupational transfer shock or decided to destroy their match do not make any of the decisions in the remaining subperiods.

Next, in the fourth subperiod, the occupational transfer decisions are made by workers

[36]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.

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.[37] Finally, production takes place in the sixth and last subperiod.

3.2 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:

$$\begin{aligned} W^U(p,z,x_h) = b + \beta \mathbb{E}_{p',z'} \Bigg[\max_{\rho^u(\cdot)} \Bigg\{ \rho^u(p',z',x_h) \left[\int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1) dF(\tilde{z}) - c^u(p') \right] \\ + (1-\rho^u(p',z',x_h)) \Big[\lambda(\theta(p',z',x_h)) W^E(p',z',x_h) \\ + (1-\lambda(\theta(p',z',x_h))) W^U(p',z',x_h) \Big] \Bigg\} \Bigg] \end{aligned} \tag{4}$$

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 decides to change occupations ($\rho^u(p,z,x_h) = 1$) next period, she pays the cost $c^u(p')$ and will be unemployed for the remainder of the 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 $\lambda(\theta(p',z',x_h))$.[38]

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

[37] 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.

[38] 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.

$W^E(p,z,x)$ can be expressed as follows:

$$W^E(p,z,x_h) = w(p,z,x_h) + \beta \mathbb{E}_{p',z',x'} \Bigg[\max_{d(\cdot),\rho^e(\cdot)} \Bigg\{ \psi \int_{\underline{z}}^{\bar{z}} \max\left\{ W^E(p',\tilde{z},x'), W^U(p',\tilde{z},x') \right\} W^E(p',\tilde{z},x') dF(\tilde{z})$$

$$+ (1-\psi) \Bigg[d(p',z',x') W^U(p',z',x') + (1-d(p',z',x')) \Bigg[(1-\rho^e(p',z',x')) W^E(p',z',x')$$

$$+ \rho^e(p',z',x')(-c^e(p') + R^E(p',z',x')) \Bigg] \Bigg] \Bigg\} \Bigg] \tag{5}$$

$$R^E(p',z',x') = \int_{\underline{z}}^{\bar{z}} \left[(1-\lambda(\theta(p',\tilde{z},x_1))) W^E(p',z',x') \right.$$

$$\left. + \lambda(\theta(p',\tilde{z},x_1)) W^E(p',\tilde{z},x_1) \right] dF(\tilde{z}) \tag{6}$$

Here, the inclusion of the exogenous occupational transfer shock has caused the inclusion of ψ and the integral on the first line of equation (5), 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, 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[39]:

$$V(p,z,x) = -k + q(\theta(p,z,x)) J(p,z,x) + (1-q(\theta(p,z,x))) \beta \mathbb{E}_{p'} \left[V(p',z,x) \right] \tag{7}$$

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 (5), 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:

$$J(p,z,x_h) = y(p,z,x_h) - w(p,z,x_h) + \beta \mathbb{E}_{p',z',x'} \Bigg[\max_{\sigma(\cdot)} \Bigg\{ \psi \int_{\underline{z}}^{\bar{z}} \max\left\{ J(p',\tilde{z},x'), V(p',\tilde{z},x') \right\} dF(\tilde{z})$$

$$+ \ (1-\psi) \left[(1-\sigma(\cdot))(1-\hat{\rho}(p',z',x')) J(p',z',x') \right.$$

$$\left. + \ (1-\sigma(\cdot)) \hat{\rho}(p',z',x') \beta \mathbb{E}_{p''}[V(p'',z',x')] + \sigma(\cdot) V(p',z',x') \right] \Bigg\} \Bigg] \tag{8}$$

[39]Note that the timing of this value function is slightly different than the others. This inconsistency is implemented to avoid expectations in this value function, as firms decide on vacancies after separation subperiod.

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.

3.3 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 mass of workers flowing in and out of unemployment across periods. These transitions can be summarized by 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 following 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 $x_t = x_h$:

$$\begin{aligned} u_o'(z, x_h) = &\int_{\underline{z}}^{\bar{z}} (1 - \lambda(\theta(p, \tilde{z}, x_h)))(1 - \rho^u(p, \tilde{z}, x_h))(1 - \phi) u_o(\tilde{z}, x_h) dF(z|\tilde{z}) d\tilde{z} \\ &+ \int_{\underline{z}}^{\bar{z}} \hat{d}(p, \tilde{z}, x_h)(1 - \phi) e_o(\tilde{z}, x_h) dF(z|\tilde{z}) d\tilde{z} \\ &+ (\mathbb{1}_{h=1}) \left[\sum_{\tilde{o} \neq o} \sum_{h=1}^{H} \left[\int_{\underline{z}}^{\bar{z}} \rho^u(p, \tilde{z}, \tilde{x}_h)(1 - \phi) u_{\tilde{o}}(\tilde{z}, \tilde{x}_h) d\tilde{z} \right] \right] \frac{dF(z)}{O - 1} \\ &+ (\mathbb{1}_{h=1}) \frac{\phi}{O} dF(z) \end{aligned} \tag{9}$$

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 (9) 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, or received the transfer shock and chose to destroy their match. Here, the inclusion of $\hat{d}(p, \tilde{z}, x_h)$ rather than $d(p, \tilde{z}, x_h)(1 - \psi)$ reflects that this term reflects both channels. In particular, one could think of this as representing $\hat{d}(p, \tilde{z}, x_h) = d(p, \tilde{z}, x_h)(1 - \psi) + \psi \int_{\underline{z}}^{\bar{z}} \max \mathbb{1}_{W^E(p', \tilde{z}, x') < W^U(p', \tilde{z}, x')} dF(\tilde{z})$. 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 channels through which a worker can be 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 (10):

$$
\begin{aligned}
\frac{e'_o(z,x_h)}{1-\phi} &= \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p,\tilde{z},x_h))(1-\rho^u(p,\tilde{z},x_h))u_o(\tilde{z},x_h)dF(z|\tilde{z})d\tilde{z} \\
&+ \chi(x_h|x_h)\int_{\underline{z}}^{\bar{z}} (1-\hat{\rho}(p,\tilde{z},x_h))(1-d(p,\tilde{z},x_h))(1-\psi)e_o(\tilde{z},x_h)dF(z|\tilde{z})d\tilde{z} \\
&+ \mathbb{1}_{h>1}\left[\chi(x_h|x_{\tilde{h}})\int_{\underline{z}}^{\bar{z}} (1-\hat{\rho}(p,\tilde{z},x_{\tilde{h}}))(1-d(p,\tilde{z},x_{\tilde{h}}))(1-\psi)e_o(\tilde{z},x_{\tilde{h}})dF(z|\tilde{z})d\tilde{z}\right] \\
&+ \left[(\mathbb{1}_{h=1})\sum_{\tilde{o}\neq o}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}[1-d(p,\tilde{z},\tilde{x}_h)]\rho^e(p,\tilde{z},\tilde{x}_h)\lambda(\theta(p,z,x_1))(1-\psi)e_{\tilde{o}}(\tilde{z},\tilde{x}_h)d\tilde{z}\right. \\
&\left. + \sum_{\tilde{o}\neq o}\left[\int_{\underline{z}}^{\bar{z}} \mathbb{1}_{W^E(p',\tilde{z},x_h)\geq W^U(p',\tilde{z},x_h)}\psi e_{\tilde{o}}(\tilde{z},x_h)d\tilde{z}\right]\right]\frac{dF(z)}{O-1}
\end{aligned}
\tag{10}
$$

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 (10) 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), defining $\hat{\rho}(p',z',x')$ to equal $\rho^e(p',z',x')\int_{\underline{z}}^{\bar{z}} \lambda(p',\tilde{z},x_1)dF(\tilde{z})$. 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. 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.

3.4 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* (4)*,* (5)*,* (7)*, and* (8)
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* (3)
4. *The laws of motion for* u_o *and* e_o *satisfy equations* (9) *and* (10)

Proposition 1. *The model has a unique block-recursive equilibrium.*

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 for all* p *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 (2021) and Menzio and Shi (2011). In the case of Carrillo-Tudela and Visschers (2021) this deviation is not surprising, 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 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

For the purpose of the estimation of the model in the previous section, I assume that the production function takes the simple form $y = pzx$ and the matching function takes the form $M(u, v) = \frac{uv}{u+v}$. Furthermore, I slightly simplify the model by assuming that the cost of changing occupations does not change over the business cycle, i.e. $c^e(p) = \bar{c^e}$ and $c^u(p) = \bar{c^u}$.[40] The model presented in the previous section is then characterized by a total of $17 + H$ parameters, 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.[41] As I follow Carrillo-Tudela and Visschers (2021) in setting $H = 3$, this leaves a total of 20 parameters to be calibrated. For

[40] In appendix D, I show how the estimation results change when allowing these costs to vary by the aggregate productivity p, i.e. either $c^e(p) = p \cdot \hat{c^e}$ and $c^u(p) = p \cdot \hat{c^u}$ or $c^e(p) = \bar{c^e} + p \cdot \hat{c^e}$ and $c^u(p) = \bar{c^u} + p \cdot \hat{c^u}$.

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

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 $\{O, x_1, \mu_p, \phi, \chi, \beta, b, \eta\}$. The number of occupations O is set to 6, consistent with the number of 1-digit occupations considered in section 2. Both parameters x_1 (the lowest level of occupational human capital) and μ_p (the mean value of aggregate productivity p) are 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 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, 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 $\beta = (1-\phi)/(1+r) \approx 0.9987$. Similarly, the value of unemployment benefit b is set to 0.738, corresponding to the value found when estimating the model from Carrillo-Tudela and Visschers (2021) without occupation targeting,[42] while the firm's bargaining weight η is set to 0.5, corresponding to symmetric bargaining.

Given the above parameters, the remaining 12 parameters $\{\sigma_p, \sigma_z, \rho_p, \rho_z, \mu_z, k, \bar{c^u}, \bar{c^e}, x_2, x_3, \delta, \psi\}$ are estimated in the calibration to match a set of 26 moments as close as possible.[43] 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. Note that 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, as discussed below

The first set of moments is selected to inform the aggregate productivity process and the occupational human capital grid values. Some of the productivity parameters have a clear

[42]Note that this value of b is fairly close to the value of 0.716 found in Menzio and Shi (2011).

[43]To be specific, I set the parameters to minimize the sum of differences between model and data moments, with weights related to the standard error of it's measured value in the data.

[44]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.

Moment	Source	Data	Model
Average job-finding rate	SIPP	0.468	0.8358
Average proportion of employed workers experiencing 1+ unemployment spell in the next year	SIPP	0.051	0.0767
Average aggregate productivity	Normalization	1	1.7205
Persistence of aggregate productivity	BLS	0.719	0.8878
Volatility of aggregate productivity	BLS	0.009	0.0562
Returns to occupational experience (5 years)	KM09	0.1616	0.138
Returns to occupational experience (10 years)	KM09	0.2526	0.2951
Unemployment rate of unexperienced workers	SIPP	0.072	0.0443
Unemployment rate of experienced workers	SIPP	0.049	0.0049
Unemployment survival rate (4 months)	SIPP	0.560	0.1647
Unemployment survival rate (8 months)	SIPP	0.387	0.0307
Unemployment survival rate (12 months)	SIPP	0.295	0.0064
Occupational mobility rate for workers unemployed for at least 1 month	SIPP	0.431	0.5285
Occupational mobility rate for workers unemployed for at least 3 months	SIPP	0.473	0.8207
Occupational mobility rate for workers unemployed for at least 6 months	SIPP	0.474	0.8475
Occupational mobility rate for workers unemployed for at least 9 months	SIPP	0.473	0.8659
Occupational mobility rate for workers unemployed for at least 12 months	SIPP	0.470	0.875
Subsequent mobility rate	SIPP	0.741	0.946
Relative occupational mobility rate of unexperienced workers	SIPP	1.077	1.9808
Occupational mobility rate for employed workers	SIPP	0.036	0.0349
Relative occupational mobility rate for unexperienced employed workers	SIPP	2.156	1.3295
Occupational mobility rate for employed workers without employer change	SIPP	0.011	0.029
Fraction of occupational transfers going through unemployment	SIPP	0.175	0.1161
Coefficient $\hat{\gamma}$ in equation (11)	SIPP	2.13	2.0414
Coefficient $\hat{\gamma}$ in equation (12), E-switchers	SIPP	-0.001	0.3139
Coefficient $\hat{\gamma}$ in equation (12), U-switchers	SIPP	0.015	0.3546

Table 2: *The moments targeted in the calibration. The second column names the source of the data counterpart of the moment. 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.*[44]

counterpart in the data. 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 1600 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 calculated using the results in Kambourov and Manovskii (2009b).

The next set of moments corresponds to the idiosyncratic productivity process and the cost of reallocation for an unemployed worker (c^u). The average value of the idiosyncratic productivity is set to target an average productivity of 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^u and the wage $w(p, z, x)$. In order to estimate the remaining parameters of the idiosyncratic productivity process as well as the reallocation cost c^u, I 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 relative occupational mobility rate of unexperienced workers, and the subsequent mobility rate, where the latter is defined as the probability that a worker switches occupations during their next unemployment spell conditional on having switched during their previous unemployment spell.[45]

The third set of moments targets the parameters that govern the worker's job-to-job occupational mobility decision (in particular cost c^e) as well as the occupational transfer shock ψ. In order to set these parameters, I include the average occupational mobility rate for employed workers (also displayed in figure 3), the occupational mobility rate for unexperienced employed workers (relative to experienced workers), and the occupational mobility rate for employed workers specific to switches made without an employer change.

[45] 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.

A number of parameters also appear in the basic search and matching model.[46] The moments corresponding to these parameters are generally moments that can also be calculated with the basic model. Specifically, the moments corresponding to the parameters δ (exogenous separation rate) and k (vacancy cost) are the proportion of employed workers experiencing at least one unemployment spell in the next year, the unemployment rates of the unexperienced and experienced worker, and the average job finding rate.

Finally, in order to reasonably match the patterns uncovered in section 2 of this paper, I target the average fraction of occupational switches going through unemployment, as well as a set of results from three simple regression estimations. In particular, I regress the aforementioned fraction of occupational switches going through unemployment on the unemployment rate at the time of the materialization of the shock, as displayed in equation (11), thus essentially fitting a line through the scatter plot displayed in the right panel of figure 2. Finally, I also regress the wage differentials experienced by either occupational U-switchers or E-switchers on this same unemployment rate at the time of the materialization of the shock, as displayed in equation (12):

$$\text{Frac}_t^u = \alpha + \gamma U_t + \varepsilon_t \tag{11}$$

$$\Delta w_t = \alpha + \gamma U_t + \epsilon_t \tag{12}$$

O	x_1	μ_p	ϕ	χ	β	b	η
6	1	1	0.0005	0.0042	0.9987	0.738	0.500

σ_p	σ_z	ρ_p	ρ_z	μ_z	k	$\bar{c^u}$	$\bar{c^e}$	x_2	x_3	ψ	δ
0.037	0.051	0.986	0.987	1.036	1.579	-0.691	0.258	1.39	1.883	0.002	0.0037

Table 3: *Values of parameters used to obtain the results in Section 5. Parameters are either 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. The parameter value that stands out here is the cost of changing occupations through unemployment c^u, which is calibrated to be negative. Naturally, this negative cost results in newly unemployed workers being very likely to choose to switch occupations, especially when they did not accumulate any occupational human capital, as reflected in the results in section 5. Table 3 also shows that the calibrated values for k is fairly high, reflecting that the cost of posting a vacancy is close to one period's worth of

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

output. On the other hand, the cost of switching occupations on the job is fairly low, while still positive, with the cost c^e corresponding to less than a quarter of a period's worth of output.

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. In particular, the model generates very high job finding rates, leading to excessively low unemployment (survival) rates. As shown in section 5, this is primarily driven by newly unemployed workers often immediately choosing to switch occupations. Despite this, the model generates too many job-to-job occupational switches compared to switches through unemployment, although it is worth noting that the cyclical pattern of the fraction of of occupational transfers going through unemployment, a key moment for the purpose of this paper, is matched quite well. Furthermore, the model does reasonably well when it comes to the returns to occupational experience, and the occupational mobility rate for employed workers.

5 Results

5.1 Model Fit

From the discussion in the previous section it can be concluded that the fit of the model in terms of the targeted moments is not perfect. However, despite these imperfections, the model does seem to be able to match the distinctive patterns of U- and E-switching over the business cycle. In this subsection, I will further explore these patterns, as well as their implications for the switchers' subsequent earnings, through the lens of the model.

5.1.1 Mobility Rates

In figure 11, I show the cyclical patterns of the occupational U-mobility (left panel) and E-mobility rates (right panel). In both panels, the range of the horizontal axis clearly reflects the fact that the model implies an excessively low unemployment rate throughout the simulation. As can be seen in the left panel of the figure, the model predicts the occupational E-mobility rate to be slightly procyclical, which is in line with the observations I made from the SIPP in section 2 and appendix A.2. The occupational U-mobility rate, on the other hand, is found to be countercyclical, as seen

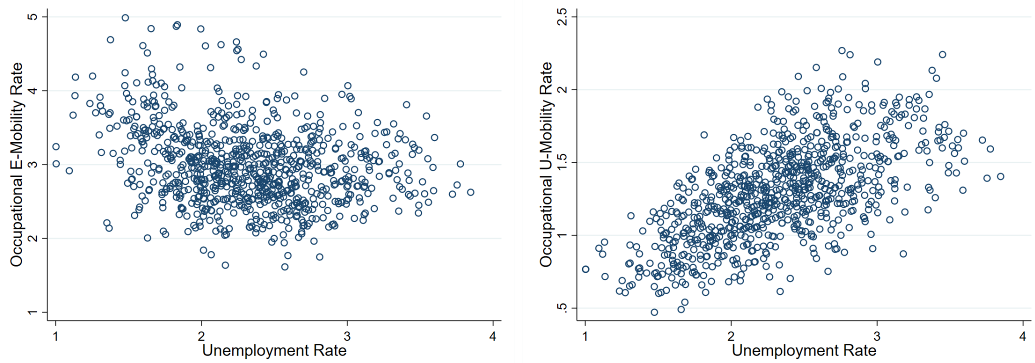

Figure 11: *The occupational U-mobility rate (counting only U-switchers, left) or E-mobility rate (counting only E-switchers, right), plotted against the corresponding month's unemployment rate, using model-generated data.*

in the right panel of figure 11. The model needs this countercyclical U-mobility rate in order to generate the cyclical pattern in the fraction of occupational switchers going through unemployment, which was targeted more directly in the estimation and therefore matches quite well with the pattern found in the data, as can be seen in figure 12.

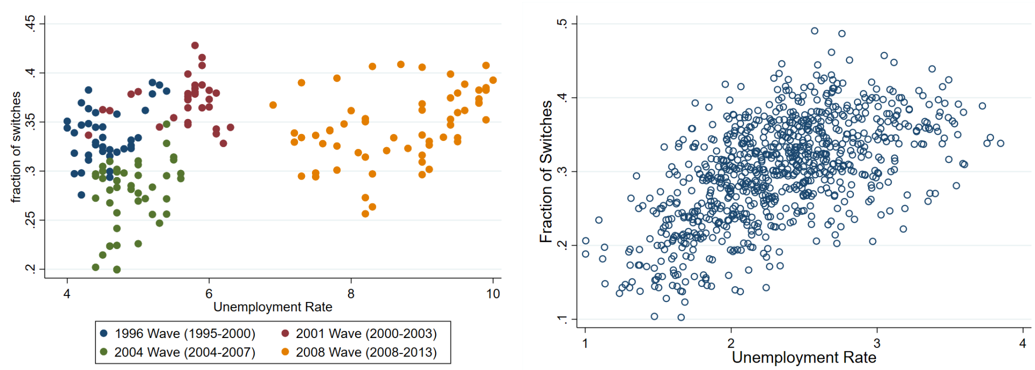

Figure 12: *The fraction of occupational switchers going through unemployment and the corresponding month's unemployment rate, as found in the data (left) and as generated by the model (right).*

Focusing on the underlying mechanisms that generate the patterns discussed above, it should be recognized that there are three decisions made by the worker 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 the left panel of figure 13. In the model, all the action is taking place at the low occupational human capital level x_1: once the worker progresses to the second of the three levels of occupational human capital, she is no longer willing to (voluntarily) switch occupations or destroy her match with the firm. For this reason, the thresholds for these higher levels of occupational human capital are omitted from the figure.

It is also worth noting that in the left panel of figure 13, the reallocation threshold for unemployed workers lies above the separation threshold at all values of aggregate productivity p. This implies that any worker who decides to destroy her match with her employer will also decide to switch occupations in the next period, as long as she does not receive a large positive shock in her idiosyncratic productivity in the next period. As a result of this, the model does not feature any rest unemployment, as workers who are situated below the separation threshold, and therefore face a zero probability of matching in the current period, decide to switch occupations instead of waiting for conditions to improve. This is confirmed in appendix D.1, where I decompose the model-generated unemployment into rest, reallocation, and search unemployment.

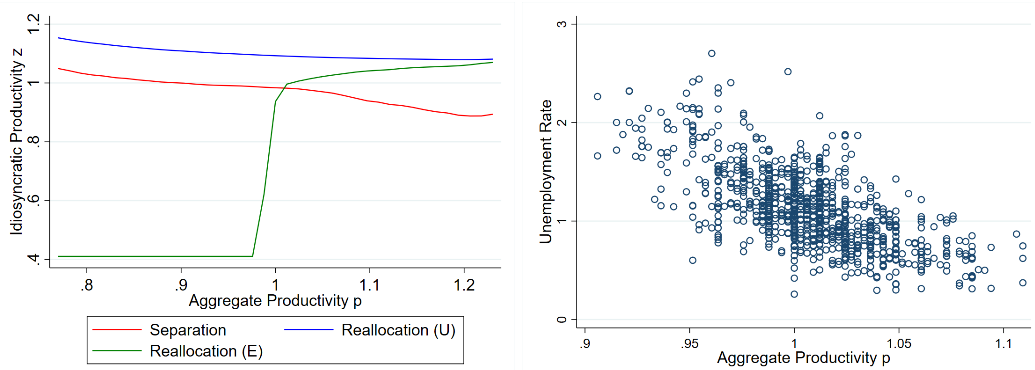

Figure 13: *Right: Threshold values of idiosyncratic productivity z below which a worker (with human capital level x_1) chooses to separate, reallocate when unemployed, or reallocate when employed, for different values of aggregate productivity p in the model. Left: model-simulated unemployment rates for different levels of aggregate productivity p.*

Shifting the focus to cyclical patterns, it can be observed in the left panel of figure 13 that the thresholds for on-the-job reallocation are generally increasing in aggregate productivity, while the thresholds for separation and reallocation during unemployment are decreasing in aggregate productivity. Keeping everything else constant, these patterns cause a countercyclical

U-mobility rate, a countercyclical unemployment rate, and a procyclical E-mobility rate. For the unemployment rate, this pattern is confirmed in the right panel of figure 13, which plots the model-generated unemployment rate against the aggregate productivity, generating a noisy but clearly downward sloping pattern.

The fact that the decision thresholds shown in the left panel of figure 13 are not all constant in aggregate productivity p is also visible in Figure 14, which shows the distribution of unemployed (left) and employed (right) workers over different combinations of values of idiosyncratic productivity z and aggregate productivity p. Looking at the left panel, for unemployed workers, the threshold for reallocation (while unemployed at the lowest level of occupational human capital) is clearly visible (and plotted as the dashed white line for clarity). Furthermore, one can also see the separation threshold for these workers, as shown in the figure using the red dashed line. The high concentration below this threshold also indicates that a majority of the workers in the simulation have a higher level of occupational human capital. This is also reflected in the right panel, which shows the distribution of employed workers, and does not show a clear threshold.

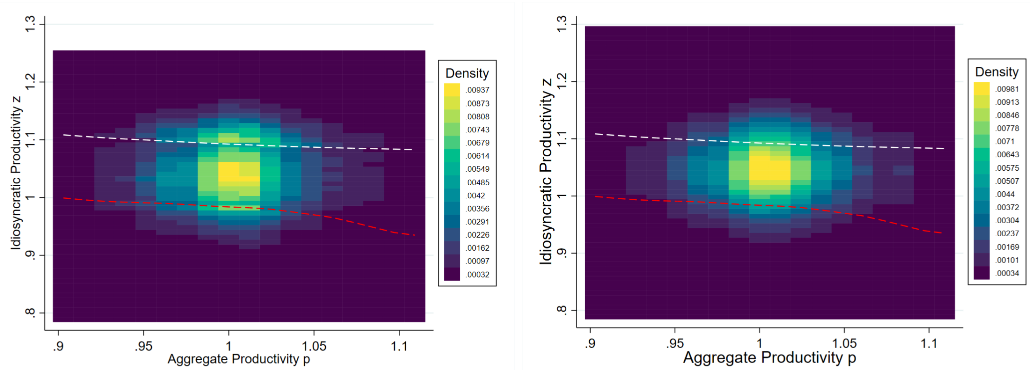

Figure 14: *The distribution of unemployed (left) or employed (right) workers over different combinations of aggregate productivity p and idiosyncratic productivity z, generated from the model simulation. The separation (red) and reallocation (white) thresholds for the worker with the lowest level of occupational human capital are added to clarify the interpretation of the plots.*

5.1.2 Subsequent Earnings

While the cyclical patterns of the mobility rates, and especially the cyclicality of the fraction of occupational switchers going through unemployment, were in part explicitly targeted when estimating the model in section 4, this is not the case for the subsequent earnings paths experienced by occupational switchers. When it comes to these patterns, the only directly related moments targeted in the estimation are the regression coefficients on equation (12) (specific to either U-switchers or E-switchers). These moments, however, only take into consideration the wage earned by the switcher directly after the switch materialized, and is therefore not informative on the subsequent earnings path experienced by these workers. In this subsection, I explore how the model performs in matching these subsequent earnings paths, as observed in section 2.

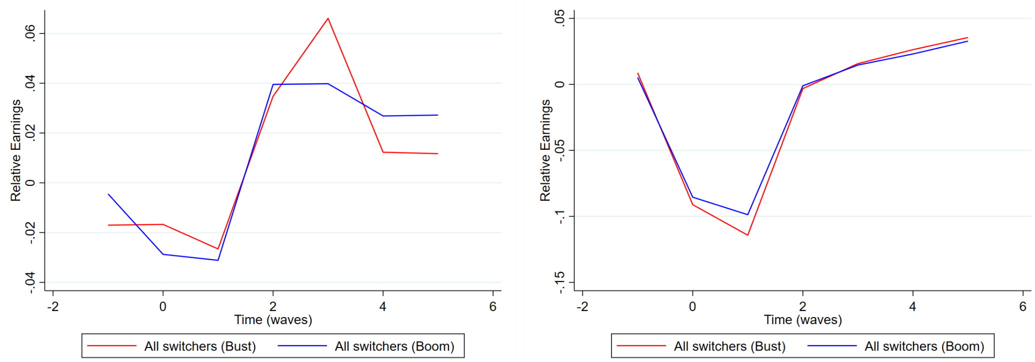

Figure 15: *The effect of occupational switches on real earnings, relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the estimates from the data (left) and the estimates obtained from model-generated simulation data (right).*

In figure 15, I show the results of an estimation using the three-step estimation method from Borusyak et al. (2022) on real earnings, where I do not distinguish between E-switchers and U-switchers. The left panel shows the results obtained from the data, as shown earlier in the right panel of figure 9, whereas the right panel repeats the same estimation on model-generated simulation data. Comparing the two figures, it can be seen that the model overshoots the earnings lossed observed in the data, regardless of the economic conditions at the time of the occupational switch. However, the model is consistent with the data in not identifying a clear cyclical pattern in the earnings paths experienced by occupational switchers after the materialization of their switch.

In figure 16 I display the results of repeating the estimation while allowing for different treatment effects for U-switchers and E-switchers. Again, the left panel repeats the observation from the data, and corresponds to the right panel of figure 10. As can be seen by comparing the findings in the left panel to those obtained from model-generated simulation data, as displayed in the right panel of figure 16, the difference between E-switchers and U-switchers is fairly similar between the data and the model in the short run. However, it is worth noting that the model does not match the countercyclicality of the post-switch earnings paths for U-switchers as observed in the data, and furthermore suggests a faster recovery in earnings than I found in the data. Especially the latter of these two observations is likely to be a consequence of the model's tendency to generate excessively high job finding rates, as pointed out earlier in section 4.

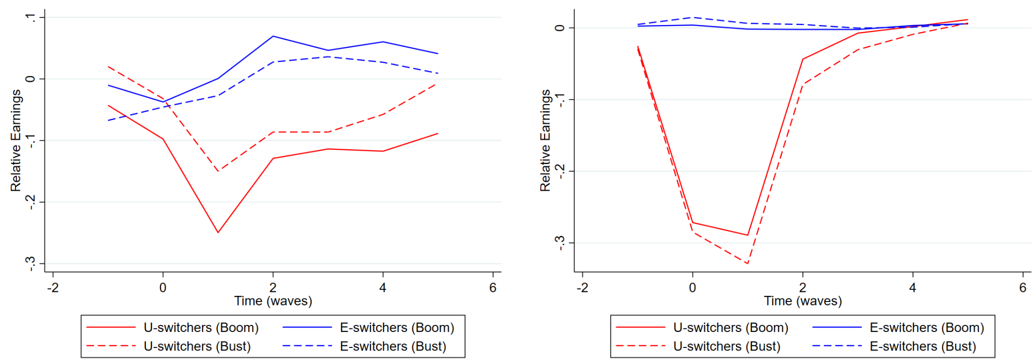

Figure 16: *The effect of occupational switches on real earnings, relative to the counterfactual of never switching, by type of switch, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the estimates from the data (left) and the estimates obtained from model-generated simulation data (right).*

5.2 Model Implications

In the previous subsections, I showed that the model is able to generate the countercyclical fraction of occupational switchers going through unemployment that I observed in the data in section 2, and furthermore generates a fairly acyclical pattern in terms of earnings experienced by occupational switchers on average after the materialization of their switch. Earlier in this paper, I hypothesized that this acyclicality of the earnings path likely masks the effects of a composition change, where many workers do worse after an occupational change simply because they switched through unemployment rather than through a job-to-job transition. As the model is able to generate such compositional changes, I will now proceed to analyze the extent to which these compositional changes drive the cyclicality of the post-switch earnings path.

In figure 17, I show how the model-based estimation of the cyclicality of the post-

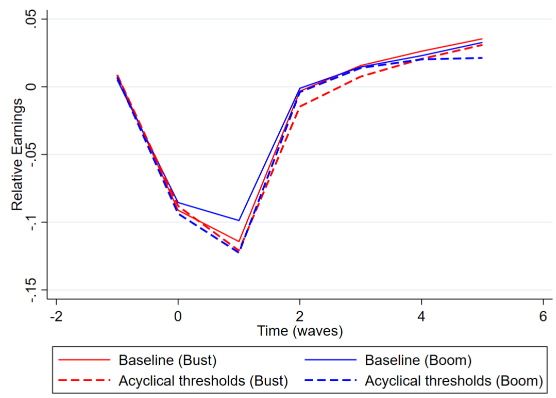

Figure 17: *The impact of cyclical reallocation thresholds on the model-generated (BJS) effect of occupational switches on real earnings, relative to the counterfactual of never switching, and aggregated separately for switches materializing during a boom or a bust. The figure combines the estimates obtained from the baseline model (solid) and a model in which separation and reallocation thresholds are forced to be constant in aggregate productivity (dashed).*

switch real earnings paths changes if I force the reallocation thresholds to be constant over the business cycle. In particular, I generate this figure by forcing workers to base their separation and reallocation decisions while unemployed or employed on a comparison of values at the average aggregate productivity level, $p = 1$, rather than the current aggregate productivity level. The result of this change is that the thresholds in the left panel of figure 13 would be horizontal at their level for $p = 1$ rather than decreasing in p (for separation and reallocation through unemployment) or increasing in p (for job-to-job reallocation).

As can be seen in figure 17, taking out this cyclical component has a fairly mild impact on the estimated post-switch real earnings path. This is because, as shown in figure 13, the reallocation and separation thresholds are fairly flat in this estimation, and thereby did not change much when forcing it to be completely horizontal. The exception to this is the job-to-job reallocation threshold, which is now forced to be positive in a recession whereas it previously dropped off at values of p slightly below 1. This may explain why the average earnings losses after an occupational switch in a bust have slightly worsened for across the entire estimated earnings path after the materialization takes place. Furthermore, it is worth noticing that removing the cyclicality of the thresholds has reversed the overall pattern from very mildly countercyclical to very mildly procyclical.

One important way in which the model in this paper differs from most models in the existing literature is by including the possibility of switching occupations without having to go

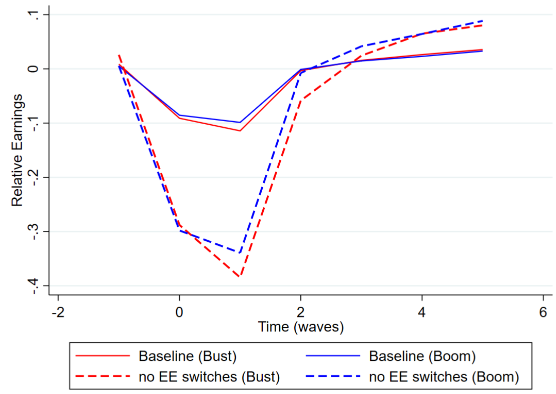

Figure 18: *The impact of including job-to-job transitions on the model-generated (BJS) effect of occupational switches on real earnings, relative to the counterfactual of never switching, and aggregated separately for switches materializing during a boom or a bust. The figure combines the estimates obtained from the baseline model (solid) and a model without either type of job-to-job occupational transfers (dashed).*

through unemployment. As seen in the data as well as in the model (see figure 16), workers who switch through unemployment tend to experience much larger earnings losses than job-to-job switchers, who in most cases do not face any losses at all. Naturally, including these E-switchers therefore has a large impact on the earnings losses after an occupational switch as implied by the model. This is stressed in figure 18, which plots estimates of the average earnings loss after an occupational switch in an alternative version of the model which does not allow for job-to-job reallocation, compared to the baseline model. As can be seen in the figure, only allowing for switches through unemployment implies that the model will predict very large consequences of an occupational switch on subsequent earnings, which is not representative in practice for (the majority of) workers who decided to switch while staying on the job.

In this paper's model, I allow for two distinct ways of switching occupations while staying on the job. The first channel is an exogenously imposed reallocation shock which forces the worker to reallocate but not separate from her employer, whereas the second channel is driven by the worker's (endogenous) choice to search for a job in a different occupation and with a different employer. In figure 19, I decompose the cyclicality of the average earnings consequences of an occupational change into these two channels, as well as a residual channel, which reflects the remaining cyclicality after taking out all job-to-job transitions and therefore reflects the difference between the two dashed lines in figure 18. In order to accurately assign contributions to each of the job-to-job transition channels, I use a Shapley-Shorrocks decomposition (see Shorrocks, 2013), which aims to calculate contributions that are independent of the order in which the channels are switched off.[47]

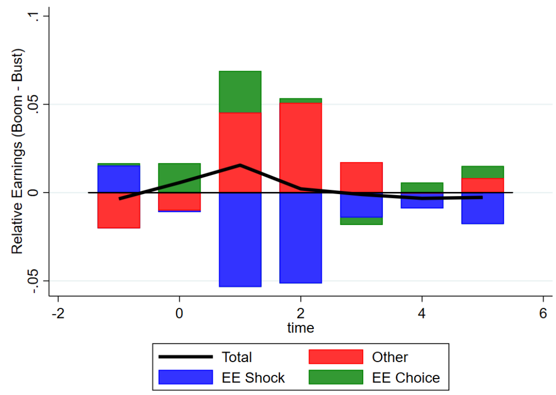

Figure 19: *The impact of including job-to-job transitions on the model-generated (BJS) cyclicality in the effect of occupational switches on real earnings. The figure displays the separate impact of the occupational transfer shock and job-to-job occupational transfer choices, obtained using a Shapley-Shorrocks decomposition.*

As can be seen in figure 19, the exogenous reallocation shock has a large impact on the cyclicality of the average earnings consequences of an occupational change, and this impact is consistently negative, thus indicating that this reallocation shock pushes the earnings losses to be countercyclical. The endogenous choice channel as well as the residual channel, however, are generally pushing the earnings consequences to be procyclical. In other words, while this decomposition suggests that the composition effect that ensures that the fraction of switchers through unemployment is larger in a recession has a procyclical effect on average earnings losses after an occupational switch (as evidenced by the positive impact of including endogenous job-to-job transitions on the cyclicality), this is offset by the acyclical reallocation shock, which goes in the other direction. This result therefore points to a need to further explore these transitions that occur on-the-job and within a firm in order to fully understand all the cyclical properties of the earnings consequences of occupational mobility.

[47]In practice, this means that I do the decomposition for each possible order of channels separately, and then take the average across decompositions for each channels. For a decomposition such as this one, in which I am only interested in two channels, this is fairly straightforward and only requires one additional simulation. However, in a decomposition with more channels, this becomes computationally infeasible rather quickly as the number of required simulations explodes.

6 Conclusion

In this paper, I study occupational mobility and its effect on subsequent earnings and wages, focusing in particular on the business cycle properties of these effects. In doing so, I distinguish between three types of occupational transitions: transitions that move through unemployment, job-to-job occupational transitions that also involve an employer change, and job-to-job occupational transitions without such an employer change. Using data from the Survey of Income and Program Participation, I find that the fraction of occupational switchers who switch through unemployment is countercyclical, and while these workers generally do worse in terms of earnings than workers who make a job-to-job transition, their earnings and wage patterns may slightly improve in recessions, whereas the patterns slightly deteriorate for occupational switchers on average. I hypothesize that this reflects a composition effect, where deterioration of the average patterns are driven by a larger fraction of occupational switchers doing so through unemployment, and occupational transfers through unemployment generally being associated with large earnings losses.

In order to quantify the effect of this composition effect on the earnings patterns of occupational switchers, I propose a DMP-style job search model of occupational mobility, which includes each of the aforementioned three types of occupational mobility. In this model, the endogenous separation probability increases in a recession, while (keeping all else constant) workers are also more willing to search in a different occupation while unemployed. The willingness to search in a different occupation decreases for job-to-job transitions in a recession, thus generating the countercyclical fraction of occupational switchers who switch through unemployment as observed in the data. Quantifying the effect of this changing composition on the average earnings consequences of occupational mobility, I find that this composition channel pushes the earnings consequences to be more procyclical, but is offset by the (acyclical) within-firm occupational changes which drive the earnings consequences to be countercyclical.

While the model is fairly successful in generating a changing composition of occupational switchers over the business cycle, the fit of the model is fairly weak in some other dimensions. In particular, the model generates job finding rates that are too large, therefore leading to low unemployment rates. In future work, I plan to further investigate and address this apparent shortcoming of the model.

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, like in Carrillo-Tudela et al. (2021). 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, especially given it's important role in explaining the cyclicality of the earnings patterns after occupational transfers. Future work that further investigates this channel could build on some existing work in this area, such as Papageorgiou (2018).

Other limitations of the model 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. One 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 has been subject to some discussion in some recent work, 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 (2019) 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. I chose not to include these extensions in the model presented in this paper, as they present a substantial complication to the model, without a clear benefit in terms of the goal of the model. However, given the empirical importance of several of these channels, and the model's current challenges in matching transitions out of unemployment, these are interesting extensions that should be explored in future work.

Finally, it is worth mentioning that while the Survey of Income and Program Participation is a fairly commonly used dataset to investigate occupational mobility, it comes with the limitation of fairly short panels, which might hamper the ability of the empirical methods to accurately estimate the earnings and wage paths experienced by occupational switchers. Future work could seek to further improve on these estimates by using rich administrative data that allows one to follow an individual over an extended period of time.

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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 used in Section 4 to estimate the model.

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.[48] After running these programs, one can start using the data to create the dataset of interest. At this point I impose the sample restrictions, thus dropping any observations belonging to individuals who did not participate in the first wave (interview) of the panel, are aged below 23 or over 61, are self- or dual-employed, or work for the government.

In order to create the measure for occupational mobility, I compare the respondent's occupation in a certain month to their 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 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. Unfortunately, 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), so that 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. In order to avoid creating such a discontinuity, I recode all occupations using the consistent panel of occupations from Dorn (2009). Table A.1 lists all the 1-digit and 2-digit occupational codes that the tables in the main text and in the next sections refer to.

[48]These programs are available at http://ceprdata.org/sipp-uniform-data-extracts/sipp-recoding-programs/

	1-digit occupations	2-digit occupations
1	Management, Professional, Technical, Financial Sales, and Public Security Occupations	Executive, Administrative and Managerial Occupations
2	Administrative Support and Retail Sales Occupations	Management Related Occupations
3	Low-skill Services Support Occupations	Professional Specialty Occupations
4	Precision Production and Craft Occupations	Technicians and Related Support Occupations
5	Machine Operators, Assemblers, and Inspectors	Financial Sales and Related Occupations
6	Transportation, Construction, Mechanics, Mining, and Agricultural Occupations	Fire Fighting, Police, and Correctional Institutions
7		Retail Sales Occupations
8		Administrative Support Occupations
9		Housekeeping, Cleaning, Laundry
10		Supervisors of Guards; Guards
11		Food Preparation and Service Occupations
12		Health Service Occupations
13		Building and Grounds Cleaning and Maintenance Occupations
14		Personal Appearance Occupations
15		Recreation and Hospitality Occupations
16		Child Care Workers
17		Misc. Personal Care and Service Occupations
18		Precision Production Occupations
19		Machine Operators, Assemblers, and Inspectors
20		Transportation and Material Moving Occupations
21		Construction Trades
22		Mechanics and Repairers
23		Extractive Occupations
24		Farm Operators and Managers
25		Other Agricultural and Related Occupations

Table A.1: *1-digit (left) and 2-digit (right) occupation codes according to the system from Dorn (2009).*

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 their 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.[49]

In order to identify whether respondents went through an unemployment spell, I use the SIPP's employment status recode variable, which can take 8 different values. I define respondents to be unemployed if they are 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*".
As a result, I define respondents to be employed if they are 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 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

[49] In appendix A.2, I show that the overall occupational mobility as well as the fraction of occupational switchers going through unemployment exhibits similar but clearer patterns as those identified in the main text if I do not impose these checks for "genuine" switches.

Appendix C. Using the measure created for the occupational mobility rate for employed workers, I then create the Figure 3 in the main text.

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 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.[50] 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.

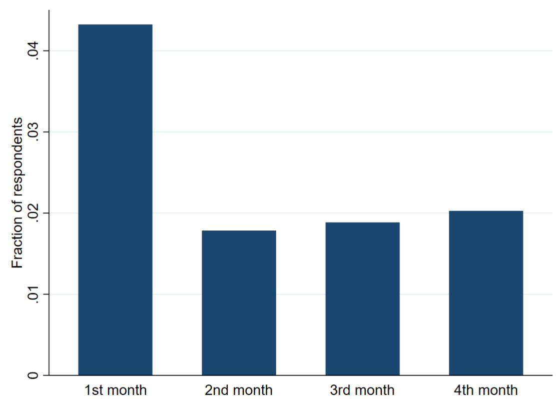

Figure A.1: *The fraction of respondents who change employment status compared to the previous month, by interview reference month.*

A.2 Further Results on 1-digit occupational mobility

In this section, I present some additional observations on 1-digit occupational mobility, made from 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.

[50]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.

A.2.1 Mobility Rates

	1	2	3	4	5	6
1	0	16465	6222	1049	1830	5368
2	17540	0	7783	903	2108	5436
3	6921	8271	0	784	2016	5352
4	1249	860	868	0	1237	1673
5	1762	2311	2104	1383	0	4698
6	5496	5240	5151	1521	4436	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.[51] 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 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 Table 1 in the main text is repeated in Tables A.3 to A.10 for subsets of the data. In particular, Tables A.3 to A.6 look at the 1996, 2001, 2004, or 2008 panel only, Tables A.7 and A.8 count only U-switches, and Tables A.9 and A.10 count only E-switches (where Tables A.7 and A.9 are the equivalents of Table A.2 above for U- or E-switchers only) . 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 switches in and out of occupation 1 (*Management, Professional, Technical, Financial Sales, and Public Security Occupations*). For this occupation, the inflow seems much larger than the outflow when it comes to E-switches and the outflow is much larger than the inflow for U-switches, which makes sense as one could imagine many within-firm promotions going into managerial positions.[52]

In Figure A.2, I plot the 1-digit occupational mobility rate over time. Compared to Figure 1 in the main text, this figure also includes occupational switches that could not be verified

[51] Note that Table 1 and A.2 do not use the sample weights. If the tables are tabulated using sample weights, the conclusions remain unchanged. These results are available upon request

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

Occupation	1	2	3	4	5	6
Observations	333379	209511	108962	31914	85566	171214
Observations (wave 1)	9754	6231	3474	956	2615	5224
Inflow	10931	10918	6285	1921	4479	7843
Outflow	10112	11312	6955	1849	4763	7386
Net Inflow	819	-394	-670	72	-284	457

Table A.3: *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 (in the first wave only and in the entire panel), for the 1996 panel only. For a list of the occupations corresponding to these codes, see Appendix A.1.*

Occupation	1	2	3	4	5	6
Observations	224018	121972	74030	17902	42079	106756
Observations (wave 1)	10386	5701	3543	886	2078	5059
Inflow	5886	5786	3806	874	1934	4301
Outflow	5593	5699	4052	953	2250	4040
Net Inflow	293	87	-246	-79	-316	261

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 (in the first wave only and in the entire panel), for the 2001 panel only. For a list of the occupations corresponding to these codes, see Appendix A.1.*

Occupation	1	2	3	4	5	6
Observations	290365	179748	106275	30468	52491	130816
Observations (wave 1)	11004	6954	4209	1167	2098	5176
Inflow	9202	9033	6402	1812	3024	5823
Outflow	8464	9507	6663	1869	3181	5612
Net Inflow	738	-474	-261	-57	-157	211

Table A.5: *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 (in the first wave only and in the entire panel), for the 2004 panel only. For a list of the occupations corresponding to these codes, see Appendix A.1.*

Occupation	1	2	3	4	5	6
Observations	390268	224551	150353	31621	53345	156083
Observations (wave 1)	10698	6125	4243	931	1546	4920
Inflow	6949	7410	5635	1033	2190	4560
Outflow	6765	7252	5674	1216	2064	4806
Net Inflow	184	158	-39	-183	126	-246

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 (in the first wave only and in the entire panel), 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
1	0	5118	1918	237	561	1598
2	4236	0	3102	268	811	1969
3	1732	3100	0	217	887	2246
4	206	271	315	0	392	586
5	517	996	931	363	0	1914
6	1518	1922	2202	520	1952	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
Observations	1238030	735782	439620	111905	233481	564869
Inflow	8209	11407	8468	1605	4603	8313
Outflow	9432	10386	8182	1770	4721	8114
Net Inflow	-1223	1021	286	-165	-118	199

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
1	0	11347	4304	812	1269	3770
2	13304	0	4681	635	1297	3467
3	5189	5171	0	567	1129	3106
4	1043	589	553	0	845	1087
5	1245	1315	1173	1020	0	2784
6	3978	3318	2949	1001	2484	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
Observations	1238030	735782	439620	111905	233481	564869
Inflow	24759	21740	13660	4035	7024	14214
Outflow	21502	23384	15162	4117	7537	13730
Net Inflow	3257	-1644	-1502	-82	-513	484

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.*

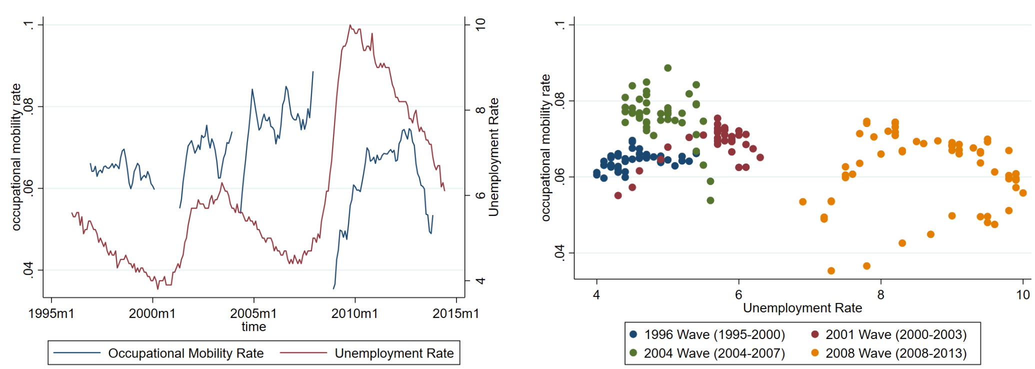

Figure A.2: *The 1-digit occupational mobility rate and the corresponding month's unemployment rate from the BLS, plotted over time (left) and against each other in a scatter plot (right), including both verified and unverified occupational switches.*

as coinciding with a change in employer, industry, working hours, or hourly wage. This implies that some of the occupational switches included in Figure A.2 may be caused by a measurement error. Nevertheless, it can be observed that additionally including the non-verified switches leads the within-panel negative trend in the occupational mobility rate (visible in Figure 1, among others) to disappear, thereby revealing a seemingly countercyclical trend. Nevertheless, when plotting the rates against the corresponding unemployment rates reveals a negative relation, thus confirming the fact that the overall occupational mobility rate is procyclical, as concluded in the main text after detrending the occupational mobility rate based on verified switches only.

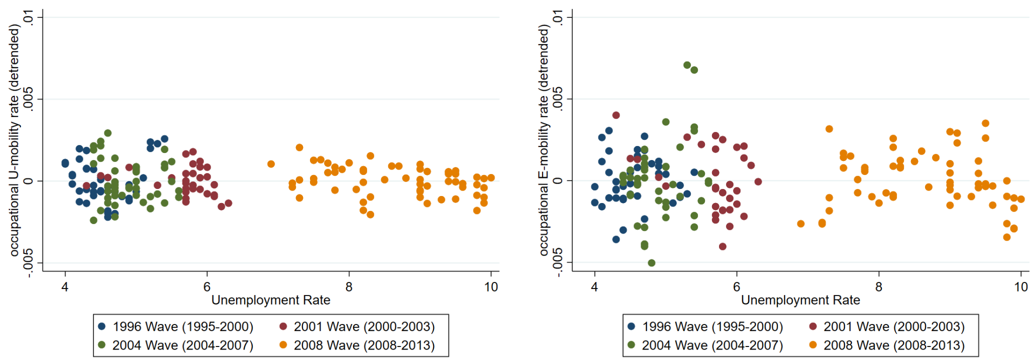

Figure A.3: *The detrended 1-digit occupational U-mobility rate (counting only U-switchers, left) or E-mobility rate (counting only E-switchers, right), plotted against the corresponding month's unemployment rate from the BLS.*

Figure A.3 plots the unemployment rate as well as the occupational mobility rate separately for workers who change occupations with and without going through an unemployment spell (U-switchers and E-switchers). As can be seen by comparing the two panels of Figure A.3, the occupational U-mobility rate, which counts only those going through unemployment, seems much less volatile than the occupational E-mobility rate. In terms of cyclicality, the two panels look fairly similar. Indeed, a simple (naive) OLS regression (of the mobility rate on the unemployment rate) gives a coefficient of -0.00003 for the U-switchers and -0.00002 for the E-switchers, thus suggesting both rates to be mildly procyclical. The fact that the fraction of occupational switchers going through unemployment is so strongly countercyclical, as shown in Figure 2 in the main text, therefore does not necessarily seem to be due to the occupational U-mobility rate itself being countercyclical. However, it should be noted here that it is likely that this result is partially influenced by the detrending of the mobility rates being too aggressive and taking out some of the variation that is driving the result.[53] Indeed, looking at Figure A.4, which is the non-detrended version of Figure A.3, both mobility rates still seem procyclical, but now it is clear that the procyclicality of the occupational U-mobility rate is much milder than that of the occupational E-mobility rate.

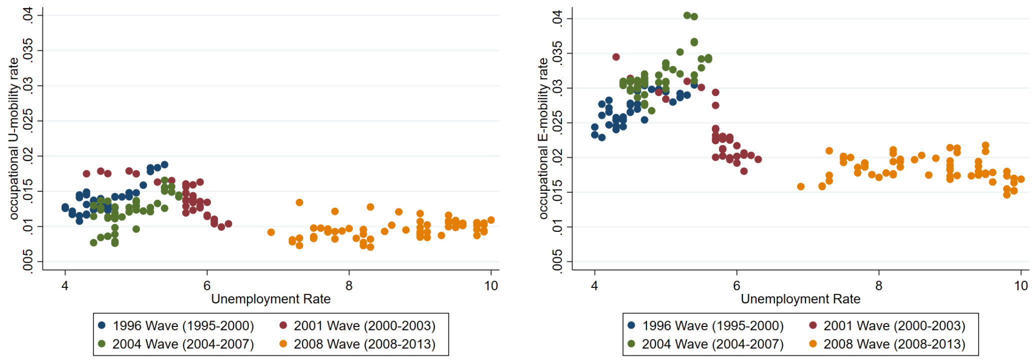

Figure A.4: *The (non-detrended) 1-digit occupational U-mobility rate (counting only U-switchers, left) or E-mobility rate (counting only E-switchers, right), plotted against the corresponding month's unemployment rate from the BLS.*

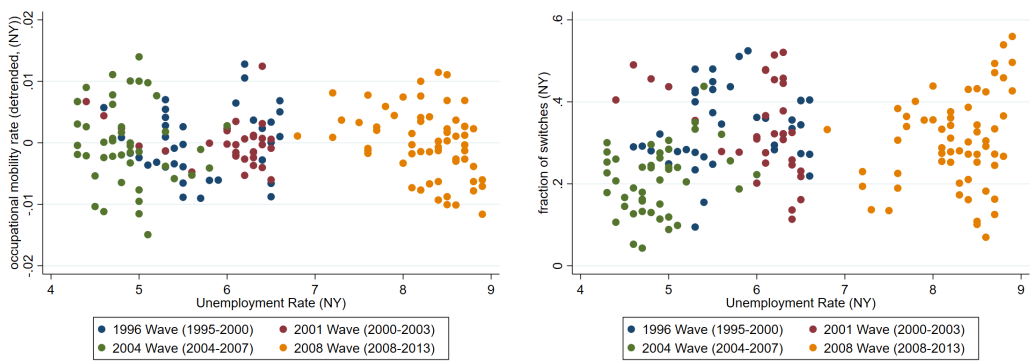

Figure A.5: *The total 1-digit occupational mobility rate (left) and the fraction of occupational switchers (1-digit) going through unemployment (right) for New York, plotted against the unemployment rate in a scatter plot.*

To show that the results discussed in Section 2 still hold on a state-level, Figure A.5 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 procyclical (left), and the fraction of the switches that goes through unemployment still shows a countercyclical pattern,

[53]This complication is likely to be the result of the fact that most of the SIPP panels under consideration in this paper cover only a single (upward or downward) movement in the general business cycle.

although the pattern becomes substantially noisier. A similar conclusion can be reached when considering only male respondents, as done in Figure A.6, although the pattern of the fraction of switches that goes through unemployment (right panel) shows a much stronger countercyclical pattern than the one specific to the state of New York (but still including female respondents).

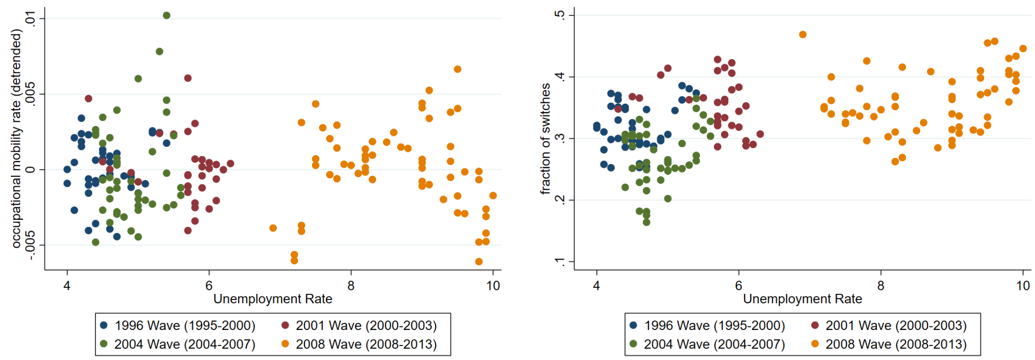

Figure A.6: *The total 1-digit occupational mobility rate (left) and the fraction of occupational switchers (1-digit) going through unemployment (right) for male respondents only, plotted against the unemployment rate in a scatter plot.*

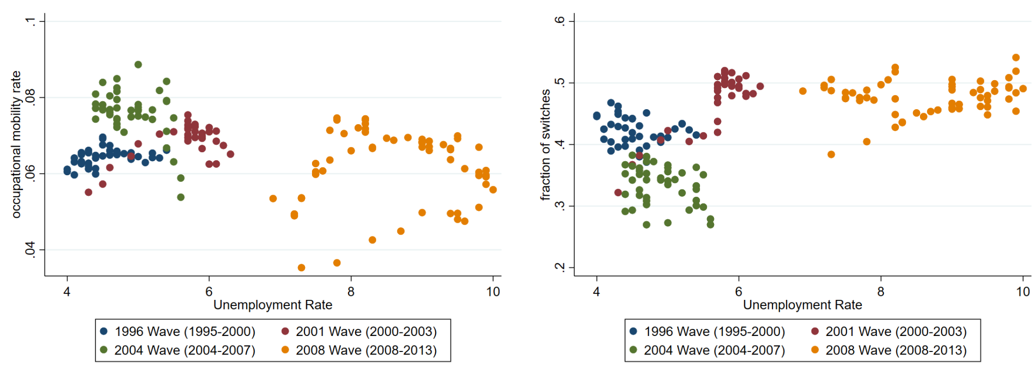

Figure A.7: *The total 1-digit occupational mobility rate (left) and the fraction of occupational switchers (1-digit) going through unemployment (right), plotted against the unemployment rate in a scatter plot, including both verified and unverified occupational switches.*

In Figure A.7, I expand the sample by additionally including occupational switches that could not be verified as coinciding with a change in employer, industry, working hours, or hourly wage. The left panel, which corresponds to Figure A.2, confirms the procyclicality of the total occupational mobility rate.[54] The right panel confirms the countercyclicality of the fraction of oc-

[54]Note that in order to create the left panel of Figure A.7, I did not detrend the occupational mobility rates. I chose

cupational switchers going through unemployment, although it should be noted that including the non-verified switches has slightly increased the level of this fraction across all panels.

Similarly, Figure A.8 plots occupational mobility rates (including non-verified switches) including only switches through employment, thus corresponding to Figure 3 in the main text. As can be seen in the figure, including the non-verified switches does not change my conclusion that roughly a quarter to a third of employed workers switching occupations do so without changing employers.

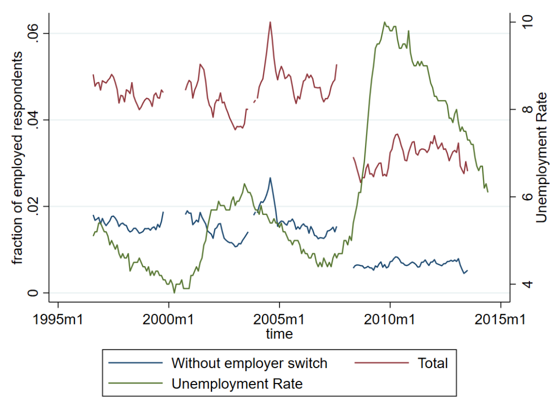

Figure A.8: *The fraction of employed workers switching occupations in the next 4 months, and the fraction of employed workers doing so without switching employer, including both verified and unverified occupational switches, plotted over time together with the corresponding month's unemployment rate from the BLS.*

A.2.2 Subsequent Earnings and Wages

In Figure A.9, I plot the average real wage for occupational U- and E-switchers, 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).[55] In the right panel (which corresponds to Figure 4 in the main text) I restrict the respondents to have observations in all periods in the time frame, whereas the left panel does not make that restriction. Furthermore, to put the observations from the main text in context,

not to do this because the original reason for detrending in the main text (the within-panel negative trends) are no longer visible when including the non-verified switches.

[55] As in the main text, the wage for U-switchers before the switch refers to the wage in their previous job.

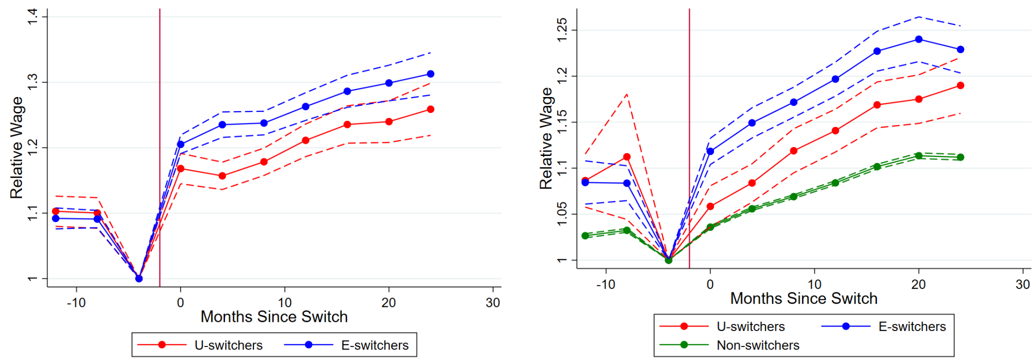

Figure A.9: *Real wage paths over time for occupational U-switchers and E-switchers, with (right) and without (left) removal of outlier wages. The switch takes place between time -4 and 0, as represented by the vertical line at -2. The right panel additionally includes the relative real wage path for non-switchers.*

I added the corresponding wage paths for non-switchers to the figure in the right panel. As can be seen in the figure, the restriction to respondents with sufficient observations does not substantially alter the conclusions, although the real wage paths for both types of switchers are situated slightly higher when estimating without these restrictions. In the right panel, it is worth noticing that the real wage paths for non-switchers lie below those for either type of occupational switcher. This is likely to be a consequence of the baseline level of the real wage being much higher for non-switchers, as pointed out later in this section when discussing Table A.11.

In Figure A.10, I repeat the analysis from Figure 4 and the right panel of Figure A.9, additionally including switchers whose occupational switch could not be verified with a coinciding change in employer, industry, working hours, or hourly wage. As can be observed when comparing Figure A.10 with either Figure 4 or the right panel of Figure A.9, additionally including these unverified occupational switches in the sample does not change the conclusion.

In Figures A.11 and A.12, I repeat the analysis of Figure 5 by plotting the real wage immediately after the switch (relative to the pre-switch real wage) against the unemployment rate at the time of the switch. Compared to the figure in the main text, Figure A.11 additionally includes switchers whose occupational switch could not be verified with a coinciding change in employer, industry, working hours, or hourly wage. Figure A.12, on the other hand, considers only male (verified) occupational switchers. Despite creating these graphs with different samples than the one used in the main text, it can be seen that the conclusion from the graph is unchanged: overall wage

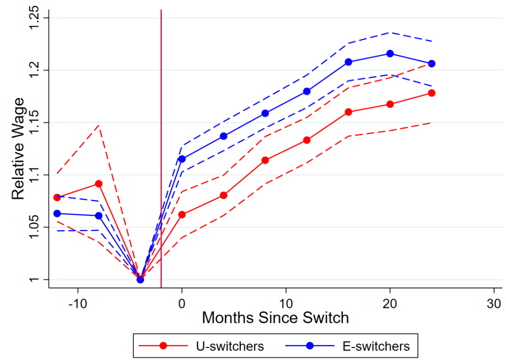

Figure A.10: *Real wage paths over time for occupational U-switchers and E-switchers, including both verified and unverified occupational switches. The switch takes place between time -4 and 0, as represented by the vertical line at -2.*

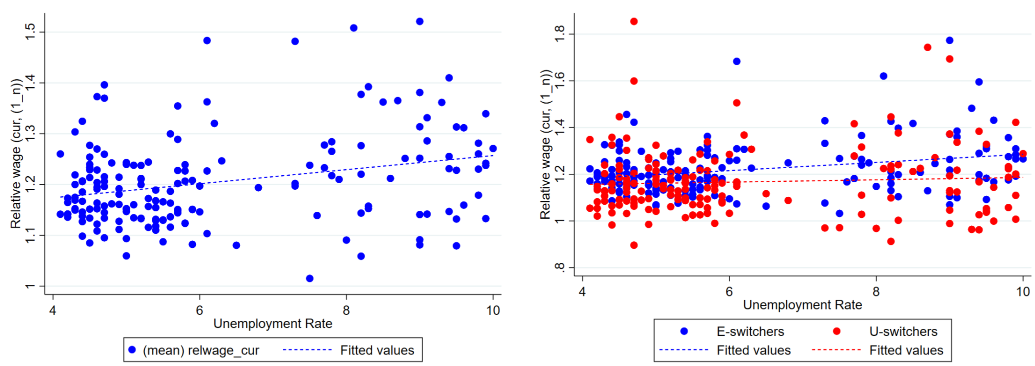

Figure A.11: *Real wages immediately after the occupational switch, relative to the real wage before the switch, for all occupational switchers (left) or for occupational U-switchers and E-switchers (right), plotted against the unemployment rate at the time of the switch, including both verified and unverified occupational switches. Dashed lines show fitted values corresponding to a simple OLS regression.*

differentials for occupational switchers are mildly countercyclical (left panel), and this primarily reflects the countercyclicality of the relative real wages for E-switchers whereas the relative real wages for U-switchers appear to be acyclical (right panel).

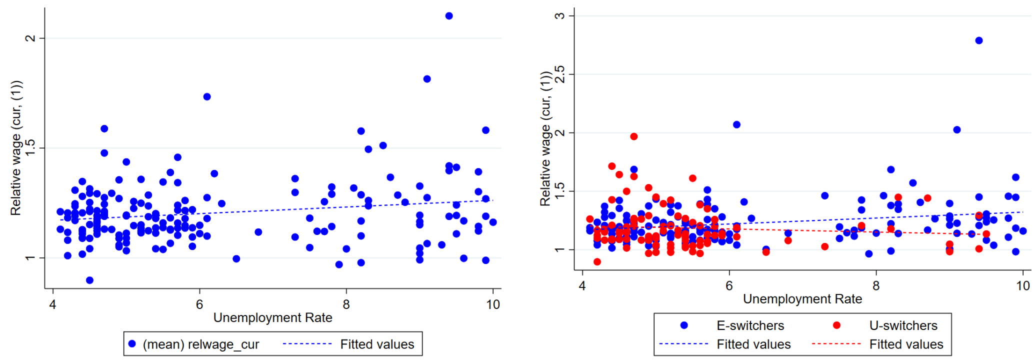

Figure A.12: *Real wages immediately after the occupational switch, relative to the real wage before the switch, for all occupational switchers (left) or for occupational U-switchers and E-switchers (right), plotted against the unemployment rate at the time of the switch and using male respondents only. Dashed lines show fitted values corresponding to a simple OLS regression.*

To stress the point made that workers who switch occupations while unemployed (U-switchers) and job-to-job occupational switchers (E-switchers) are different, Table A.11 provides some descriptive statistics on 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 (which is measured on a 5-point scale). This difference points towards low-educated and younger workers mainly switching through unemployment and highly educated and 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.

When considering how the composition of U- and E-switchers changes over the business cycle, it can be seen in Table A.12 that while the description of the average U- and E-switcher does not change much in terms of their age (slightly lower in recessions), education (slightly higher in recessions) or gender, both the pre-switch and post-switch wage are substantially lower in recessions. Furthermore, this decrease is generally more pronounced for U-switchers than for E-switchers, both in absolute and in relative terms, and it can be noted that the majority of switches

	Non-Switchers	U-Switchers	E-Switchers	t
Age	41.079 (0.006)	36.338 (0.052)	37.579 (0.036)	19.402
Education	2.888 (0.001)	2.544 (0.005)	2.735 (0.003)	31.278
Gender (Female)	0.486 (0.000)	0.504 (0.003)	0.482 (0.002)	-7.030
Wage (Before)	-	12.637 (0.140)	13.499 (0.051)	7.153
Wage (After)	-	11.244 (0.059)	13.981 (0.051)	31.891
Wage	18.878 (0.012)	-	-	-
Observations	3133472	36704	81364	

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.*

	U-Switchers		E-Switchers	
	Boom	Recession	Boom	Recession
Age	36.508 (0.147)	36.313 (0.056)	38.007 (0.112)	37.530 (0.038)
Education	2.498 (0.014)	2.551 (0.005)	2.719 (0.011)	2.736 (0.004)
Gender (Female)	0.480 (0.007)	0.507 (0.003)	0.485 (0.005)	0.481 (0.002)
Wage (Before)	14.276 (0.461)	12.397 (0.145)	14.408 (0.160)	13.394 (0.054)
Wage (After)	12.650 (0.225)	11.038 (0.059)	15.008 (0.218)	13.863 (0.051)
Observations	4684	32020	8432	72932

Table A.12: *Descriptive statistics for U-switchers and E-switchers, by economic conditions at the time of (materialization of) the switch, with standard errors in parentheses.*

of both types take place in recessions.

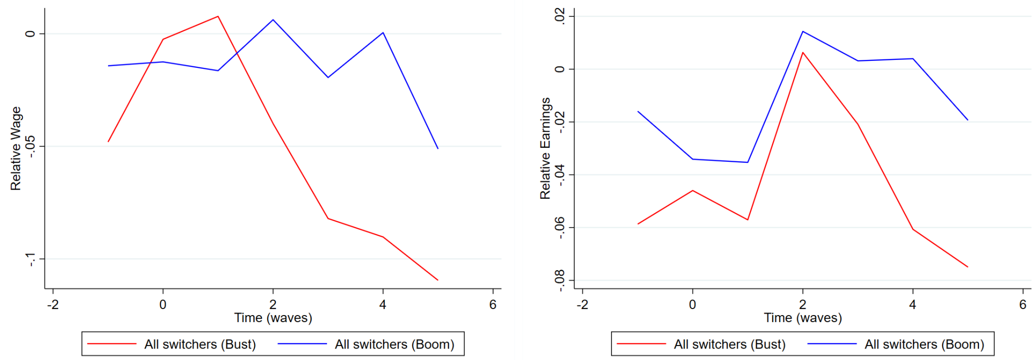

Figure A.13: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method, and including both verified and unverified occupational switches. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

In Figures A.13 and A.14 I show the results of a regression-based estimation of the relative (real) earnings and wage paths after an occupational switch of either type. As these results are obtained using the three-step estimation method from Borusyak et al. (2022), these figures are similar to Figure 9 in the main text. Compared to the figure in the main text, however, Figure A.14 shrinks the sample by considering only male workers, whereas Figure A.13 expands the sample by also considering switchers whose switch could not be verified with a coinciding change in employer, industry, working hours, or hourly wage. As can be seen by comparing Figures A.13 to Figure 9, expanding the sample with unverified switches negatively affects the post-switch wage and earnings paths, especially for switches that materialized during a bust. Thereby, the procyclicality of the wage losses strengthened, whereas the earnings path is now also observed to be mildly procyclical. Similarly, restricting the sample to male workers only, as in Figure A.14 lead the results to weaken to such an extent that neither the real wage path nor the real earnings path is clearly procyclical anymore.

In Figures A.15 to A.18 I repeat the estimation from Figure 10 in the main text, thus estimating (using the three-step estimation method) how the difference in the post-switch real wage and real earnings paths changes over the business cycle. Each of the Figures A.15 to A.18 imposes a change in the sample on which the estimation is performed. In particular, in Figure A.15 I only consider occupational changes that materialize in the first (reference) month of the wave. Given

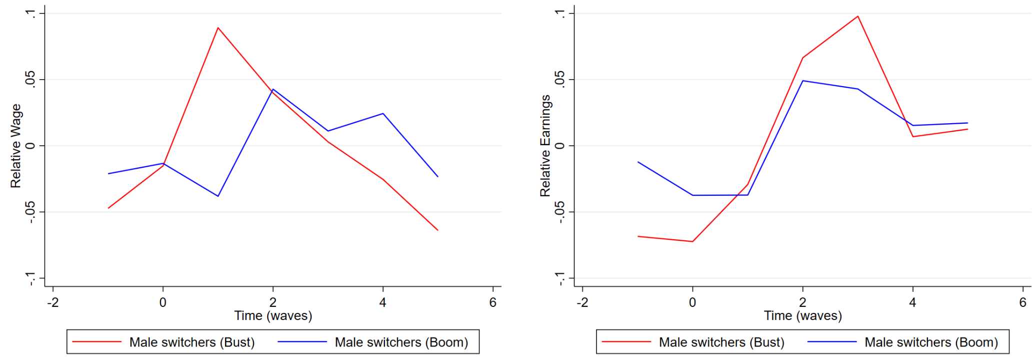

Figure A.14: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method, and including male switchers only. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

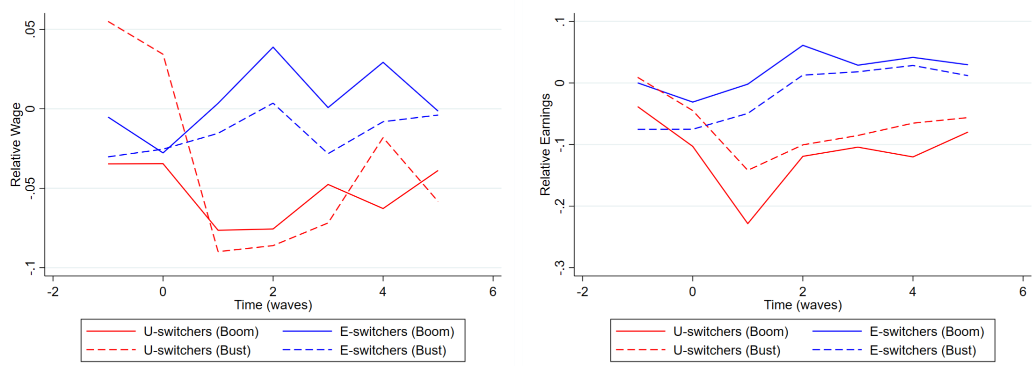

Figure A.15: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, by type of switch (including only occupational switches materializing in the first month of the wave), using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

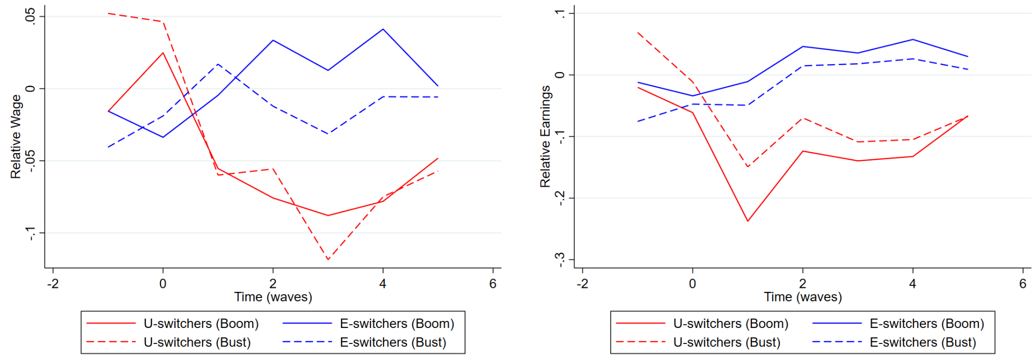

Figure A.16: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, by type of switch (including both verified and unverified occupational switches), using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

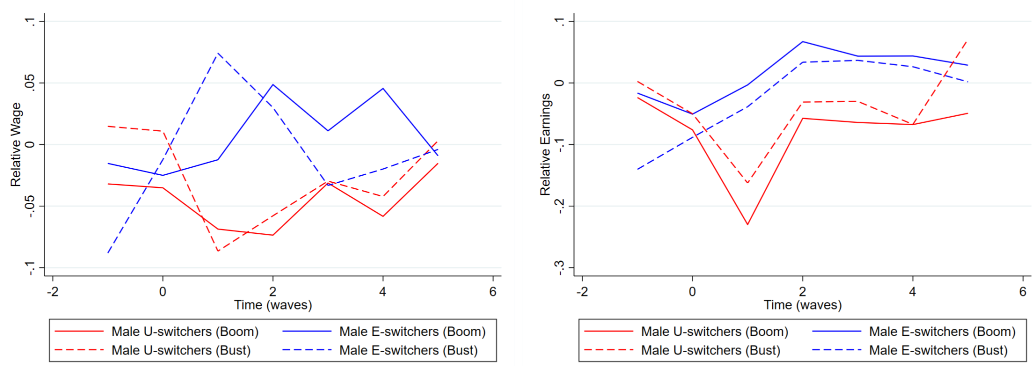

Figure A.17: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, by type of switch, using estimated coefficients obtained using the three-step estimation method, and including male switchers only. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

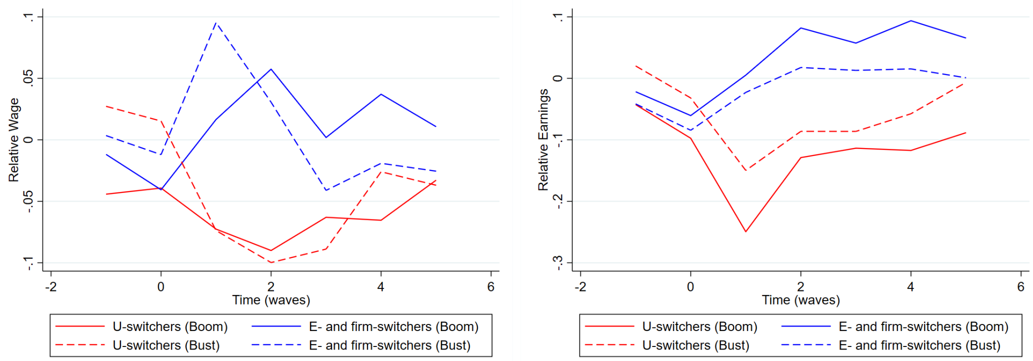

Figure A.18: *The effect of occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, by type of switch (using only switches that coincide with a change in employer), using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

the prevalence of the seam bias, as discussed in Appendix A.1, which is stronger for occupational changes than it is for employment status changes, this does not change the sample substantially. In Figure A.16, I expand the sample by additionally including unverified occupational switches, whereas in Figure A.17 I further restrict the sample by only considering (verified) switched made by male respondents. Finally, Figure A.18 considers only occupational switches that coincide with an employer change. As can be seen by comparing each of Figures A.15 to A.18 to the corresponding figure in the main text (Figure 10), none of these changes in the sample affect the conclusion. In each of these figures, the real wage and especially the real earnings path is procyclical for E-switchers, whereas the real earnings path for U-switchers is countercyclical (and the real wage path is fairly inconclusive).

Finally, I mentioned in the section 2 that the three-step method from Borusyak et al. (2022) is not the only method proposed to take into account potential contamination of the event study estimates by effects from earlier and later periods or subsequent and prior treatments. Below, I use the interaction-weighted estimator from Sun and Abraham (2021) instead. In practice, this means that I am estimating the following equation:

$$w_{it} = \alpha_i + \gamma_t + \sum_{C \neq 0} \sum_{\substack{k=-2 \\ k \neq -1}}^{K} \delta_k^C D_{it}^{C,k} + u_{it} \tag{13}$$

Equation (13) follows the same notation as equation (1) in the main text. As such, α_i and γ_t

represent the person- and time fixed effects, and u_{it} is an error term. Similarly, the dependent variable, w_{it}, corresponds to individual i's wage in period t, like before. The main difference with equation 1 is that rather than estimating the equation for each base period separately, the above specification is only estimated once. However, the specification still allows for a different treatment effect (and different dynamics of this treatment effect) depending on which treatment cohort C the individual belongs to, with $C = 0$ corresponding to the cohort of individuals who I do not observe switching occupations at all. This "never-treated" group acts as the control group. Furthermore, note that rather than omitting one value of k, I follow the discussion in Borusyak et al. (2022) by omitting two values of k. This is because generally the set of relative time indicators D_{it}^{C} is collinear with itself as well as with the time fixed effect. The first period I omit is $k = -1$, and the second omitted period is the earliest period, $k = -3$ (as reflected by the summation over k starting at $k = -2$). These periods are chosen to maximize the distance between the two omitted periods, thereby making the resulting estimate less sensitive to any possible fluctuations (or trend) between these two periods. Finally, note that specification (13) no longer allows for the inclusion of control variables $\bar{e}_{it}$ (recent earnings) and X_{it} (the quadratic polynomial in age).

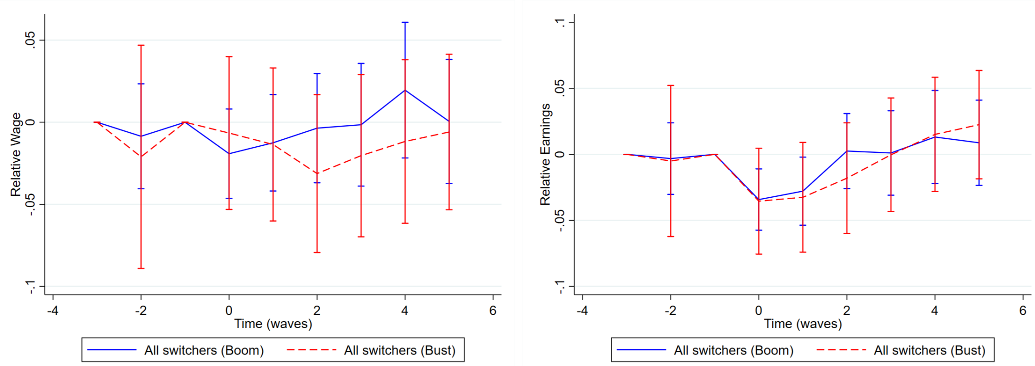

Figure A.19: *The effect of occupational switches on wages (left) and earnings (right), relative to the control group of never-switching workers, using estimated coefficients from equation* (13). *The plots show separate estimates of the effect for switches materializing during a boom or a bust. The error bars correspond to 95% pointwise confidence intervals.*

In Figure A.19, I show the results of an estimation of equation (13) where I do not distinguish between E-switchers and U-switchers. Compared to Figure 9, the estimation results are very similar: the real wage paths are very mildly procyclical (and not statistically significant), whereas no clear cyclical pattern is visible for the real earnings.

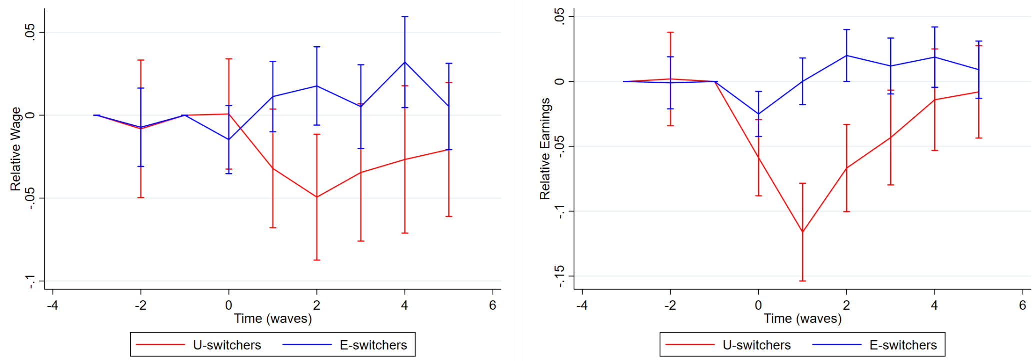

Figure A.20: *The effect of occupational switches on wages (left) and earnings (right), relative to the control group of never-switching workers, by type of switch, using estimated coefficients from equation* (13)*. The error bars correspond to 95% pointwise confidence intervals.*

Figure A.20 displays the results of estimating specification (13) while allowing for the treatment effect to be different for the two types of switches. As can be seen in the left panel, the difference between E-switchers and U-switchers observed earlier (in Figure 7 in the main text) remains intact, and even strengthens slightly for earnings. Similarly, when it comes to the cyclicality of these real wage paths, the results from estimating specification (13) confirm the observations made from Figure 10 in the main text: there is a procyclical pattern for E-switchers and no clear pattern for U-switchers (as seen in the left panel of Figure A.21). On the other hand, the conclusions on the real earnings path are weakened in Figure A.21 (right panel) compared to Figure 10: while there is still some procyclicality for E-switchers and countercyclicality for U-switchers, the pattern is much weaker than the pattern observed in the main text.[56]

A.3 Results on 2-digit and 3-digit occupational mobility

In this section, I repeat the analysis of the data from Section 2 and parts of Section A.2 using (primarily) 2-digit and (in one case) 3-digit occupations instead of 1-digit occupations. 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 main text (which are identified in the discussion of each table and figure below).

[56]It should be noted that for both panels of Figure A.21, all changes between the estimates for switches materializing during a boom or a bust are not statistically significant.

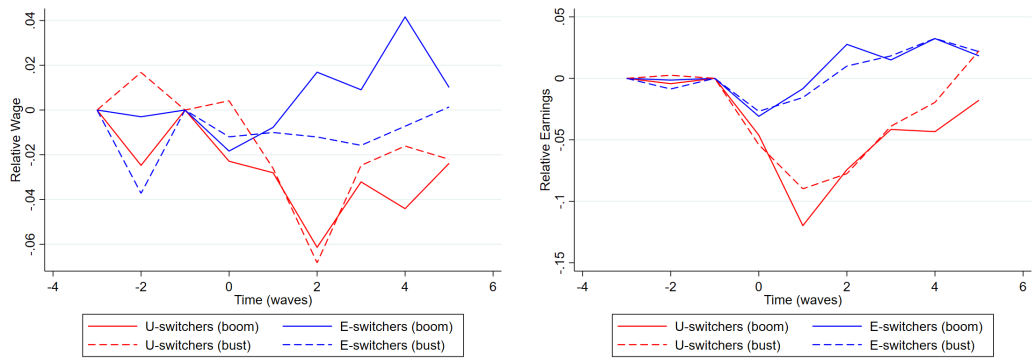

Figure A.21: *The effect of occupational switches on wages (left) and earnings (right), relative to the control group of never-switching workers, by type of switch, using estimated coefficients from equation* (13)*. The plots show separate estimates of the effect for switches materializing during a boom or a bust. The 95% pointwise confidence intervals for the are available upon request.*

A.3.1 Mobility Rates

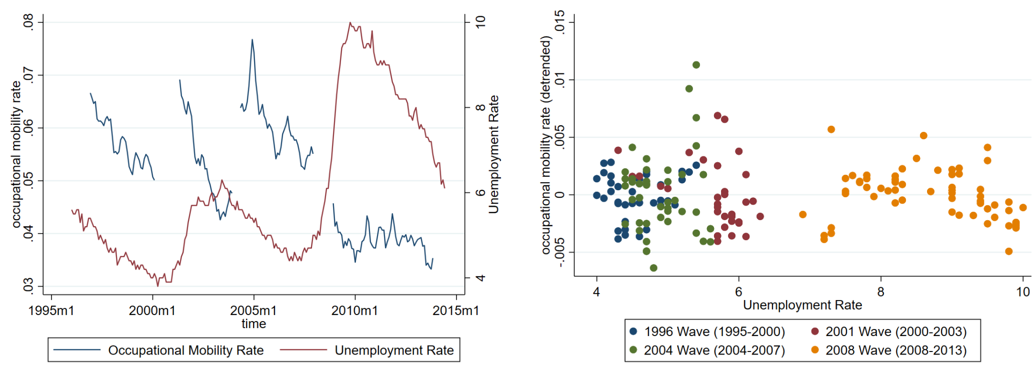

Figure A.22: *The 2-digit occupational mobility rate and the corresponding month's unemployment rate from the BLS, plotted over time (left) and against each other in a scatter plot (right).*

In Figure A.22, I plot the 2-digit (4 month) occupational mobility rate over time (left panel) and against the unemployment rate (right panel). As can be seen by comparing Figure A.22 with it's counterpart in the main text (Figure 1), the occupational mobility rates on the 2-digit level are slightly higher than on the 1-digit level, with rates ranging from 3.5% to 7.5%. However, when it comes to the cyclical patterns of the occupational mobility rates, the conclusion is similar: the left panel of Figure A.22 does not show a clear pattern, although a naive OLS regression yields the conclusion that the occupational mobility rate is mildly procyclical.

Looking at the left panel of Figure A.22, it can be seen that just like the 1-digit rate, the 2-digit occupational mobility rate seems to exhibit negative within-panel trends. Just like with the 1-digit rate, this is likely to be a consequence of the validation exercise. Indeed, re-plotting Figure A.22 with the unverified switches included, as I do in Figure A.23 (which is therefore the 2-digit equivalent of Figure A.2), again reveals a seemingly clearer countercyclical pattern of the (2-digit) occupational mobility rate, with the scatter plot in the right panel clarifies that the 2-digit occupational mobility rate is in fact procyclical.

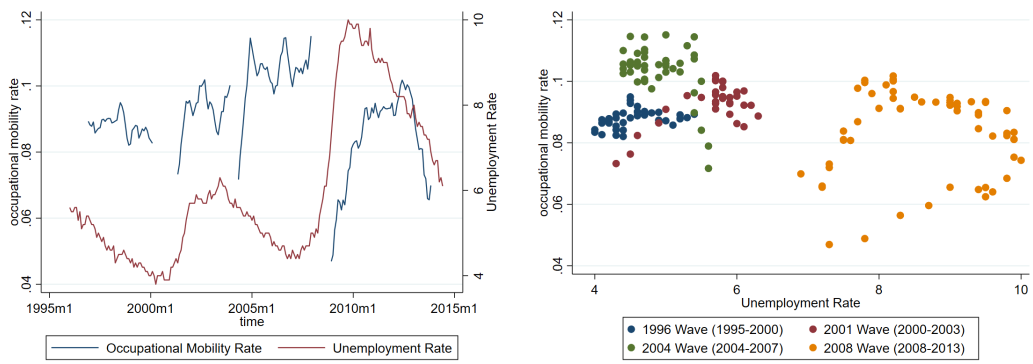

Figure A.23: *The 2-digit occupational mobility rate and the corresponding month's unemployment rate from the BLS, plotted over time, including both verified and unverified occupational switches.*

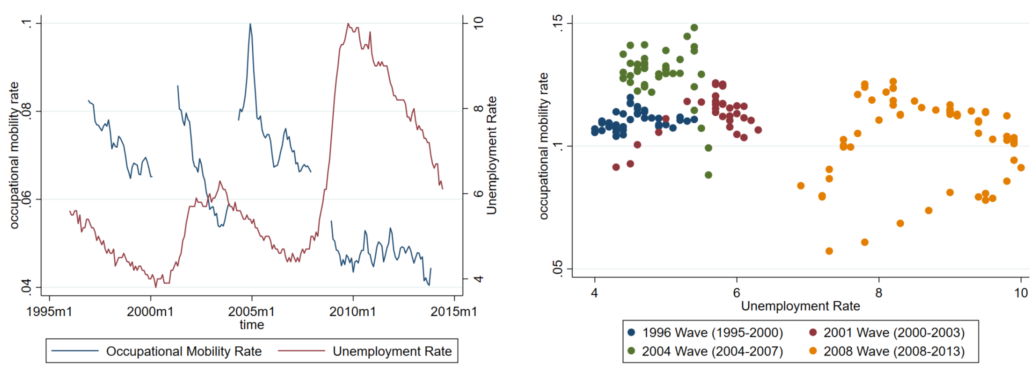

Figure A.24: *The 3-digit occupational mobility rate, plotted over time together with the corresponding month's unemployment rate from the BLS. The left panel only considers verified occupational switches (and plots the rates against the unemployment rate rather than time), whereas the right panel additionally includes unverified occupational switches.*

In Figure A.24, I go one step further and plot the 3-digit occupational mobility rate, which is the rate that is most commonly reported in the literature. 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 4 to 10% with an average rate of approximately 6 to 7%. Keeping in mind that the rates in the figures are 4-month rates instead of yearly rates, this rate seems roughly consistent with the 18% yearly rate found in Kambourov and Manovskii (2008). Further including the occupational switches which could not be verified as coinciding with a change in employer, industry, working hours, or hourly wage, as I do in the right panel of Figure A.24, again reveals a clear procyclical pattern of the occupational mobility rate.

Occupation	1	2	3	4	5	6	7	8	9
Observations	344138	138122	456500	145415	151122	2733	217221	518561	39179
Inflow	15840	7556	15627	5971	8282	383	15590	24943	2607
Outflow	14856	7244	14494	6313	8405	313	16547	24609	2682
Net Inflow	984	312	1133	-342	-123	70	-957	334	-75

Occupation	10	11	12	13	14	15	16	17
Observations	23586	142496	99857	80911	15663	11642	14784	11502
Inflow	1541	9331	5483	5945	587	1043	1229	876
Outflow	1683	10427	5228	5761	694	1083	1389	911
Net Inflow	-142	-1096	255	184	-107	-40	-160	-35

Occupation	18	19	20	21	22	23	24	25
Observations	111905	233481	268968	126894	132884	3636	4697	27790
Inflow	5640	11627	16836	6599	5963	264	342	1911
Outflow	5887	12258	16482	6387	5813	243	339	1968
Net Inflow	-247	-631	354	212	150	21	3	-57

Table A.13: *Total number of incoming and outgoing switches found in the data for every 2-digit occupation, 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.*

Tables A.14 and A.13 list the number of occupational changes observed in the data for every possible combination of 2-digit occupations, and the corresponding total in- and outflow for each occupation. The observations that can be drawn from these tables are identical to those made for 1-digit occupations (from Tables A.2 and 1): it does not seem like there is specific occupation from which workers are changing or a specific occupation that workers are changing to.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	0	1437	2564	569	1420	30	1594	3123	71	87	830	225	221	22	109	71	84	312	521	814	344	338	16	24	30
2	1512	0	957	182	622	4	541	2208	51	28	170	120	57	8	29	27	20	67	174	256	63	99	4	12	33
3	2809	926	0	1511	471	40	1212	2850	91	97	532	970	240	67	129	240	71	334	506	582	258	463	7	33	55
4	617	320	1770	0	176	12	331	1115	32	19	149	387	78	8	20	17	23	143	338	320	147	271	8	4	8
5	1456	476	568	163	0	0	1735	1709	34	56	356	108	87	28	46	30	12	177	279	614	122	299	4	16	30
6	4	12	42	13	8	0	20	27	4	33	16	8	4	0	0	0	0	16	12	55	16	15	0	0	8
7	1597	572	1415	409	1823	24	0	4019	290	169	1461	556	405	72	93	152	96	344	791	1372	339	415	8	32	93
8	3292	2484	3175	1145	1568	36	3367	0	420	270	1516	1070	479	138	183	266	147	559	1317	2206	371	458	7	20	115
9	91	31	101	31	28	0	266	321	0	23	345	281	443	12	8	36	24	49	250	228	47	12	8	0	47
10	90	42	122	27	69	15	181	264	20	0	93	55	70	4	20	24	7	51	107	276	63	80	0	0	3
11	990	215	743	230	325	20	1700	1699	286	76	0	495	489	82	77	82	78	301	707	1261	271	185	8	15	92
12	254	116	1141	363	113	16	482	1002	255	43	420	0	127	24	60	97	19	103	241	233	31	39	4	4	41
13	231	70	203	78	83	12	446	527	365	87	564	167	0	4	54	23	28	212	557	1098	423	335	3	12	179
14	38	35	43	0	23	0	102	168	4	4	46	56	15	0	4	16	43	24	27	39	0	0	0	3	4
15	91	18	131	20	39	0	122	233	12	32	62	60	53	10	0	8	32	12	16	72	22	35	0	0	3
16	69	44	242	17	31	0	202	326	47	13	99	95	29	10	23	0	8	16	59	46	0	5	4	0	4
17	95	28	63	16	28	0	92	138	16	8	107	40	59	12	16	8	0	16	52	62	19	8	0	8	20
18	443	101	327	142	220	16	332	528	69	52	277	161	257	16	11	18	7	0	1237	789	400	358	16	12	98
19	498	168	505	317	259	15	860	1451	228	120	721	279	611	31	19	57	38	1383	0	2893	746	765	20	12	262
20	802	242	668	308	553	68	1254	2128	192	227	1057	253	1208	31	103	41	71	753	2656	0	2068	1097	93	56	553
21	422	91	266	117	160	40	268	428	50	58	246	32	440	0	6	0	12	324	728	1977	0	589	38	1	94
22	384	84	452	286	226	23	361	505	16	23	173	37	359	4	23	4	20	333	737	1048	622	0	12	12	69
23	4	4	12	0	0	4	0	7	4	0	0	0	4	0	0	4	0	24	12	91	46	20	0	0	7
24	24	16	8	4	4	4	30	44	0	0	8	0	8	0	0	0	12	8	16	70	8	12	0	0	63
25	27	24	109	23	33	4	92	123	50	16	83	28	202	4	10	8	24	79	287	434	173	65	4	66	0

Table A.14: *Number of switches found in the data for every combination of 2-digit occupations. Rows correspond to the previous occupations, and columns correspond to new occupations. Horizontal and vertical lines group 2-digit occupations belonging to the same 1-digit occupation. For a list of the occupations corresponding to these codes, see Appendix A.1.*

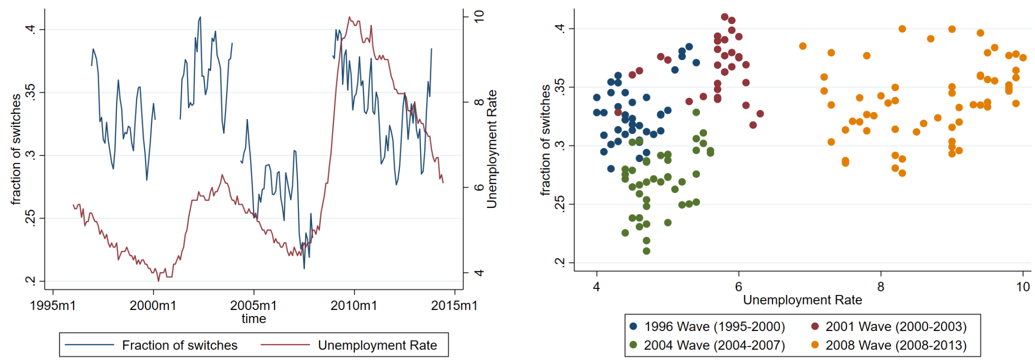

Figure A.25: *The fraction of occupational switchers (2-digit) going through unemployment and the corresponding month's unemployment rate from the BLS, over time (left) and plotted against each other in a scatter plot (right).*

In Figure A.25, I analyze the fraction of 2-digit occupational switchers going through an unemployment spell. Similar to my findings for 1-digit occupations (in Figure 2), I find that the fraction of switches that goes through unemployment shows a clear countercyclical pattern, even if the average fraction is slightly lower than it was for 1-digit switchers.

Figure A.26: *The fraction of employed workers switching occupations (2-digit) 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. The left panel only considers verified occupational switches, whereas the right panel additionally includes unverified occupational switches.*

Finally, Figure A.26 plots the 2-digit occupational mobility rate considering only switches through employment (similar to what Figure 3 did for 1-digit occupational switches). Comparing Figures A.26 and 3, it can be seen that slightly more,but still roughly a third, of the employed workers who switch occupations do so without changing employers, thereby re-confirming the importance of considering job-to-job occupational mobility without employment changes when modeling occupational mobility.

A.3.2 Subsequent Earnings and Wages

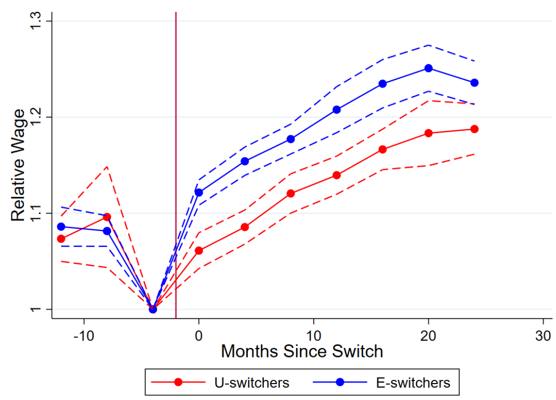

Figure A.27: *Real wage paths over time for (2-digit) occupational U-switchers and E-switchers. The switch takes place between time -4 and 0, as represented by the vertical line at -2. The dashed lines correspond to the (pointwise) 95% confidence interval.*

In Figure A.27, I plot the equivalent of Figure 4 from the main text, using 2-digit occupational switchers instead. Thus, it plots the average real wage for U- and E-switchers, from 12 months before until 24 months after the occupational switch materializes, relative to the last observed real wage before the switch. As can be seen by comparing Figures A.27 and it's 1-digit equivalent 4, using 2-digit instead of 1-digit occupational switchers does not make a substantial difference in terms of the subsequent relative real wage paths. Just like in the main text, it can be concluded that U-switchers tend to do worse than E-switchers.

In order to analyze whether the pattern changes over the business cycle, I plot the 2-digit equivalent of Figure 5 in Figure A.28, which thus show how cyclical the relative real wages observed immediately after the switch are. Once again, the conclusions from the figure are almost identical to those obtained in the main text: Overall, wage differentials seem to be countercyclical, and this is primarily coming from the countercyclicality of the wage differentials for E-switchers, while the wage differentials for U-switchers appear to be acyclical.

In Figure A.29, I plot the results of an estimation of equation (1) where I do not distinguish between E-switchers and U-switchers, using 2-digit occupational switchers (with the 1-digit

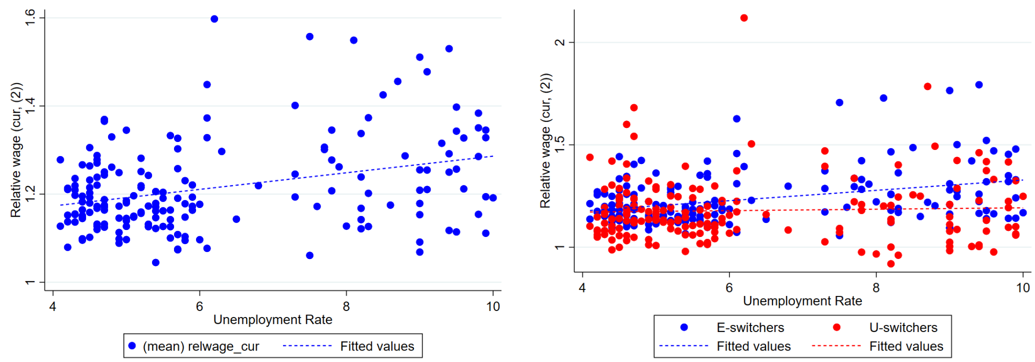

Figure A.28: *Real wages immediately after the occupational switch, relative to the real wage before the switch, for all (2-digit) occupational switchers (left) or for occupational U-switchers and E-switchers (right), plotted against the unemployment rate at the time of the switch. Dashed lines show fitted values corresponding to a simple OLS regression.*

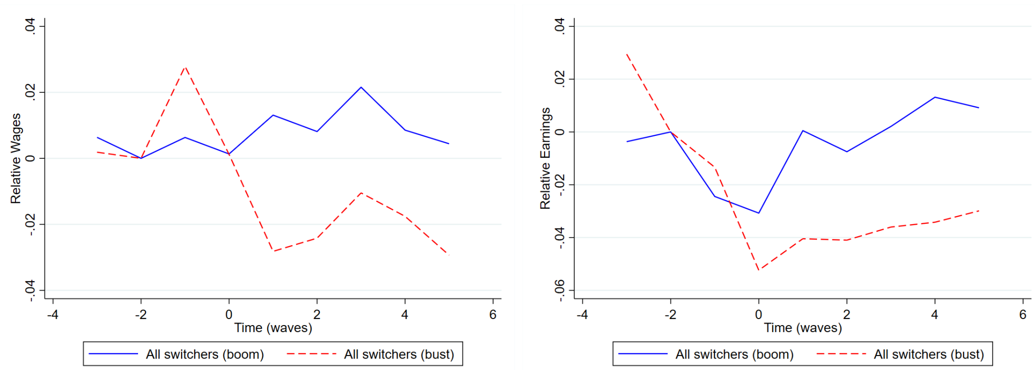

Figure A.29: *The effect of (2-digit) occupational switches on real wages (left) and real earnings (right), relative to the control group of never-switched workers, using estimated coefficients from equation* (1)*,specific to switches that materialized in booms or busts.*

equivalent being Figure 6 in the main text). Similar to what was found for 1-digit occupational switchers, the subsequent wage and earnings outlook of 2-digit occupational switchers is worse for workers who switch occupations during a recession.

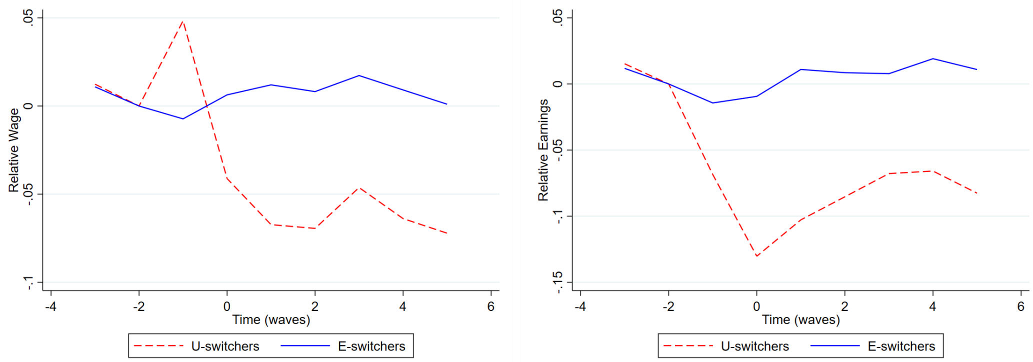

Figure A.30: *The effect of (2-digit) occupational switches on real wages (left) and real earnings (right), relative to the control group of never-switched workers, by type of switch, using estimated coefficients from equation* (1).

Moving to the distinction between E-switchers and U-switchers, Figure A.30 shows the results of estimating equation (1) while allowing the treatment effects to be different for E- and U-switchers at the 2-digit level. Similar to what was observed for the 1-digit level in Figure 7, U-switchers are observed to do substantially worse than E-switchers, both in terms of real wages and real earnings.

When considering how these separate real wage and real earnings paths for E- and U-switchers change over the business cycle (for 2-digit switchers), Figure A.31 yields a similar conclusion as its 1-digit equivalent in the main text (Figure 8): Following this estimation, the paths seem to be procyclical for both E-switchers and U-switchers.

Finally, using the three-step estimation method from Borusyak et al. (2022) instead of the standard two-way fixed effects approach yields similar results on the 2-digit level compared to the 1-digit level. When estimating a single treatment effect for all switcher types, it can be seen in Figure A.32 (which corresponds to Figure 9 in the main text) that the subsequent real wage path seems clearly procyclical, whereas the real earnings path is only very mildly procyclical (as opposed to acyclical as seen in the main text). Further splitting out these results by switcher types, as done in Figure A.33 (the 2-digit equivalent of Figure 10), slightly strengthens the results from the main text: A clear countercyclical pattern is visible for U-switchers, especially when it comes to real earnings, but also (albeit much milder) for real wages.

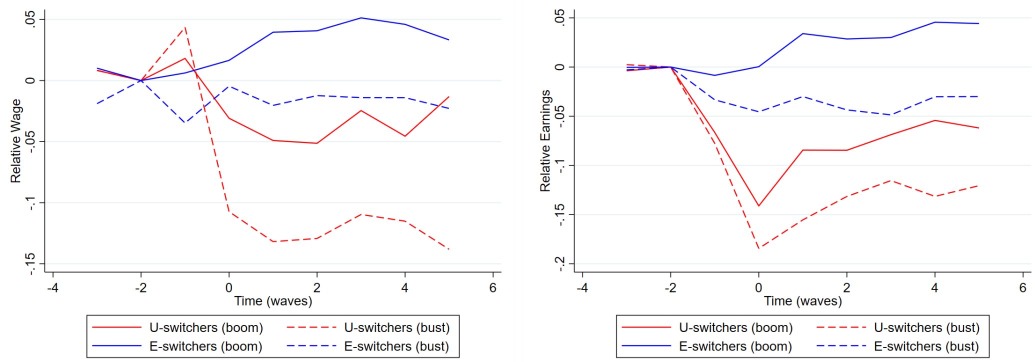

Figure A.31: *The effect of (2-digit) occupational switches on real wages (left) and real earnings (right), relative to the control group of never-switched workers, by type of switch, using estimated coefficients from equation* (1)*, specific to switches that materialized in booms or busts (right panel).*

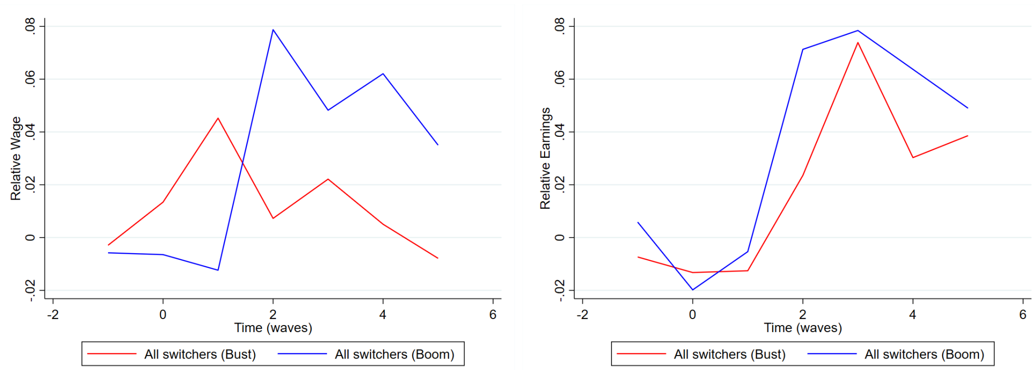

Figure A.32: *The effect of (2-digit) occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

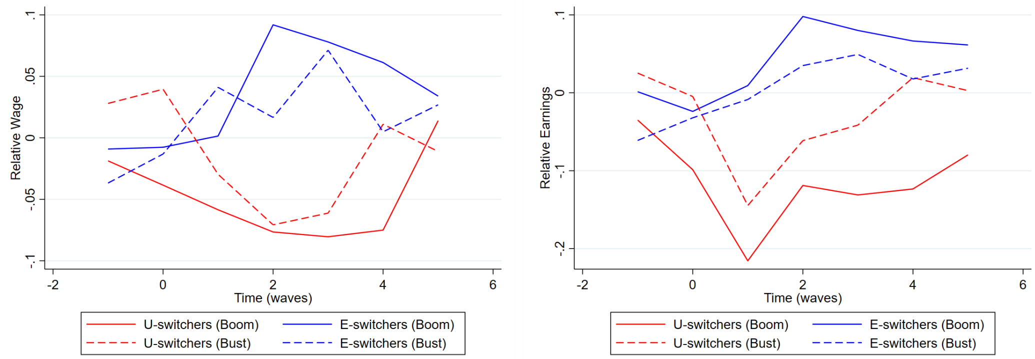

Figure A.33: *The effect of (2-digit) occupational switches on real wages (left) and real earnings (right), relative to the counterfactual of never switching, by type of switch, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust.*

B Omitted Proofs

B.1 Proposition 1

Proposition 1: The model has a unique block-recursive equilibrium.

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 (5) and (8), 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')):

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

$$
\begin{aligned}
&= y(p,z,x) + \beta \mathbb{E}_{p',z',x'} \Bigg[\max_{\hat{\sigma}(\cdot)} \Bigg\{ \psi \int_{\underline{z}}^{\bar{z}} \max\left\{ M(p',\tilde{z},x'), W^U(p',\tilde{z},x') \right\} dF(\tilde{z}) + (1-\psi) \Bigg[\hat{\sigma}(\cdot) W^U(\cdot) \\
&\quad + (1-\hat{\sigma}(\cdot)) \Bigg[\max_{\rho^e(\cdot)} \Bigg\{ \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) W^E(\cdot) \\
&\quad + \rho^e(\cdot) \left(-c^e(p') + \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) W^E(p',\tilde{z},x_1) dF(\tilde{z}) \right) \Bigg\} \\
&\quad + \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) J(\cdot) \Bigg] \Bigg] \Bigg\} \Bigg] \\
&= y(p,z,x) + \beta \mathbb{E}_{p',z',x'} \Bigg[\max_{\hat{\sigma}(\cdot)} \Bigg\{ \psi \int_{\underline{z}}^{\bar{z}} \max\left\{ M(p',\tilde{z},x'), W^U(p',\tilde{z},x') \right\} dF(\tilde{z}) + (1-\psi) \Bigg[\hat{\sigma}(\cdot) W^U(\cdot) \\
&\quad + (1-\hat{\sigma}(\cdot)) \Bigg[\max_{\rho^e(\cdot)} \Bigg\{ \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) \left[M(\cdot) - \frac{k\theta(\cdot)}{\lambda(\theta(\cdot))} \right] \\
&\quad + \rho^e(\cdot) \left(-c^e(p') + \int_{\underline{z}}^{\bar{z}} [\lambda(\theta(p',\tilde{z},x_1)) M(p',\tilde{z},x_1) - k\theta(p',\tilde{z},x_1)] dF(\tilde{z}) \right) \Bigg\} \\
&\quad + \left(1 - \rho^e(\cdot) \int_{\underline{z}}^{\bar{z}} \lambda(\theta(p',\tilde{z},x_1)) dF(\tilde{z}) \right) \frac{k\theta(\cdot)}{\lambda(\theta(\cdot))} \Bigg] \Bigg] \Bigg\} \Bigg] \qquad (14)
\end{aligned}
$$

Here, the second equality uses that by Nash bargaining, $W^E > W^U$ implies $J > V$ and vice versa, so that $\max\left\{W^E(p',\tilde{z},x'), W^U(p',\tilde{z},x')\right\}$ and $\max\left\{J(p',\tilde{z},x'), V(p',\tilde{z},x')\right\}$ can be combined to $\max\left\{M(p',\tilde{z},x'), W^U(p',\tilde{z},x')\right\}$ (using that $V = 0$ in equilibrium). Furthermore, 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)):

$$
\begin{aligned}
T(\Gamma(p,z,x,1)) &= b + \beta \mathbb{E}_{p',z'} \Bigg[\max_{\rho^u(\cdot)} \Bigg\{ \rho^u(\cdot) \left[-c^u(p') + \int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1) dF(\tilde{z}) \right] \\
&\quad + (1-\rho^u(\cdot)) \left[\lambda(\theta(\cdot)) W^E(\cdot) + (1-\lambda(\theta(\cdot))) W^U(\cdot) \right] \Bigg\} \Bigg] \\
&= b + \beta \mathbb{E}_{p',z'} \Bigg[\max_{\rho^u(\cdot)} \Bigg\{ \rho^u(\cdot) \left[-c^u(p') + \int_{\underline{z}}^{\bar{z}} W^U(p',\tilde{z},x_1) dF(\tilde{z}) \right] \\
&\quad + (1-\rho^u(\cdot)) \left[\lambda(\theta(\cdot)) M(\cdot) - k\theta(\cdot) + (1-\lambda(\theta(\cdot))) W^U(\cdot) \right] \Bigg\} \Bigg] \qquad (15)
\end{aligned}
$$

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 (14) and (15) reduce to equations (16) and (17) below:

$$T(\Gamma(p,z,x,0)) = \bar{y} + \beta\mathbb{E}\left[\max_{\hat{\sigma}}\left\{\psi\int_{\underline{z}}^{\bar{z}}\max\{\tilde{M},\tilde{W^U}\}dF(\tilde{z}) + (1-\psi)\left[\hat{\sigma}W^U\right.\right.\right.$$

$$+(1-\hat{\sigma})\left[\max_{\rho^e}\left\{\rho^e\left(-c^{e\prime}+\int_{\underline{z}}^{\bar{z}}[\tilde{\lambda}\tilde{M}-k\tilde{\theta}]dF(\tilde{z})\right)\right.\right.$$

$$\left.\left.\left.\left.\left.+\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)[M-k\theta/\lambda]\right\}+\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)\frac{k\theta}{\lambda}\right]\right]\right\}\right] \tag{16}$$

$$T(\Gamma(p,z,x,1)) = b + \beta\mathbb{E}\left[\max_{\rho^u}\left\{\rho^u\left[-c^{u\prime}+\int_{\underline{z}}^{\bar{z}}\tilde{W^U}dF(\tilde{z})\right]\right.\right.$$

$$\left.\left.+(1-\rho^u)\left[\lambda M - k\theta + (1-\lambda)W^U\right]\right\}\right] \tag{17}$$

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) and the choice between $\tilde{W^U}$ and $\tilde{M}$ after the occupational transfer shock ψ. 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 (17) 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 $T(f+a) \le T(f) + \beta a$ $\forall f \in \Gamma$, $\forall a \ge 0$, and $\forall (p,z,x)$. To show that this condition also holds, one can replace all M and W^U in equations (16) and (17) by $M + a$ and $W^U + a$:

$$
\begin{aligned}
T(\Gamma(p,z,x,0)+a) &= \bar{y} + \beta\mathbb{E}\Bigg[\max_{\hat{\sigma}}\Bigg\{\psi\int_{\underline{z}}^{\bar{z}}(\max\{\tilde{M},\tilde{W^U}\}+a)dF(\tilde{z}) + (1-\psi)\Bigg[\hat{\sigma}(W^U+a) \\
&\quad +(1-\hat{\sigma})\Bigg[\max_{\rho^e}\Bigg\{\rho^e\left(-c^{e\prime}+\int_{\underline{z}}^{\bar{z}}[\tilde{\lambda}(\tilde{M}+a)-k\tilde{\theta}]dF(\tilde{z})\right) \\
&\quad +\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)[M+a-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] \\
T(\Gamma(p,z,x,0)+a) &= \bar{y} + \beta\mathbb{E}\Bigg[\max_{\hat{\sigma}}\Bigg\{\psi\int_{\underline{z}}^{\bar{z}}\max\{\tilde{M},\tilde{W^U}\}dF(\tilde{z}) + \psi\int_{\underline{z}}^{\bar{z}}adF(\tilde{z}) \\
&\quad +(1-\psi)\Bigg[\hat{\sigma}W^U+\hat{\sigma}a+(1-\hat{\sigma})\Bigg[\max_{\rho^e}\Bigg\{\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)\left[M-\frac{k\theta}{\lambda}\right] \\
&\quad +\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)a + \rho^e\left(-c^{e\prime}+\int_{\underline{z}}^{\bar{z}}[\tilde{\lambda}\tilde{M}-k\tilde{\theta}]dF(\tilde{z})+\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}adF(\tilde{z})\right)\Bigg\} \\
&\quad +\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)\frac{k\theta}{\lambda}\Bigg]\Bigg]\Bigg\}\Bigg] \\
T(\Gamma(p,z,x,0)+a) &= \bar{y} + \beta\mathbb{E}\Bigg[\max_{\hat{\sigma}}\Bigg\{\psi\int_{\underline{z}}^{\bar{z}}\max\{\tilde{M},\tilde{W^U}\}dF(\tilde{z}) + \psi a + (1-\psi)\Bigg[\hat{\sigma}W^U+\hat{\sigma}a \\
&\quad +(1-\hat{\sigma})\Bigg[a+\max_{\rho^e}\Bigg\{\rho^e\left(-c^{e\prime}+\int_{\underline{z}}^{\bar{z}}[\tilde{\lambda}\tilde{M}-k\tilde{\theta}]dF(\tilde{z})\right) \\
&\quad +\left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)\left[M-\frac{k\theta}{\lambda}\right]\Bigg\} + \left(1-\rho^e\int_{\underline{z}}^{\bar{z}}\tilde{\lambda}dF(\tilde{z})\right)\frac{k\theta}{\lambda}\Bigg]\Bigg]\Bigg\}\Bigg] \\
T(\Gamma(p,z,x,0)+a) &= \bar{y} + \beta\mathbb{E}\Bigg[\max_{\hat{\sigma}}\Bigg\{\psi\int_{\underline{z}}^{\bar{z}}\max\{\tilde{M},\tilde{W^U}\}dF(\tilde{z}) + (1-\psi)\Bigg[\hat{\sigma}W^U \\
&\quad +(1-\hat{\sigma})\Bigg[\max_{\rho^e}\Bigg\{\rho^e\left(-c^{e\prime}+\int_{\underline{z}}^{\bar{z}}[\tilde{\lambda}\tilde{M}-k\tilde{\theta}]dF(\tilde{z})\right) \\
&\quad +\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] + \beta a \\
T(\Gamma(p,z,x,0)+a) &= T(\Gamma(p,z,x,0)) + \beta a \qquad (18) \\
T(\Gamma(p,z,x,1)) &= b + \beta\mathbb{E}\Bigg[\max_{\rho^u}\Bigg\{\rho^u\left[-c^{u\prime}+\int_{\underline{z}}^{\bar{z}}(\tilde{W^U}+a)dF(\tilde{z})\right] \\
&\quad +(1-\rho^u)\left[\lambda(M+a)-k\theta+(1-\lambda)(W^U+a)\right]\Bigg\}\Bigg]
\end{aligned}
$$

$$
\begin{aligned}
&T(\Gamma(p,z,x,1)) = b + \beta \mathbb{E}\left[\max_{\rho^u}\left\{\rho^u\left[-c^{u\prime} + \int_{\underline{z}}^{\bar{z}} \tilde{W^U} dF(\tilde{z}) + \int_{\underline{z}}^{\bar{z}} a dF(\tilde{z})\right]\right.\right. \\
&\quad \left.\left. +(1-\rho^u)\left[\lambda M - k\theta + (1-\lambda)W^U + a\right]\right\}\right] \\
&T(\Gamma(p,z,x,1)) = b + \beta \mathbb{E}\left[\max_{\rho^u}\left\{\rho^u a + \rho^u\left[-c^{u\prime} + \int_{\underline{z}}^{\bar{z}} \tilde{W^U} dF(\tilde{z})\right]\right.\right. \\
&\quad \left.\left. +(1-\rho^u)a + (1-\rho^u)\left[\lambda M - k\theta + (1-\lambda)W^U\right]\right\}\right] \\
&T(\Gamma(p,z,x,1)) = b + \beta \mathbb{E}\left[\max_{\rho^u}\left\{\rho^u\left[-c^{u\prime} + \int_{\underline{z}}^{\bar{z}} \tilde{W^U} dF(\tilde{z})\right]\right.\right. \\
&\quad \left.\left. +(1-\rho^u)\left[\lambda M - k\theta + (1-\lambda)W^U\right]\right\}\right] + \beta a \\
&T(\Gamma(p,z,x,1)) = T(\Gamma(p,z,x,1)) + \beta a
\end{aligned} \tag{19}
$$

From equations (18) and (19) 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 3), 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 17), and $w(p,z,x)$ can be calculated from the expression for $J(p,z,x)$ (equation 8). Finally, the expression for $W^E(p,z,x)$ (equation 5) 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 4, 5, and 8) 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.

□

B.2 Proposition 2

Proposition (Proposition 2)**.** *Unless c^e is prohibitively high for all p 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 $\Omega_t^j = \{n_t, o_t, p_t, z_t, x_h, \mathcal{E}_t^j\}$ be the state space for a worker at the start of subperiod j of period t. Here, n_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:

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

s.t. equations (9) and (10), and initial p_0 and $\mathcal{E}_0$ (20)

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:

$$T^{SP}W^{SP}(\Omega^{prod}) = \max_{d(\cdot),\rho^u(\cdot),\rho^e(\cdot),v(\cdot)} \Bigg\{ \sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} \Big(e_{o,t}(z,x_h)y(p_t,z,x_h)$$
$$+u_{o,t}(z,x_h)b\Big)\,dz + \beta\mathbb{E}_{p',z',x'}\Bigg[-\Bigg(k\sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} v_o(p',z',x'_h,\mathcal{E}^{mat\prime})dz'$$
$$+c^e(p')\sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} \rho^e(p',z',x'_h,\mathcal{E}^{re\prime})(1-\psi)(1-d(p',z',x'_h,\mathcal{E}^{sep\prime}))e_o(z',x'_h)dz'$$
$$+c^u(p')\sum_{o=1}^{O}\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}} \rho^u(p',z',x'_h,\mathcal{E}^{re\prime})u_o(z',x'_h)dz'\Bigg) + W^{SP}(\Omega^{prod\prime})\Bigg]\Bigg\} \tag{21}$$

Note that the maximization here is still subject to the flow equations (9) and (10) 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:

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

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 (21) 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 $\mathcal{E}_t^j$. 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 $U(p,z,x_h)$ and $S(p,z,x_h)$, one could thus write

$$W^{SP}(\Omega^{prod}) = \sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}\Big[U(p,z,x_h)u(z,x_h) + S(p,z,x_h)e(z,x_h)\Big]\,dz \tag{22}$$

Plugging this equation into the recursive formulation of the social planner's problem, equation (21), then gives:

$$
\begin{aligned}
T^{SP}W^{SP}(\Omega^{prod}) = &\max_{d(\cdot),\rho^u(\cdot),\rho^e(\cdot),\theta(\cdot)} \Bigg\{ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \left(u(z,x_h)b + e(z,x_h)y(p,z,x_h)\right) dz \\
&+\beta \mathbb{E}_{p',z',x'} \Bigg[-c^u(p') \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \rho^u(p',\tilde{z},x'_h)u(\tilde{z},x_h)d\tilde{z} \\
&-c^e(p') \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \rho^e(p',\tilde{z},x'_h)(1-\psi)(1-d(p',\tilde{z},x'_h))e(\tilde{z},x'_h)d\tilde{z} \\
&-k \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \theta(p',\tilde{z},x'_h) \Bigg[(1-\rho^u(p',\tilde{z},x'_h))u(\tilde{z},x'_h) \\
&+\mathbb{1}_{h=1} \sum_{\tilde{h}=1}^{H} \int_{\underline{z}}^{\bar{z}} (1-d(p',\ddot{z},x'_{\tilde{h}}))\rho^e(p',\ddot{z},x'_{\tilde{h}})(1-\psi)e(\ddot{z},x'_{\tilde{h}})d\ddot{z}dF(\tilde{z}) \Bigg] d\tilde{z} \\
&+\sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} U(p',\tilde{z},x'_h)u(\tilde{z},x'_h)d\tilde{z} + \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} S(p',\tilde{z},x'_h)e(\tilde{z},x'_h)d\tilde{z} \Bigg] \Bigg\}
\end{aligned} \tag{23}
$$

Again, the maximization here is still subject to the flow equations (9) and (10) 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 $e(z,x_h)$ (thus essentially plugging in the flow equations for the terms $e(\tilde{z},x'_h)$ and $u(\tilde{z},x'_h)$ on the last line of equation (23)). Then, and with some further rearrangement, the equation can be rewritten as the following recursive problem, only subject to initial conditions for p and $\mathcal{E}$:

$$
\begin{aligned}
T^{SP}W^{SP}(\Omega^{prod}) = &\max_{d(\cdot),\rho^u(\cdot),\rho^e(\cdot),\theta(\cdot)} \Bigg\{ \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} bu(z,x_h)dz \\
&+\sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} \beta \mathbb{E}_{p',z'} u(z,x_h) \Big[-k\theta(p',z',x_h)(1-\rho^u(p',z',x_h)) \\
&-c^u(p')\rho^u(p',z',x_h) \Big] dz + \sum_{h=1}^{H} \int_{\underline{z}}^{\bar{z}} y(p,z,x_h)e(z,x_h)dz
\end{aligned}
$$

$$+\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}\beta\mathbb{E}_{p',z',x'}\left[-c^{e}(p')\rho^{e}(p',z',x'_{h})(1-d(p',z',x'_{h}))\right](1-\psi)e(z,x_{h})dz$$

$$+\int_{\underline{z}}^{\bar{z}}\beta\mathbb{E}_{p',z'}\left[-k\theta(p',z',x_{1})\sum_{\tilde{h}=1}^{H}\int_{\underline{z}}^{\bar{z}}(1-d(p',\tilde{z},x'_{\tilde{h}}))\rho^{e}(p',\tilde{z},x'_{\tilde{h}})(1-\psi)\right.$$

$$\left.\times e(\tilde{z},x'_{\tilde{h}})d\tilde{z}dF(z)\right]dz+\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}\beta\mathbb{E}_{p',z'}\left[\rho^{u}(p',z',x_{h})\int_{\underline{z}}^{\bar{z}}U(p',\tilde{z},x_{1})dF(\tilde{z})\right.$$

$$+(1-\rho^{u}(p',z',x_{h}))\left[\lambda(\theta(p',z',x_{h}))S(p',z',x_{h})\right.$$

$$\left.\left.+(1-\lambda(\theta(p',z',x_{h})))U(p',z',x_{h})\right]\right]u(z,x_{h})dz$$

$$+\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}\beta\mathbb{E}_{p',z',x'}\left[\psi\int_{\underline{z}}^{\bar{z}}\max\left\{S(p',\tilde{z},x'_{h}),U(p',\tilde{z},x'_{h})\right\}dF(\tilde{z})\right.$$

$$+(1-\psi)\Big(d(p',z',x'_{h})U(p',z',x'_{h})$$

$$+(1-d(p',z',x'_{h}))\left[\rho^{e}(p',z',x')\int_{\underline{z}}^{\bar{z}}\lambda(\theta(p',\tilde{z},x_{1}))S(p',\tilde{z},x_{1})dF(\tilde{z})\right.$$

$$\left.\left.\left.+\left(1-\rho^{e}(p',z',x')\int_{\underline{z}}^{\bar{z}}\lambda(\theta(p',\tilde{z},x_{1}))dF(\tilde{z})\right)S(p',z',x')\right]\Big)\right]e(z,x)dz\right\} \tag{24}$$

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

$$T^{SP}W^{SP}(\Omega^{prod})=\max_{d(\cdot),\rho^{u}(\cdot),\rho^{e}(\cdot),\theta(\cdot)}\left\{\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}u(z,x_{h})\Big(b\right.$$

$$+\beta\mathbb{E}_{p',z'}\left[\left(\int_{\underline{z}}^{\bar{z}}U(p',\tilde{z},x_{1})dF(\tilde{z})-c^{u}(p')\right)\rho^{u}(\cdot)\right.$$

$$\left.+(1-\rho^{u}(\cdot))\Big(\lambda(\theta(\cdot))S(\cdot)+(1-\lambda(\cdot))U(\cdot)-k\theta(\cdot)\Big)\right]\Big)dz$$

$$+\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}e(z,x_{h})\Big(y(p,z,x_{h})+\beta\mathbb{E}_{p',z',x'}\left[\psi\int_{\underline{z}}^{\bar{z}}\max\left\{S(p',\tilde{z},x'),U(p',\tilde{z},x')\right\}dF(\tilde{z})\right.$$

$$+(1-\psi)\left[d(\cdot)U(\cdot)+(1-d(\cdot))\left[\left(1-\rho^{e}(\cdot)\int_{\underline{z}}^{\bar{z}}\lambda(\theta(p',\tilde{z},x_{1}))dF(\tilde{z})\right)S(\cdot)\right.\right.$$

$$\left.\left.\left.\left.+\rho^{e}(\cdot)\left(\int_{\underline{z}}^{\bar{z}}\left[\lambda(\theta(p',\tilde{z},x_{1}))S(p',\tilde{z},x_{1})-k\theta(p',\tilde{z},x_{1})\right]dF(\tilde{z})-c^{e}(p')\right)\right]\right]\right]\Big)dz\right\} \tag{25}$$

Given that most functions that are being chosen in this problem only appear in part of the rewritten problem in equation (25), this equation can be rewritten as follows:

$$T^{SP}W^{SP}(\Omega^{prod}) = \max_{\theta(\cdot)}\left\{\sum_{h=1}^{H}\int_{\underline{z}}^{\bar{z}}\Big[U_{\max}(p,z,x_h)u(z,x_h)+S_{\max}(p,z,x_h)e(z,x_h)\Big]\,dz\right\} \tag{26}$$

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

$$\begin{aligned} U_{\max}(p,z,x_h) = \max_{d(\cdot),\rho^u(\cdot)} & \left\{b+\beta\mathbb{E}_{p',z'}\left[\left(\left(\int_{\underline{z}}^{\bar{z}} U(p',\tilde{z},x_1)dF(\tilde{z})-c^u(p')\right)\rho^u(\cdot)\right.\right.\right. \\ & \left.\left.\left.+(1-\rho^u(\cdot))\Big(\lambda(\theta(\cdot))S(\cdot)+(1-\lambda(\cdot))U(\cdot)-k\theta(\cdot)\Big)\right]\right]\right\} \end{aligned} \tag{27}$$

$$\begin{aligned} S_{\max}(p,z,x_h) = \max_{\rho^e(\cdot)} & \left\{y(p,z,x_h)+\beta\mathbb{E}_{p',z',x'}\left[\psi\int_{\underline{z}}^{\bar{z}}\max\left\{S(p',\tilde{z},x'),U(p',\tilde{z},x')\right\}dF(\tilde{z})\right.\right. \\ & +(1-\psi)\left[d(\cdot)U(\cdot)+(1-d(\cdot))\left[\left(1-\rho^e(\cdot)\int_{\underline{z}}^{\bar{z}}\lambda(\theta(p',\tilde{z},x_1))dF(\tilde{z})\right)S(\cdot)\right.\right. \\ & \left.\left.\left.\left.+\rho^e(\cdot)\left(\int_{\underline{z}}^{\bar{z}}\Big[\lambda(\theta(p',\tilde{z},x_1))S(p',\tilde{z},x_1)-k\theta(p',\tilde{z},x_1)\Big]dF(\tilde{z})-c^e(p')\right)\right]\right]\right]\right\} \end{aligned} \tag{28}$$

Note the resemblance between $S_{\max}(p,z,x_h)$ and $T(\Gamma(p,z,x_h,0))$ (in equation 14) and between $U_{\max}(p,z,x_h)$ and $T(\Gamma(p,z,x_h,1))$ (in equation 15), taking $\hat{\sigma}(\cdot)=d(\cdot)$, and replacing S and U with M and W^U respectively. Nevertheless, if one looks closely at $S_{\max}(p,z,x_h)$ in equation (28) and $T(\Gamma(p,z,x_h,0))$ in equation (14), it can be seen that the two are not exactly identical. After all, in equation (14), 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 (14), 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 (14) to equation (28). 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 constrained 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 $\rho^e(p, z, x_h) = 0$. □

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 Rouwenhorst 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), and μ_p (μ_z for z_t). 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 ($h \neq 1$).

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 (3) 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 (7)), 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 (7) 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 (4), 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 (4), 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 (5)) 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 (6)) 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 (8)) and the values obtained above, solve for $d(p,z,x)$ and $\sigma(p,z,x)$: From equation (8), 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 $d(p,z,x) = \sigma(p,z,x)$.[57]

8. Now update $M(p,z,x)$ and $W^U(p,z,x)$ for all triples (p,z,x), using equations (14) and (15) (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 (5) or (8). As the solutions will differ 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 (9) and (10).

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 26 moments. These parameters are then set to minimize the distance

[57] 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.

between these moments and the corresponding moments from the data, weighted by the inverse of the standard deviation of the estimated values in 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[58] 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 $N_{sim} = 15$ such time series, each with a length of $T_{sim} = 240$ periods and $I_{sim} = 2000$ individuals, and each period corresponds to approximately one week[59], I end up with a panel of 30000 individuals, followed over 5 years. This panel will contain information on each individual's age, wage, 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 26 moments are esti-

[58]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.

[59]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.

mated. 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, where workers are unemployed if they spend the entire month in unemployment. 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.

- Average proportion of employed workers experiencing at least one unemployment spell in the next year: Just like the moment described above, this moment is straightforward to estimate, using a similar procedure. For each month in the simulation, I take all workers who are employed (for the entire moonth). Then, mimicking the wave structure of the SIPP, I look at the employment status 4, 8, and 12 months ahead. The proportion of interest will then be the proportion of those workers who are unemployed in either of those three periods. The average proportion is then once again simply the average of these period-specific proportions.

- 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 rate of unexperienced and experienced workers: I define a worker as unexperienced in this context if her age is 30 or lower, whereas a worker falls in the category of experienced workers if her age is between 35 and 55.[60] The model counterpart of the moment is calculated by first calculating the unemployment rate for these two groups separately each month. Taking the average of these two unemployment rates then gives the two numbers of interest. Note that for purposes of the model, a worker is only defined as unemployed for a month if she is without a job in all 4 weeks, similar to the definition used to calculate the average job finding rate.

- 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 (for the entire month) 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 occupational switches for the purpose of this moment. After all, I would not have observed these switches 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 (2021), 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

[60] Note that this ignores the workers between the age of 56 and 61. However, as one may see workers of this age retiring in the SIPP and my model does not include early retirement, I do not believe this to be a problem.

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): Once again, 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). This can also be done separately for unexperienced and experienced workers, thus yielding the relative rate for unexperienced workers. Furthermore, using the additional criterion that the worker is still working for the same employer yields the occupational mobility rate for employed workers without an employer change.

- Fraction of occupational transfers going through unemployment: Using the above definitions of occupational transfers for unemployed and employed workers, I can calculate the month-specific fraction of occupational transfers going through unemployment by collecting the number of occupational transfers of each type by simulation month. Taking the average of the resulting fraction across all simulation months then yields the moment value.

- Regressions (11) and (12): For these regressions, I calculate the monthly unemployment by counting the fraction of workers who are unemployed for the entire month. For equation (11), the dependent variable is taken directly from the calculations of the previous moment. For equation (12), I calculate the wage differences (which are used as the dependent variable) by comparing the last observed wage before the materialization of the occupational switch to the first wage observed after this materialization. The wage differential used as the dependent variable is then calculated by dividing the new wage by the old wage and averaging the resulting value across all workers whose occupational switch materialized in the simulation month.

D Additional Simulation Results

D.1 Further results using the baseline estimation

In this subsection I discuss some further results using the baseline estimation as discussed in sections 4 and 5 of the main text.

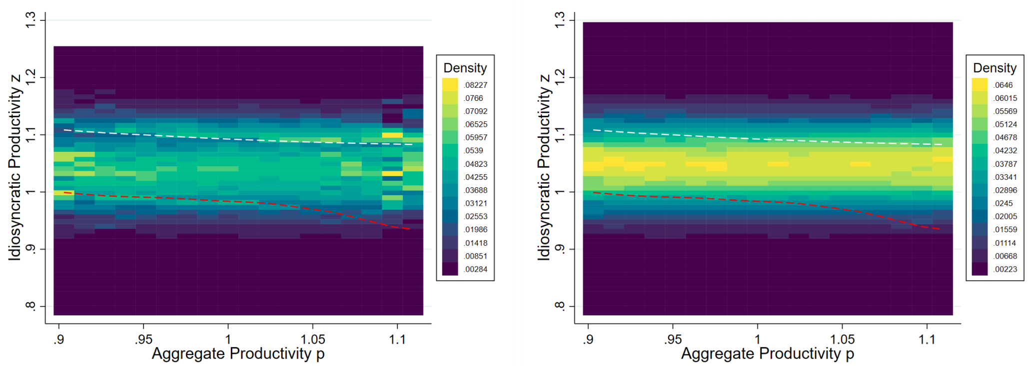

Figure D.1: *The distribution of unemployed (left) or employed (right) workers over different combinations of aggregate productivity p and idiosyncratic productivity z, generated from the model simulation. The heatmaps are generated separately for each value of p, so the values are relative to the total number of (un)employed workers with the same value of p.*

In figure D.1, the distribution of unemployed (left) and employed (right) workers over different combinations of values of idiosyncratic productivity z for each value of aggregate productivity p. As such, figure D.1 corresponds to figure 14 in the main text, after rescaling the densities in that figure so that they add up to 1 for each level of aggregate productivity p. The resulting graph once again clearly shows the thresholds for reallocation through unemployment and separation, which are added to the figure for clarity.

As mentioned in the main text, all unemployed workers in the model are either rest, search, or reallocation unemployed, depending on where they are located relative to the reallocation and separation thresholds. Therefore, 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, no unemployed workers are rest unemployed any value of aggregate productivity p, reflecting that the reallocation threshold for unemployed

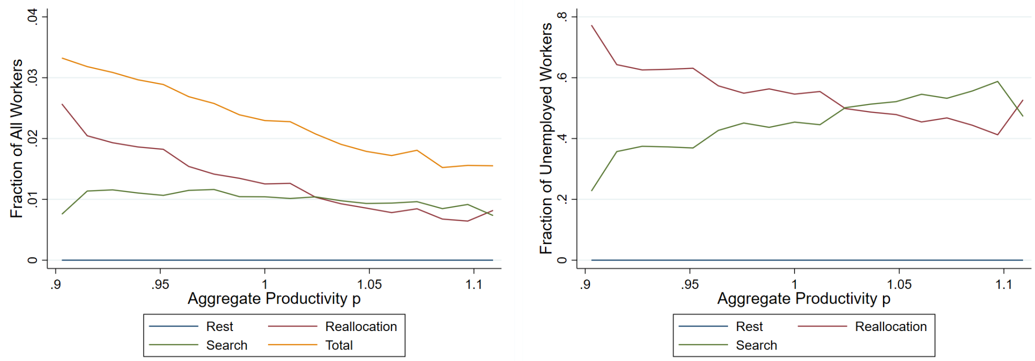

Figure D.2: *The decomposition of the unemployment rate into search, rest, and reallocation unemployment, for different values of aggregate productivity p. Different types of unemployment are plotted either as a fraction of the total population (left) or as a fraction of unemployed workers (right).*

workers is always above the separation threshold. 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 threshold in Figure 13 is decreasing in p.

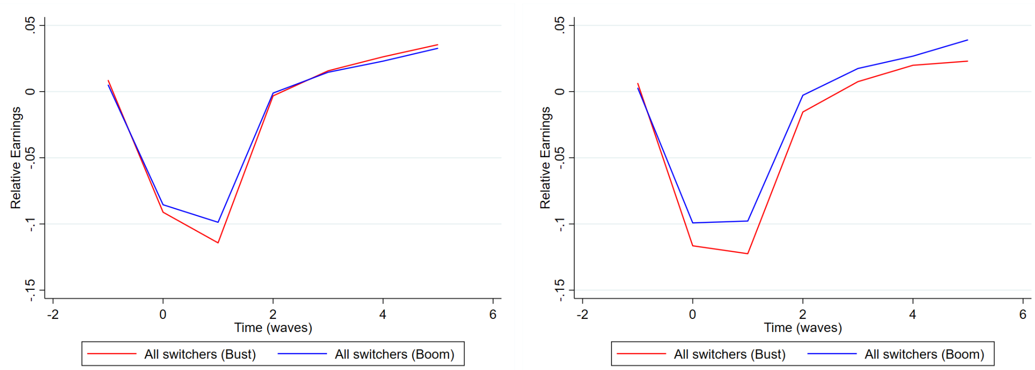

Figure D.3: *The effect of occupational switches on real earnings, relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the model-based estimates from the data-based definition (left) and a model-based definition of occupational mobility(right).*

When it comes to analyzing the earnings consequences of occupational mobility, both on average and by switcher type, I followed the SIPP-based definition of occupational mobility throughout my analysis in the main text. In other words, I look four months (16 model periods) back in the simulation in order to identify occupational switches as well as the type of occupational switch. However, given that the model-based simulation allows me to precisely identify the moment of the transfer at the period (weekly) level, it is not strictly necessary to follow this definition in the model. In figures D.3 and D.4 I show how using a model-based (weekly) definition of occupational mobility alters the results on the earnings consequences of occupational mobility. Comparing the results using the model-based definition (in the right panel of each figure) to the results presented in the main text (replicated in the left panel of each figure), it can be seen that the model-based definition predicts a mildly procyclical earnings loss after occupational mobility, a result which is primarily driven by the level of the earnings loss after an occupational U-switch being lower, while the cyclicality by switch type has not changed substantially. In other words, using the model-based definition seems to strengthen the composition effect in influencing the cyclicality of the average earnings losses after an occupational transfer.

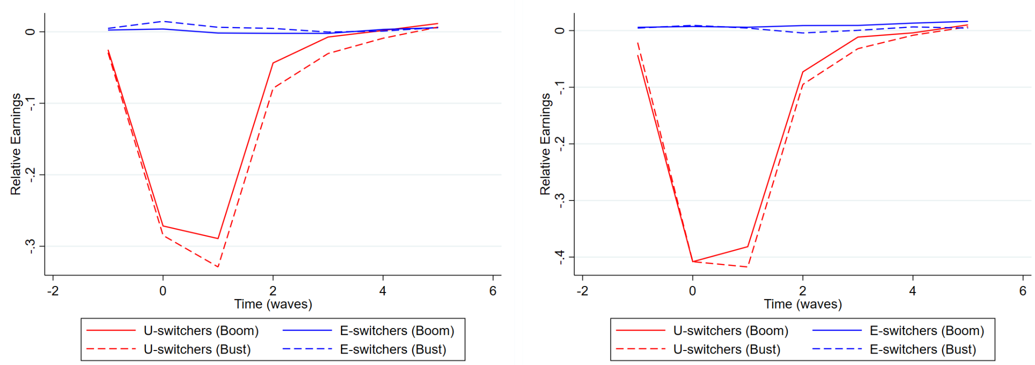

Figure D.4: *The effect of occupational switches on real earnings, relative to the counterfactual of never switching, by type of switch, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the model-based estimates from the data-based definition (left) and a model-based definition of occupational mobility(right).*

While most of the discussion in section 5 focuses on earnings, it is worth noting that section 2 also contains results on wages rather than earnings. I did not focus on these results in the model, as the model simplifies this analysis substantially by assuming away the intensive margin of employment. Therefore, the wages in the model are essentially equivalent to the earnings per week, conditional on being employed. Indeed, if I repeat the analysis from figures D.3 and D.4 using wages instead, the results are not very encouraging, as shown in figures D.5 and D.6: Although

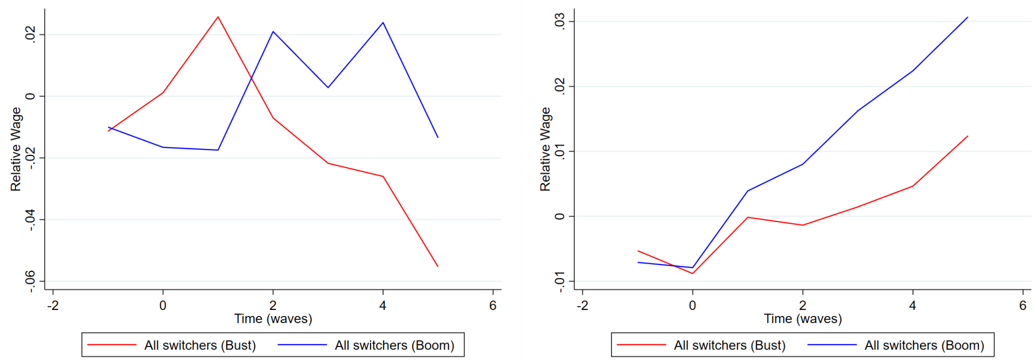

Figure D.5: *The effect of occupational switches on real wages, relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the estimates from the data (left) and the estimates obtained from model-generated simulation data (right).*

the cyclicality of the wage paths is not that far off from what I found in the data, the model-based simulation shows a clear upward trend, which is not present in the data.

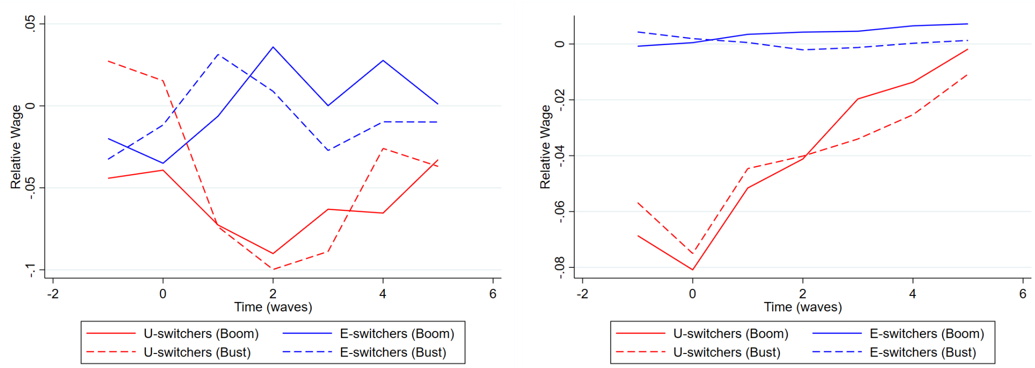

Figure D.6: *The effect of occupational switches on real wages, relative to the counterfactual of never switching, by type of switch, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the estimates from the data (left) and the estimates obtained from model-generated simulation data (right).*

Finally, figure D.7 repeats the analysis from figure 16 using an alternative estimation method. In particular, figure D.7 uses the method from Sun and Abraham (2021) rather than the three-step estimation method from Borusyak et al. (2022), both for the data result and the

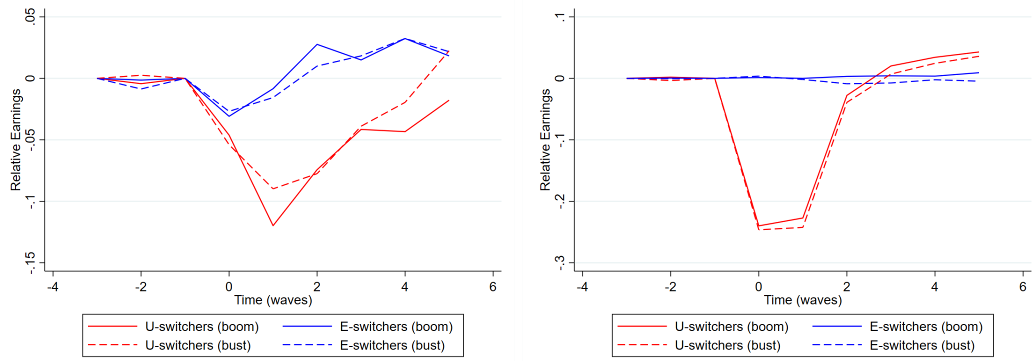

Figure D.7: *The effect of occupational switches on earnings, relative to the control group of never-switching workers, by type of switch, using estimated coefficients from equation* (13)*, and comparing the estimates from the data (left) and the estimates obtained from model-generated simulation data (right).*

model-based result. As can be seen in the figure, the data result looks slightly different from it's equivalent in the main text (as also discussed in appendix A.2), but the model-based estimation is almost identical to that obtained using the three-step method, thus indicating that the estimation method does not seem to substantially influence the model-based results.

D.2 Results using cyclical mobility costs

In the baseline estimation of the model in the main text, I assumed the cost of reallocation, either through unemployment or while staying on the job, to be constant in aggregate productivity. This assumption was driven by the fact that there does not exist a lot of evidence in the literature on the magnitude of such costs. The little evidence that has been provided to date, such as the calculations in Lalé (2017), are generally focusing on estimating an average cost of reallocation, and do not make any statements regarding the cyclicality of such costs. However, it is not unreasonable to expect that these costs could have a cyclical component to them, especially if they are driven by foregone earnings. For this reason, I allowed the costs to depend on aggregate productivity when setting up the model in section 3. In this subsection, I will investigate how the estimation of the model in section 4 as well as the subsequent results in section 5 change when allowing for this cyclicality in costs.

In table D.1, I show the results of two alternative estimations, compared to the baseline estimation. In particular, I consider two simple functions for the reallocation costs. In both of these functions, the costs depend linearly on the aggregate productivity, with the slope being one of the

Moment	**Data**	**Baseline**	$C = p \cdot \hat{c}$	$C = \bar{c} + p \cdot \hat{c}$
Average job-finding rate	0.468	0.8358	0.9322	0.915
Average proportion of employed workers experiencing 1+ unemployment spell in the next year	0.051	0.0767	0.05	0.017
Average aggregate productivity	1	1.7205	1.591	1.185
Persistence of aggregate productivity	0.719	0.8878	0.7709	0.9869
Volatility of aggregate productivity	0.009	0.0562	0.0537	0.1039
Returns to occupational experience (5 years)	0.1616	0.138	0.1487	0.0868
Returns to occupational experience (10 years)	0.2526	0.2951	0.3194	0.1811
Unemployment rate of unexperienced workers	0.072	0.0443	0.0273	0.021
Unemployment rate of experienced workers	0.049	0.0049	0.0025	0.0017
Unemployment survival rate (4 months)	0.560	0.1647	0.0676	0.0852
Unemployment survival rate (8 months)	0.387	0.0307	0.0056	0.008
Unemployment survival rate (12 months)	0.295	0.0064	0.0007	0.0008
Occupational mobility rate for workers unemployed for at least 1 month	0.431	0.5285	0.7484	0.5561
Occupational mobility rate for workers unemployed for at least 3 months	0.473	0.8207	0.8613	0.6557
Occupational mobility rate for workers unemployed for at least 6 months	0.474	0.8475	0.875	0.6818
Occupational mobility rate for workers unemployed for at least 9 months	0.473	0.8659	0.7857	0.5625
Occupational mobility rate for workers unemployed for at least 12 months	0.470	0.875	0.5	0.75
Subsequent mobility rate	0.741	0.946	0.8667	0.7465
Relative occupational mobility rate of unexperienced workers	1.077	1.9808	1.2527	1.8726
Occupational mobility rate for employed workers	0.036	0.0349	0.0373	0.0543
Relative occupational mobility rate for unexperienced employed workers	2.156	1.3295	1.3276	1.0924
Occupational mobility rate for employed workers without employer change	0.011	0.029	0.0319	0.0511
Fraction of occupational transfers going through unemployment	0.175	0.1161	0.1828	0.0336
Coefficient $\hat{\gamma}$ in equation (11)	2.13	2.0414	2.0452	1.979
Coefficient $\hat{\gamma}$ in equation (12), E-switchers	-0.001	0.3139	0.0957	0.136
Coefficient $\hat{\gamma}$ in equation (12), U-switchers	0.015	0.3546	0.0693	-0.113

Table D.1: *The moments targeted in the calibration, and their model counterparts in the baseline model from the main text, as well as two alternative calibrations that allow for dependence of the reallocation costs on aggregate productivity p.*

parameters to be estimated in the calibration exercise. However, in one version I additionally allow for a acyclical component of the reallocation cost. Note that I do not add any additional moments to the calibration exercise, and therefore it is not entirely unexpected that this second alternative calibration does not perform as well, since it adds two additional parameters to the model.

By comparing the columns in table D.1, it can be seen that both alternative calibrations are performing worse than the baseline model when it comes to the transitions out of unemployment. Both alternative calibrations severely overshoot the job finding rate, and as a result underestimate the unemployment rate more than the baseline model did. The second alternative calibration does better than the baseline when it comes to the rate of occupational mobility through unemployment, but does worse than the baseline (and the first alternative) for occupational mobility through employment. Nevertheless, both alternative calibrations are able to match the countercyclical fraction of occupational switches going through unemployment, just like the baseline model.

Parameter	**Baseline**	$C = p \cdot \hat{c}$	$C = \bar{c} + p \cdot \hat{c}$
σ_p	0.037	0.037	0.067
σ_z	0.051	0.058	0.041
ρ_p	0.986	0.967	0.996
ρ_z	0.987	0.981	0.995
μ_z	1.036	0.951	0.716
k	1.579	0.913	1.937
$\bar{c^u}$	-0.691	-	0.57
$\hat{c^u}$	-	-0.536	0.224
$\bar{c^e}$	0.258	-	0.26
$\hat{c^e}$	-	1.148	0.149
x_2	1.39	1.258	1.522
x_3	1.883	1.954	1.856
ψ	0.002	0.0005	0.0034
δ	0.0037	0.0017	0.0004

Table D.2: *Values of parameters used to obtain the results in Section 5, and their counterparts from the two alternative calibrations that allow for the reallocation costs to depend on aggregate productivity* p*.*

Table D.2 compares the parameter estimates from both alternative calibrations to the baseline estimates used to obtain the results in section 5. Naturally, the first set of parameters of interest when comparing the three calibrations concern the reallocation costs. As mentioned in section 4, one value that stood out in the baseline calibration was the cost of reallocation through unemployment, which was estimated to be negative. This is also the case in the first alternative calibration, which furthermore estimates the cost to be more negative in booms than in recessions. In the second alternative calibration, however, the pattern reverses, with the cost generally being positive and increasing in aggregate productivity. Furthermore, this second alternative calibration estimates the cost of reallocation through unemployment to be higher than the cost of job-to-job occupational transfers. Aside from these key differences, it can be noted that the second alternative calibration seems to suggest that aggregate productivity is more volatile than idiosyncratic productivity, and both alternatives (as well as the baseline) suggest a very low value for the exogenous separation rate δ.

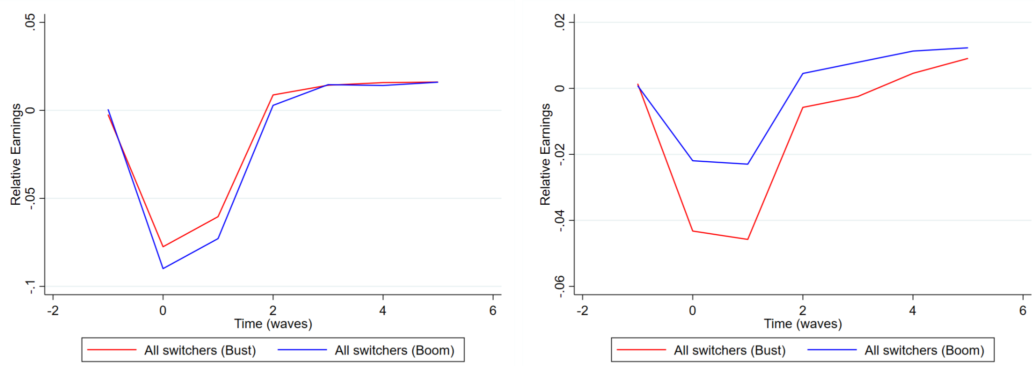

Figure D.8: *The effect of occupational switches on real earnings, relative to the counterfactual of never switching, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the estimates from two alternative calibrations, using* $C = p \cdot c$ *(left) or* $C = \bar{c} + p \cdot c$ *(right).*

In figure D.8, I show how the two alternative calibrations perform when it comes to the average earnings consequences of occupational mobility. Comparing the figure to figure 15 in the main text, it can be seen that the second alternative calibration does not match the data very well, and suggests a strongly procyclical pattern (though performing better than the baseline model when it comes to the levels), whereas the first alternative calibration's performance is fairly similar to the baseline model.

A similar conclusion can be reached when comparing the two alternative calibrations and the baseline model for earnings consequences specific to E-switchers and U-switchers. As figure D.9 shows, the second alternative calibration suggests strongly countercyclical earnings consequences of U-switches, whereas the first alternative calibration stays closer to the baseline model in terms of cyclicality, and both alternative calibrations match the levels of the earnings losses to a similar extent as the baseline model.

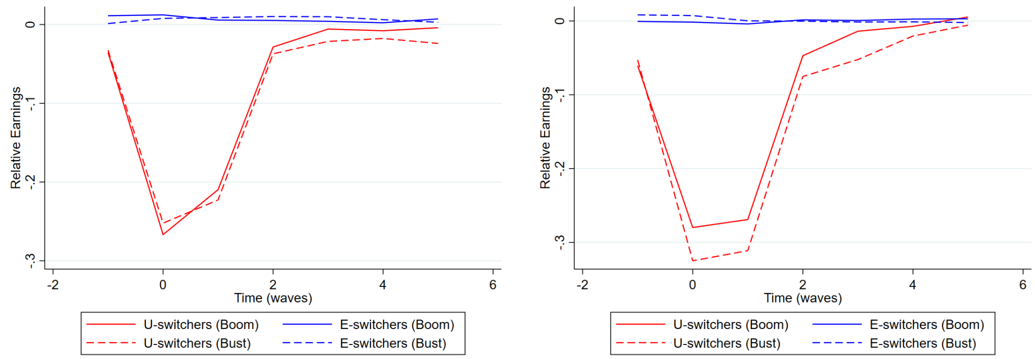

Figure D.9: *The effect of occupational switches on real earnings, relative to the counterfactual of never switching, by type of switch, using estimated coefficients obtained using the three-step estimation method. The plots show separate estimates of the effect for switches materializing during a boom or a bust, and compare the estimates from two alternative calibrations, using* $C = p \cdot c$ *(left) or* $C = \bar{c} + p \cdot c$ *(right).*

In figure D.10, the counterpart of figure 17 in the main text, I show the impact of forcing reallocation and separation thresholds to be acyclical on the average earnings consequences of occupational mobility in the alternative calibrations. As can be seen in the left panel of figure D.10, the effect of taking out the cyclical reallocation and separation thresholds completely disappears under the first alternative calibration. This is because the job-to-job reallocation in this version of the model is coming purely from the exogenous reallocation shock, which was already acyclical, whereas the separation threshold is very flat in this estimation, and thereby did not change much when forcing it to be completely horizontal. The right panel of figure D.10, on the other hand, shows that shutting down the cyclicality of these thresholds in the second alternative calibration deteriorates the outcomes for workers who switch occupations in booms, but not for workers who switch in a bust. In many ways, the reason for this is similar to the reasons mentioned in the main text for the baseline model: in this second alternative calibration, the threshold for job-to-job occupational mobility jumps up at a value of p slightly above 1 (rather than slightly below 1 as in the baseline model), so forcing the threshold to be acyclical shuts down most of the endogenous job-to-job transitions that occurred in booms.

In figure D.11, I repeat the analysis from figure 18 in the main text for the two alternative calibrations. Just like in the main text, it can be observed that not including either type of job-to-job mobility leads to a much larger average earnings loss after an occupational transfer.

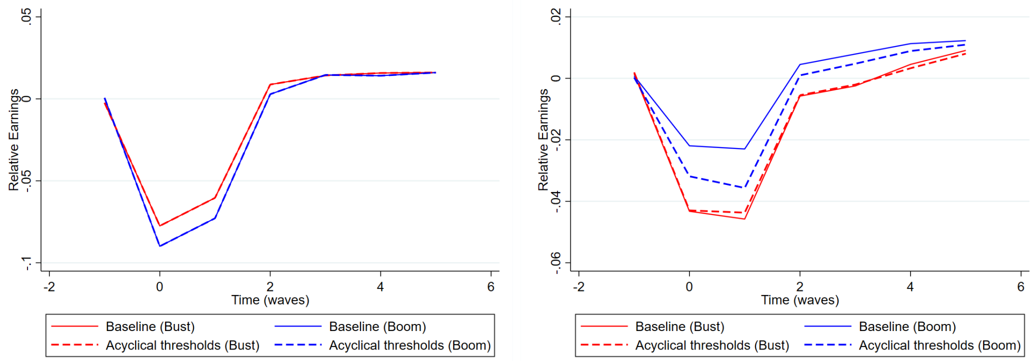

Figure D.10: *The impact of cyclical reallocation thresholds on the model-generated (BJS) effect of occupational switches on real earnings, relative to the counterfactual of never switching, and aggregated separately for switches materializing during a boom or a bust. The figure combines the estimates obtained from the baseline model (solid) and a model in which separation and reallocation thresholds are forced to be constant in aggregate productivity (dashed), and compare the estimates from two alternative calibrations, using $C = p \cdot c$ (left) or $C = \bar{c} + p \cdot c$ (right).*

Finally, figure D.12 shows the results of the decomposition of the cyclicality of the average earnings consequences of occupational transitions into the two types of job-to-job mobility and a residual component. As mentioned above, all job-to-job transitions in the first alternative calibration occur through the exogenous reallocation shock, thus leaving no contribution whatsoever to the endogenous choice of job-to-job mobility in this alternative. The decomposition of the second calibration, on the other hand, is fairly close to the one discussed in the main text, with a generally positive role for the endogenous choice of job-to-job occupational mobility, and a negative (countercyclical) force coming from the exogenous reallocation shock. This therefore reinforces the need for better understanding these reallocations within the firm, as concluded in the main text.

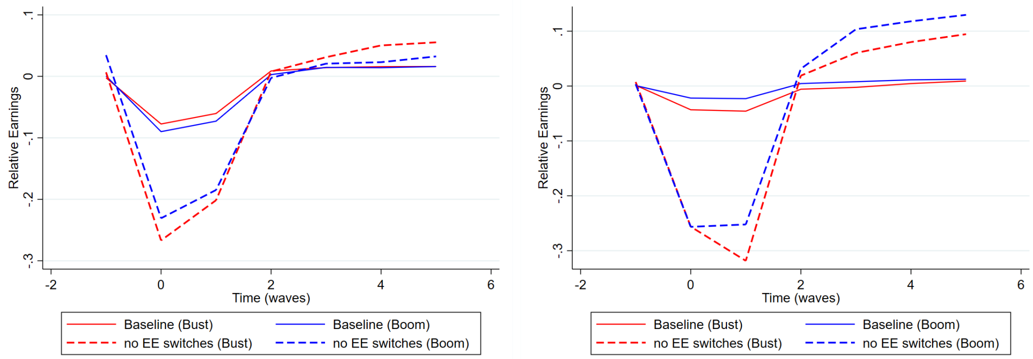

Figure D.11: *The impact of including job-to-job transitions on the model-generated (BJS) effect of occupational switches on real earnings, relative to the counterfactual of never switching, and aggregated separately for switches materializing during a boom or a bust. The figure combines the estimates obtained from the baseline model (solid) and a model without either type of job-to-job occupational transfers (dashed), and compare the estimates from two alternative calibrations, using* $C = p \cdot c$ *(left) or* $C = \bar{c} + p \cdot c$ *(right).*

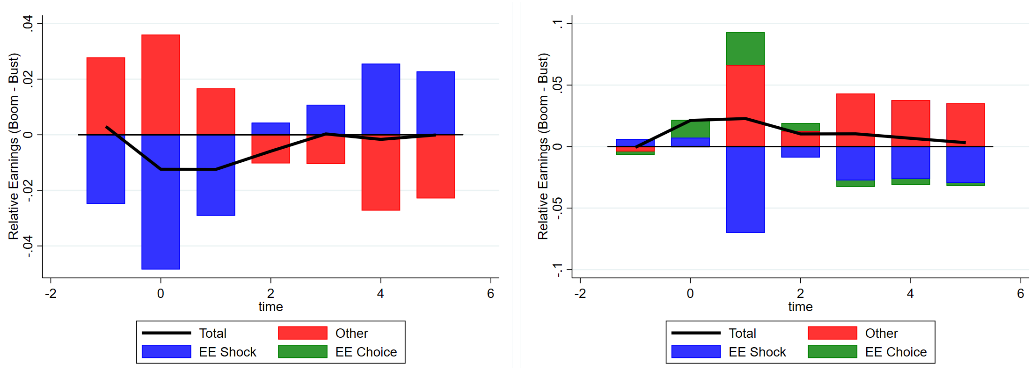

Figure D.12: *The impact of including job-to-job transitions on the model-generated (BJS) cyclicality in the effect of occupational switches on real earnings. The figure displays the separate impact of the occupational transfer shock and job-to-job occupational transfer choices, obtained using a Shapley-Shorrocks decomposition, using alternative calibrations with either* $C = p \cdot c$ *(left) or* $C = \bar{c} + p \cdot c$ *(right).*