Unemployment and Endogenous Reallocation over the Business Cycle *†

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Abstract

This paper studies the extent to which the cyclicality of occupational mobility shapes that of aggregate unemployment and its duration distribution. Using the SIPP, we document the relation between workers' occupational mobility and unemployment duration over the long run and business cycle. To interpret this evidence, we develop a multi-sector business cycle model with heterogenous agents. The model is quantitatively consistent with several important features of the US labor market: procyclical gross and countercyclical net occupational mobility, the large volatility of unemployment and the cyclical properties of the unemployment duration distribution, among others. Our analysis shows that occupational mobility due to workers' changing career prospects interacts with aggregate conditions to drive fluctuations of aggregate unemployment and its duration distribution.

Keywords: Unemployment, Business Cycle, Rest, Search, Occupational Mobility.

JEL: E24, E30, J62, J63, J64.

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1 Introduction

Occupational mobility is an important part of an unemployed worker's job finding process. On average 44% of workers who went through a spell of unemployment in the US changed "major occupational groups" at re-employment.[1] These occupation movers also take longer to find a job and contribute to the cyclical changes in long-term unemployment. For every extra month it takes an occupation stayer to find a job during a downturn, movers take 40% longer. This suggests that the willingness and ability of individuals to move across different sectors of the economy can have important consequences for aggregate labor market fluctuations. This paper builds on this evidence and studies the implications of unemployed workers occupational mobility for the cyclical behaviour of the unemployment duration distribution and the aggregate unemployment rate.

We propose and quantitatively assess a multi-sector business cycle model in which the unemployed face search frictions in, and reallocation frictions across, heterogeneous occupations. The economy we consider further exhibits idiosyncratic worker-occupation productivity shocks, orthogonal to occupation-wide productivities, to capture the evolving career prospects of a worker within an occupation. Workers accumulate occupation-specific human capital through learning-by-doing, but face skill loss during unemployment. Even with this rich level of heterogeneity, workers' job separations and reallocation decisions can be characterised by simple reservation productivity cutoffs that respond to aggregate and occupational-wide productivities.

A key success of the framework is that it can simultaneously generate the observed cyclical fluctuations of aggregate unemployment and its duration distribution as well as a strongly downward-sloping Beveridge curve. Underlying these fluctuations, the cyclical responses of the model's aggregate job separation and job finding rates are in line with the data (see Shimer, 2005, Hall and Milgrom, 2008, and Hagedorn and Manovskii, 2008). In addition, the model generates the observed procyclicality of gross occupational mobility among the unemployed and the stronger countercyclicality of unemployment duration among occupational movers. It also generates the observed increase in net reallocation of workers across occupations during recessions (see Dvorkin, 2014, Pilossoph, 2014, Wiczer, 2015 and Chodorow-Reich and Wieland, 2020).

Our approach provides a novel insight. We find that it is the interaction between worker's evolving career prospects within an occupation and aggregate conditions, and not occupation-wide productivity differences, that drive cyclical unemployment. The main mechanism is as follows. The estimation implies that within each occupation the job separation cutoffs consistently lie above the reallocation cutoffs. With uncertain returns and costly reallocation, those unemployed with idiosyncratic productivities between the cutoffs prefer the option of waiting and remaining attached to their pre-separation occupations instead of reallocating. During recessions the area between these cutoffs widens endogenously and workers spend a longer period of their jobless spells waiting even though there are no jobs posted for them. This drives up (long-term) unemployment more for occupational movers than stay-

[1] Major occupational groups are broad categories that can be thought of as representing one-digit occupations. For example, managers, sales, mechanic and repairers, construction/extraction, office/admin support, elementary trades, etc. The above proportion is obtained after correcting for measurement error.

ers during recessions, and helps create strong cyclical amplification in the aforementioned aggregate labor market variables.

The importance of idiosyncratic career productivity shocks in the model's mechanism reflects the prominence of *excess* mobility, i.e. moves that cancel each other out at the occupation level, in driving the unemployed's occupational mobility patterns in the data. We use the observed high propensity to change occupations and its increase with unemployment duration to uncover the stochastic process of the idiosyncratic career shocks. The estimated process then shapes workers' incentive to wait, generates procyclical excess and gross mobility inline with the data, and determines the cyclical performance of the model.

A prominent literature of multi-sector models in the spirit of Lucas and Prescott (1974) "islands" framework typically emphasise countercyclical net reallocation of unemployed workers across sectors (or "islands") as the main underlying force behind unemployment fluctuations (see Lilien, 1982, Rogerson, 1987). Countercyclical unemployment can arise when more workers engage in time consuming switches from sectors that have been affected harder in a recession to those sectors which offer relatively higher job finding prospects. To incorporate these insights we use an imperfect directed search approach to model search across occupations over the business cycle (see also Cheremukhin et al. 2020 and Wu, 2020). Nevertheless, as gross occupational mobility flows are an order of magnitude greater than net flows, adding this dimension does not change the importance of workers' evolving career prospects over occupation-wide productivities in explaining labor market fluctuations or the procyclical nature of occupational mobility. This occurs because the option value of waiting in the pre-separation occupation remains important within (cyclically) declining and expanding occupations.

Although net mobility has a small role in explaining aggregate unemployment fluctuations, it has a clear cyclical pattern. During recessions a higher proportion of workers lose their jobs in routine manual occupations and do not come back to these jobs; while a higher proportion of workers find jobs in non-routine manual occupations at re-employment. We show that these patterns substantially contribute to the long-run decline of the employment share of routine occupations and long-run increase in the employment share of non-routine occupations (see also Cortes et al., 2020). Hence, there is no contradiction between changing career prospects playing a very important role in shaping cyclical unemployment, and worker flows through unemployment contributing meaningfully to the changing sizes of occupations particularly during recessions.

The empirical study of occupational (or industry) mobility focused exclusively on workers who went through unemployment has received relatively little attention. This is in contrast to the larger amount of research investigating occupational mobility among pooled samples of employer movers and stayers (see Jovanovic and Moffitt, 1990, Kambourov and Manovskii, 2008, and Moscarini and Thomsson, 2007, among others).[2] There is no reason, a priori, to conclude that the mobility patterns uncovered by these studies apply to the unemployed. Therefore, we use data from the Survey of Income and Programme Participation (SIPP) between 1983-2014 to document relevant patterns link-

[2]A few recent exceptions are Şahin et al. (2014), Fujita and Moscarini (2017), Carrillo-Tudela et al. (2016), Faberman and Kudlyack (2019) and Huckfeldt (2021).

ing individuals' occupational mobility with their unemployment duration outcomes. We also use the Panel Survey for Income Dynamics (PSID) and the Current Population Survey (CPS) to corroborate our results.

As the levels of gross and excess occupational mobility are crucial for our analysis, a major concern is the extent to which coding errors creates spurious mobility and inflate our statistics (see Kambourov and Manovskii, 2008, and Moscarini and Thomsson, 2007). We show that one cannot use existing correction estimates based on samples pooling all workers when attempting to correct the occupational mobility of the unemployed. Instead we develop a novel classification error model that allows us to estimate the extent of coding error at the level of each occupation.

We calibrate our model using simulation method of moments and find that the nature of unemployment changes over the cycle. Rest/wait unemployment becomes relative more prominent in recession and search unemployment in expansions.[3] Alvarez and Shimer (2011) also study the relative importance of rest and search unemployment using a multi-sector model, but in an aggregate steady state. Their analysis implies that the individual transitions between work, rest and search are not determined.[4] In contrast, the estimated dynamics of workers' career prospects in our framework determines the transitions between employment and the different types of unemployment. This allows us to analyse the relationship between unemployment duration, occupational mobility and job finding probabilities, both in the long-run and over the cycle.

The large and persistent rise in unemployment observed during and in the aftermath of the Great Recession generated a renewed interest in multi-sector business cycle models as useful frameworks to investigate cyclical unemployment. Like in our paper, Pilossoph (2014) finds a muted effect of net reallocation across sectors on aggregate unemployment. Chodorow-Reich and Wieland (2020) build on this work and link net reallocation of workers across industries/locations to increases in total unemployment. They find this link only for the recession-to-recovery phase of the cycle, arguing for a crucial role of wage rigidity. In these papers, gross mobility is constant or countercyclical, which is at odds with the data.[5] Their focus is also not on the cyclical unemployment duration patterns nor cyclical patterns in the relationship between individuals' unemployment duration and their occupational mobility, features that are central to our paper.

Closer to our analysis is Wiczer (2015), who studies the role of occupations on long-term unemployment over the cycle in a multi-sector model. In contrast, unemployed workers in our framework take into account the potential recovery of their occupational productivities when making job separations and occupational mobility decision. It is this feature that takes us a long way in replicating the overall volatility of cyclical unemployment, while remaining consistent with the cyclical behaviour of the short and long-term unemployed.

[3]The concept of rest/wait unemployment was introduced by Jovanovic (1987), using a business cycle multi-sector model. However, he did not link it to occupational mobility, the unemployment duration distribution, or investigated its quantitative properties. See also Hamilton (1988) and Gouge and King (1997).

[4]With perfectly competitive labor markets workers in their model are considered search unemployed when in transit between sectors and are indifferent between work and rest or between work, rest and search.

[5]To the best of our knowledge Dvorkin (2014) is the only one who attempts to reproduce the procyclicality of gross mobility together with the countercyclicality of net mobility. However, his calibrated model generates nearly acyclical series and hence is not able to reproduce the observe strong cyclicality of these series (see his Table 9).

As we are interested on how occupational mobility affects unemployment fluctuations, worker heterogeneity in our model is naturally time variant. There is also a growing literature that incorporates time-invariant worker heterogeneity to the Mortensen and Pissarides (1994) model to generate enough cyclical volatility in aggregate unemployment (see Bils et al., 2012, Chassambouli, 2013 and Murtin and Robin, 2018). We share with these papers that some unemployed workers do not provide incentive for vacancies to enter the labor market during periods in which their productivities lie below the job separation cutoff. These models, however, do not capture that during recessions the stronger lengthening of unemployment spells among the larger group of occupation movers significantly contributes to the increase in long-term unemployment. The addition of the reallocation cutoff enable us to explain the cyclical behaviour of short and long-term unemployment of occupational movers and stayers.

In addition to workers' evolving career prospects within an occupation, occupational human capital plays an important in our analysis. Like in Kambourov and Manovskii (2009a) and Alvarez and Shimer (2012), it generates an additional waiting motive that implies older, more experienced workers tend to switch occupations less than younger less experienced ones. Different to these papers, however, differences in human capital implies that during recessions the composition of unemployment and separations moves towards the (on-average) more productive group of prime-aged workers (see Mueller, 2017).

The rest of the paper proceeds as follows. Section 2 presents the empirical evidence that motivates our paper. Section 3 describes and characterises the model and its main implications. In Sections 4 and 5 we quantitatively assess this model and show the importance of changing career prospect in explaining cyclical unemployment outcomes. Section 6 concludes. All proofs, detailed data, quantitative analysis and robustness exercises are relegated to several online appendices.

2 Occupational Mobility of the Unemployed

Our main statistical analysis is based on the sequence of 1984-2008 SIPP panels, covering the 1983-2014 period. The sample restricts attention to those workers who were observed transiting from employment to unemployment and back within a given panel (EUE flows), and excludes those in self-employment, in the armed forces, or in the agricultural occupations.[6] In our baseline analysis we consider workers who have been unemployed throughout their non-employment spells, but show that our main results also hold when using mixed unemployment/out-of-labor-force spells. To minimize the effects of censoring that arise due to the SIPP structure, we consider unemployment spells for which re-employment occurs as from month 16 since the start of the corresponding SIPP panel and impose that workers at the moment of re-employment have at least 14 months of continuous labor market history within their panel. In Supplementary Appendix B.7 we provide further details and

[6]The self-employed are not included in our analysis as they might face a very different frictional environment and choices than those in dependent employment. Indeed, we find that 50% of those who transited from self-employment to unemployment in the SIPP went to back self-employment. This suggests that self-employment begets self-employment, a feature we do not capture in our model. On the other hand, 96% of those who transited from dependent employment into unemployment returned to dependent employment and are captured in our model.

analyse the implications of these restrictions.

We found that among all unemployment to employment transitions, only about 5% transited into self-employment. Furthermore, 50% of those who transited from self-employment to unemployment went to back self-employment. This suggests that self-employment begets self-employment.

An individual is considered unemployed if he/she has not been working for at least a month after leaving employment and reported "no job - looking for work or on layoff". Since we want to focus on workers who have become unattached from their previous employers, we consider those who report to be "with a job - on layoff", as employed.[7] After dropping all observations with imputed occupations, we compare each workers' reported occupations before and after the non-employment spell. To capture meaningful career changes we use the 21 "major" occupational groups of the 2000 Census Occupational Classification (2000 SOC) as well as their aggregation into the task-based occupational categories proposed by Autor and Dorn (2013) and Cortes et al. (2020). In the SIPP, however, the occupation information of a worker newly hired from unemployment is collected under independent interviewing, which is known to generate occupational coding errors.[8] Without correcting for miscoding we could potentially be inflating the importance of occupational mobility among the unemployed. We address this issue by developing a classification error model, which we briefly present in the next subsection.

After adjusting our data for misclassification error we use the relationship between occupational mobility and unemployment duration to investigate the degree of "attachment" workers have to their pre-separation occupations and how it evolves with their spell duration. We also investigate how this attachment differs across demographic groups, occupational categories and across unemployment spells, how it depends on excess and net mobility (defined below) and the business cycle. Supplementary Appendix B present a more detailed analysis of our long-run and business cycle findings, as well as extensive robustness exercises and provides details on the data construction and measurement.

2.1 Correcting for Coding Errors in Occupation Mobility

In order to correctly measure the level and cyclicality of excess and net occupational mobility we propose an approach that allows us (i) to correct for the potentially large heterogeneity in (the propensity of) coding errors in the flows between particular occupations, and thereby capture more accurately coding errors for those occupations that weigh more among the unemployed; (ii) to correct for the effect of miscoding on net mobility; (iii) to correct sequential occupational mobility observations across

[7] Fujita and Moscarini (2017) find that the unemployed (as typically defined by the BLS) consist of two groups that behave very differently: "temporary laid-off workers" and "permanent separators". The latter group are those who lost their job with no indication of recall. Similarly, Hornstein (2013) and Ahn and Hamilton (2018) consider two groups among the unemployed in terms of fixed characteristics: those with "high job finding rates" and those with "low job finding rates". Excluding from our unemployment measure those workers who are "with a job - on layoff" and those who find employment within a month means that our unemployment sample is close to Fujita and Moscarini's "permanent separators" sample and to Hornstein's and Ahn and Hamilton's "low job finding rate" workers. In Supplementary Appendix B.4.4, we further discuss this issue.

[8] This implies that the occupational question is asked without reference to the answers giving by the respondent in previous interviews. A professional coder then assigns an occupational code based on the respondent's answer, also without reference to occupational codes previously assigned or previous answers given by the same respondent.

two unemployment spells, where a single coding mistake can create two spurious moves; and (iv) to easily incorporate it in our quantitative analysis.

Suppose that coding errors are made according to a garbling matrix $\mathbf{\Gamma}$ of size OxO, where O denotes the number of occupational categories. The element γ_{ij} is the probability that the true occupation $i = 1, 2, ..., O$ is coded as occupation $j = 1, 2, ..., O$, such that $\sum_{j=1}^{O} \gamma_{ij} = 1$. Let $\mathbf{M}$ denote the matrix that contains workers' *true* occupational flows, where element m_{ij} is the flow of workers from occupation i to occupation j. Under independent interviewing such a matrix appears as $\mathbf{M^I} = \mathbf{\Gamma}'\mathbf{M}\mathbf{\Gamma}$, where the pre- and post-multiplication by $\mathbf{\Gamma}$ takes into account that the observed occupations of origin and destination would be subject to coding error. Knowledge of $\mathbf{\Gamma}$ (and of its invertibility) allows us to de-garble $\mathbf{M}$ as $\mathbf{\Gamma^{-1}}'\mathbf{M^I}\mathbf{\Gamma^{-1}}$.[9]

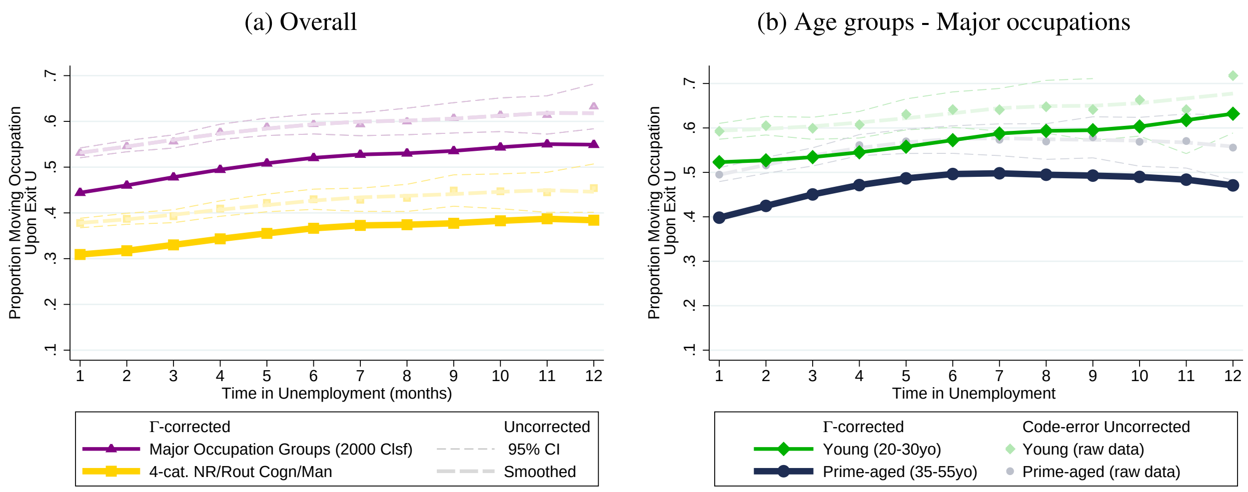
Online Appendix A and Supplementary Appendix A describes formally this correction methodology. There we prove that $\mathbf{\Gamma}$ can be identified and estimated from our data by making three assumptions. (*A1*) *Independent classification errors*: conditional on the true occupation, the realization of an occupational code does not depend on workers' labor market histories, demographic characteristics or the time it occurred in our sample. (*A2*) *"Detailed balance" in miscoding*: coding mistakes are symmetric in that the number of workers whose true occupation i gets mistakenly coded as j is the same as the number of workers whose true occupation j gets mistakenly coded as i. (*A3*) *Strict diagonal dominance*: It is more likely to correctly code occupation i than to miscoded it. In Supplementary Appendix A we also use SIPP, PSID and CPS data to evaluate the plausibility of these assumptions. We then implement our method using the change from independent to dependent interviewing that occurred between the 1985 and 1986 SIPP panels.

Applying the $\mathbf{\Gamma}$-correction to the occupational flows of workers who go through unemployment results in an average miscoding of about 10% each time information is collected when using "major" occupational categories of the 2000 SOC. This implies that at re-employment true occupational stayers have on average about a 20% chance of appearing as occupational movers. Further, we do find that different occupations have very different propensities to be assigned a wrong code and, given a true occupation, some coding mistakes are much more likely than others. This matters for our measures of net mobility, where we find a sizeable *relative increase* in net mobility after correction.

Supplementary Appendix A also presents an alternative correction based on the PSID retrospective occupation - industry supplementary data files (see also Kambourov and Manovskii, 2008) to evaluate the robustness of our $\mathbf{\Gamma}$-correction. We show that the level and cyclicality of the $\mathbf{\Gamma}$-corrected occupational mobility rate at re-employment are in line with the ones derived from the PSID. In Supplementary Appendix B we use the SIPP to provide further robustness based on two alternative measures of occupational mobility: (i) simultaneously mobility of major occupational and major industrial groups at re-employment and (ii) self-reported duration of occupational tenure obtained from the topical modules. The first measure is considered less sensitive to miscoding as it typically requires

[9]This formulation builds on Poterba and Summers (1986) and Abowd and Zellner (1985), who focus on miscoding of labor force status. They are able to directly observe miscoding from CPS re-interviews, where discrepancies in labor force status are explicitly reconciled by the Census, under the assumption that re-interviews uncovers the true worker's status. In contrast, our challenge is that we do not observe the garbling matrix of occupations directly from the data.

Figure 1: Extent of occupational mobility by unemployment duration



Notes: Each mobility-duration profile shows for a given unemployment duration x, the proportion of workers who changed occupations at re-employment among all workers who had unemployment spells which lasted at least x months.

errors to be made simultaneously along two dimensions. The second captures the worker's own perception of occupational mobility and is not based on occupational coding. We find a very consistent picture across all methods. In what follows, all statistics are corrected for miscoding, unless otherwise stated.

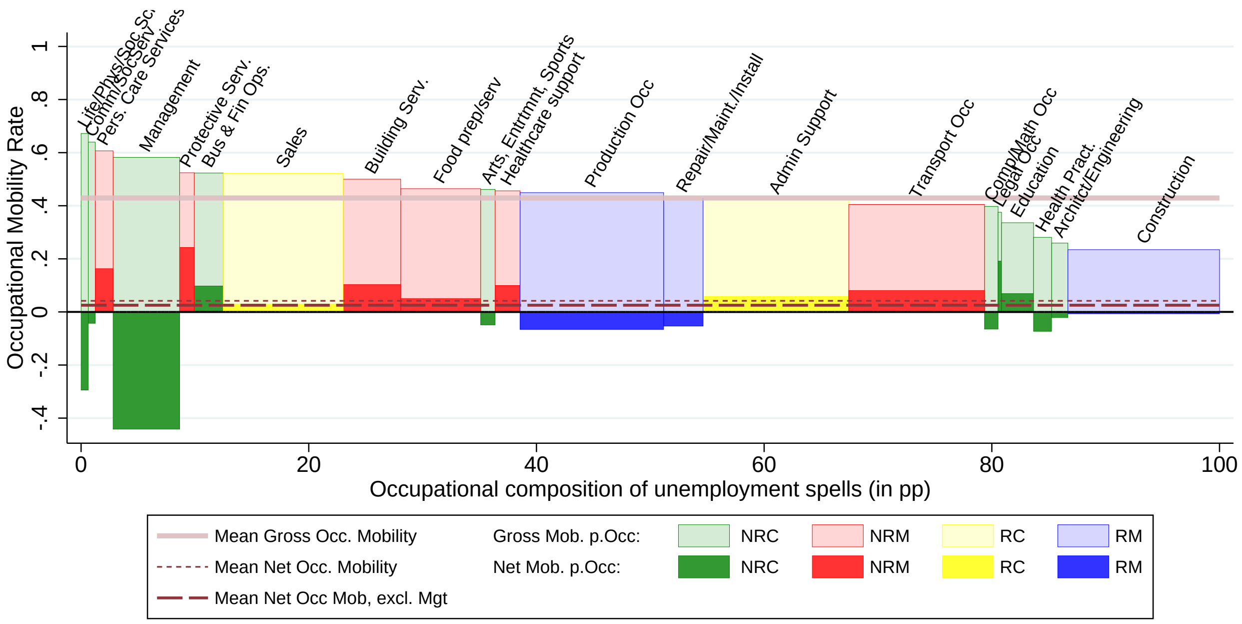
2.2 Gross Occupational Mobility and Unemployment Duration

We now document the degree of attachment workers have to their pre-separation occupation as their unemployment duration increases. In Figure 1 we pool the SIPP panels to generate mobility-duration profiles. They show, for a given unemployment duration x, the proportion of workers who changed occupations at re-employment among all workers who had unemployment spells which lasted at least x months.

Figure 1a shows that 44.4% of workers who had at least one month in unemployment changed occupation at re-employment, while 53.7% of workers who had at least 9 months in unemployment changed occupation at re-employment. This evidence thus shows that gross occupational mobility at re-employment is *high* and *increases moderately* with unemployment duration. The moderate increase implies that a large proportion of long-term unemployed, over 45%, still return to their previous occupation at re-employment.[10] The figure shows that a similar pattern arises when considering mobility across four task-based occupational categories: non-routine cognitive (NRC), routine cognitive (RC), non-routine manual (NRM) and routine manual (RM) occupations. In Supplementary Appendix B.1 we show this pattern also holds when using non-employment spell that include at least one month of unemployment, simultaneous industry/occupation mobility or self-reported duration of occupational

[10]Kambourov and Manovskii (2008) compare two measures of year-to-year occupational mobility of pooled employer movers and stayers using the PSID, one that includes and one that excludes the unemployed. They find that the inclusion of unemployed workers raises the year-to-year occupational mobility rate by 2.5 percentage points, using a two-digit aggregation. In Supplementary Appendices A and B.5 we relate in more detail our analysis to theirs. Moscarini and Thomsson (2007) find high occupational mobility among employer-to-employer movers in the CPS, using a sample of workers who changed employers directly or with an intervening spell of non-employment of at most one month.

Figure 2: Gross and Net Occupational Mobility per Occupation



Notes: *Gross mobility:* The height of each light-colored bar is given by E_iUE_{-i}/E_iUE, where E_iUE_{-i} denotes the number of EUE spells of individuals who lost their jobs in occupation i and found re-employment in occupations other than i; and E_iUE denotes all EUE spells of those who lost their job in occupation i, including those who were re-employed in i. The width of each bar corresponds to E_iUE/EUE. Occupations are then sorted in decreasing order by workers' gross mobility. *Net mobility:* The height of each dark-colored bar corresponds $(E_{-i}UE_i - E_iUE_{-i})/E_iUE$. A positive value refers to net inflows, while a negative value refers to net outflows. The area of each of these bars gives the occupation-specific net flows as a proportion of all EUE transitions. Those occupations within the same task-based category are displayed in the same color, where NRC = non-routine cognitive, RC = routine cognitive, NRM = non-routine manual, RM = routine manual. The solid line correspond to the average gross occupational mobility rate. The dashed lines correspond to the average net mobility rate with and without managerial occupations. All data is corrected for miscoding using the method outlined in Section 2.1.

tenure.

Demographics In Supplementary Appendix B.1 we also show that the high level of occupational mobility and the moderate loss of attachment with duration is shared across men and women, education and race groups. However, we find that the level of gross occupational mobility decreases substantially with age, from 52.5% when young, (20-30yo), to 39.7% when prime-aged, (35-55yo). Figure 1b shows that the mobility-duration profile of prime-aged workers is below of that of young workers typically by about 9-13 percentage points but has a very similar slope. Thus, prime-aged workers display a higher level of attachment to their occupation but lose it in a similar gradual way with duration as young workers.

Mobility by occupation Figure 2 shows that most occupations share high mobility rates. The gross mobility of an occupation i (height of each light-colored bar) is defined as the percentage of unemployed workers previously employed in i finding employment in a different occupation. This finds that occupations with gross occupational mobility rates above 40% cover more than 80% of all EUE spells in our data. Apart from small and specialized occupations (as engineers, architects, and doctors), construction is the only large occupation with a meaningfully lower occupational mobility, which is still close to 25%.

In Supplementary Appendix B.1 we show that the moderate increase of occupational mobility with unemployment duration is also shared across (origin) occupations. Further, we cannot reject the equality of the slopes (and semi-elasticities) across all occupation-specific mobility-duration profiles. The slope of the aggregate duration profile does not arise because some occupations with relatively high unemployment durations have particularly high occupational outflows – rather, it appears that the unemployed across all occupations lose their attachment gradually.

2.3 Excess and Net Mobility

To assess the importance of occupational moves that result in certain occupations experiencing net inflows (outflows) through unemployment, we divide gross occupational mobility into net and excess mobility. Denote by E_iUE_{-i} the number of unemployment spells that involve a move from occupation i to any of the other occupations. The dark bars in Figure 2 depict the net flows per occupation, defined as $(E_{-i}UE_i - E_iUE_{-i})/E_iUE$, where the numerator denotes the difference between gross inflows and outflows for occupation i and the denominator captures all unemployment spells that originate from occupation i. It is evident that net flows are an order of magnitude smaller than gross outflows across almost all occupations, the main exception being managerial occupations. The average net mobility rate, $0.5\sum_i |E_{-i}UE_i - E_iUE_{-i}|/EUE$ (where $EUE = \sum_i E_iUE$) equals only 4.2%. This means that 4.2% of workers' EUE spells make up the contribution of the unemployed to the changing size of occupations.[11] Although small relative to unemployment flows, we observe a clear pattern: net outflows from the routine manual occupations (RM) and net inflows into the non-routine manual (NRM) occupations.

Excess mobility is the most important component of occupational mobility, across all occupations except for management. Aggregating across occupations, the average excess mobility rate $\sum \min\{E_{-i}UE_i, E_iUE_{-i}\}/EUE$ implies that 40.2% of all EUE spells represent excess mobility, about 90% of all gross mobility. Supplementary Appendix B.2 extends this analysis and shows these results are robust to alternative occupational classifications and considering non-employment spells instead of only unemployment spells.[12]

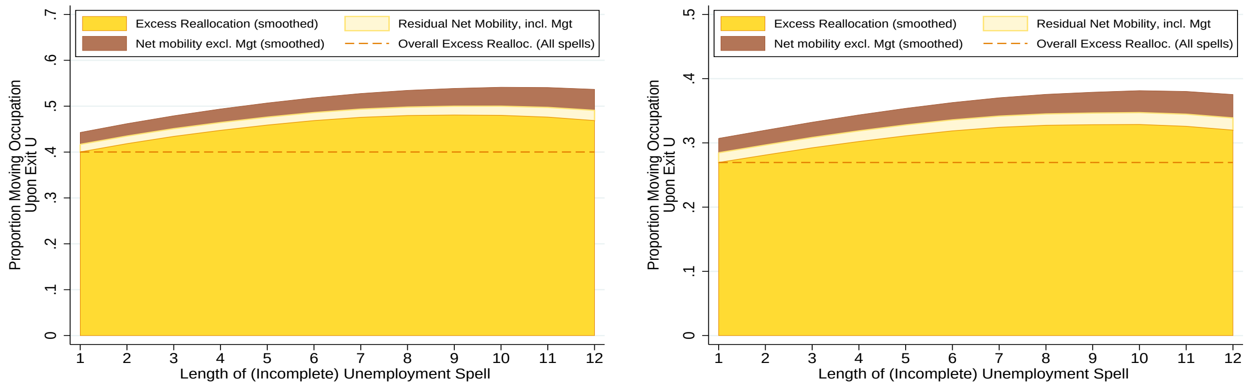
Excess and net mobility-duration profile Figure 3 shows that the moderate increase of gross mobility with unemployment duration is associated with an increase in excess mobility. For each duration $x = 1, 2, 3, ..., 12$ we re-compute the average net and excess mobility rates defined above but using only those EUE spells that have unemployment episodes of at least x months. We then decompose the mobility-duration profile into three categories: excess mobility, net mobility among non-management occupations (by dropping all the management flows), and the difference between these two, which we label "residual net mobility". This finds that, while for the long-term unemployed occupational moves are more common, those moves still overwhelmingly cancel out at an occupational level. Therefore, although there is a small absolute increase in net mobility with duration, Figure 3 does not support the conjecture that long-term unemployment is associated with a subset of occupations that workers are particularly eager to leave for a different and disjunct set of occupations that

[11] The pre-multiplication by 0.5 reflects that each net outflow in some occupation is simultaneously also counted as a net inflow in other occupations. Note that coding error matters for the level of net mobility, where in the raw data the average net mobility rate is below 3%. Miscoding will mistakenly convert some true mobility flows into occupational stays, while miscoding for stayers is completely symmetric with respect to origin and destination occupations, and therefore should not give rise to spurious net mobility.

[12] For pooled samples of employer stayers and movers, Jovanovic and Moffitt (1990) and Kambourov and Manovskii (2008) have also highlighted the importance of excess relative to net mobility across industries or occupations.

Figure 3: Gross, Net and Excess Occupational Mobility by unemployment duration

(a) Major Occupational Groups (2000 SOC) (b) Task-based categories (NRC/RC/NRM/RM)



Notes: At each duration $x = 1, 2, 3, ..., 12$ we compute the average net mobility rate $0.5 \sum |E_{-i}UE_i - E_iUE_{-i}|/EUE$ using EUE spells that have completed unemployment episodes of at least x months. The net mobility rate among non-management occupations drops all management flows from this calculation. The average excess mobility rate is computed as $\sum \min\{E_{-i}UE_i, E_iUE_{-i}\}/EUE$, once again only using the EUE spells that have completed unemployment episodes of at least x months. The horizontal dashed line across these graphs reflect the average excess mobility rate of 40.2% among those workers who had at least one month in unemployment.

offer better conditions.

2.4 Repeat Mobility

The SIPP allows us to investigate the evolution of a worker's attachment to occupations across multiple unemployment spells. These "repeat mobility" statistics tell us whether typically workers who changed (did not change) occupations after an unemployment spell, will change occupation subsequently after a following unemployment spell.[13] Here we can also use the $\mathbf{\Gamma}$-correction to counteract coding error in three-occupation histories (surrounding two unemployment spells).[14]

We find that from all those stayers who became unemployed once again, 64.9% of these workers remain in the same occupation after concluding their second unemployment spell. This percentage is higher for prime-aged workers, 69.3%, and lower for young workers, 57.1%. However, the loss of occupational attachment itself also persists. Among workers who re-enter unemployment after changing occupations in the preceding unemployment spell, we find that 55.8% of these workers move again. This percentage is lower for prime-aged workers, 50.8%, and higher for the young, 63.8%. Supplementary Appendix B.5 shows a similar pattern in the PSID.

[13]Our repeat mobility statistics are measured within the SIPP 3.5 to 5 years windows and are based on 610 of observations of individuals with multiple spells across all panels when considering only pure unemployment spells and 1,306 when considering non-employment spells that include months of unemployment. For further details see Supplementary Appendix B.7. Note that workers with two consecutive unemployment spells within this window are not necessarily representative of all unemployed workers, nor of behavior in unemployment spells that are further apart. Nevertheless, these statistics are valuable and will inform our modelling choices and quantitative analysis, where we construct our simulated measures in the same way as we do in the SIPP.

[14]With O the total number of occupations, let the matrix $\mathbf{M^r}$ (with elements m^r_{ijk}) be the $O \times O \times O$ matrix of true repeat flows. Then, this matrix relates to the *observed* repeat flow matrix $\mathbf{M^{r,obs}}$ through $\mathbf{vec}(\mathbf{M^r})' = \mathbf{vec}(\mathbf{M^{r,obs}})'(\mathbf{\Gamma} \otimes \mathbf{\Gamma} \otimes \mathbf{\Gamma})^{-1}$, where $\mathbf{vec}(\mathbf{M})$ is the vectorization of matrix $\mathbf{M}$, and $\otimes$ denotes the Kronecker product. Since $\mathbf{\Gamma}$ is invertible, $\mathbf{\Gamma} \otimes \mathbf{\Gamma} \otimes \mathbf{\Gamma}$ is also invertible.

2.5 Occupational Mobility of the Unemployed over the Cycle

Unemployed workers' attachment to their previous occupations changes over the business cycle. In expansions unemployed workers change occupations more frequently than in recessions. Panel A of Table 1 investigates the cyclicality of occupational mobility by regressing the (log) gross occupational mobility rate on the (log) unemployment rate. Columns (i) and (ii) relate the HP-filtered quarterly series of the $\mathbf{\Gamma}$-corrected and uncorrected occupational mobility rates obtained from the SIPP to HP-filtered series of the unemployment rate, all with a filtering parameter of 1600. Because there are proportionally more stayers and hence more spurious mobility in recessions, the corrected series yields a somewhat stronger cyclicality than the uncorrected one. Column (iii) presents the regression results based on (uncorrected) occupational mobility data from the CPS for the period 1979-2019. We use the CPS as in this case the quarterly mobility series does not suffer from gaps as does the SIPP (see also Supplementary Appendix B.5.[15] We observe that the uncorrected SIPP and CPS series have a very similar degree of procyclicality, suggesting that data gaps do not meaningfully affect our conclusion.

Table 1: Occupational mobility and unemployment duration over the business cycle

	HP-filtered Qtrly Occ. Mobility			Unfiltered Occ Mobility			
	(i) SIPP $\mathbf{\Gamma}$-corrected	(ii) SIPP uncorrected	(iii) CPS uncorrected	(iv) SIPP $\mathbf{\Gamma}$-corrected	(v) SIPP uncorrected	(vi) CPS uncorrected	(vii) SIPP uncorrected
	Panel A: Mobility regression, not controlling for non-employment duration						
HP U	-0.170***	-0.100***	-0.106***	-0.154**	-0.114**	-0.087***	-0.129***
	(0.060)	(0.030)	(0.039)	(0.062)	(0.049)	(0.032)	(0.043)
Controls	-	-	-	-	-	-	D,T, S.O.
	Panel B: Mobility regression, controlling for non-employment duration						
HP U	-	-	-	-0.199***	-0.150***	-0.116***	-0.174***
	-	-	-	(0.063)	(0.050)	(0.035)	(0.044)
Dur. coef	-	-	-	0.0161***	0.0133***	0.0102***	0.0142***
	-	-	-	(0.002)	(0.002)	(0.001)	(0.002)
Controls	-	-	-	-	-	-	D,T, S.O.

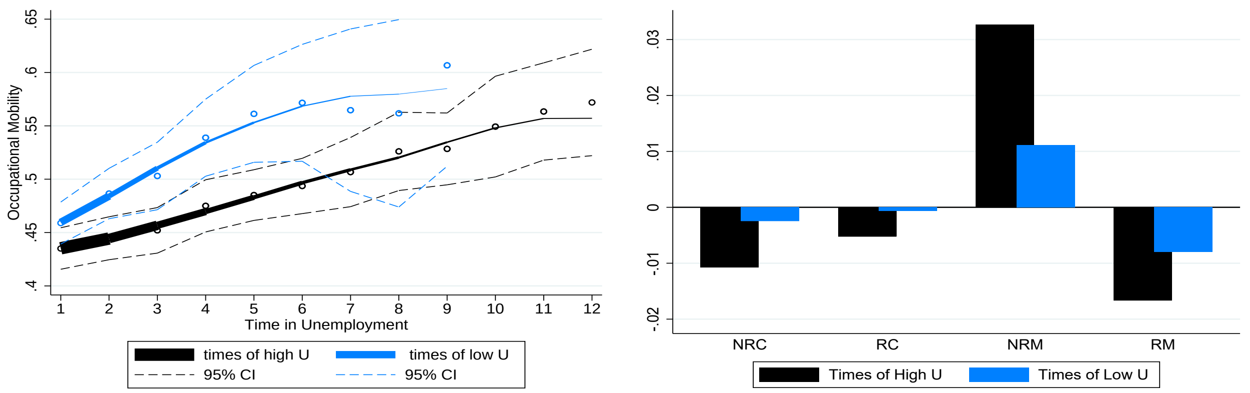
Notes: */**/*** denotes significance at 10%, 5%, 1% level. SIPP sample is restricted to quarters where the data allows the full spectrum of durations between 1-12 months to be measured. Standard errors clustered on quarters. Dur Coef. is the coefficient on completed durations. Underlying the regression sample are spells with completed durations between 1 and 14 months, not involving agricultural occupations; for further restrictions, see Supplementary Appendix B.7. Regressions (i)-(iii) and (iv)A on quarterly data; (iv)B on ($\mathbf{\Gamma}$-corrected) quarter x duration data; (v)-(vii) on individual-level panel data. CPS data described and cyclicality further analyzed in Supplementary Appendix B.5, (vi) on period 1984-2014 for comparability with SIPP. ***Controls***: D=demographic controls (gender, race, education, and a quartic in age); T=time controls (linear time trend, and a dummy for the classification in which data was originally reported); S.O.= source occupation.

Columns (iv)-(vii) presents the results of regressions relating unfiltered occupational mobility series to the HP-filtered unemployment rate as further robustness. Again, both SIPP and CPS data sets give a broadly similar procyclicality. The last column adds further individual-level controls and shows that these do not meaningfully change our results. This indicates that the procyclicality of occupational mobility is not the result of a compositional shift towards occupations or demographics characteristics that are associated with higher mobility when the economy is in an expansion. In

[15] These occupational mobility series have data missing due to non-overlapping SIPP panels combined with our sampling restrictions (to avoid censoring issues), as described in Supplementary Appendix B.7. To deal with these gaps, we use TRAMO-SEATS (Gomez and Maravall, 1996) for interpolation, HP-filter the series and then discard all quarters that were interpolated.

Figure 4: Cyclicality of occupational mobility, 1985-2014

(a) Occ. Mobility - Duration Profile Shift (b) Net Occupational Mobility - Task-based categories



Notes: *Left panel:*The circular markets depict the raw data and the solid curves represent the smoothed mobility-duration profile. The thickness of the profiles indicates the amount of spells surviving at a given duration. *Right panel:* The net mobility rate for each task-based category is computed excluding Managers and constructed as $(E_{-i}UE_i - E_iUE_{-i})/EUE$, separately for periods of high and low unemployment. The version including Managers can be found in the Supplementary Appendix B.

Supplementary Appendix B.3 we provide an extensive set of robustness exercises based on the SIPP all showing the procyclicality of gross occupational mobility. Supplementary Appendix B.5 further shows a procyclical occupational mobility rate among the unemployed when using the PSID for the period 1968 to 1997.

Cyclicality of the mobility-duration profile Figure 4a depicts the cyclical shift of the mobility-duration profile. It plots the profile separately for those spells that ended in times of high unemployment and for spells that ended in times of low unemployment. Times of high (low) unemployment are defined as periods in which the de-trended (log) unemployment rate was within the bottom (top) third of the de-trended (log) unemployment distribution. The thickness of the profiles indicates the amount of spells surviving at a given duration, showing the faster reduction of spells with duration in expansions. Occupational mobility at any unemployment duration is lower in recessions, corroborating the procyclicality of gross occupational mobility documented in Table 1. Both in times of high and low unemployment, an increase in unemployment duration is associated with a moderate loss of attachment to workers' previous occupation. Panel B of Table 1 shows that a roughly similar vertical shift of the mobility-duration profile over the cycle is found across SIPP and CPS and this is robust to including demographics and (origin) occupations controls.

The cyclicality of net occupational mobility Figure 4b shows the cyclical behavior of the net mobility rates for each of the four task-based categories. We compute the net mobility rate as $(E_{-i}UE_i - E_iUE_{-i})/EUE$, separately for periods of high and low unemployment.[16] Differently from Section 2.3 we normalise net flows in each task-based category by the total number of EUE spells observed in periods of either high or low unemployment. This allows us to control for the fact that the number of unemployment episodes changes over the cycle.

[16]In this case we define times of high (low) unemployment as periods in which the de-trended (log) unemployment rate was within the top (bottom) third (half) of the de-trended (log) unemployment distribution. We chose this partition as it minimises small sample bias. In Supplementary Appendix B.3 we show that the same patterns hold when defining periods of low and high unemployment in many different ways.

It is clear from the graph that across all task-based categories net mobility increases in periods of high unemployment relative to periods of low unemployment. RM occupations increase their net outflows in downturns relative to expansions, while NRM occupations increase their net inflows in downturns relative to expansions.[17] The countercyclicality of net mobility therefore implies that the cyclicality of excess mobility is the main driver behind the procyclical behaviour of gross occupational mobility among unemployed workers.[18]

Comparing unemployment spells between movers and stayers The above patterns imply that occupational movers have longer spells than stayers, on average by 0.5 month.[19] In recession, this difference grows to 1.11 months. This increase does not result from cyclically different demographics of unemployed movers or because they are more likely to be in long-duration occupations in recessions (see Supplementary Appendix B.4 for a formal regression analysis). Although the occupational mobility of the unemployed decreases in a recession, the lengthening of unemployment spells among movers is proportionally stronger. Occupational movers thus contribute to the increase in aggregate unemployment, and especially strongly so, to the increase in long-term unemployment. In Section 5 we further discuss these empirical findings put them in the context of our theoretical framework.

3 Theoretical Framework

We now develop a theory of occupational mobility of the unemployed to explain the above empirical results and link them to the cyclical behaviour of long and short term unemployment as well as the aggregate unemployment rate.

3.1 Environment

Time is discrete $t = 0, 1, 2, \ldots$ A mass of infinitely-lived, risk-neutral workers is distributed over a finite number of occupations $o = 1, \ldots, O$. At any time t, workers within a given occupation can be either employed or unemployed and differ in two components: an idiosyncratic productivity, z_t, and human capital, x_t. We interpret the z-productivity as a "career match" which captures in a reduced form the changing career prospects workers have in their occupations (see Neal, 1999). These z-productivities follow a common and bounded first-order stationary Markov process, with transition law $F(z_{t+1}|z_t)$.[20] Their realizations affect a worker both in employment and in unemployment and will drive excess occupational mobility in our model. To capture the different levels of attachment to occupations found across age groups, workers' accumulate occupational human capital through a learning-by-doing process while employed, and are subject to human capital depreciation while

[17] In Supplementary Appendix B.3 we show that the exclusion of the managerial occupations from our calculation implies that RC occupations are now experiencing net outflows instead of net inflows as suggested by Figure 2.

[18] Kambourov and Manovskii (2008) using PSID data also find countercyclical net mobility and procyclical gross mobility among a pooled sample of employer stayers and movers.

[19] This difference is economically significant: it represents nearly half of the differences between the average unemployment spell in periods of high versus low unemployment.

[20] The assumption that the z-productivity process is common across workers and occupations is motivated by our evidence showing that the change of occupational mobility with unemployment duration does not seem to differ across occupations or demographic groups.

unemployed. Conditional on the worker's employment status, his human capital x_t is assumed to evolve stochastically following a Markov chain with values $x_t \in \{x^1, ..., x^H\}$, $x^1 > 0$ and $x^H < \infty$.

Each occupation is subject to occupation-wide productivity shocks. Let $p_{o,t}$ denote the productivity of occupation o at time t and $p_t = \{p_{o,t}\}_{o=1}^{O}$ the vector that contains all the occupations' productivities at time t. Differences across $p_{o,t}$ will drive net mobility. Business cycle fluctuations occur due to changes in aggregate productivity, A_t. We allow the occupation-wide productivity process to depend on aggregate productivity. Both $p_{o,t}$ and A_t follow bounded first-order stationary Markov processes.

There is a mass of infinitely-lived risk-neutral firms distributed across occupations. All firms are identical and operate under a constant return to scale technology, using labor as the only input. Each firm consists of only one job that can be either vacant or filled. The output of a worker with current productivity z_t and human capital x_t employed in a firm in occupation o is given by the production function $y(A_t, p_{o,t}, z_t, x_t)$. The production function is strictly increasing and continuous in all of its arguments and differentiable in the first three.

All agents discount the future at rate β. Workers retire stochastically, receiving a fixed utility flow normalized to zero. They are replaced by new entrants, inexperienced workers with x^1 that are allocated across occupations following an exogenous distribution ψ. We rescale β to incorporate this retirement risk. Match break-up can occur with an exogenous (and constant) probability δ, but can also occur if the worker and the firm decide to do so, and after a retirement shock. Once the match is broken, the firm decides to reopen the vacancy and, unless retired, the worker stays unemployed until the end of the period. We assume that any unemployed worker receives b each period. Wages will be determined below.

To study business cycle behavior in a tractable way, we focus on Block Recursive Equilibria (BRE). In this type of equilibrium the value functions and decisions of workers and firms only depend on $\omega = \{z, x, o, A, p\}$ and not on the joint productivity distribution of unemployed and employed workers over all occupations. An occupation can be segmented into many labor markets, one for each pair (z, x) such that workers in different markets do not congest each other in the matching process. Each of these labor market has the Diamond-Mortensen-Pissarides (DMP) structure. Each has a constant returns to scale matching function which governs the meetings of unemployed workers and vacancies within a market. We assume that all these markets have the same random matching technology. Each market exhibits free entry of firms, where posting a vacancy costs k per period. Once an unemployed worker's z or x changes, the relevant labor market for this worker changes accordingly.[21]

Searching across occupations Instead of searching for jobs in their own occupation, unemployed workers can decide to search for jobs in different occupations. This comes at a per-period cost c and entails re-drawing their z-productivity. Workers rationally expect their initial career match in

[21] In Supplementary Appendix C we show that a competitive search model in the spirit of Moen (1997) and Menzio and Shi (2010, 2011) endogenously generates this sub-market structure, such that unemployed workers with current productivities (z, x) optimally participate only in the (z, x) market. Here we proceed by assuming this sub-market structure from the start in order to reduce unnecessary complexity in the analysis. The allocations and equilibrium outcomes are the same under both approaches (see Carrillo-Tudela and Visschers, 2013).

any occupation to be a draw from $F(z)$, which we take to be the ergodic distribution associated with the Markov process $F(z_{t+1}|z_t)$. The i.i.d. nature of the re-draws allows us to capture that some occupational movers end up changing occupations again after a subsequent jobless spell, as suggested by the repeat mobility patterns documented earlier.

The differences in occupation-wide labor market conditions p_o imply that workers are not indifferent from which occupation the draw of z comes from. To capture that in the data excess mobility is much larger than net mobility and hence that workers not always specialise their search in the occupation with the highest p_o, we model the choice of occupation following an imperfectly directed search approach in the spirit of Fallick (1993). During a period, workers have a unit of search effort to investigate their employment prospects in the remaining occupations. They can only receive at most one new draw of z per period without recall. A worker must then chose how much effort to allocate to each one of these occupations in order to maximise the probability to receiving a z. Let $s_{\tilde{o}}$ denote the search effort devoted to occupation $\tilde{o}$ such that $\sum_{\tilde{o}\in O^-} s_{\tilde{o}} = 1$, where O^- denotes the set of remaining occupations. Each $s_{\tilde{o}}$ maps into a probability of receiving the new z from occupation $\tilde{o}$. Conditional on switching from o, this probability is denoted by $\alpha(s_{\tilde{o}}; o)$, where $\alpha(.; o)$ is a continuous, weakly increasing and weakly concave function of s with $\alpha(0; o) = 0$ and $\sum_{\tilde{o}\in O^-} \alpha(s_{\tilde{o}}; o) \leq 1$ for all $o \in O$. Hence, $1 - \sum_{\tilde{o}\in O^-} \alpha(s_{\tilde{o}}; o)$ is the probability that a worker does not receive a new z during the period.

If no z is received, the above process is repeated the following period. If a z is received, the worker must sit out one period unemployed in the new occupation $\tilde{o}$ before deciding whether to sample another z from a different occupation.[22] If the worker decides to sample once again the above process is repeated. However, if the worker decides to accept the z, he starts with human capital x^1 in the new occupation. The worker's z and x then evolve as described above.[23]

3.2 Agents' Decisions

The timing of the events is summarised as follows. At the beginning of the period the new values of A, p, z and x are realised. After these realisations, the period is subdivided into four stages: separation, reallocation, search and matching, and production. To keep notation complexity to a minimum, we leave implicit the time subscripts, denoting the following period with a prime.

[22] Note that this implies that the worker is forced to move to the new occupation even if the z turns out to be low enough. To further simplify we also assume that after the worker is in the new occupation, he can sample z-productivities from previous occupations. This way we avoid carrying around the histories of occupations ever visited by a worker in the state space.

[23] Our data suggests that c and the loss of x when changing occupation should be incorporated in our model as mobility costs. This is because we find (i) a substantial proportion of stayers among young workers, which are typically associated with low levels of human capital, and (ii) substantial occupational staying among those who moved occupations but subsequently have become unemployed again. Since this occurs within the duration of a SIPP panel, these workers' occupational tenure is low, yet they also display significant occupational attachment.

Worker's Problem Consider an unemployed worker currently characterised by (z, x, o). The value function of this worker at the beginning of the production stage is given by

$$W^U(\omega) = b + \beta \mathbb{E}_{\omega'}\Big[\max_{\rho(\omega')}\Big\{\rho(\omega')R(\omega') + (1-\rho(\omega'))\Big[\lambda(\theta(\omega'))W^E(\omega') + (1-\lambda(\theta(\omega')))W^U(\omega')\Big]\Big\}\Big], \tag{1}$$

where $\theta(\omega)$ denotes the ratio between vacancies and unemployed workers currently in labor market (z, x) of occupation o, with $\lambda(.)$ the associated job finding probability. The value of unemployment consists of the flow benefit of unemployment b, plus the discounted expected value of being unemployed at the beginning of next period's reallocation stage, where $\rho(\omega)$ takes the value of one when the worker decides to search across occupations and zero otherwise. The term $R(\omega)$ denotes the expected net value of searching across occupations and is given by

$$R(\omega) = \max_{\mathcal{S}(\omega)}\Big(\sum_{\tilde{o}\in O^-}\alpha(s_{\tilde{o}}(\omega))\int_{\underline{z}}^{\overline{z}} W^U(\tilde{z}, x^1, \tilde{o}, A, p)dF(\tilde{z}) + (1 - \sum_{\tilde{o}\in O^-}\alpha(s_{\tilde{o}}(\omega)))\hat{W}^U(\omega) - c\Big), \tag{2}$$

where $\hat{W}^U(\omega) = b + \beta\mathbb{E}_{\omega'}R(\omega')$, $\mathcal{S}$ denote a vector of $s_{\tilde{o}}$ for all $\tilde{o} \in O^-$ and the maximization is subject to $s_{\tilde{o}} \in [0, 1]$ and $\sum_{\tilde{o}\in O^-} s_{\tilde{o}} = 1$. The first term denotes the expected value of drawing a new z and losing any accumulated human capital, while the second term denotes the value of not obtaining a z and waiting until the following period to search across occupations once again. The formulation of $\hat{W}^U(\omega)$ is helpful as it implies that $R(\omega)$ and $\{s_{\tilde{o}}\}$ become independent of z. It is through $R(\omega)$ that expected labor market conditions in other occupations affect the value of unemployment, and indirectly the value of employment, in the worker's current occupation. The worker's decision to reallocate is captured by the choice between the expected net gains from drawing a new $\tilde{z}$ in another occupation and the expected payoff of remaining in the current occupation. The latter is given by the expression within the inner squared brackets in equation (1).

Now consider an employed worker currently characterised by (z, x, o). The expected value of employment at the beginning of the production stage, given wage $w(\omega)$, is

$$W^E(\omega) = w(\omega) + \beta\mathbb{E}_{\omega'}\Big[\max_{d(\omega')}\{(1 - d(\omega'))W^E(\omega') + d(\omega')W^U(\omega')\}\Big]. \tag{3}$$

The second term describes the worker's option to quit into unemployment in next period's separation stage. The job separation decision is summarised in $d(\omega')$, such that it take the value of δ when $W^E(\omega') \geq W^U(\omega')$ and the value of one otherwise.

Firm's Problem Consider a firm posting a vacancy in sub-market (z, x) in occupation o at the start of the search and matching stage. The expected value of a vacancy solves the entry equation

$$V(\omega) = -k + q(\theta(\omega))J(\omega), \tag{4}$$

where $q(.)$ denotes firms' probability of finding an unemployed worker and $J(\omega)$ denotes the expected value of a filled job. Free entry implies that $V(\omega) = 0$ for all those sub-markets that yield a $\theta(\omega) > 0$, and $V(\omega) \leq 0$ for all those sub-markets that yield a $\theta(\omega) \leq 0$. In the former case, the entry condition simplifies (4) to $k = q(\theta(\omega))J(\omega)$.

Now consider a firm employing a worker currently characterized by the pair (z, x, o) at wage $w(\omega)$. The expected lifetime discounted profit of this firm at the beginning of the production stage can be described recursively as

$$J(\omega) \;\; = \;\; y(A,p_o,z,x) - w(\omega) + \beta\mathbb{E}_{\omega'}\Big[\max_{\sigma(\omega')}\Big\{(1-\sigma(\omega'))J(\omega') + \sigma(\omega')V(\omega')\Big\}\Big], \qquad (5)$$

where $\sigma(\omega')$ takes the value of δ when $J(\omega') \geq V(\omega')$ and the value of one otherwise.

Wages We assume that wages are determined by Nash Bargaining. Consider a firm-worker match currently characterised by (z, x, o) such that it generates a positive surplus. Nash Bargaining implies that the wage, $w(\omega)$, solves

$$(1-\zeta)\Big(W^E(\omega) - W^U(\omega)\Big) = \zeta\Big(J(\omega) - V(\omega)\Big), \qquad (6)$$

where $\zeta \in [0, 1]$ denotes the worker's exogenous bargaining power. This guarantees that separation decisions are jointly efficient, $d(\omega) = \sigma(\omega)$.

In what follows we impose a Cobb-Douglas matching function and the Hosios condition, such that $1 - \zeta = \eta$, where η denotes the elasticity of the job finding probability with respect to labor market tightness within sub-market (z, x). This will guarantee that firms post the efficient number of vacancies within sub-markets. It will also guarantee efficiency of our decentralized economy.

3.3 Equilibrium and Characterization

In a BRE outcomes can be derived in two steps. In the first step, decision rules are solved independently of the joint productivity distribution of unemployed and employed workers over all occupations, using (1)-(5). Once those decision rules are determined, we fully describe the dynamics of the workers' distribution, using the workers' flow equations. To prove existence and uniqueness we build on the proofs of Menzio and Shi (2010, 2011) but incorporate the value of reallocation across occupations and show it preserves the block recursive structure. The formal definition of the BRE is relegated to Supplementary Appendix C, where we also present the derivation of the flow equations and the proofs of all the results of this section.

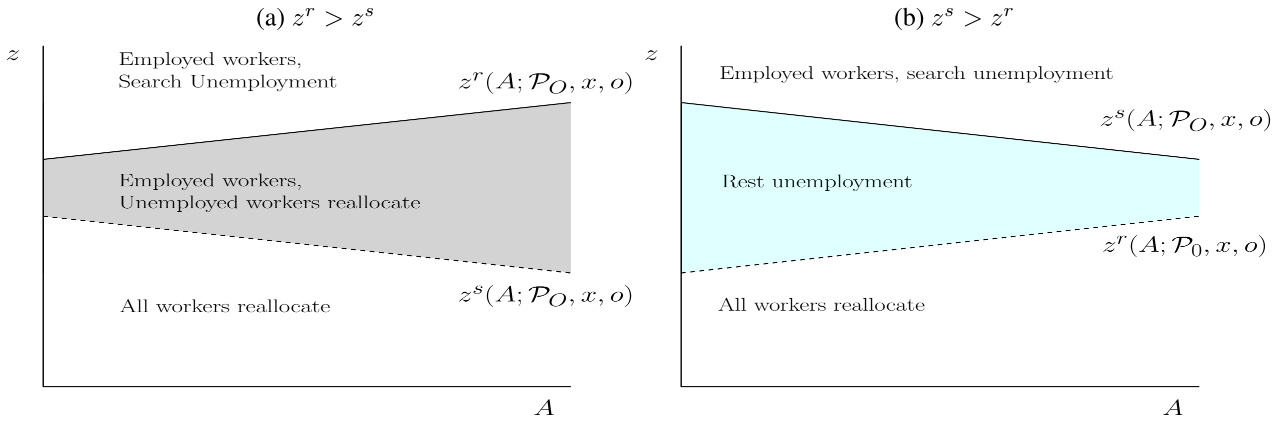
Existence Let $M(\omega) \equiv W^E(\omega) + J(\omega)$ denote the joint value of the match. To prove existence and uniqueness of the BRE we define an operator T that is shown to map $M(\omega)$, $W^U(\omega)$ and $R(\omega)$ from the appropriate functional space into itself, with a fixed point that implies a BRE. Given this result and the Banach's Fixed Point Theorem, this fixed point exists and is unique.

To prove efficiency we show that the unique solution to the planner's problem in the general state space (which includes the distribution of workers across occupations) coincides with the solution to the decentralized economy problem in the space ω. The key step is to ensure that a worker's value of searching across occupations coincides with the planner's value of making the worker search across occupations.

Proposition 1. *Given $F(z'|z) < F(z'|\tilde{z})$ for all z, z' when $z > \tilde{z}$: (i) a BRE exists and it is the unique equilibrium; and (ii) the BRE is constrained efficient.*

Characterization The decision to separate from a job and the decision to search across occupations can be characterised by z-productivity cutoffs, which are themselves functions of A, p, o and x. The job separation cutoff function, $z^s(.)$ solves $M(\omega) - W^U(\omega) = 0$ such that the match surplus becomes

Figure 5: Relative positions of the reservation productivities



zero. As in Mortensen and Pissarides (1994) it characterises endogenous separations. However, in our setup z refers to the worker's idiosyncratic productivity in an occupation, rather than to a match-specific productivity with a firm. This difference implies that when the worker becomes unemployed, his z is not lost or is reset when re-entering employment in the same occupation. Instead, the worker's z continuous evolving during the unemployment spell. It is only when the worker searches across occupations that he can reset his z. The reallocation cutoff function, $z^r(.)$ solves $R(\omega) = W^U(\omega)$ and determines when an unemployed worker decides to search across occupations. The latter occurs if and only if $z < z^r(.)$.

The relative position and the slopes of $z^r(.)$ and $z^s(.)$ are crucial determinants of the long-run and cyclical outcomes in our model. To show this, we first discuss the implications of their relative position and then those of their slopes. Figure 5a illustrates the case in which $z^r > z^s$ for all A, holding constant p, o and x. Here having a job makes a crucial difference on whether a worker stays or leaves his occupation. When an employed worker has a current $z \in [z^s, z^r)$, the match surplus is enough to keep him attached to his occupation. For an unemployed worker with a current z in the same interval, however, the probability of finding a job is sufficiently small to make searching across occupations the more attractive option, even though this worker could generate a positive match surplus if he were to become employed in his pre-separation occupation. For values of $z < z^s$, all workers search across occupations. For values of $z \geq z^r$, firms post vacancies and workers remain in their occupations, flowing between unemployment and employment over time as in the canonical DMP model.

Figure 5b instead shows the case in which $z^s > z^r$ for all A. Here workers who endogenously separate into unemployment, at least initially, do not search across occupations, while firms do not create vacancies in sub-markets associated with values of $z < z^s$. These two cutoffs create an area of inaction, in which workers become *rest unemployed* during the time their z lies in $[z^r, z^s)$: they face a very low – in the model (starkly) zero – contemporaneous job finding probability, but still choose to remain attached to their occupations. The stochastic nature of the z process, however, implies that these workers can face a positive expected job finding probability for the following period. Only after the worker's z has declined further, such that $z < z^r$, the worker searches for a new z across occupations. For values of $z \geq z^s$, the associated sub-markets function as in the DMP model.

An unemployed worker is then considered *search unemployed* during the time in which his $z \geq z^s$, as in the associated labor markets firms are currently posting vacancies. A worker whose current $z < z^r$ is considered *reallocation unemployed* only during the time in which he is trying to find another occupation that offers him a $z > z^r$. Once he finds such an occupation, he continues his unemployment spell potentially with periods in search and rest unemployment, depending on the relative position of z^s and z^r and the initial draw and evolution of his z in such an occupation. The stochastic nature of the z process implies that search, rest and reallocation unemployment are not fixed characteristics, but transient states during an unemployment spell. Therefore, to be consistent with the analysis of Section 2, an *occupational mover* is a worker who left his old occupation, went through a spell of unemployment (which could encompass all three types of unemployment) and found a job in a different occupation.

A key decision for an unemployed worker is whether to remain in his occupation, waiting for his z to improve, or to search across occupations, drawing a new z. Periods of rest unemployment arise when the option value of waiting in unemployment is sufficiently large. However, search frictions imply that there is also an option value associated with waiting in employment in an existing job match. In the face of irreversible match destruction, workers remain employed at lower output levels relative to the frictionless case because of potential future improvements in their z-productivities. This drives the separation cutoff function down.

The tension lies in that these two waiting motives work against each other. Which one dominates depends on parameter values. Using a simplified version of the model without aggregate or occupation-specific shocks, we show that the difference $z^s - z^r$ increases when c, b or x increase (see Supplementary Appendix C.1). Although it is intuitive that a higher c or x reduces z^r by making occupational mobility more costly, they also reduce z^s by increasing the match surplus and making employed workers less likely to separate. We show that, overall, the first effect dominates. A rise in b decreases z^r by lowering the effective cost of waiting, while decreasing the match surplus by increasing $W^U(.)$ and hence increasing z^s, pushing towards rest unemployment. We also show that a higher degree of persistence in the z process decreases $z^s - z^r$ as it decreases the option value of waiting.

Figure 5 shows the case of countercyclical job separation decisions ($\partial z^s(.)/\partial A < 0$) and procyclical occupational mobility decisions ($\partial z^r(.)/\partial A > 0$), as suggested by the data. The relative position of z^s and z^r is an important determinant of the cyclicality of occupational mobility decisions. Using a simplified version of the model without occupation-specific shocks, we show that when $z^s > z^r$ we obtain procyclical occupational mobility decisions without the need of complementarities in the production function (see Supplementary Appendix C.1). This arises as with search frictions wages and job finding probabilities increase with A, and complement each other to increase the expected value of occupational mobility (relative more than in the frictionless case). In addition, the presence of rest unemployment reduces the opportunity cost of mobility, making the latter less responsive to A. This occurs as any change in A does not immediately affect the utility flow of the rest unemployed.

The relative position of z^s and z^r also affects the cyclicality of job separation decisions. When z^s is sufficiently above z^r, job separation decisions mainly reflect whether or not an employed worker should wait unemployed in his current occupation for potential improvement of his z. Occupational mobility is only one possible future outcome and hence it is discounted. This implies that a sufficiently large $z^s - z^r > 0$ moderates the feedback of procyclical occupational mobility decisions on the cyclicality of job separation decisions.

As the position and slope of the z^s and z^r cutoffs can only be fully determined through quantitative analysis, we now turn to estimate the model and investigate its resulting cyclical properties.

4 Quantitative Analysis

4.1 Calibration Strategy

We set the model's period to a week and the discount factor $\beta = (1-d)/(1+r)$ is such that the exit probability, d, is chosen to match an average working life of 40 years and r such that β matches an annual real interest rate of 4%. To keep the population constant every worker that leaves the economy is replaced by a new unemployed worker. We target occupational mobility statistics based on the 2000 SOC and aggregate the simulated data to 'major' occupational groups and task-based categories (non-routine cognitive NRC, routine cognitive RN, non-routine manual NRM and routine manual RM) as done in Section 2. Our classification error model then allows us to easily correct for aggregate and occupation-specific levels of miscoding by imposing the $\mathbf{\Gamma}$-correction matrix on simulated worker occupational flows at the required level of aggregation.

Aggregate and occupation productivities The production function is assumed multiplicative and given by $y_o = Ap_oxz$ for all $o \in O$, chosen to keep close to a 'Mincerian' formulation. The logarithm of aggregate productivity, $\ln A_t$, follows an AR(1) process with persistence and dispersion parameters ρ_A and σ_A. For a given occupation o, the logarithm of the occupation-wide productivity is given by $\ln p_{o,t} = \ln \overline{p}_o + \epsilon_o \ln A_t$, where $\overline{p}_o$ denotes this occupation's constant productivity level and ϵ_o its loading with respect to changes in aggregate productivity. This formulation implies that different occupations can have different sensitivities to the aggregate shock and hence different relative attractiveness to workers over the business cycle.[24] We consider occupation-wide productivity differences at the level of task-based categories, $O = \{NRC, RC, NRM, RM\}$. All major occupations within a task-based category $o \in O$ then share the same $p_{o,t}$. This approach not only simplifies the computational burden by reducing the state space of the calibrated model, but is also consistent with the evidence presented in Figure 2 showing that within the majority of task-based categories all major occupations' net flows exhibit the same sign. To further simplify we normalize both the employment weighted average of $\overline{p}_o$ and of ϵ_o across $o \in O$ to one.

[24]The evidence presented in Supplementary Appendix C.3 suggests that our approach is consistent with the observed cyclical behaviour of net occupational flows, where the majority of occupations exhibit a very similar cyclical pattern across several recession/expansion periods.

Worker heterogeneity within occupations The logarithm of the worker's idiosyncratic productivity, $\ln z_t$, is also modelled as an AR(1) process with persistence and dispersion parameters ρ_z and σ_z. We include a normalization parameter $\underline{z}_{norm}$ that moves the entire distribution of z-productivities such that measured economy-wide productivity averages one. Occupational human capital is parametrized by a three-level process $h = 1, 2, 3$, where $x^1 = 1$. Employed workers stochastically increase their human capital one level after five years on average. With probability γ_d the human capital of an unemployed worker depreciates one level until it reaches x^1.

To allow for differences in the separation rates across young and prime-age workers that are not due to the interaction between z and x, we differentiate the probability of an exogenous job separation between low (x^1) and high human capital (x^2, x^3) workers: δ_L and δ_H. The matching function within each sub-market (z, x) in any occupation is given by $m(\theta) = \theta^\eta$.

Search across occupations The probability that a worker in a major occupation within task-based category o receives the new z from a different major occupation in task-based $\tilde{o}$ is parametrized as $\alpha(s_{\tilde{o}}; o) = \overline{\alpha}_{o,\tilde{o}}^{(1-\nu)} s_{\tilde{o}}^{\nu}$ for all $o, \tilde{o}$ pairs in $O = \{NRC, RC, NRM, RM\}$ and $s_{\tilde{o}} \in [0, 1]$.[25] The parameter $\nu \in [0, 1]$ governs the responsiveness of the direction of search across occupations that is related to differences in p_o. The parameter $\overline{\alpha}_{o,\tilde{o}}$ is a scaling factor such that $\sum_{\tilde{o}\in O} \overline{\alpha}_{o,\tilde{o}} = 1$. It captures the extent to which an unemployed worker in a major occupation within task-based category o has access to job opportunities in another major occupation in task-based category $\tilde{o}$. Since $\sum_{\tilde{o}\in O} \alpha(s_{\tilde{o}}; o) \leq 1$, this formulation implies that if a worker in o wants to obtain a new z with probability one, he will choose $s_{\tilde{o}} = \overline{\alpha}_{o,\tilde{o}}$ for all $\tilde{o} \in O$. If a worker wants to take into account current occupation-wide productivity differences, he will choose $s_{\tilde{o}} \neq \overline{\alpha}_{o,\tilde{o}}$ for at least some $\tilde{o}$. The cost of doing so is the possibility of not receiving a new z at all (i.e. $\sum_{\tilde{o}\in O} \alpha(s_{\tilde{o}}; o) < 1$) and paying c again the following period. The parameter ν determines the extent of this cost, with higher values of ν leading to lower probabilities of not receiving a new z.

The formulation of $\alpha(s_{\tilde{o}}; o)$ is convenient for it implies that the optimal value of $s_{\tilde{o}}$ can be solved explicitly,

$$s^*_{\tilde{o}}(\omega) = \frac{e^{\frac{1}{1-\nu}\log[\overline{\alpha}_{o,\tilde{o}}^{(1-\nu)}(\int_{\underline{z}}^{\overline{z}} W^U(\tilde{z},x_1,\tilde{o},A,p)dF(\tilde{z}) - \hat{W}^U(\omega))]}}{\sum_{\tilde{o}\in O^-} e^{\frac{1}{1-\nu}\log[\overline{\alpha}_{o,\tilde{o}}^{(1-\nu)}(\int_{\underline{z}}^{\overline{z}} W^U(\tilde{z},x_1,\tilde{o},A,p)dF(\tilde{z}) - \hat{W}^U(\omega))]}}$$

with $\sum_{\tilde{o}\in O^-} s^*_{\tilde{o}}(\omega) = 1$ and takes a similar form as the choice probabilities obtained from a multinomial logit model.[26] Note that parameters $\overline{\alpha}_{o,\tilde{o}}$ appear directly inside the closed form and can freely shape bilateral flows between occupations.[27] This leaves parameter ν free to capture the responsive-

[25] The identity of the major occupation within task-based $\tilde{o}$ from which the new z comes from is randomly drawn following a uniform distribution.

[26] To derive this result note that for each $s_{\tilde{o};o}$ equation (2) yields the first order condition $s^*_{\tilde{o}}(\omega) = \left[\frac{\nu\overline{\alpha}_{o,\tilde{o}}^{(1-\nu)}}{\lambda} \int_{\underline{z}}^{\overline{z}} W^U(\tilde{z}, x_1, \tilde{o}, A, p)dF(\tilde{z}) - \hat{W}^U(\omega)\right]^{1/(1-\nu)}$, where λ is the multiplier of the constraint $\sum_{\tilde{o}\in O^-} s^*_{\tilde{o}}(\omega) = 1$. Substituting out $s^*_{\tilde{o}}(\omega)$ in the constraint and using the change of variable $X^{\frac{1}{1/(1-\nu)}} = e^{\frac{1}{1/(1-\nu)}\log(X)}$ leads to the above expression. See Carrillo-Tudela et. al, (2021).

[27] Many multi-sector models use the random utility model to drive excess mobility, where additive taste shocks are distributed i.i.d Type 1 Extreme Value (see Chodorow-Reich and Wieland, 2020, Wiczer, 2015, Dvorkin, 2014 and Pilossoph, 2014, among others). In the most tractable of such settings, underlying gross flows are constant at all times (e.g. Chodorow-Reich and Wieland, 2020). More generally, when the reallocation involves $\max_{o\in O}\{U_o(.) + \epsilon_o\}$, where

ness to cyclically changing occupation-wide productivities, which in turn allows us to capture net mobility flows over the cycle. It also leaves free the *persistent* career match z-process to drive excess mobility in a way that is consistent with the patterns documented in Section 2.

Given that our data analysis covers three decades, we need to distinguish the observed long-run changes in the employment-size distribution across task-based categories from their cyclical changes. For this we first externally calibrate the initial size distribution in the simulations to match the one observed in the SIPP in 1984. This results in setting the employment proportions for NRC, RC, NRM, RM to 0.224, 0.292, 0.226 and 0.258, respectively, at the start of the simulation. In addition to the occupational mobility decisions of the unemployed, we allow this size distribution to change over time due to the mobility decisions of new entrants. Let ψ_o denote the exogenous probability that a new entrant to the economy is allocated to task-based category o such that $\sum_{o\in O}\psi_o = 1$. This worker is then randomly allocated to a major occupation within the drawn task-based category at the point of entry, and is allowed to search across occupations to obtain first employment somewhere else.

Simulation method of moments In the above parametrization $[c, \rho_z, \sigma_z, \underline{z}_{norm}]$ governs occupational mobility due to idiosyncratic reasons (excess mobility); $[x^2, x^3, \gamma_d, \delta_L, \delta_H]$ govern differences in occupational human capital; $[\overline{p}_o, \epsilon_o, \overline{\alpha}_{o,\tilde{o}}, \nu, \psi_o]$ for all $o, \tilde{o} \in \{NRC, RC, NRM, RM\}$ govern occupational mobility due to occupation-wide productivity differences (net mobility); and the remainder parameters $[k, b, \eta, \rho_A, \sigma_A]$ are shared with standard DMP calibrations. All these parameters are estimated by minimising the sum of squared distances between a set of model simulated moments and their data counterparts. For consistent measurement we generate 'pseudo-SIPP panels' within one hundred time-windows each of 30 year length and follow the same procedures and definitions to construct the moments in data and in model simulations.

Figure 6 and Table 2 show the set of moments used to recover these parameters as well as the fit of the model. The calibrated model provides a very good fit to the data across all the targeted dimensions. The mobility-duration profiles and survival functions primarily inform the excess mobility and the human capital parameters. Employer separations patterns inform the parameters shared with DMP calibrations, except for the persistence and standard deviation of the aggregate productivity process, ρ_A and σ_A, which are informed by the corresponding parameters of the series of output per worker ($outpw$) obtained from the BLS, ρ_{outpw} and σ_{outpw}, and measured quarterly for the period 1983-2014.[28] The net mobility patterns across task-based categories inform the occupation-specific productivities, occupation distribution for new entrants and the imperfect direct search technology.

$U_o(.)$ is the value of being in occupation o and ϵ_o is the taste shock, this imposes a symmetry. All mobile workers who are considering occupations in set O have the same distribution over the destinations in O, independently of where they originated. Here we want to explicitly break this symmetry to be consistent with the bilateral flows of the transition matrix, a feature we can do without giving up on a convenient closed form. Our formulation also decouples the cyclical responsiveness from the cross-sectional flows, again without giving up on the closed form. In contrast, in the additive taste shock setting hitting cross-sectional patterns constrains the mobility response to cyclical shifts in $U_o(.)$: both dimensions rely on how differences in $U_o(.)$ translate into differences in the cdf of ϵ_o (or a transformation of the latter).

[28]We cannot set ρ_A and σ_A directly because the composition of the economy changes with the cycle due to workers' endogenous separation and reallocation decisions. We measure output in the model and data on a quarterly basis (aggregating the underlying weekly process in the model). For the data, we HP-filtered the series of (log) output per worker for the period 1970 to 2016. Then, we use the persistence and the variance parameters of this series calculated over the period 1983-2014, which is the period that the SIPP and the BLS series overlap.

The latter adds a number of extra parameters to the estimation, particularly the scale parameters $\overline{\alpha}_{o,\tilde{o}}$. As mentioned above these allow us to capture very well the relevant difference observed across occupations. We now present the arguments that justify the choice of moments, keeping in mind that all parameters need to be estimated jointly.

4.2 Gross occupational mobility and unemployment duration

A worker's attachment to his pre-separation occupation during an unemployment spell depends on the properties of the z process, the human capital process and the reallocation cost c. The aggregate and age-group mobility-duration profiles depicted in Figures 6a and 6b (see also Section 2) play an important role in informing these parameters.

The aggregate mobility-duration profile contains information about c and ρ_z. As shown in Lemma 1 (see Supplementary Appendix C.1) changes in the overall level of mobility lead to opposite changes in c. The slope of the profile informs ρ_z primarily through the time it takes unemployed workers to start searching across occupations.[29] A lower ρ_z (keeping constant $F(z)$) increases the relative number of unemployed workers deciding to search across occupations at shorter durations, decreasing the slope of the model's mobility-duration profile. Lemma 1, however, also implies that a lower ρ_z reduces overall mobility (ceteris paribus), creating a tension between c and ρ_z such that an increase in ρ_z must go together with an increase in c to fit the observed mobility-duration profile as depicted in Figures 6a.

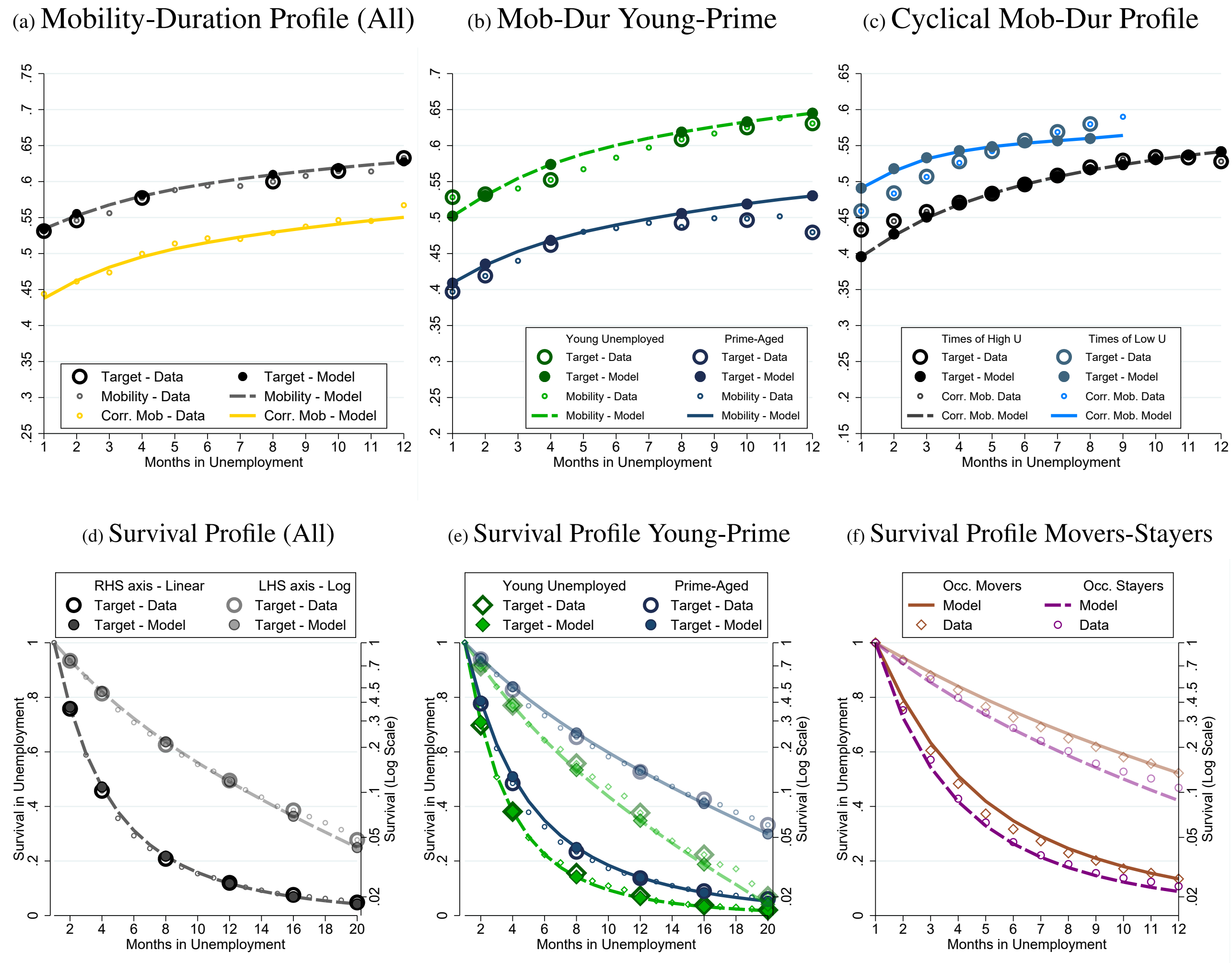
To help identify σ_z we match instead the mobility-duration profiles of young and prime-aged workers. For given values of x, a larger value of σ_z leads to a smaller importance of human capital differences relative to z differences in workers' output. This brings the simulated occupational mobility patterns across age groups closer together, creating a negative relationship between σ_z and the difference between the mobility-duration profiles of young and prime-aged workers. Figure 6b shows that the model is able to resolve this tension very well. Online Appendix C.1 shows that in addition the model remains fully consistent with the much larger contribution of excess mobility relative to net mobility in accounting for the mobility-duration profile at all durations, as depicted in Figure 3b.

To inform the human capital parameters x^2 and x^3 we target the overall level of occupational mobility among young and prime-aged workers (see Lemma 2, Supplementary Appendix C.1) as well as the observed five and ten-year returns to occupational experience. As it is difficult to accurately estimate the later with the SIPP due to the relative short nature of its panels, we use the OLS estimates for 1-digit occupations reported in Kambourov and Manovskii (2009b) from the PSID and estimate the same OLS regression in simulated data.[30]

[29] Other factors that might allow the calibrated model to generate the observed mobility-duration profile do not appear important in our estimation. In particular, the large extent of occupational mobility at short unemployment durations implies that the time it takes a typical worker to decide to search in a given occupation is small and hence does not drive the observed unemployment duration differences between occupational movers and stayers. Further, since the structure of the model implies that exogenous separated workers and occupational movers have very similar realised z-distributions, composition effects in post-reallocation outcomes do not play an important role. Finally, the changes in the mean-reversion of the z-productivity process brought about by changes in ρ_z seem to only play a minor role in shaping the mobility-duration profile.

[30] We use the OLS estimates because occupation selection occurs both in the model and in the data, where selection

Figure 6: Targeted Moments. Data and Model Comparison



(a) Mobility-Duration Profile (All) (b) Mob-Dur Young-Prime (c) Cyclical Mob-Dur Profile

(d) Survival Profile (All) (e) Survival Profile Young-Prime (f) Survival Profile Movers-Stayers

Calibrations with or without occupational human capital depreciation yield very similar long-run moments (see Online Appendix C.2). This occurs because the gradual loss of occupational attachment with unemployment duration underlying the observed mobility-duration profile can be generated by human capital depreciation or the z process. To differentiate these two forces we instead use the cyclical shift of the mobility-duration profile. During recessions longer unemployment spells imply that expected human capital depreciation is higher, making employed workers more attached to their jobs and unemployed workers less attached to their occupations. At the same time low aggregate productivity interacted with z typically makes employed workers less attached to their jobs and unemployed workers more attached to their occupations. To inform this tension and recover γ_d we fit the mobility-duration profile in recessions and expansions as depicted in Figure 6c (see also Figure 4a).

We target the unemployment survival function depicted in Figure 6d to additionally inform us about the z and x processes. The extent of duration dependence is linked to the properties of the z process (and the importance of search frictions) through its effect on the extent of true duration

arises as measured returns are a result of two opposing forces: human capital acquisition and z-productivity mean reversion.

Table 2: Targeted Moments. Data and Model Comparison

Panel A: Economy-wide moments

Moment	Model	Data	Moment	Model	Data
Agg. output per worker mean	0.999	1.000	Rel. separation rate young/prime-aged	1.999	2.044
Agg. output per worker persistence, ρ_{outpw}	0.764	0.753	Rel. separation rate recent hire/all	5.180	4.945
Agg. output per worker st. dev., σ_{outpw}	0.009	0.009	Prob (unemp. within 3 yr for empl.)	0.151	0.124
Mean unemployment	0.036	0.036	Empirical elasticity matching function	0.526	0.500
Task-based gross occ. mobility rate	0.280	0.288	5-year OLS return to occ. tenure	0.143	0.154
Repeat mobility: occ. stay after stay	0.600	0.649	10-year OLS return to occ. tenure	0.219	0.232
Occ. mobility young/prime-aged	1.167	1.163	Average u. duration movers/stayers	1.181	1.140
Occ. mobility-duration profiles:	Fig 7a,b,c		U. survival profiles	Fig 7d,e	

Panel B: Occupation-Specific Moments, Long-run

	Proportion empl. size o_{2014}		Net mobility *Mean*		Transition Matrix Model				Transition Matrix Data			
	Model	Data	Model	Data	NRC	RC	NRM	RM	NRC	RC	NRM	RM
NRC	0.337	0.329	0.008	0.006	0.763	0.164	0.055	0.018	0.722	0.167	0.084	0.028
RC	0.246	0.258	0.006	0.001	0.129	0.681	0.144	0.047	0.078	0.681	0.168	0.066
NRM	0.260	0.260	-0.027	-0.021	0.034	0.065	0.760	0.141	0.020	0.115	0.710	0.155
RM	0.157	0.154	0.011	0.015	0.037	0.069	0.247	0.647	0.013	0.066	0.188	0.733

Panel C: Occupation-Specific Moments, Cyclical

	Net mobility *Recessions*		Net mobility *Expansions*		Net mobility *Rec-Exp*		$\Delta_{exp-rec}$ (inflow o/all flows)		$\varepsilon_{UD_o,u}/\varepsilon_{UD_{avg},u}$	
	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data
NRC	-0.012	-0.011	-0.002	-0.003	-0.010	-0.008	-0.003	-0.010	0.996	1.096
RC	-0.009	-0.005	-0.005	-0.001	-0.004	-0.004	0.006	0.003	1.054	1.027
NRM	0.034	0.033	0.017	0.011	0.017	0.022	-0.066	-0.054	0.874	0.761
RM	-0.017	-0.017	-0.006	-0.008	-0.011	-0.009	0.027	0.061	1.081	1.122

dependence and dynamic selection in our model, where the latter is driven by worker heterogeneity in x and z at the moment of separation. We use the cumulative survival rates at intervals of 4 months to reduce the seam bias found in the SIPP. The model also reproduces well the associated hazard functions (see Figures 1 and 2, Online Appendix C.1). Both in the model and the data duration dependence is different across (ex post) occupational stayers and movers and across age groups, where duration dependence is stronger among occupational stayers relative to movers and among young relative to prime-aged workers. Young occupational stayers have especially high job finding at low durations, which decrease faster as duration increases. In addition, the model replicates the (untargeted) incomplete unemployment duration distribution among all workers and separately by age groups, in particular the empirical amount of long-term unemployment that occurs in the face of high occupational mobility (see Table 1, Online Appendix C.1). Finally, we target the ratio between the average unemployment durations of occupational movers and stayers.

The very good fit of all the above moments shows that the z and x processes capture very well the main forces behind the aggregate and age specific mobility-duration profiles and unemployment survival functions and duration distributions. The elasticity of the matching function, η, at the submarket (z, x) level is obtained by estimating through OLS a log-linear relation between the aggregate job finding rate (the proportion of all unemployed workers in the economy who have a job next month) and aggregate labor market tightness (aggregate vacancies over aggregate unemployed) across quarters, in simulated data. The estimated elasticity $\hat{\eta}$ is targeted to be 0.5 (Petrongolo and Pissarides, 2001) and allows us to indirectly infer η.

4.3 Employer separations

A worker's attachment to employment depends on the size of search frictions. A higher value of k leads to stronger search frictions through its effect on firm entry and labor market tightness. This pushes down the z^s cutoff relative to z^r, reducing the extent of endogenous separations.[31] Therefore to inform k (and the relative position of z^s and z^r) we use as targets the proportion of separations observed within a year of workers leaving unemployment relative to the overall yearly separation rate ("Rel. separation rate recent hire/all") and the concentration of unemployment spells over a SIPP panel among the subset of workers who start employed at the beginning of the panel ("Prob (unemp. within 3yr for empl.)"). The probability that an occupational stayer becomes an occupational mover in the next unemployment spell ("Repeat mobility") also informs endogenous separations and how these relate to occupational mobility.[32]

Given the job-finding moments, the overall separation rate follows from targeting the average unemployment rate. As we focus on those who held a job previously, we use the most direct counterpart and construct the unemployment rate only for those who were employed before and satisfied our definition of unemployment (see Section 2). Note that this unemployment rate (3.6%) is lower than the BLS unemployment rate, but we find it responsible for more than 0.75 for every one percentage point change in the BLS unemployment rate (see Online Appendix C.1 and Supplementary Appendix B.7 for details), consistent with the results of Hornstein (2013), Fujita and Moscarini (2017) and Ahn and Hamilton (2018).

The ratio of separation rates between young and prime-aged workers ("Rel. separation rate young/prime-aged") as well as their survival functions in Figure 6e inform δ_L, δ_H and b. A relatively higher δ_L shifts the realised z-distribution of newly separated inexperienced workers away from their z^s cutoff towards higher z levels and hence affect their extent of duration dependence in unemployment, especially at shorter durations. The extent of separations for young and prime-aged workers also informs us about b through the positions of the z^s cutoffs of low and high human capital workers

[31] Intuitively, note that with $z^s < z^r$ and a persistent z process (as in the calibration) workers who endogenously separate will immediately change occupation (see Figure 5). Since these workers will be above their z^r cutoffs in the new occupation, they face a lower risk of further endogenous separations damping down this margin. However, with $z^s > z^r$ workers who endogenously separate and managed to become re-employed in the same occupation will remain close to z^s, facing once again a high job separation probability. Among those who changed occupations, there will still be a mass of workers close to their z^s cutoffs who face a high risk of future job separation. This leads to a larger amount of endogenous separations for both stayers and movers when $z^s > z^r$. As shown below, in the calibrated model $z^s > z^r$ and the hazard rate of job separations among new hires out of unemployment is greater for occupational stayers, 0.035, than for occupational movers, 0.027, as suggested by the previous arguments. This is qualitatively consistent with SIPP data, where we find a hazard rate among new hires of 0.026 for stayers and 0.024 for movers.

[32] The model also remains consistent with the (untargeted) probability that a worker who changed occupation after an unemployment spell, changed occupation after a subsequent unemployment spell. This probability is 0.54 in the model and 0.56 in the data (see Section 2.4).

relative to the average of these workers' productivities.

4.4 Net occupational mobility

Variation over the business cycle can naturally inform the cyclical sensitivity of occupation-wide productivities. In particular, to recover ϵ_o we target the levels of net mobility each task-based category exhibits in recessions and expansions ("Net mobility o, *Recessions* and Net mobility o, *Expansions*") as well as their implied difference ("Net mobility o, *Rec-Exp*"). We also regress (for each o) the completed (log) unemployment durations of those workers whose pre-separation task-based category was o on the (log) unemployment rate and a time trend, and target the ratio between the estimated unemployment duration elasticity and the average elasticity across task-based categories, $\varepsilon_{UD_o,u}/\varepsilon_{UD_{avg},u}$ (see Online Appendix C.1 for details). The advantage of this approach is that it allows us to leave untargeted the cyclicality of aggregate unemployment, which we separately evaluate in Section 5. To inform the values of $\overline{p}_o$ we target the average net mobility level of each o ("Net mobility o, *Mean*").

We also use cyclical variation to inform the degree of directness in workers' search across occupations. To recover ν we exploit the observed differences in the cyclicality of inflows across task-based categories. As ν increases, workers should be more sensitive (ceteris paribus) to cyclical differences in p_o when choosing occupations, making the inflows to occupations with the higher p_o respond stronger. To capture how cyclically sensitive are the inflows we compute, separately for expansions and recessions, the ratio of inflows into task-based category o over the sum of all flows. For each o we target the difference between the expansion and recession ratios, $\Delta_{exp-rec}$ (inflow o/all flows). To recover $\overline{\alpha}_{o,\tilde{o}}$ we target the observed task-based occupation transition matrix. To recover the set of ψ_o we use the employment-size distribution of task-based categories observed in 2014, the end of our sample period, "Prop (empl. size o_{2014})". We also target the average gross mobility rate across task-based categories ("Task-based gross occ. mobility rate") so that the model remains consistent with gross mobility at this level of aggregation.

Table 3: Calibrated Parameters

Agg. prod. and search frictions		ρ_A	σ_A	b	k	η	
		0.9985	0.0020	0.830	124.83	0.239	
Occ. human capital process		x^2	x^3	γ_d	δ_L	δ_H	
		1.171	1.458	0.0032	0.0035	0.0002	
Occupational mobility		c	ρ_z	σ_z	$\underline{z}_{norm}$	ν	
		7.603	0.9983	0.0072	0.354	0.04	
Occupation-specific	$\overline{p}_o$	ϵ_o	ψ_o	$\overline{\alpha}_{o,NRC}$	$\overline{\alpha}_{o,RC}$	$\overline{\alpha}_{o,NRM}$	$\overline{\alpha}_{o,RM}$
Non-routine Cognitive	1.019	1.082	0.620	0.436	0.560	0.004	0.000
Routine Cognitive	0.988	1.120	0.145	0.407	0.383	0.210	0.000
Non-routine Manual	1.000	0.532	0.087	0.000	0.093	0.384	0.524
Routine Manual	0.988	1.283	0.147	0.000	0.140	0.767	0.094

4.5 Estimated parameters

Table 3 reports the resulting parameter values implied by the calibration. The estimated value of b represents about 80% of total average output, y, not too far off from Hall and Milgrom's (2008) estimate, though we use different information. Vacancy cost k translates to a cost of about 30% of weekly output to fill a job. The elasticity of the matching function in each submarket (z, x) within an occupation is estimated to be $\eta = 0.24$, about half of $\widehat{\eta} = 0.5$ when aggregating across all submarkets across occupations.[33]

The actual returns to occupational experience x_2 and x_3 are higher than the OLS returns, because occupational entrants select better z-productivities that typically mean-revert over time, dampening the average evolution of composite xz-productivity. The parameter γ_d implies that a year in unemployment costs an experienced worker in expectation about 5% of his productivity. The estimated values of δ_L and δ_H imply that exogenous separations are much more prevalent for low rather than high human capital workers, leading to a larger importance of endogenous separations among the latter, as implied by the prime-aged survival and mobility-duration profiles. The estimated value of c and the sampling process imply that upon starting a job in a new occupation, a worker has paid on average a reallocation cost of 15.18 weeks (or about 3.5 months) of output. This suggests that reallocation frictions are important and add to the significant lose in occupational human capital when changing occupation.[34]

The process driving workers' idiosyncratic productivities within an occupation has a broadly similar persistence (at a weekly basis) as the aggregate shock process driving the business cycle. However, its larger variance implies there is much more dispersion across workers' z-productivities than there is across values of A. We also find that workers' idiosyncratic productivities are much more dispersed than occupation-wide productivities. For example, the max-min ratio of p_o is 1.13 (1.09) at the highest (lowest) value of A, where the RM task-based category is the most responsive to aggregate shocks and NRM the least. In contrast, the max-min ratio among z-productivities is 2.20. To gauge whether the dispersion across z-productivities is reasonable we calculate the implied amount of frictional wage dispersion using Hornstein et al. (2012) Mm ratio. These authors find an Mm between 1.46 and 1.90

[33]The difference between η and $\widehat{\eta}$ is mainly due to the effect of aggregation across submarkets that exhibit rest unemployment. Workers in episodes of rest unemployed entail no vacancies, have zero job finding rates, do not congest matching in other submarket, but are included in the aggregate number of unemployed. Hence they are included in the denominator of the aggregate labor market tightness and the aggregate job finding rate. It can be shown that this creates a wedge between η and $\hat{\eta} = 0.5$ that is governed by $\frac{0.5-\eta}{1-\eta}\varepsilon_{\hat{\theta},A} = \varepsilon_{u^s,A}$, where $\varepsilon_{\hat{\theta},A}$ and $\varepsilon_{u^s,A}$ denote the cyclical elasticity of aggregate labor market tightness, $\hat{\theta}$, and the proportion of search unemployment over total unemployment, u^s, respectively. Since in the calibrated model both elasticities are positive, $\frac{0.5-\eta}{1-\eta}$ must also be strictly positive and hence $\eta < \widehat{\eta} = 0.5$. In addition, each submarket within an occupation has its own concave matching function and hence aggregating these concave functions across submarkets also imply that the calibrated value of η will further diverge from 0.5.

[34]The average reallocation cost is computed as the product of c and the number of times workers sample a new occupation, which is 1.996 times. The value of c reported in Table 3 is consistent with the large proportion of unemployed workers who changed occupation. Given that in the data occupational changes are typically accompanied by changes in industries (based in our own calculations) and, to a lesser extent, by geographical location (see Papageorgiou, 2018), the estimated value of c could also be capturing the moving costs associated with these changes. Indeed, Alvarez and Shimer (2011) find also large reallocation costs across industries, while Kennan and Walker (2011) and Papageorgiou (2018) find large reallocation costs across geographical locations.

using the PSID, while the estimated z-dispersion yields 1.40.

The estimated value of ν implies that the ability of workers to access job opportunities in other task-based categories plays an important role in shaping the direction of their search. The estimated values of $\overline{\alpha}_{o,\tilde{o}}$ imply that on average workers in NRC have a low probability of drawing a new z from manual occupations and vice versa; while workers in NRM and RM occupations mostly draw a new z from these same two categories, although drawing from RC is not uncommon. In addition, the value of ν implies workers significantly adjust their direction of search as a response to cyclical occupation-wide productivity differences. This is evidenced by the ability of the model to reproduce the observed cyclical changes in the net mobility patterns presented in Section 2 and Table 2, where RM occupations have the strongest cyclical response of net outflows, increasing in recessions, as well as the strongest response in the inflow proportion, also larger in recessions. In contrast, NRM occupations are the ones which experience the largest increase in net inflows in recessions and the largest increase in inflows as destination category (see also Online Appendix C.1, Figure 4). Taken together, these estimates show a high degree of directness when workers search across task-based categories.

Further, Table 6 in Section 5 shows an important role of occupational mobility through unemployment in changing the relative sizes of NRM and RM occupations. In contrast, the high value of ψ_{NRC} captures that the NRC category did not increase its size between 1984 and 2014 because of inflows through unemployment, but rather because of a significant proportion of labor market entrants taking up jobs there.

5 Cyclical Unemployment Outcomes

We now turn to investigate the cyclical patterns of aggregate unemployment and its duration distribution generated by the model, noting that these were not targeted in our estimation procedure. Our aim is to evaluate the importance of excess and net occupational mobility in generating these patterns. We first present the implications of the full model as estimated above. We then discuss the implications of a re-estimated version of the model where we shut down the heterogeneity in occupation-wide productivities.[35]. An alternative exercise would be to maintain productivity differences across occupations but not allow workers to chose in which occupations to search on. Given that the estimated dispersion of z-productivities is much larger than that of p_o productivities, this exercise would not generate meaningfully different results. A second alternative could be to re-estimate a version of the model where we shut down the z-productivity process, making workers decide whether to change occupations based only on p_o productivities differences. It is clear, however, that this version of the model will not be able to reproduce many of the occupational mobility patterns documented in Section 2. With a slight abuse of terminology, we label this version "excess mobility model" as unemployed workers' occupational mobility decisions are based solely on the changing nature of their z-productivities and their interaction with A and x. In Online Appendix C.2 we present the estimation

[35] In this version the observed net mobility patterns can be imposed exogenously to keep the model's gross occupational mobility patterns consistent with the evidence presented in Section 2 and Supplementary Appendix B

results of the excess mobility model.

Table 4: Logged and HP-filtered Business Cycle Statistics. Data (1983-2014) and Model

	Volatility and Persistence							Correlations with u and outpw							
	u	v	θ	s	f	$outpw$	$occm$		u	v	θ	s	f	$outpw$	$occm$
Data															
σ	0.14	0.11	0.25	0.10	0.09	0.01	0.03	u	1.00	-0.92	-0.98	0.80	-0.82	-0.47	-0.52
ρ_{t-1}	0.98	0.99	0.99	0.94	0.91	0.93	0.91	$outpw$		0.56	0.51	-0.39	0.27	1.00	0.38
Full Model															
σ	0.14	0.05	0.17	0.07	0.10	0.01	0.04	u	1.00	-0.61	-0.96	0.79	-0.88	-0.94	-0.82
ρ_{t-1}	0.93	0.90	0.92	0.87	0.92	0.88	0.93	$outpw$		0.76	0.96	-0.90	0.93	1.00	0.83
Exc. Mob. Model															
σ	0.14	0.05	0.18	0.07	0.10	0.01	0.04	u	1.00	-0.63	-0.97	0.78	-0.88	-0.94	-0.80
ρ_{t-1}	0.95	0.89	0.94	0.88	0.93	0.94	0.90	$outpw$		0.77	0.96	-0.87	0.93	1.00	0.83

Note: The excess mobility model considers only occ. mobility decisions based on the z-productivity process. Each model's aggregate time series arise from the distributions of employed and unemployed workers across all labor markets, combined with agents' decisions. Times series are centered 5Q-MA series of quarterly data (both model and data), to smooth out the discreteness in the relatively flat cutoffs (relative to the grid) discussed further in the computational appendix. The cyclical components of the (log) of these time series are obtained by using an HP filter with parameter 1600. See Online Appendix C.1 for further details and results without the 5Q-MA smoothing.

Aggregate unemployment Table 4 shows the cyclical properties of the aggregate unemployment, vacancy, job finding and separation and gross occupational mobility rates, computed from the data and the simulations.[36] It shows that the full model is able to generate a countercyclical unemployment rate, together with a countercyclical job separation rate, procyclical job finding and gross occupational mobility rates. Table 4 also shows that the cyclical volatilities and persistence of the aggregate unemployment, job finding, separation and gross occupational mobility rates are very close to the data.

Note that this aggregate behavior is not driven by a higher cyclicality of young workers' unemployment rate. In Online Appendix C.1 we show that the responsiveness of the unemployment rate to aggregate output per worker is slightly stronger for prime-aged workers than for young workers, leading to a countercyclical ratio of unemployment rates between young and prime-aged workers. Therefore, in the model the pool of unemployment shifts towards high human-capital, prime-aged workers during recessions, a feature noted by Mueller (2017). This occurs mostly due to the larger increase in endogenous job separations among prime-aged relative to young workers.

The model also generates a strongly negatively-sloped Beveridge curve as in the data. The latter stands in contrast with the canonical DMP model, where it is known that endogenous separations hamper this model from achieving a Beveridge curve consistent with the data. It also stands in contrasts with the predictions of many multi-sector models where unemployment fluctuations arise from the time-consuming reallocation of workers from the sector that experienced a negative shock to the one that experienced a positive shock. As argued by Abraham and Katz (1986), these models typically imply an upward sloping Beveridge curve as more vacancies are created in the latter sector (see Chodorow-Reich and Wieland, 2020, for a recent exception). We return to this point in Section 5.2, where we discuss the role of occupation-wide heterogeneity.

Unemployment duration distribution Panel A in Table 5 evaluates the ability of the model to reproduce the shifts in the incomplete unemployment duration distribution with respect to changes in the unemployment rate. It shows that the shares of unemployed workers by duration exhibit a very

[36] Both in the model and data the unemployment, job finding and separation rates are computed based on the same unemployment definition used in the previous sections, while the cyclical properties of the occupational mobility rate are computed using major occupational groups and after applying the $\mathbf{\Gamma}$-correction matrix. In Online Appendix C.1 we provide the full set of correlations.

Panel A: Cyclicality of Duration Distribution						
Unemp.	Elasticity wrt u			Semi-elasticity wrt u		
Duration	Full Model	Excess Model	Data	Full Model	Excess Model	Data
$1-2$m	-0.435	-0.447	-0.464	-0.168	-0.165	-0.169
$1-4$m	-0.316	-0.329	-0.363	-0.178	-0.179	-0.186
$5-8$m	0.388	0.350	0.320	0.074	0.070	0.071
$9-12$m	1.083	1.033	0.864	0.061	0.060	0.072
> 13m	1.787	1.513	1.375	0.047	0.048	0.044
Panel B: Semi-Elasticity Duration wrt u by Occupational Mobility						
Unemp.	HP-filtered			Log u linearly detrended		
Duration by Mob.	Full Model	Excess Model	Data	Full Model	Excess Model	Data
Movers	2.9	2.9	3.2	2.4	2.3	2.0
Stayers	1.5	1.4	2.5	1.2	1.2	1.6

Note: The elasticities are constructed using the cyclical component of the series of the shares of unemployed workers by durations, the aggregate unemployment rate.

Table 5: Cyclical duration distribution

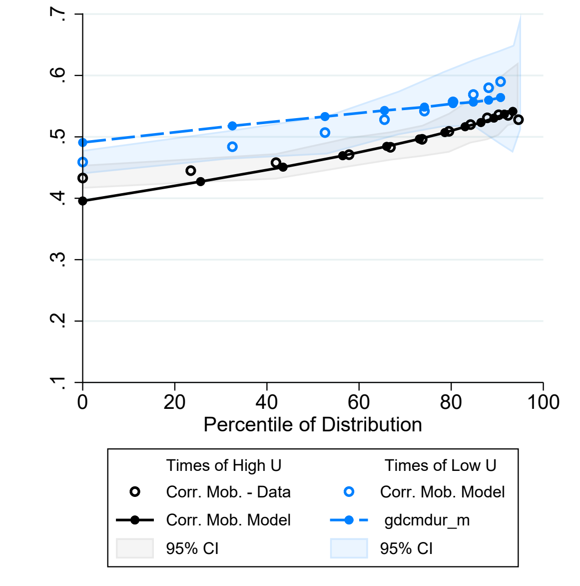


Figure 7: Cyclical Shift of Distribution

similar degree of responsiveness with cyclical unemployment as in the data. Crucially the elasticity measure shows that the model creates a strong response in the shares of unemployment at long durations. When using the semi-elasticity measure the model generates a nearly perfect fit. Thus, in our model as in the data cyclical changes in the aggregate unemployment rate are driven by particularly strong cyclical changes in long-term unemployment.

An important force behind the increase in long-term unemployment during recessions is the larger increase in the unemployment duration of occupational movers relative to stayers. Panel B in Table 5 shows the cyclical responses of the average unemployment duration of movers and stayers using different measures. Along all of these measures the model's average unemployment duration of occupational movers increases more than the average unemployment duration of stayers, an increase that is consistent with the data. Stayers' durations respond somewhat less relative to the data, between 60% (relative to the log HP-filtered unemployment measure) and 80% (relative to the linearly detrended unemployment measure). Relative to the lack of amplification in conventional DMP models, this still constitutes a large response. As in the data, the lengthening of movers' unemployment duration contributes meaningfully to the increase in long-term unemployment during recessions.

Figure 7 shows how the untargeted shift in unemployment durations combines with the targeted shift of the mobility-duration profile. At any percentile of the unemployment duration distribution, the model generates a drop in occupational mobility in recessions. By comparing the observations' x-coordinates, this figure also illustrates that the cyclical shift of the model's duration distribution follows the data.

Excess vs. net mobility A key insight from Tables 4 and 5 is that the aforementioned cyclical patterns are nearly identical to the ones generated by the excess mobility model. In Online Appendix C.2 we show that this model also fits very well the economy-wide targets described in Table 2 and the estimated values of $[c, \rho_z, \sigma_z, \underline{z}_{norm}, x^2, x^3, \gamma_d, \delta_L, \delta_H, k, b, \eta, \rho_A, \sigma_A]$ are nearly identical to the estimated in the full model. This comparison demonstrates that allowing workers to chose in which occupations to search in due to occupation-wide productivity differences is not the reason why the model is able to replicate the cyclical patterns of aggregate unemployment and its duration distribution. Instead, the excess mobility calibration highlights the importance of the worker-occupation idiosyncratic productivity process and its interaction with aggregate productivity in generating these cyclical patterns.

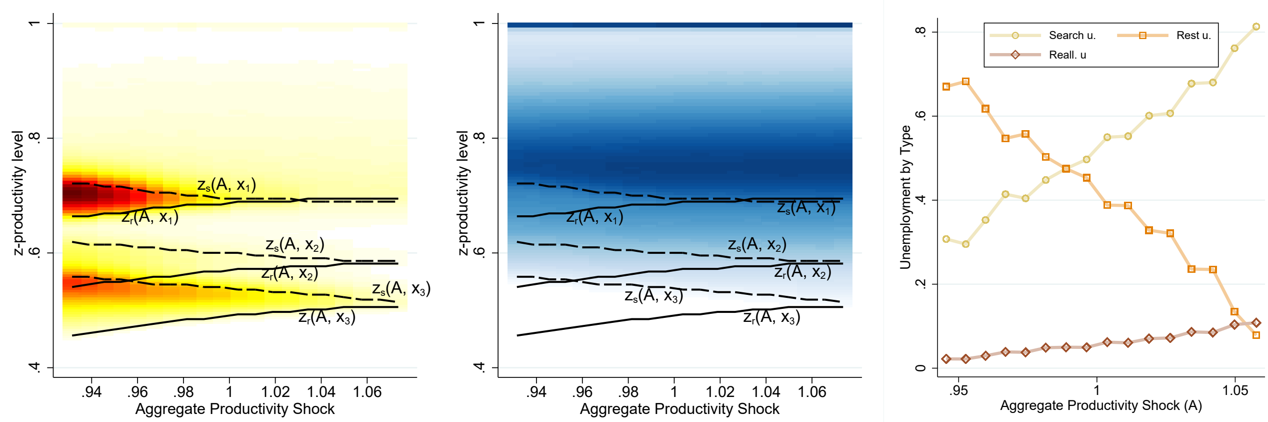
The excess mobility model and the full model calibrations are successful in these dimensions because they yield similar implications for search, rest and reallocation unemployment during workers' unemployment spells. In Section 5.1 we first demonstrate this claim using the excess mobility model's calibration. This also allows us to show in more detail the importance of having a persistent z-productivity process for the cyclical performance of the model. In Section 5.2 we show that the same forces occur within each task-based category in the full model, although modulated by differences in the level and cyclical responsiveness of p_o across occupations.

5.1 Main mechanism

As argued in Section 3.3, the relative position and slopes of z^s and z^r are key determinants of the long-run and cyclical implications of our model. We now discuss these in the context of the calibrations.

Relative position of z^s and z^r Figure 8a depicts the cutoff functions generated by the excess model calibration as a function A given x, where all occupations share the same cutoff functions. It shows that $z^s \geq z^r$ for nearly all A and $h = 1, 2, 3$. The exception being $z^s(A; x^1) < z^r(A; x^1)$ for the highest values of A. This implies that periods of search, rest and reallocation unemployment can occur within the same unemployment spell as A and z evolve. Further z^s and z^r decrease with x such that, as predicted by our theory, workers with higher human capital are less likely to change occupations relative to those with lower human capital. As $z^s(., x^3) < z^s(., x^1)$ the average level of separations is also lower for high human capital workers (noting that δ_L and δ_H also contribute to this difference). Once separated, high human capital workers spend on average a longer time in unemployment due to the larger distance between their z^s and z^r cutoffs.

Given the values of x, our theory shows that c, ρ_z and σ_z are key determinants of the distance between z^s and z^r, and therefore of the presence of episodes of rest unemployment. To illustrate why values of these parameters that lead to $z^s \geq z^r$ allow the model to match the mobility-duration profile and survival functions, consider a set of workers with the same x who just endogenously separated. Given $z^s \geq z^r$ and a persistent z process (as in the calibration), these workers will be initially close to z^s. A small positive shock would then suffice to move them above z^s, while only large negative shocks would take them below z^r. Hence at short durations these workers face relatively high job finding rates and, if re-employed, they will be most likely occupational stayers. Those who stayed unemployed for longer would have on average experienced further negative z shocks and would face a higher probability of crossing z^r. However, the stochastic properties of the z-process imply there will still be many of these workers that end up crossing z^s. As a result, the likelihood of an occupational move increases moderately with unemployment duration, while the job finding rate decreases with unemployment duration.



(a) Unemployment Distribution (b) Employment Distribution (c) Unemployment Decomposition

Figure 8: Cutoffs, Unemployment Distribution and Decomposition

Slope of z^s and z^r Figures 8a,b show that $\partial z^s/\partial A < 0$ and $\partial z^r/\partial A > 0$ for each x. This property implies that during recessions there is an increased scope for episodes of rest unemployment; while in expansions there is an increased scope for episodes of search unemployment. Figure 8c illustrate this last feature by showing the proportion of workers facing an episode of search, rest or reallocation unemployment for a given value of A. Although both rest and search unemployment are counter-cyclical, search unemployment episodes are relatively more common when the economy moves from mild recessions up to strong expansions. It is only as recessions get stronger that rest unemployment episodes become more common.

The slopes of the cutoffs reveal a cyclical area of inaction, $[z^r(A; x), z^s(A; x)]$, for each x. These areas of inaction are key to understand the cyclical performance of unemployment and vacancies. The negative slope of the z^s cutoffs together with the large mass of workers right above them (see Figure 8b) imply that a decrease in A leads to a large increase in the inflow of workers into rest unemployment episodes. The positive slope of the z^r cutoffs implies that the same decrease in A also leads to a large decrease in the outflow from rest unemployment via reallocation. These forces significantly add to the density of unemployed workers already "trapped" within these areas (see Figure 8a). Given that no firm in an occupation expects to be able to make a profit by hiring these workers, vacancy creation falls as well. As conditions improve the areas of inaction narrow considerably such that rest unemployed workers are now much more likely to get a z shock that takes them below (or above) z^r (z^s).[37] As the surplus from hiring these workers becomes positive and higher occupational mobility flows help workers increase their z-productivities, vacancy creation goes up across all occupations.

The strong cyclical responses of rest and search unemployment to the changes in the areas of inaction imply that aggregate unemployment, u, also becomes highly responsive to A. Episodes of reallocation unemployment, however, make a small contribution to the cyclicality of u because they only capture the time spent transiting between occupations, which is about 2 weeks on average, after which workers continue their jobless spell in episodes of rest or search before finding a job in a new

[37] In recessions that involve a 5% reduction in A relative to the mean, workers still face an average probability of about 25% of transitioning out of rest unemployment within a month; and this probability sharply increases with aggregate productivity.

occupation. In Online Appendix C.2 we show that these patterns occur across low and high human capital levels, explaining why we obtain unemployment, job finding and separations rates across age groups with similar cyclical responses.

The widening of the area of inaction during recessions also imply that long-term unemployed workers require a sequence of more and larger good z shocks before becoming search unemployed in their pre-separation occupation. They would also require a sequence of more and larger bad shocks before deciding to change occupations. In contrast, for those workers who have just endogenously separated z^s is the cutoff that weighs most on their future outcomes. For these workers the distance to the nearest cutoff is therefore not as responsive to A as for the long-term unemployed. Hence, we observe that the outflow rate of long-term unemployed workers responds more to changes in aggregate conditions relative to the outflow rate of shorter-term unemployed workers. This mechanism then translates into a stronger increase in the share of long-term unemployed in recessions as shown in Table 5, stronger than the one predicted based on the decline of f alone. The same mechanism also implies that at low values of A the time spent in rest unemployment increases more for (ex-post) occupational movers than for occupational stayers. This rationalizes the stronger increase in average unemployment duration among occupational movers relative to stayers during recessions documented in Section 2.4.

The role of human capital depreciation Human capital depreciation is important in determining these dynamics as it affects the cyclical changes in the areas of inaction. Workers with a z-productivity much lower than z^s take into account that even with a sequence of positive z realizations they might experience depreciation and reallocate anyway, decreasing the option value of waiting in their occupations and flattening the z^r cutoff. At separation a similar argument operates: increases in $z^s - z^r$ during recessions imply that depreciation more often leads to a reallocation than otherwise, increasing the option value of staying employed and flattening the z^s cutoff. In Online Appendix C.2 we demonstrate that this mechanism is important by re-estimating the model without human capital depreciation. Such a version of the model exhibits a stronger amplification of rest unemployment and, as a consequence, generates too large a volatility of the aggregate unemployment rate as well as too little occupational mobility during recessions.

The role of occupational mobility The cyclical sensitivity of the areas of inaction is also tightly linked with the existence of the z^r cutoff and the properties of the z-productivity process. To show this we re-estimate the model not allowing workers to change occupations. We use all the same moments outlined before except those pertaining to occupational mobility. In Online Appendix C.3 we show that the calibrated one-sector model with no occupational mobility can do well in fitting most of the targeted long-run moments, particularly the unemployment survival functions for all workers and by age groups. However, the aggregate unemployment, vacancy, job finding and separation rates now exhibit below half the cyclical volatility observed in their data counterparts, 0.04, 0.02, 0.03 and 0.03, respectively, and the correlation between unemployment and vacancies drops to -0.32. The cyclicality of the unemployment duration distribution is also far from the data, generating too little cyclical response across all durations, but particularly among the long-term unemployed.

The main reason why this version generates such a low cyclical response is that the new area of rest unemployment is defined by the set of z-productivities that lie in $[\underline{z}, z^s(A;x)]$, where $\underline{z}$ denotes the lowest value of z. This implies that any cyclical changes in the size of this area now solely depend on the responsiveness of z^s relative to the workers' z distribution. Although $\partial z^s/\partial A < 0$ and hence separations are countercyclical, this model cannot resolve a key trade-off: in the absence of the z^r cut-off the z process is less persistent and exhibits a much larger standard deviation, which creates enough heterogeneity in unemployment durations to allow it to match the empirical unemployment survival functions. However, the new estimated properties of the z process also increase the heterogeneity in z-productivities relative to the cyclical range of A. This dampens the model's cyclical performance as it implies less responsive z^s cutoffs, weakening the cyclical responses of job separations and the rate at which workers leave the area of rest unemployment.

In Online Appendix C.3 we show that an alternative version of the one-sector calibration with a more persistent and less volatile z process can create a much larger cyclical amplification of the unemployment rate and a stronger Beveridge curve, but at the cost of missing many of the unemployment duration targets and generating too much long-term unemployment even in expansions. It then also misses the cyclicality of the unemployment duration distribution, generating too little response in long-term unemployment. Thus, the one-sector version of our model appears unable to reconcile the observe cyclical fluctuations in aggregate unemployment with those of its duration distribution. This trade-off disappears once unemployed workers are allowed to weigh the option of waiting for their conditions to improve in their occupation with that of reallocating, as the z^r cutoffs create narrower and more cyclically sensitive areas of inactions for each x.

5.2 Occupation Heterogeneity and Cyclical Unemployment

We now show that the same mechanisms described above hold within each task-based category but their strength varies across these occupational groups. Consequently, unemployed workers face different unemployment outcomes that depend also on the identity of the occupation. Both the long-run and cyclical dimensions of occupation-wide productivity differences are relevant. To understand the former, column 5 in Table 6 shows the contribution of unemployed occupational switchers in changing the observed sizes of the task-based categories in our calibration. This is compared to the contribution of the exogenous entry and exit process as captured by d and ψ_o (column 4 "Entrants"), such that for each task-based category the two values add up to the change in the employment stock. The calibration shows that NRM occupations increased in size due to more unemployed workers switching to these occupations than away from them. In contrast, RM and RC decrease in size as more unemployed workers move away from these occupations than to them.

The last two columns of Table 6 show the contribution of mobility through unemployment separately by periods of high and low unemployment, where we categorise these periods by comparing the HP-filtered unemployment rate to its median. We observe that it is during recessions that mobility through unemployment particularly accelerates the changing size of NRM and RM occupations, representing about two-thirds and three-quarters of the total contribution of this channel, respectively.

Table 6: Role Unemployment in the Changing Size of Occupations

Task-Based	Distributions			Model Decomposition of Distribution Change			
	Initial	End Distribution		Entrants	Occ. Mob through Unemployment		
Occupational Categories	Distribution	Data	Model	All Qtrs	All Qtrs	Qtrs $u < u^{median}$	Qtrs $u \geq u^{median}$
Non-routine Cognitive	0.224	0.329	0.337	0.133	-0.020	-0.011	- 0.009
Routine Cognitive	0.292	0.258	0.246	-0.019	-0.027	-0.009	- 0.018
Non-routine Manual	0.226	0.260	0.260	-0.036	0.070	0.025	0.045
Routine Manual	0.258	0.154	0.157	-0.067	-0.034	-0.008	- 0.026

Jaimovich and Siu (2020) already documented the importance of recessions in changing the size of routine occupations. Here we show that the net mobility patterns described in Section 2 together with the endogenous response in unemployment yield precisely such a pattern within our model. Figure 9 illustrates the mechanism behind this.

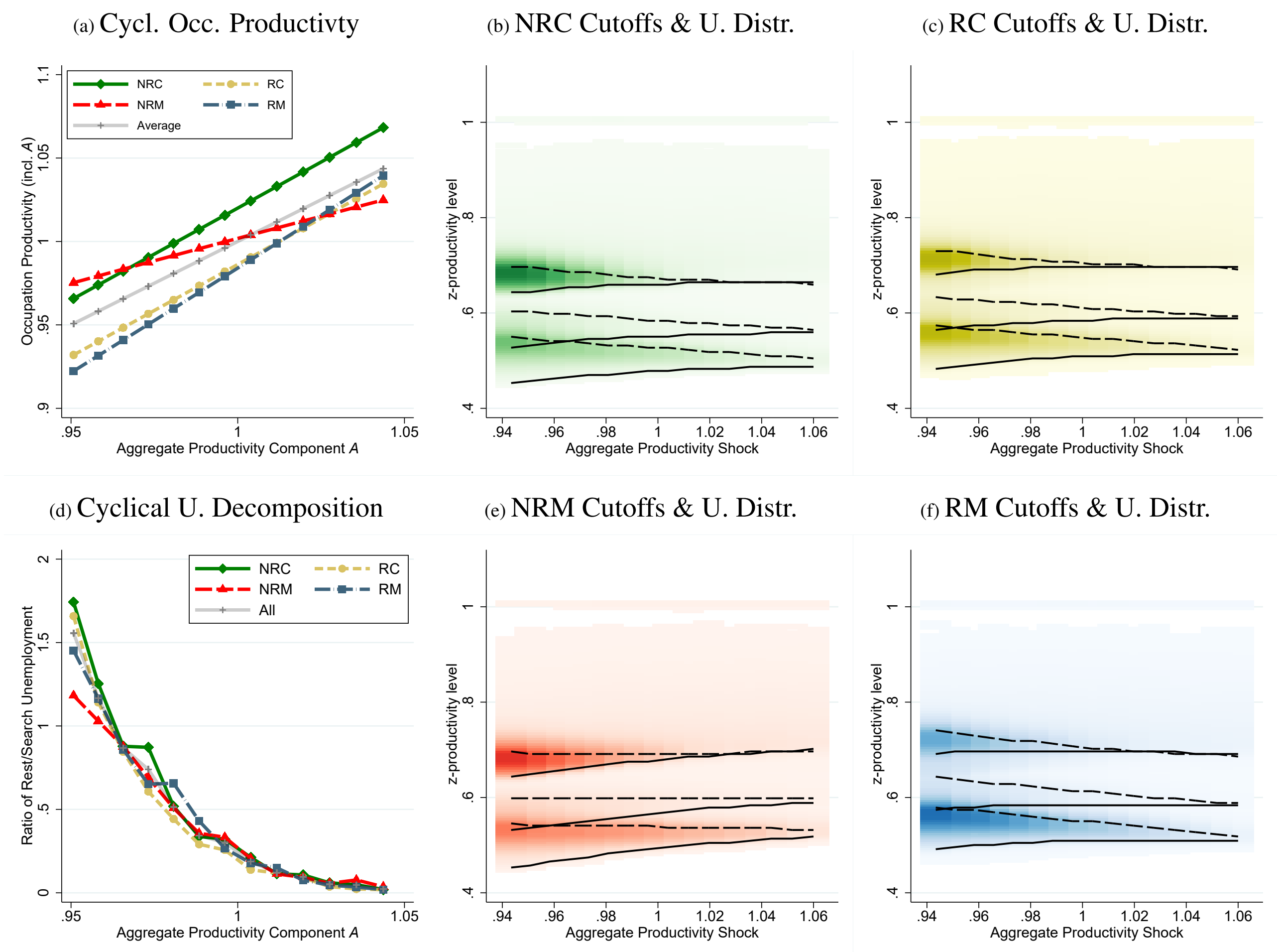
Figure 9a shows the levels and cyclicalities of the estimated occupation-wide productivities for the range of A. Reflecting the estimated values of ϵ_o, it shows that RM and RC occupations are strongly negatively affected in recessions, but catch up with the average in expansions. In contrast, NRM occupations are the least attractive in expansions but become more attractive in recessions. NRC occupations are consistently above average over the cycle (more so in expansions).

Figures 9b, 9c, 9e, 9f show that these different cyclical productivities result in different separation and reallocation cutoffs. Although their levels are not that different across task-based categories, in RM occupations the separation cutoffs decreases more steeply, while the reallocation cutoffs are nearly horizontal. In NRM occupations the separation cutoffs are nearly horizontal and the reallocation cutoffs are strongly upward-sloping. This implies that in recessions job separations are more prominent in RM than in NRM occupations.

Despite the differences in slopes, all task-based categories exhibit cutoffs with the $z^s > z^r$ property. Further, the distance between these cutoffs creates areas of inaction that increase in recessions and narrow in expansions as described earlier. Figure 9d shows that as a result rest unemployment episodes are more common than search unemployment episodes in recessions within each task-based category. As the economy recovers search unemployment episodes are the most common ones.

The observed countercyclical net mobility patterns then occur for mainly two reasons: (i) a differential cyclical response in the outflows across task-based categories, such that some task-based categories shed more workers during recessions relative to the average; and (ii) a differential cyclical response in the inflows, such that those workers who have decided to change occupations choose their destination task-based category differently in recessions than in expansions. The widening of the area of inactions as A decreases implies that overall occupational mobility falls during recessions in all task-based categories. However, the differential responses in occupation-wide productivities across the cycle imply that the decrease in outflows is stronger in NRM occupations and weaker in RM occupations relative to the average, as observed in the data. At the same time, Table 2 shows that the model is also able to reproduce the shift in the inflow distribution towards RM and away from NRM occupations that occurs in recessions.

Figure 9: Heterogeneity across Occupation across the Cycle



Accompanying these countercyclical net mobility patterns, vacancy creation in every occupation is procyclical. As mentioned earlier, this feature stands in contrast with many multi-sector models in the spirit of Lucas and Prescott (1974) were vacancy creation increases in recessions, generating an upward sloping Beverdige curve. In our framework, in contrast, all occupation-wide productivities co-move with the common aggregate productivity shock and the loadings ϵ_o only create relative productivity differences across occupations. These relative difference are economically important, driving the net mobility patterns.

6 Conclusions

In this paper we show that there is no tension between the cyclical behavior of individual unemployment outcomes, procyclical gross occupational mobility and countercyclical net mobility through unemployment. While individual outcomes are to a large extent driven by the interaction between worker-occupation idiosyncratic and aggregate shocks, net mobility is affected by occupation-wide productivity differences and unemployed workers' differential responses to these. Further, given that net mobility increases in recessions, transitions through unemployment play a meaningful role in shaping the changing size of RM, RC and NRM occupations.

Along with the high mobility rate increasing with duration, many long-term unemployed still return to their previous occupation. The model interprets this as a sizeable option value of waiting for prospects to improve in one's previous occupation. In recessions, this option value becomes more important and increases the unemployment durations of stayers and more so of movers, a pattern observed in the data. This implies that in the model the nature of unemployment changes over the cycle. In expansions (and mild recessions) the typical worker is not able to find jobs that are currently available to him due to standard search frictions and search unemployment becomes the main source of aggregate unemployment. As recessions get stronger the typical worker is not able to find jobs because there are no jobs posted for him. In this case, rest or wait unemployment becomes the main source of aggregate unemployment. These dynamics translate into large cyclical changes in aggregate unemployment and its duration distribution.

The concept of rest unemployment is closely related to that of mismatch, stock-flow and rationing unemployment. Shimer (2007) defines mismatch unemployment as those workers who remain attached to a local labor market even though there are currently no jobs for them. In stock-flow matching, unemployed workers in the stock wait for new jobs to arrive, as existing vacancies do not offer suitable employment opportunities. In Michaillat (2012) rationing unemployment occurs because workers are currently unproductive and no jobs are posted for them. As conditions improve, they become productive and employable once again. A key difference with all these models, is that here workers in rest unemployment episodes always have the option of looking for jobs in alternative occupations. Crucially, the occupational mobility decision changes over the cycle, with a larger proportion of workers deciding not to use this option in recessions.

Throughout, our analysis we have considered workers who are currently in a rest unemployment episodes as part of the labor force, still searching and expecting a positive job finding probability in the near future. Episodes of rest unemployment, however, could conceptually be extended to incorporate marginally attached workers. In terms of occupational mobility patterns, Supplementary Appendix B shows that our analysis is robust to introducing periods of non-participation within workers' jobless spells. Online Appendix C.2 shows that considering non-participation periods in our targeted statistics does not alter the quantitative performance of our model. These exercises suggest that our results are robust to inclusion of the marginally attached.

Although other models have been successful in replicating some of the cyclical unemployment patterns described here, Bils et al. (2011) argue that these models would typically have difficulty in jointly explaining the observed cyclicality of the aggregate unemployment rate and generating realistic dispersion in wage growth. This should not be an issue in our framework. As shown in Sections 4 and 5 our calibration generates the observed cyclicality of unemployment together with a realistic amount of wage dispersion as measured by Hornstein et al. (2011) Mm ratio. In this paper we have emphasised labor market flows pertaining to the unemployed, but extending the analysis to include heterogeneity in firm-worker matches and on-the-job search would allows us to study the cyclical relationship between wages, occupational mobility, unemployment fluctuations. We leave this for future research.

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Online Appendix

A Correcting for Occupational Coding Errors

This Appendix complements Section 2.1 of the paper. Supplementary Appendix A provides the full version of this appendix. There we provide all results and proofs, present the estimate of $\mathbf{\Gamma}$-correction matrix, show that our method is successful out of sample, and that it affects differently employer/activity movers and pooled samples of all workers, also when the same (in)dependent interviewing procedure is applied to both groups in the survey. We further compare the implied extent of coding error across different occupation (and industry) categories. We also show that our correction method implies an average occupational mobility rate at re-employment that is in line with the one derived from the PSID retrospective occupation-industry supplementary data files. Finally, we discuss the plausibility of the assumption used to recover $\mathbf{\Gamma}$. To save space, here we only summarise the main mathematical results. We use this error correction model to produce the results in the main text and Supplementary Appendix B.

The elements of garbling matrix $\mathbf{\Gamma}$ are defined to be the probabilities that an occupation i is miscoded as an occupation j, for all $i, j = 1, 2, ..., O$. We make three assumptions that allows us to identify and estimate $\mathbf{\Gamma}$. (*A1*) *Independent classification errors*: conditional on the true occupation, the realization of the occupational code is independent of worker history, worker characteristics or time. (*A2*) *"Detailed balance" in miscoding*: $\mathbf{diag}(\mathbf{c})\mathbf{\Gamma}$ is symmetric, where $\mathbf{c}$ is a Ox1 vector that describes the distribution of workers across occupations and $\mathbf{diag}(\mathbf{c})$ is the diagonal matrix of $\mathbf{c}$. (*A3*) *Strict diagonal dominance*: $\mathbf{\Gamma}$ is strictly diagonally dominant in that $\gamma_{ii} > 0.5$ for all $i = 1, 2, ..., O$.

To estimate $\mathbf{\Gamma}$ we exploit the change of survey design between the 1985 and 1986 SIPP panels. Until the 1985 panel the SIPP used independent interviewing for all workers: in each wave all workers were asked to describe their job anew, without reference to answers given at an earlier date. Subsequently, a coder would consider that wave's verbatim descriptions and allocate occupational codes. This practise is known to generate occupational coding errors. In the 1986 panel, instead, the practise changed to one of dependent interviewing. Respondents were only asked "independently" to describe their occupation if they reported a change in employer or if they reported a change in their main activities without an employer change. If respondents declared no change in employer *and* in their main activities, the occupational code assigned to the respondent in the previous wave is carried forward.

To identify $\mathbf{\Gamma}$ it is important to note that during February 1986 to April 1987, the 1985 and 1986 panels overlap, representing the *same* population under different survey designs. The identification theory we develop in the next section refers to this population. We then show how to consistently estimate $\mathbf{\Gamma}$ using the population samples.

A.1 Identification of $\mathbf{\Gamma}$

Consider the population represented by 1985/86 SIPP panels during the overlapping period and divide it into two groups of individuals across consecutive interviews by whether or not they changed employer or activity. Label those workers who stayed with their employers in both interviews and did not change activity as "employer/activity stayers". By design this group *only* contains true occupational stayers. Similarly, label those workers who changed employers or changed activity within their employers as "employer/activity changers". By design this group contains all true occupational movers and the set of true occupational stayers who changed employers.

Suppose that we were to subject the employer/activity stayers in this population to dependent interviewing as applied in the 1986 panel. Let $\mathbf{c_s}$ denote the Ox1 vector that describes their *true* distribution across occupations and let $\mathbf{M_s} = \mathbf{diag}(\mathbf{c_s})$. Let $\mathbf{c_s^D}$ denote the Ox1 vector that describes their *observed* distribution across occupations under dependent interviewing and let $\mathbf{M_s^D} = \mathbf{diag}(\mathbf{c_s^D})$. Note that $\mathbf{c_s^D} = \mathbf{\Gamma}'\mathbf{M_s}\overrightarrow{\mathbf{1}}$, where $\overrightarrow{\mathbf{1}}$ describes a vector of ones. $\mathbf{M_s}$ is pre-multiplied by $\mathbf{\Gamma}'$ as true occupations would have been miscoded in the first of the two consecutive interviews. Assumption *A2* implies that $\mathbf{c_s^D} = \mathbf{diag}(\mathbf{c_s})\mathbf{\Gamma}\overrightarrow{\mathbf{1}} = \mathbf{c_s}$ and hence $\mathbf{M_s^D} = \mathbf{M_s}$.

Next suppose that instead we were to subject the employer/activity stayers in this population to independent interviewing as applied in the 1985 panel. Let $\mathbf{M_s^I}$ denote the matrix that contains these workers' *observed* occupational transition *flows* under independent interviewing. In this case $\mathbf{M_s^I} = \mathbf{\Gamma}'\mathbf{M_s}\mathbf{\Gamma}$. Here $\mathbf{M_s}$ is pre-multiplied by $\mathbf{\Gamma}'$ and post-multiplied by $\mathbf{\Gamma}$ to take into account that the observed occupations of origin and destination would be subject to coding error.

Let $\mathbf{M_m}$ denote the matrix that contains the *true* occupational transition *flows* of employer/activity changers in this population. The diagonal of $\mathbf{M_m}$ describes the distribution of true occupational stayers across occupations among employer/activity changers. The off-diagonal elements contain the flows of all true occupational movers. Under independent interviewing $\mathbf{M_m^I} = \mathbf{\Gamma}'\mathbf{M_m}\mathbf{\Gamma}$. Once again $\mathbf{M_m}$ is pre-multiplied by $\mathbf{\Gamma}'$ and post-multiplied by $\mathbf{\Gamma}$ as the observed occupations of origin and destination would be subject to coding error.

Letting $\mathbf{M^I} = \mathbf{M_m^I} + \mathbf{M_s^I}$ denote the matrix that contains the aggregate occupational transition flows across two interview dates under independent interviewing, it follows that $\mathbf{M_s^I} = \mathbf{M^I} - \mathbf{M_m^I} = \mathbf{\Gamma}'\mathbf{M_s}\mathbf{\Gamma}$. By virtue of the symmetry of $\mathbf{M_s}$ and assumption *A2*, $\mathbf{M_s}\mathbf{\Gamma} = \mathbf{\Gamma}'\mathbf{M_s}' = \mathbf{\Gamma}'\mathbf{M_s}$. Substituting back yields $\mathbf{M_s^I} = \mathbf{M_s}\mathbf{\Gamma}\mathbf{\Gamma}$. Next note that $\mathbf{M_s^I} = \mathbf{M_s}\mathbf{T_s^I}$, where $\mathbf{T_s^I}$ is the occupational transition probability matrix of the employer/activity stayers in this population *observed* under independent interviewing. Substitution yields $\mathbf{M_s}\mathbf{T_s^I} = \mathbf{M_s}\mathbf{\Gamma}\mathbf{\Gamma}$. Multiply both sides by $\mathbf{M_s^{-1}}$, which exists as long as all the diagonal elements of $\mathbf{M_s}$ are non-zero, yields the key relationship we exploit to estimate $\mathbf{\Gamma}$,

$$\mathbf{T_s^I} = \mathbf{\Gamma}\mathbf{\Gamma}. \tag{1}$$

To use this equation we first need to show that it implies a unique solution for $\mathbf{\Gamma}$. Towards this result, we now establish that $\mathbf{\Gamma}$ and $\mathbf{T_s^I}$ are diagonalizable. For the latter it is useful to interpret the coding error process described above as a Markov chain such that $\mathbf{\Gamma}$ is the one-step probability matrix associated with this process.

Lemma A.1: *Assumptions A2 and A3 imply that* $\mathbf{\Gamma}$ *and* $\mathbf{T_s^I}$ *are diagonalizable.*

In general one cannot guarantee the uniqueness, or even existence, of a transition matrix that is the (nth) root of another transition matrix. Here, however, existence is obtained by construction: $\mathbf{T_s}$

is constructed from $\mathbf{\Gamma}$, and in reverse, we can find its roots. The next result shows that $\mathbf{T_s}$ has a unique root satisfying assumptions *A2* and *A3*.

Proposition A.1: *$\mathbf{\Gamma}$ is the unique solution to $\mathbf{T_s^I} = \mathbf{\Gamma}\,\mathbf{\Gamma}$ that satisfies assumptions A2 and A3. It is given by $\mathbf{P\Lambda^{0.5}P^{-1}}$, where $\mathbf{\Lambda}$ is the diagonal matrix with eigenvalues of $\mathbf{T_s^I}$, $0 < \lambda_i \leq 1$, and $\mathbf{P}$ is the orthogonal matrix with the associated (normalized) eigenvectors.*

The above results imply that under assumptions *A2* and *A3*, $\mathbf{\Gamma}$ is uniquely identified from the transition matrix of true occupational stayers under independent interviewing, $\mathbf{T_s^I}$.

A.2 Estimation of $\mathbf{\Gamma}$

The next lemma provides an intermediate step towards estimating $\mathbf{\Gamma}$. For this purpose let $PDT(.)$ denote the space of transition matrices that are similar, in the matrix sense, to positive definite matrices.

Lemma A.2: *The function $f : PDT(\mathbb{R}^{O\times O}) \to PDT(\mathbb{R}^{O\times O})$ given by $f(\mathbf{T}) = \mathbf{T^{0.5}}$ exists and is continuous with $f(\mathbf{T_s^I}) = \mathbf{\Gamma}$* in the spectral matrix norm.

Let $\mathbf{\hat{T}_s^I}$ denote the sample estimate of $\mathbf{T_s^I}$ and let $\mathbf{\hat{\Gamma}}$ be estimated by the root $(\mathbf{\hat{T}_s^I})^{0.5} \in PDT(\mathbb{R}^{O\times O})$ such that $\mathbf{\hat{\Gamma}} = (\mathbf{\hat{T}_s^I})^{\mathbf{0.5}} = \mathbf{\hat{P}\hat{\Lambda}^{0.5}\hat{P}^{-1}}$, where $\mathbf{\hat{\Lambda}}$ is the diagonal matrix with eigenvalues of $\mathbf{\hat{T}_s^I}$, $0 < \hat{\lambda}_i^{0.5} \leq 1$ and $\mathbf{\hat{P}}$ the orthogonal matrix with the associated (normalized) eigenvectors. We then have the following result.

Proposition A.2: *$\mathbf{\Gamma}$ is consistently estimated from $(\mathbf{\hat{T}_s^I})^{0.5} \in PDT(\mathbb{R}^{O\times O})$ such that $\mathbf{\hat{\Gamma}} = (\mathbf{\hat{T}_s^I})^{\mathbf{0.5}} = \mathbf{\hat{P}\hat{\Lambda}^{0.5}\hat{P}^{-1}}$. That is, $plim_{n\to\infty}\mathbf{\hat{\Gamma}} = \mathbf{\Gamma}$.*

Note that to identify and estimate $\mathbf{\Gamma}$ in the SIPP it is not sufficient to directly compare the aggregate occupational transition flows under independent interviewing with the aggregate occupational transition flows under dependent interviewing. To show this let $\mathbf{M^D} = \mathbf{M_m^I} + \mathbf{M_s^D}$ denote the matrix that contains the aggregate occupational transition flows across two interview dates under dependent interviewing for employer/activity stayers and under independent interviewing for employer/activity movers. Subtracting $\mathbf{M^I} = \mathbf{M_m^I} + \mathbf{M_s^I}$ from $\mathbf{M^D}$ yields $\mathbf{M_s^D} - \mathbf{M_s^I} = \mathbf{M_s} - \mathbf{\Gamma'M_s\Gamma}$. Given the symmetry assumed in *A2*, the latter expression has $0.5n(n-1)$ exogenous variables on the LHS and $0.5n(n+1)$ unknowns (endogenous variables) on the RHS, leaving $\mathbf{\Gamma}$ (and $\mathbf{M_s}$) unidentified.

In addition to $\mathbf{M^D} - \mathbf{M^I} = \mathbf{M_s} - \mathbf{\Gamma'M_s\Gamma}$ one can use $\mathbf{M^D} = \mathbf{\Gamma'M_m\Gamma} + \mathbf{M_s}$, which contains the remainder information. When $\mathbf{M_m}$ has mass on its diagonal, however, this additional system of equations has n^2 exogenous variables on the LHS and n^2 unknowns (arising from $\mathbf{M_m}$) on the RHS. This implies that with the n unknowns remaining from $\mathbf{M^D} - \mathbf{M^I} = \mathbf{M_s} - \mathbf{\Gamma'M_s\Gamma}$, one is still unable to identify $\mathbf{\Gamma}$ and $\mathbf{M_s}$.

Corollary A.1: *If $\mathbf{M_m}$ has mass on its diagonal, $\mathbf{\Gamma}$ cannot be identified from $\mathbf{M^I}$ and $\mathbf{M^D}$ alone.*

The intuition behind this result is that by comparing aggregate occupational transition flows under dependent and independent interviewing, it is unclear how many workers are 'responsible' for the change in occupational mobility between $\mathbf{M^D}$ and $\mathbf{M^I}$. Only when the diagonal of $\mathbf{M_m}$ contains exclusively zeros, identification could be resolved and one can recover $\mathbf{M_s}$, $\mathbf{\Gamma}$ and $\mathbf{M_m}$ as the number of equations equals the number of unknowns.[1] An implication of the above corollary is that interrupted time-series analysis that is based on the difference in occupational mobility at the time of a switch from independent to dependent interviewing, does not identify the precise extent of the average coding error, but provides a downwards biased estimate.

To identify Γ, however, Proposition A.2 implies that one can use the observed occupational transition flows of a sample of *true* occupational stayers that are subject to two rounds of independent interviewing. Some of these workers will appear as occupational stayers and some of them as occupational movers. Ideally, such a sample of workers should be isolated directly from the 1985 panel. Unfortunately, the questions on whether the individual changed activity or employer were only introduced in the 1986 panel, as a part of the switch to dependent interviewing. As a result, the 1985 panel by itself does not provide sufficient information to separate employer/activity stayers from employer/activity movers. Instead we use 1986 panel to estimate $\hat{\mathbf{M}}^{\mathbf{I}}_{\mathbf{m}}$. We can infer $\mathbf{M}^{\mathbf{I}}_{\mathbf{s}}$ indirectly by subtracting the observed occupational transition flow matrix $\hat{\mathbf{M}}^{\mathbf{I}}_{\mathbf{m}}$ in the 1986 panel from the observed occupational transition flow matrix $\hat{\mathbf{M}}^{\mathbf{I}}$ in the 1985 panel. This is possible as the 1986 panel refers to the same underlying population as the 1985 panel and separates the employer/activity changers, who are independently interviewed.

Corollary A.2: $\hat{\Gamma}$ *is consistently estimated from* $\hat{\mathbf{T}}^{\mathbf{I}}_{\mathbf{s}}$ *when the latter is estimated from* $\hat{\mathbf{M}}^{\mathbf{I}} - \hat{\mathbf{M}}^{\mathbf{I}}_{\mathbf{m}}$

This result is important to implement our approach. It follows as the population proportions underlying each cell of $\hat{\mathbf{M}}_{\mathbf{s}}$, the sample estimate of $\mathbf{M}_{\mathbf{s}}$, are consistently estimated. In turn, the latter follows from the standard central limit theorem for estimating proportions, which applies to $\hat{\mathbf{M}}^{\mathbf{I}}$, $\hat{\mathbf{M}}^{\mathbf{I}}_{\mathbf{m}}$ and its difference. Proposition A.2 then implies that $\hat{\Gamma}$ is consistently estimated.

B Theory

This Appendix complements Section 3 of the paper. However, to save space, here we refer the reader to Supplementary Appendix C. There, we present the equations describing worker flows, provide the definition of a BRE, and the proof of Proposition 2 (in the main text) and the proof of existence of the separation and reallocation cutoffs. We also provide the details of the competitive search version of the model that underpins the sub-market structure used in the main text. We further investigate the conditions under which rest unemployment arises – Lemmas 1 and 2 – and the cyclical properties of workers' job separation and occupational mobility decisions, Lemma 3, with the associated proofs.

C Quantitative Analysis

This Appendix is divided into three parts that complement Sections 4 and 5 of the paper. The first part provides further details of the full model calibration done in Section 4. The second part presents the calibration results from the "excess mobility model", where we analyse its ability to reproduce the long-run and cyclical patterns of several labor market variables. Here we also consider two additional excess mobility calibrations: one based on a model without human capital depreciation and the

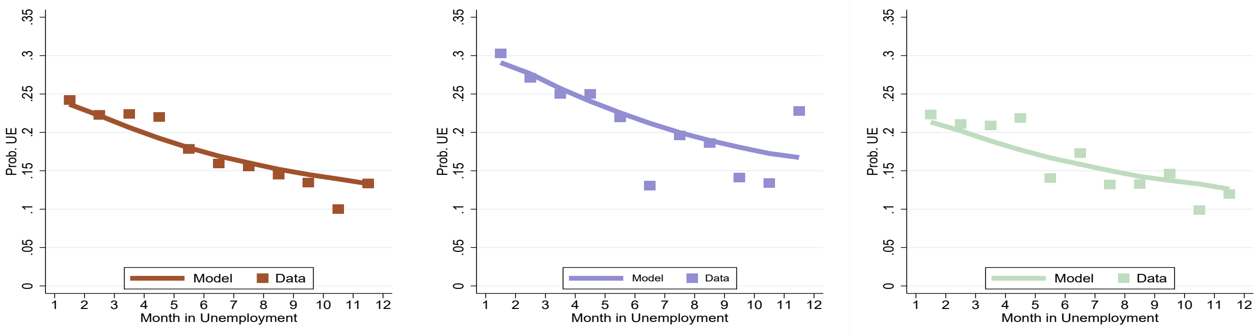
[1] However, in the SIPP this case is empirically unreasonable as it requires that all employer/activity changers be true occupational movers.

other using job spells that contain transitions between unemployment and non-participation instead of pure unemployment spells. The third part provides the details of the calibration were we shut down occupational mobility and assess the ability of a one-sector model to jointly replicate the cyclical behaviour of unemployment and its duration distribution.

C.1 Full Model: Gross and Net Mobility

In the main text we show that the calibrated version of the full model is able to replicate well all the targeted long-run occupational mobility, job separation, job finding and unemployment patterns of the US labor market. It does so by generating within each task-based category periods of search, rest and reallocation unemployment as A, p_o and z evolve.

Here we expand on the analysis presented in Sections 4 and 5 along three dimensions. First, we further show the model's implied unemployment durations by presenting (i) the job finding rates as a function of duration (also as a function of workers' occupational mobility status), (ii) the (incomplete) unemployment duration distribution and (iii) the relationship between occupational mobility and unemployment duration (mobility-duration profile) decomposed by excess and net mobility. Second, we provide further details of the differences between occupational categories with respect to their relative cyclical unemployment responses, and the cyclical inflow and net flow responses that are used to estimate occupation-specific cyclical differences in the model. Third, we present the full correlation tables describing the cyclical performance of the model using the 5Q-MA smoothed and Quarterly HP-filtered measures. We also discuss the cyclicality of an alternative unemployment measure that includes entrants; show the cyclicality of the unemployment, job finding and job separation rates by age groups; and present the decomposition of search, rest and reallocation unemployment episodes for a given value of A in a comparable way to the one derived for the excess mobility mobility model discussed in Section 5.1 of the main text.



(a) All workers (b) Young workers (c) Prime-aged workers

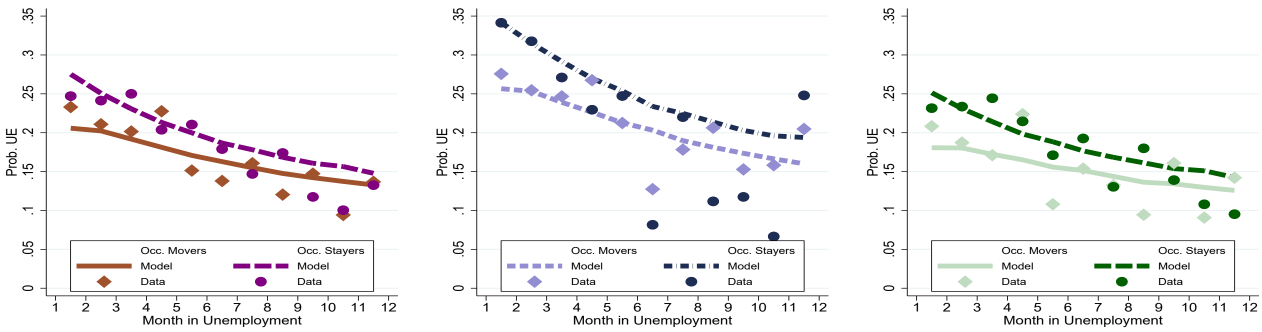
Figure 1: Hazard Functions. Data and Model Comparison

Unemployment duration moments Figure 1 shows the aggregate and age-specific unemployment hazard functions, comparing the model to the data.[2] We observe that the model captures very well the observed duration dependence patterns, where the young exhibit a stronger decline in the job finding

[2]In the SIPP hazard functions we observe the effects of the seams present in these data. The model's estimates do not have this issue and hence are much smoother.

rate with duration than the prime-aged. Note that in our sample (and hence in the calibration) the degree of negative duration dependence in the unemployment hazard is relatively weak as we have tried to minimise the presence of unemployed workers who were in temporary layoff and/or returned to their previous employers (see Supplementary Appendix B.4 for a further discussion of this issue).

Figure 2 shows the aggregate and age-specific unemployment hazard functions separately for occupational movers and stayers. Here we observe that the model also captures well these hazards functions, separately for occupational movers and stayers, where we find both in the model and data a stronger degree of negative duration dependence among occupational stayers than occupational movers, particularly among young workers.



(a) All workers

(b) Young workers

(c) Prime-aged workers

Figure 2: Occupational Movers/Stayers Hazard Functions. Data and Model Comparison

The observed unemployment duration distribution is also well matched by the model. Table 1 shows it reproduces very well both the proportion of short and long durations spells across the distribution. Further, this fit is achieved when pooling together all workers and when separately considering young and prime-aged workers. Crucially, the fit of the duration distribution is not implied by targeting the empirical unemployment survival functions. The reported duration distribution is constructed by averaging duration distributions across quarters, while the survival functions are derived from pooling all observations. For example, the observed long-term unemployment in the pooled survival functions occur mainly in recessions and these observations get down-weighted when averaging across quarters (instead of counting each observation equally). Indeed, we show in Section 3 of this appendix that matching the survival functions does not imply also matching the duration distribution. We show this in the context of a version of the model without occupational mobility. Instead, allowing for the latter we obtain a good fit in both the survival functions and the unemployment duration distributions.

Figure 3, Section 2 of the main text shows that both excess and net mobility increase with unemployment duration. Further, this figure shows that it is excess mobility that mainly drives the overall increase in the mobility-duration profile. Figure 3a (below) depicts the model's equivalent decomposition using task-based categories and without considering the "management" occupation (see Figure 3b of the main text). In the model both excess and net mobility increase with unemployment duration. Given the countercyclicality of net mobility, the latter occurs as net mobility is more prominent in recessions where workers' unemployment durations are typically longer. Further, excess mobility

Table 1: Incomplete Unemployment Duration Distribution Behavior (1-18 months)

	All workers			Young workers			Prime-aged workers		
Unemp. Duration	Full Model	Excess Model	Data	Full Model	Excess Model	Data	Full Model	Excess Model	Data
1-2 m	0.43	0.42	0.43	0.53	0.52	0.47	0.40	0.39	0.41
1-4 m	0.65	0.64	0.67	0.75	0.75	0.71	0.62	0.61	0.65
5-8 m	0.20	0.21	0.20	0.17	0.17	0.19	0.22	0.22	0.21
9-12 m	0.09	0.09	0.08	0.05	0.05	0.07	0.10	0.10	0.09
13-18m	0.06	0.06	0.05	0.03	0.03	0.03	0.07	0.07	0.06

Table 2: Task-based Unemployment Duration Elasticities

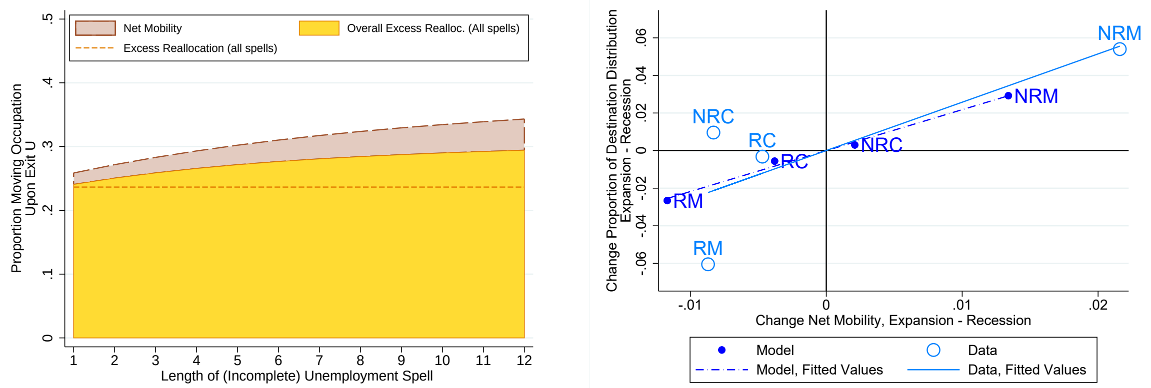
	NRC	RC	NRM	RM
$\varepsilon^{Data}_{UD_o,u}$	0.409	0.383	0.284	0.419
(s.e.)	(0.068)	(0.050)	(0.045)	(0.053)
$\varepsilon^{Model}_{UD_o,u}$	*0.390*	*0.413*	*0.342*	*0.423*
$\varepsilon^{Data}_{UD_o,u}/\varepsilon^{Data}_{UD_{avg},u}$ (targeted)	1.096	1.027	0.761	1.122
(s.e.)	(0.183)	(0.132)	(0.119)	(0.141)
$\varepsilon^{Model}_{UD_o,u}/\varepsilon^{Model}_{UD_{avg},u}$	*0.996*	*1.054*	*0.874*	*1.081*

is the main driver of the mobility-duration profile as in the data.

Task-based occupational categories over the cycle In the model the cyclical productivity loadings ϵ_o are the only four cyclical parameters that explicitly differ across task-based categories $o \in \{NRC, RC, NRM, RM\}$. Together with the elasticity of the cross-occupation search, ν, these parameters shape the differential cyclical response of each category o along three dimensions, summarised by 12 moments in Table 3 in the main text. (i) The cyclical response of net mobility for each task-based category ("Net mobility o, *Recessions* and Net mobility o, *Expansions*"), (ii) the cyclical change in the proportion of occupational movers that choose an occupation category o ($\Delta_{exp-rec}$ (inflow o/all flows)), and (iii) the strength of each category's unemployment durations response relative to the economy-wide average response to the aggregate unemployment rate ($\varepsilon_{UD_o,u}/\varepsilon_{UD_{avg},u}$).

We highlight that in (iii) we target the unemployment duration elasticities for each task-based category *relative* to the economy-wide elasticity. We do this as we want to leave untargeted the amplification of aggregate unemployment. In particular, as a first step to derive these elasticities in the SIPP we regress for each task-based category the log unemployment durations of workers who lost their job in o on the log (aggregate) unemployment rate and a linear trend. Let $\varepsilon_{UD_o,u}$ for $o \in \{NRC, RC, NRM, RM\}$ denote the resulting unemployment duration elasticities with respect to aggregate unemployment. The first row of Table 2 presents these elasticities and compares them to the simulated ones in the calibration. These elasticities show that NRM occupations have a more muted cyclical response in unemployment duration than RM occupations. This differential response is also statistically significant: a Wald test on equality of the two corresponding coefficients has an associated p-value of 0.02. In the second step, we normalize each elasticity by the (occupation size-weighted) average of all four elasticities. The resulting normalized elasticities are the ones we target in the model. The last two rows of Table 2 shows these ratios (see also Table 2 in the main text), showing that model fits the data well. In particular, it shows that RM occupations are the most cyclically sensitive in terms of unemployment durations (highest value of $\varepsilon_{UD_o,u}/\varepsilon_{UD_{avg},u}$); while NRM occupations are the least cyclically sensitive (the lowest value of $\varepsilon_{UD_o,u}/\varepsilon_{UD_{avg},u}$). We observe that the model's elasticities are in line with the data. Below we show that the model is also successful in generating the untargeted aggregate unemployment amplification.

As shown in the Table 2 of the main text, the model is also consistent with the cyclical changes in net mobility as well as the cyclical changes in the inflows for each task-based category. This occurs as differences in ϵ_o translate into cyclically changing incentives for workers to leave an occupation in category o and, depending on ν, to sample z-productivities from another occupation in category o'. Figure 3b displays the relationship between these two set of moments in the model and in the data. For each task-based category, it shows the relationship between the cyclical changes in net mobility on the x-axis ("Net mobility o, *Expansions* - Net mobility o, *Recessions*") and the cyclical changes in inflows as a proportion of all occupational movers on the y-axis ($\Delta_{exp-rec}$ (inflow o/all flows)). We observe that RM occupations have the strongest cyclical response of net outflows, increasing in recessions, as well as the strongest response in the inflow proportion, also larger in recessions. In contrast, NRM occupations are the ones which experience the largest increase in net inflows in recessions and the largest increase in inflows as destination category.



(a) Decomposition of the mobility-duration profile

(b) Cyclical Shifts across Occupation Categories in Netflows vs Inflows

Figure 3: Task-Based Occupational Mobility

As Figure 3b and Table 2 show, the model captures well the co-movement along dimensions (i), (ii) and (iii) discussed above. In particular, with only one set of parameters indexed by task-based occupation category, ϵ_o, the model reproduces well the average co-movement of the cyclical inflow shift with the cyclical changes in net flows. Figure 3b shows that when comparing the fitted regression lines in the data and the model both display very similar slopes, where changing the net flow by 1% goes together with an inflow response of more than 2%.

Economy-wide cyclical outcomes In terms of the cyclical properties of the unemployment, vacancies, job finding and separation rates, Table 3 show the full set of correlations for the model and data. The model's aggregate time series arise from the distributions of employed and unemployed workers across all labor markets, combined with agents' decisions. The top panel compares the data and model using centered 5Q-MA time series of quarterly data. The cyclical components of the (log) of these time series are obtained by using an HP filter with parameter 1600. It shows that the model is able to replicate very well the volatility and persistence of the empirical time series of the unemployment, job finding and separation rates and generate a strong downward-sloping Beveridge curve.

To understand the reason why we present our benchmark results using a centered 5Q-MA on quarterly data, the bottom panel compares the data and model without using this smoothing procedure. The model now yields vacancy and job separation rates that are much less persistent than their data counterparts. This happens because in this case we have used a relative coarse grid for the simulated productivity process, as making the productivity grid finer will make the computational time of the calibration unmanageable. This implies that the discreteness of the z^s and z^r cutoffs functions (relative to the productivity grid) makes the vacancy and job separation rates change value too often. Using a centered 5Q-MA on quarterly data alleviates this feature without further compromising on computation time. Note, however, that this comes at the cost of slightly reducing the volatility of the vacancy rate (and labor market tightness) in the model from 0.07 to 0.05 (0.26 to 0.21), while in the data they remain stable. Similarly on the data side, the job finding rates, measured in a consistent way with the model while taking into account censoring in the SIPP, are also somewhat noisy at quarterly frequency. Smoothing this time-series using the 5Q-MA helps diminish this noise.

As argued in main text (and in Supplementary Appendix B.7) we consider the unemployment rate of those workers who are unemployed between jobs (EUE), so that the occupational mobility of these workers can be straightforwardly measured. The resulting EUE unemployment rate (EUE/(EUE+E)), under the definitions and restrictions we explained in the main text, is significantly lower than the BLS at 3.6% (vs 6.3%), but drives much of its changes. In particular, for every one percentage point change in the BLS unemployment rate, we find that about 0.75 percentage points originate from the response of the EUE unemployment rate. This means that the relative cyclical response of the EUE unemployment rate is much stronger than the relative response of the BLS unemployment rate. Indeed, the volatility of the HP-filtered logged quarterly EUE unemployment rate is 0.16 while the corresponding BLS unemployment measure (which includes inflows from non-participation) over the same period is 0.11. For the 5Q-MA smoothed time series, the difference is from 0.14 (EUE) to 0.10 (BLS). The above also means that the focus on EUE unemployment raises the bar further to achieve sufficient amplification. Nevertheless, Table 3 shows that our model performs well.

In the model we also can calculate a measure of unemployment that includes unemployment following first entry into the labor market. Relative to the BLS measure, this measure still excludes unemployment associated with workers who re-enter the labor market during their working life or who subsequently leave the labor force but not before spending time in unemployment. Including entrants in unemployment raises the average total unemployment rate to 5.2% in the model, exhibiting a lower

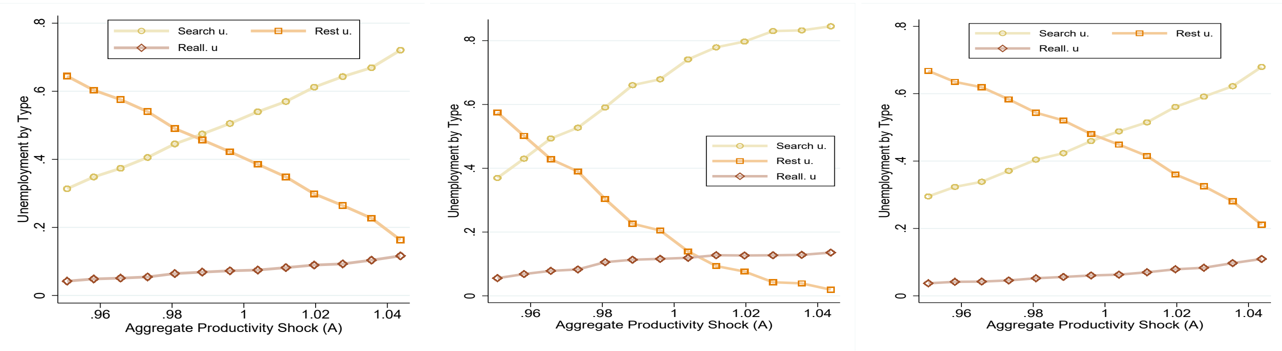
Table 3: Logged and HP-filtered Business Cycle Statistics - Full Model

Smoothed data: centred 5Q MA time series of quarterly data												
	Data (1983-2014)						**Full Model**					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.14	0.11	0.25	0.10	0.09	0.01	0.14	0.05	0.17	0.07	0.10	0.01
ρ_{t-1}	0.98	0.99	0.99	0.94	0.91	0.93	0.93	0.90	0.92	0.87	0.92	0.88
	Correlation Matrix											
u	1.00	-0.92	-0.98	0.80	-0.82	-0.47	1.00	-0.61	-0.96	0.79	-0.88	-0.94
v		1.00	0.98	-0.76	0.76	0.56		1.00	0.77	-0.74	0.85	0.76
θ			1.00	-0.80	0.81	0.51			1.00	-0.83	0.95	0.96
s				1.00	-0.75	-0.39				1.00	-0.85	-0.90
f					1.00	0.27					1.00	0.93
$outpw$						1.00						1.00
Un-smoothed data												
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.16	0.11	0.26	0.16	0.19	0.01	0.16	0.07	0.21	0.12	0.12	0.01
ρ_{t-1}	0.85	0.96	0.94	0.58	0.42	0.75	0.86	0.47	0.82	0.34	0.72	0.76
	Correlation Matrix											
u	1.00	-0.83	-0.97	0.63	-0.58	-0.38	1.00	-0.46	-0.95	0.50	-0.78	-0.87
v		1.00	0.94	-0.71	0.57	0.45		1.00	0.72	-0.61	0.76	0.69
θ			1.00	-0.69	0.61	0.42			1.00	-0.612	0.88	0.93
s				1.00	-0.53	-0.26				1.00	-0.73	-0.76
f					1.00	0.16					1.00	0.88
$outpw$						1.00						1.00

volatility of 0.12 (5Q-MA smoothed). The latter arises as with this unemployment measure, roughly 60% of the way from the the EUE to BLS unemployment measures, its volatility gets closer to that of the BLS measure. Cross-correlation and autocorrelation statistics of this alternative unemployment measure are very similar to the EUE unemployment measure.

The ability of the model to replicate the cyclical behavior of many labor market variables is down to the coexistence of episodes of search, rest and reallocation unemployment during workers' jobless spells. Figure 4 shows that when aggregating across all occupations the distribution of these types of unemployment episodes across values of A is very similar to the one generated by the excess mobility model as depicted in Figure 8c in the main text. That is, search unemployment episodes are the most common when the economy moves from mild recessions up to strong expansions. It is only as recessions get stronger that rest unemployment episodes become more common.

The middle and right panels of Figure 4 shows that among young and prime-aged workers the calibration generates similar search and rest unemployment dynamics over the business cycle. This yields high and similar cyclical volatilities for the unemployment, job finding and separation rates across age groups. In particular, the u volatilities for the young and the prime-aged are 0.139 and 0.141, the volatilities of f for young and prime-aged workers are 0.099 and 0.096; and the volatilities of s are 0.059 for young workers and 0.063 for prime-aged workers. We return to this point in the next section when presenting the calibration details of the excess mobility model.



(a) All workers (b) Young workers (c) Prime-aged workers

Figure 4: Unemployment decomposition - Full model

C.2 Excess Mobility and Cyclical Unemployment

To show the importance of idiosyncratic occupation-worker (z) productivity shocks in allowing the full model to replicate the cyclical behavior of many labor market variables, we re-estimate the model by shutting down occupation-wide heterogeneity (level and business cycle loadings), effectively setting $p_{o,t} = 1$ at all t. In this case, a worker's productivity at time t in an occupation o is completely described by aggregate productivity A, worker-occupation match productivity z and occupation-specific human capital x. Workers do not (and do not want to) prefer a new occupation over another before knowing their z. Note that although we label it as the "excess mobility model", it can easily be made consistent with the observed average net flows by imposing an exogenous transition matrix that governs the probabilities with which a worker in occupation o observes a z in a different occupation o'.[3] This is in contrast to our full model, where occupational productivities $p_o, p_{o'}$ differ and change relative to one another over the cycle and in response workers change the direction of their cross-occupation search. As such the full model can be considered as the "endogenous net mobility" model, while the excess mobility model as the "exogenous net mobility" model.

C.2.1 Benchmark Excess Mobility Model

This version of the model corresponds to the excess mobility model in the main text. Except for occupation-wide productivity differences and a cross-occupation search decisions, everything else remains as described in Section 3 of the main text. We use the same functional forms as done to calibrate the full model in Section 4 of the main text. This implies that to capture economic choices and gross mobility outcomes, we now have a set of 14 parameters to recover, where $[c, \rho_z, \sigma_z, \underline{z}_{norm}]$ governs occupational mobility due to idiosyncratic reasons (excess mobility); $[x^2, x^3, \gamma_d, \delta_L, \delta_H]$ governs differences in occupational human capital; and the remainder parameters $[k, b, \eta, \rho_A, \sigma_A]$ are shared with standard DMP calibrations. We jointly calibrate these parameters by matching the moments reported in Table 4 and Figure 5.

The excess mobility model matches very well the targeted occupational mobility moments as well as the job finding and job separation moments. The fit is comparable with the one of the full model. In particular, the excess mobility model replicates well the aggregate mobility-duration profile and

[3] With a cyclically varying exogenous transition matrix, we would also be able to match the observed cyclical net flows.

Table 4: Targeted Moments. Excess Mobility Calibration

Moments	Model	Data
Aggregate Productivity		
outpw	1.005	1.000
ρ_{outpw}	0.760	0.753
σ_{outpw}	0.0094	0.0094
Aggregate Matching Function		
$\hat{\eta}$	0.506	0.500
Unemployment Rate		
u	0.0355	0.0355
U. Survival all workers		
2 months	0.763	0.758
4 months	0.472	0.457
8 months	0.221	0.208
12 months	0.120	0.120
16 months	0.071	0.076
20 months	0.045	0.048
Occ. Mobility-Duration Profile All		
1 month	0.523	0.531
2 months	0.548	0.546
4 months	0.579	0.577
8 months	0.612	0.600
10 months	0.621	0.615
12 months	0.627	0.633

Moments	Model	Data
U Survival w. Age		
Young 2 months	0.713	0.697
Young 4 months	0.387	0.381
Young 8 months	0.146	0.156
Young 12 months	0.069	0.073
Young 16 months	0.037	0.038
Young 20 months	0.020	0.020
Prime 2 months	0.783	0.777
Prime 4 months	0.506	0.485
Prime 8 months	0.251	0.234
Prime 12 months	0.142	0.137
Prime 16 months	0.086	0.090
Prime 20 months	0.055	0.061
Occ. Mobility-Duration Profile w. Age		
Young 2 months	0.613	0.608
Young 4 months	0.646	0.613
Young 8 months	0.685	0.669
Young 10 months	0.695	0.679
Young 12 months	0.706	0.725
Prime 2 months	0.520	0.513
Prime 4 months	0.553	0.556
Prime 8 months	0.591	0.568
Prime 10 months	0.599	0.577
Prime 12 months	0.606	0.565

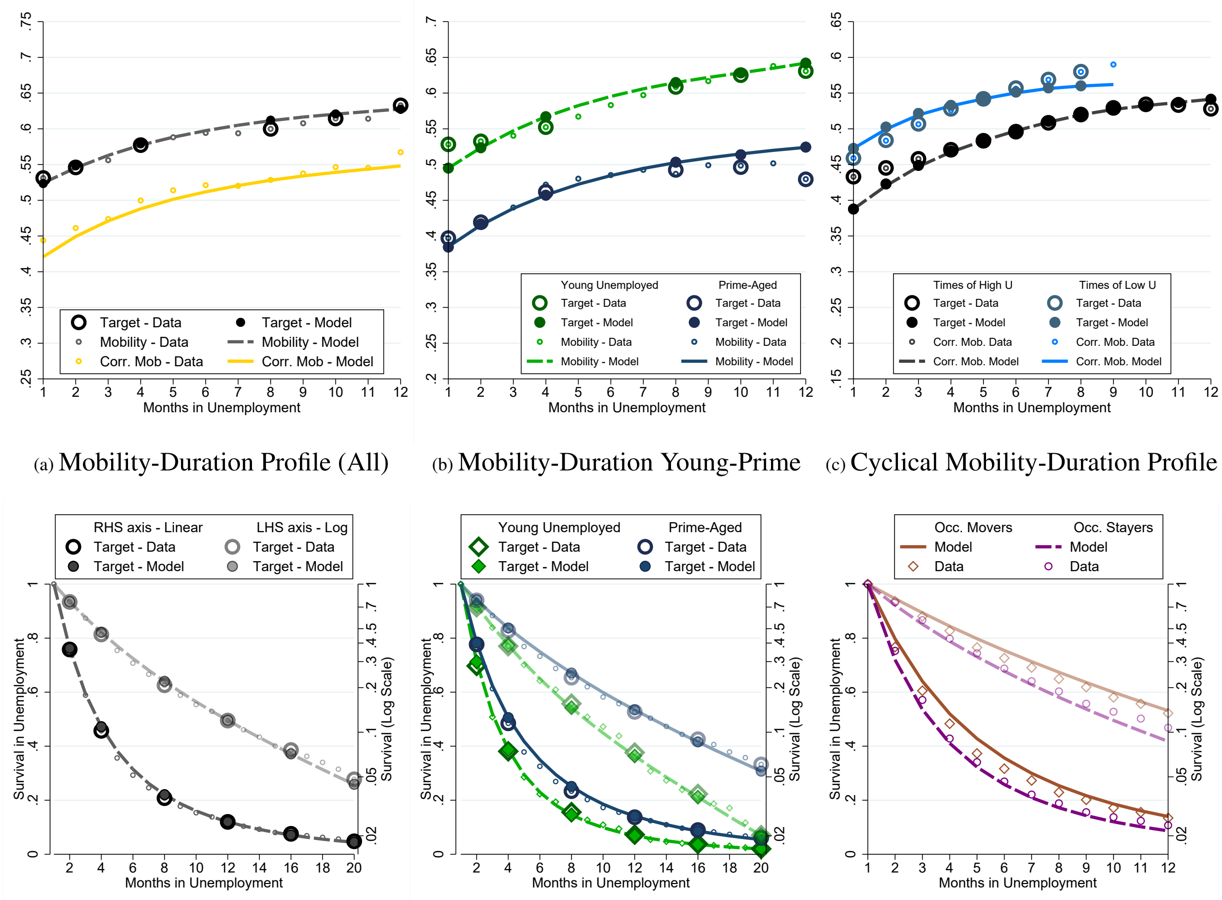
Moments	Model	Data
Returns to Human Capital		
5 years (OLS)	0.150	0.154
10 years (OLS)	0.230	0.232
Empirical Separation moments		
rel. sep rate young/prime	2.146	2.004
prob (u within 3yrs for empl.)	0.148	0.124
rel sep rate recent hire/all	5.221	4.945
Cyclical Mobility-Duration Profile Shift		
Times Low U. - 1 month	0.473	0.459
Times Low U. - 2 months	0.503	0.484
Times Low U. - 3 months	0.522	0.507
Times Low U. - 4 months	0.533	0.528
Times Low U. - 5 months	0.542	0.542
Times Low U. - 6 months	0.551	0.557
Times Low U. - 7 months	0.557	0.569
Times Low U. - 8 months	0.560	0.580
Times High U. -1 month	0.388	0.433
Times High U. -2 months	0.423	0.445
Times High U. -3 months	0.449	0.458
Times High U. -4 months	0.469	0.471
Times High U. -5 months	0.484	0.483
Times High U. -6 months	0.497	0.496
Times High U. -7 months	0.511	0.509
Times High U. -8 months	0.520	0.520
Times High U. -9 months	0.529	0.531
Times High U. -10 months	0.532	0.536
Times High U. -11 months	0.537	0.535
Times High U. -12 months	0.541	0.528

the mobility-duration profiles of young and prime-aged workers. Figure 5c shows also a good fit with respect to the aggregate mobility-duration profile in expansions and recessions. Similarly, the model is able to replicate well the aggregate unemployment survival function and the survival functions of young and prime-aged workers.

This model also matches well the untargeted moments pertaining to workers' gross occupational mobility and job finding hazards discussed in the previous section. For example, Table 1 shows that the excess mobility model is able to reproduce the observed unemployment duration distribution for all workers and by age groups. The fit of other untargeted moments is not shown here to save space, but available upon request. The estimated parameter values in this calibration are also very similar to the ones obtained in the full model. These are $c = 7.549$, $k = 125.733$, $b = 0.843$, $\eta = 0.241$, $\delta_L = 0.0034$, $\delta_H = 0.0004$, $\underline{z}_{corr} = 0.349$, $\rho_A = 0.998$, $\sigma_A = 0.00198$, $\rho_z = 0.998$, $\sigma_z = 0.00707$, $x^2 = 1.181$, $x^3 = 1.474$ and $\gamma_h = 0.0039$.

The first key insight from this exercise is that to match the targeted gross occupational mobility, job finding and job separation moments one does not need endogenous net mobility. Instead this calibration highlights that worker-occupation idiosyncratic productivity shocks and human capital accumulation on their own can fit all of the above patterns.

As shown in the main text, the excess mobility calibration is also able to fit a wide range of cyclical features of the labor market. The left panel of Table 6 (below) shows the time series properties of the unemployment, vacancy, job finding and job separation rates and of labor market tightness as well as



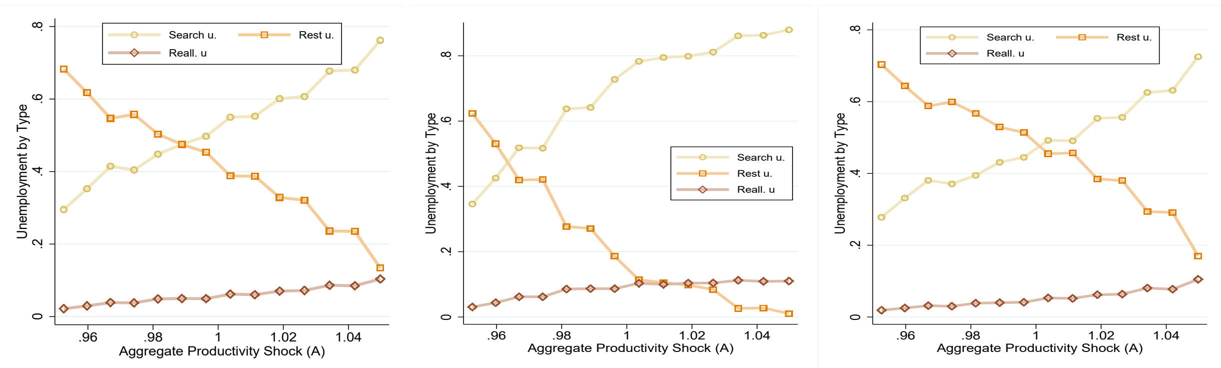
(a) Mobility-Duration Profile (All) (b) Mobility-Duration Young-Prime (c) Cyclical Mobility-Duration Profile

(d) Survival Profile (All) (e) Survival Profile Young-Prime (f) Survival Profile Movers-Stayers

Figure 5: Targeted Moments. Data and Model Comparison

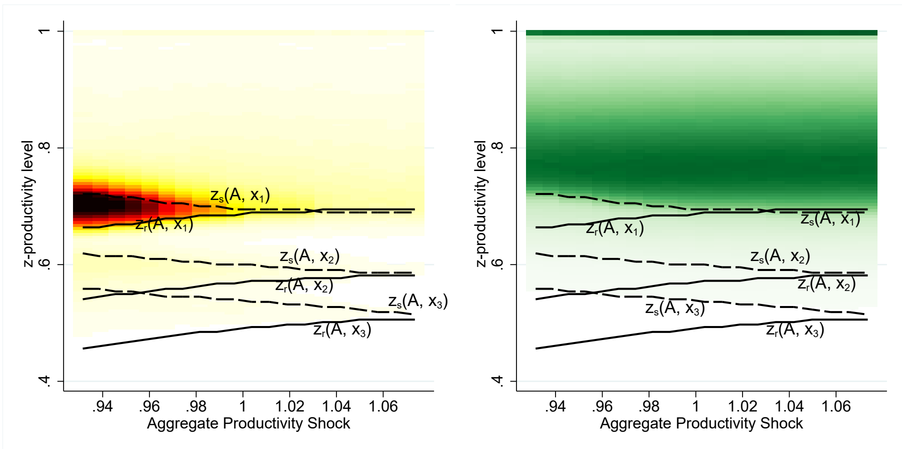
the full set of correlations between them, obtained from the excess mobility calibration. Here we find that the cyclical implications of the excess mobility model are very similar to that of the full model. These results highlight the second key insight from this exercise: endogenous net mobility does not play an important role in making the model replicate the aforementioned cyclical labor market features. As shown in the main text (Table 5) the same conclusion holds when evaluating the role of endogenous net mobility in making the model replicate the cyclical behaviour of the unemployment duration distribution.

The main reason why the excess mobility model is able to replicate all these cyclical features is because the importance of search, rest and reallocation unemployment episodes during a jobless spell is driven by the interaction between the aggregate shock and the worker-occupation match z-productivity. The difference between the z^s and z^r cutoffs creates an area of inaction that widens during recessions "trapping" workers for a longer time in rest unemployment episodes and thus lengthening their unemployment spells. As the economy recovers the difference between these cutoffs narrows and the area of inaction shrinks allowing workers to escape by crossing both the z^s and z^r cutoffs. These features then yield the procyclicality of gross (and excess) occupational mobility and the countercyclicality of job separations. Hence, the decomposition in Figure 6a looks very similar to Figure 4a for the full model.

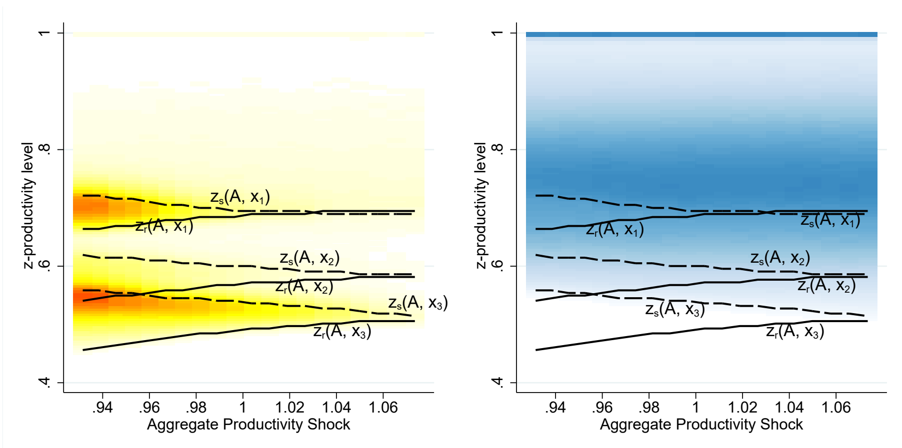


(a) All workers (b) Young workers (c) Prime-aged workers

Figure 6: Unemployment decomposition - Excess mobility model



(a) Young unemp. distribution (b) Young emp. distribution



(c) Prime-aged unemp. distribution (d) Prime-aged emp. distribution

Figure 7: Unemployment decomposition and aggregate productivity by age groups

Age patterns Figure 6 shows that the above dynamics not only happen when pooling all workers together but for each age group, as in the full model. Figure 7 shows these age group dynamics more clearly by depicting the distribution of unemployed and employed workers among young and prime-aged workers. It shows that during recessions unemployment among young workers is concentrated both slightly above $z^s(., x^1)$ and between $z^s(., x^1)$ and $z^r(., x^1)$. During expansions, however, unemployment is located above the $z^s(.,x^1)$ cutoff. In the case of prime-aged workers, the concentration of unemployment during recessions and expansions occurs mostly above $z^s(.,x^3)$ and between $z^s(.,x^3)$ and $z^r(.,x^3)$, but also between the $z^s(.,x^1)$ and $z^r(.,x^1)$ cutoffs. This difference implies that during expansion episodes of rest unemployment are still prevalent among prime-aged workers, while for young workers these episodes basically disappear (as shown in Figure 6) and are consistent with a lower occupational mobility rate among prime-aged workers.

As in the full model, the excess mobility calibration obtains a similar cyclicality for the unemployment, job finding and separations rates across age-groups. In both models this occurs because the estimated z-productivity process places enough workers on the z^s cutoffs across the respective human capital levels. Figure 7 shows that, as is the case for low human capital workers, many high human capital workers enjoy high z-productivities, but for a number of them their z-productivities have drifted down, positioning themselves close to $z^s(.,x^3)$. Some of these high human capital workers will subsequently leave the occupation, but over time the stock of workers close to $z^s(.,x^3)$ will be replenished by those workers who currently have high z-productivities but will suffer bad z-realizations in near future. As $z^s(.,x^3) < z^s(.,x^1)$ we observe that the average level of separations is lower for high human capital workers, but this nevertheless does not preclude the similarity in the aforementioned cyclical responsiveness.

Given that it is clear the excess mobility model is able to replicate on its own many critical features of the full model, in what follows we use it to perform two key exercises. The first one highlights the effect of human capital depreciation in attenuating the cyclical properties of the above labor market variables and motivates our use of the cyclical shift of the mobility-duration profile as a target. The second exercise investigates the quantitative implications of our model when considering that a worker's varying job finding prospects (due to the stochastic nature of the z-productivity process) during a jobless spell can be linked to observed transitions between the states of unemployment and non-participation (or marginally attached to the labor force) as defined in the SIPP. For this exercise we recompute all of the relevant empirical targets using non-employment spells that contain a mix of periods of unemployment and non-participation. We refer to this last exercises in the Conclusions of the main text.

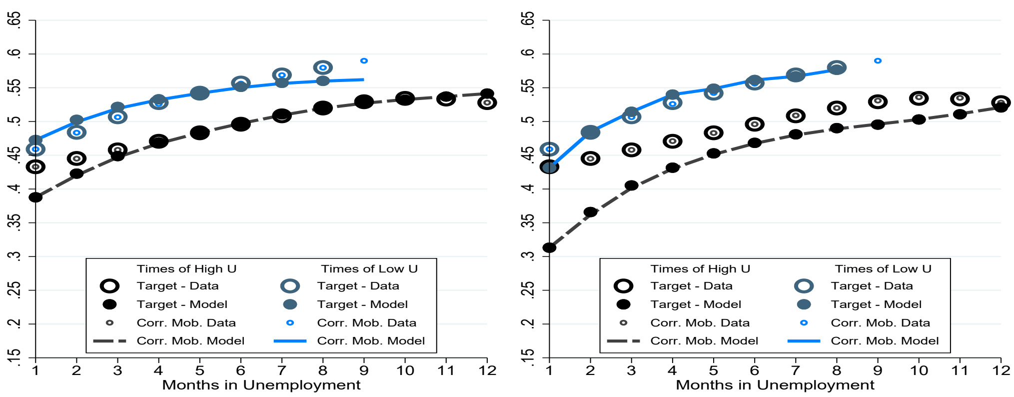
C.2.2 The Importance of Human Capital Depreciation

To estimate the full and the excess mobility models we used the mobility-duration profiles at different durations during recessions and expansions. These patterns informed us about the rate of occupational human capital depreciation during spells of unemployment. In the main text, we argued that these profiles were crucial in helping us identify the depreciation parameter, γ_h. The reason for the latter is that a model which did not incorporate human capital depreciation will generate very similar long-run moments as a model which did incorporate depreciation, but generate different cyclical predictions. To show this, we now present the estimation results from the excess mobility model without human capital depreciation. We target the same *long-run* moments as in the calibration described above, but do not target the cyclical behaviour of the mobility-duration profile.

Table 5: Targeted Moments. No Occupational Human Capital Depreciation

Moments	Model	Data	Moments	Model	Data	Moments	Model	Data
Aggregate Productivity			**U Survival w. Age**			**Returns to Human Capital**		
outpw	1.001	1.000	Young 2 months	0.721	0.697	5 years (OLS)	0.148	0.154
ρ_{outpw}	0.776	0.753	Young 4 months	0.406	0.381	10 years (OLS)	0.246	0.232
σ_{outpw}	0.0093	0.0094	Young 8 months	0.161	0.156			
Aggregate Matching Function			Young 12 months	0.075	0.073	**Empirical Separation moments**		
$\hat{\eta}$	0.503	0.500	Young 16 months	0.039	0.038	rel. sep rate young/prime	1.944	2.004
Unemployment Rate			Young 20 months	0.021	0.020	prob (u within 3yrs for empl.)	0.141	0.124
u	0.0358	0.0355				rel sep rate recent hire/all	6.311	4.945
U. Survival all workers			Prime 2 months	0.749	0.777			
2 months	0.744	0.758	Prime 4 months	0.480	0.485			
4 months	0.460	0.457	Prime 8 months	0.246	0.234			
8 months	0.223	0.208	Prime 12 months	0.143	0.137			
12 months	0.124	0.120	Prime 16 months	0.089	0.090			
16 months	0.075	0.076	Prime 20 months	0.057	0.061			
20 months	0.048	0.048						
Occ. Mobility-Duration Profile All			**Occ. Mobility-Duration Profile Young**			**Occ. Mobility-Duration Profile Prime**		
1 month	0.481	0.532	Young 2 months	0.581	0.608	Prime 2 months	0.496	0.513
2 months	0.520	0.546	Young 4 months	0.632	0.613	Prime 4 months	0.542	0.556
4 months	0.567	0.576	Young 8 months	0.688	0.669	Prime 8 months	0.584	0.568
8 months	0.612	0.605	Young 10 months	0.696	0.679	Prime 10 months	0.594	0.577
10 months	0.619	0.622	Young 12 months	0.709	0.725	Prime 12 months	0.599	0.565
12 months	0.627	0.639						

Table 5 shows that the fit of the model is very good, similar to the models which incorporates human capital depreciation. Although not shown here, it also does well in matching the same untargeted long-run moments described above. The estimated parameter values are also similar with $c = 9.853$, $k = 152.073$, $b = 0.820$, $\eta = 0.181$, $\delta_L = 0.0025$, $\delta_H = 0.0008$, $z_{corr} = 0.407$, $\rho_A = 0.997$, $\sigma_A = 0.0019$, $\rho_z = 0.999$, $\sigma_z = 0.0053$, $x^2 = 1.158$ and $x^3 = 1.491$. Further, this calibration finds that periods of search, rest and reallocation unemployment can arise during a worker's jobless spell across all levels of occupational human capital; i.e $z^s > z^r$ for all A and x.



(a) Model with HC Dep.

(b) Model without HC Dep.

Figure 8: Cyclical Mobility-Duration Profile

Figure 8 shows the first key difference between the excess mobility model with and without occupational human capital depreciation. We plot the mobility-duration profile in times of expansions and recessions (low and high unemployment, respectively), where Figure 8a shows the mobility-duration profiles from the model with human capital depreciation and Figure 8b shows the ones for the model

Table 6: Logged and HP-filtered Business Cycle Statistics

	Excess Mobility Model with HC dep.						Excess Mobility Model with No HC dep.					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.14	0.05	0.18	0.07	0.10	0.01	0.20	0.06	0.25	0.10	0.14	0.01
ρ_{t-1}	0.95	0.89	0.94	0.88	0.93	0.94	0.94	0.87	0.94	0.88	0.94	0.94
	Correlation Matrix						**Correlation Matrix**					
u	1.00	-0.63	-0.97	0.78	-0.88	-0.94	1.00	-0.62	-0.97	0.78	-0.89	-0.92
v		1.00	0.80	-0.68	0.85	0.77		1.00	0.76	-0.61	0.77	0.72
θ			1.00	-0.81	0.95	0.96			1.00	-0.78	0.94	0.93
s				1.00	-0.82	-0.87				1.00	-0.81	-0.84
f					1.00	0.93					1.00	0.89
$outpw$						1.00						1.00

Note: Each model's aggregate time series arise from the distributions of employed and unemployed workers across all labor markets, combined with agents' decisions. Times series are centered 5Q-MA series of quarterly data to smooth out the discreteness in the relatively flat cutoffs (relative to the grid). The cyclical components of the (log) of these time series are obtained by using an HP filter with parameter 1600.

without human capital depreciation. The latter finds that the lack of human capital depreciation does not allow the model to match the mobility-duration profile at low durations during expansions and completely misses the profile at all durations during recessions. Is precisely this lack of fit that motivated us to add the cyclical patterns of the mobility-duration profile as targets in order to help identify the rate of human capital depreciation.

Table 6 shows the second key difference. The model without depreciation generates a larger amount of cyclical volatility in the aggregate unemployment, job finding and job separation rates in relation to the model with human capital depreciation. Relative to the data, Table 3 shows an overshooting in the volatilities of the unemployment and job finding rates. To understand why this is the case and why it misses on the cyclical shift of the mobility-duration profile, Figure 9 presents the distribution of search, rest and reallocation unemployment episodes for each level of A. This figure shows that the calibration without occupational human capital depreciation also has the property that rest unemployment is the more prevalent episode during recessions while search unemployment is the more prevalent during expansions among all workers and by age groups.

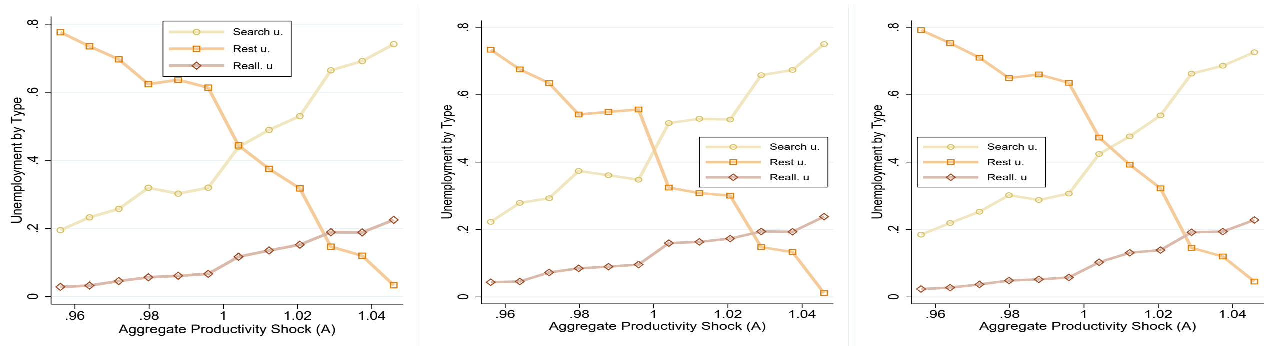


Figure 9: Unemployment decomposition - No occupational human capital depreciation

This mechanism, however, becomes more powerful when we do not include human capital depreciation. Figure 9 shows this through a sharper drop in the proportion of rest unemployment and a sharper rise in the proportions of search and reallocation unemployment as the economy improves.

Human capital depreciation attenuates these effects. In particular, job separations become somewhat less countercyclical because now workers take into account that if they decide to separate they will face the prospect of human capital loss and hence lower job finding rates. At the same time rest unemployed workers with human capital levels x^2 and x^3 now face a lower expected opportunity cost of mobility (even if their z would improve, a depreciation shock might trigger a reallocation anyway), leading to a lower proportion of rest unemployment episodes for all A and crucially to a significantly less procyclical job finding and unemployment rates.

C.2.3 The Unemployed and Marginally Attached

In the previous calibrations we built the analysis based on the interpretation that, although a worker who is currently in a rest unemployment episode cannot find a job, he would want to search for jobs (as opposed to stay idle at home) because he still faces a positive expected job finding probability in the near future. Episodes of rest unemployment, however, could conceptually be extended to incorporate marginally attached workers. To investigate the latter we expand our analysis to capture more broadly the occupational mobility decisions of the unemployed and marginally attached in shaping the cyclicality of aggregate unemployment.

We do this by re-estimating the excess mobility model, recomputing the targets using non-employment spells in which workers transition between unemployment and non-participations as labelled in the SIPP. In particular, we consider non-employment spells with at least one period of unemployment, which we label 'NUN' spells. To avoid maternity and related issues in non-participation we restrict the focus to men. We show that when considering non-participation periods the model still reproduces the observed cyclical amplification in the non-employment rate of those unemployed and marginally attached workers.[4]

Table 7 shows the targets and the fit of this estimation. As documented in more detail in Supplementary Appendix B, the mobility-duration profile including NUN spells does not differ much from the profile of only the unemployed. The survival probability in NUN spells, however, shifts up significantly at longer durations, compared to the corresponding patterns for unemployment spells, both for all workers and across age groups. For example, pooling the entire sample, around 10% of NUN spells last 20 months or more (relative to less than 5% for unemployment spells). Even for young workers around 8% of NUN spells last more 20 months or more (relative to about 2% for unemployment spells). Including the marginally attached also implies a higher jobless rate. Nevertheless, the model can capture these features well, as it does for the other moments, including the cyclical shift of the mobility-duration profile.

The estimated parameter values are also broadly similar to the ones in the previous versions of the excess mobility model, changing in expected directions. In this case we obtain that $c = 10.822$, $k = 3.161$, $b = 0.804$, $\eta = 0.524$, $\delta_L = 0.0046$, $\delta_H = 0.0015$, $\underline{z}_{corr} = 0.428$, $\rho_A = 0.998$, $\sigma_A = 0.0020$, $\rho_z = 0.997$, $\sigma_z = 0.0134$, $x^2 = 1.146$, $x^3 = 1.712$ and $\gamma_d = 0.0084$. Note that the z-productivity process is now somewhat more volatile, but the higher reallocation cost implies that

[4] Here we also focus on spells of at least one month and workers who say that they are "without a job", mirroring these sample restrictions for unemployment spells.

Table 7: Targeted Moments. NUN spells

Moments	Model	Data	Moments	Model	Data	Moments	Model	Data
Aggregate Productivity			**U Survival w. Age**			**Returns to Human Capital**		
outpw	1.005	1.000	Young 2 months	0.783	0.797	5 years (OLS)	0.156	0.154
ρ_{outpw}	0.781	0.753	Young 4 months	0.527	0.515	10 years (OLS)	0.257	0.232
σ_{outpw}	0.0093	0.0094	Young 8 months	0.273	0.290			
Aggregate Matching Function			Young 12 months	0.159	0.172	**Empirical Separation moments**		
$\hat{\eta}$	0.503	0.500	Young 16 months	0.097	0.116	rel. sep rate young/prime	2.263	2.004
NUN nonemployment Rate			Young 20 months	0.062	0.080	prob (u within 3yrs for empl.)	0.161	0.124
NUN/(NUN+E)	0.053	0.052				rel sep rate recent hire/all	4.848	4.945
U. Survival all workers			Prime 2 months	0.832	0.853			
2 months	0.818	0.836	Prime 4 months	0.608	0.586	**Cyclical Mobility-Duration Profile Shift**		
4 months	0.585	0.570	Prime 8 months	0.357	0.334	Times Low U. - 1 month	0.464	0.454
8 months	0.334	0.326	Prime 12 months	0.227	0.216	Times Low U. - 2 months	0.484	0.474
12 months	0.208	0.213	Prime 16 months	0.150	0.157	Times Low U. - 3 months	0.497	0.493
16 months	0.135	0.153	Prime 20 months	0.103	0.115	Times Low U. - 4 months	0.509	0.522
20 months	0.092	0.117				Times Low U. - 5 months	0.521	0.545
						Times Low U. - 6 months	0.531	0.557
Occ. Mobility-Duration Profile All			**Occ. Mobility-Duration Profile w. Age**			Times Low U. - 7 months	0.545	0.546
1 month	0.522	0.537	Young 2 months	0.593	0.593	Times Low U. - 8 months	0.552	0.544
2 months	0.543	0.551	Young 4 months	0.618	0.615			
4 months	0.572	0.590	Young 8 months	0.652	0.658	Times High U. -1 month	0.416	0.441
8 months	0.613	0.623	Young 10 months	0.665	0.678	Times High U. -2 months	0.445	0.458
10 months	0.629	0.650	Young 12 months	0.675	0.719	Times High U. -3 months	0.466	0.477
12 months	0.640	0.677				Times High U. -4 months	0.486	0.508
			Prime 2 months	0.522	0.520	Times High U. -5 months	0.504	0.512
			Prime 4 months	0.553	0.570	Times High U. -6 months	0.517	0.531
			Prime 8 months	0.595	0.590	Times High U. -7 months	0.532	0.536
			Prime 10 months	0.613	0.613	Times High U. -8 months	0.544	0.555
			Prime 12 months	0.625	0.619	Times High U. -9 months	0.556	0.578
						Times High U. -10 months	0.564	0.608
						Times High U. -11 months	0.572	0.605
						Times High U. -12 months	0.582	0.639

the area of inaction between the separation and reallocation cutoffs is (in relative terms) also larger. The latter leaves more scope for workers to get "trapped" for longer periods in rest unemployment episodes, thus creating an increase in the survival functions across all, young and prime-aged workers as observed in the data. Further, although k is estimated to have a much smaller value, the cost of posting a vacancy in this version of the model is actually higher than in our benchmark calibration at 0.986 of weekly output. We also estimate the elasticity of the matching function in each submarket to be about twice as big as the one in the benchmark calibration. These differences, however, do not affect our main conclusions.

Table 8 shows the main takeaway of this exercise. The model remains able to generate cyclical movements of the non-employment, job finding and job separation rates as well as a relatively strong Beveridge curve. In particular, the cyclical volatilities of the non-employment and job finding rates are the same as in the data. As in the previous estimations, here we also find that the reason for the amplification of the non-employment rate is that the model generates period of search, rest and reallocation unemployment, whose relative importance changes over the cycle. Figure 10 shows that episodes of rest unemployment are the more prevalent type during recessions while episodes of search unemployment are the more prevalent type during expansion.

Note that including marginally attached workers in our analysis increases the overall importance of rest unemployment in normal times. This is consistent with the fact that in these times the non-employment rate is higher and the associated job finding rate lower, compared to our benchmark

Table 8: Logged and HP-filtered Business Cycle Statistics

	Data (1983-2014) - NUN spells						Excess Mobility Model - NUN spells					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.09	0.11	0.19	0.09	0.07	0.01	0.09	0.04	0.11	0.05	0.08	0.01
ρ_{t-1}	0.98	0.99	0.99	0.94	0.91	0.93	0.95	0.81	0.93	0.84	0.92	0.94
	Correlation Matrix						Correlation Matrix					
u	1.00	-0.91	-0.97	0.74	-0.96	-0.40	1.00	-0.40	-0.95	0.63	-0.80	-0.87
v		1.00	0.98	-0.76	0.91	0.56		1.00	0.66	-0.37	0.61	0.53
θ			1.00	-0.77	0.95	0.48			1.00	-0.64	0.86	0.89
s				1.00	-0.84	-0.39				1.00	-0.59	-0.75
f					1.00	0.36					1.00	0.83
$outpw$						1.00						1.00

Note: Each model's aggregate time series arise from the distributions of employed and unemployed workers across all labor markets, combined with agents' decisions. Times series are centered 5Q-MA series of quarterly data to smooth out the discreteness in the relatively flat cutoffs (relative to the grid). The cyclical components of the (log) of these time series are obtained by using an HP filter with parameter 1600.

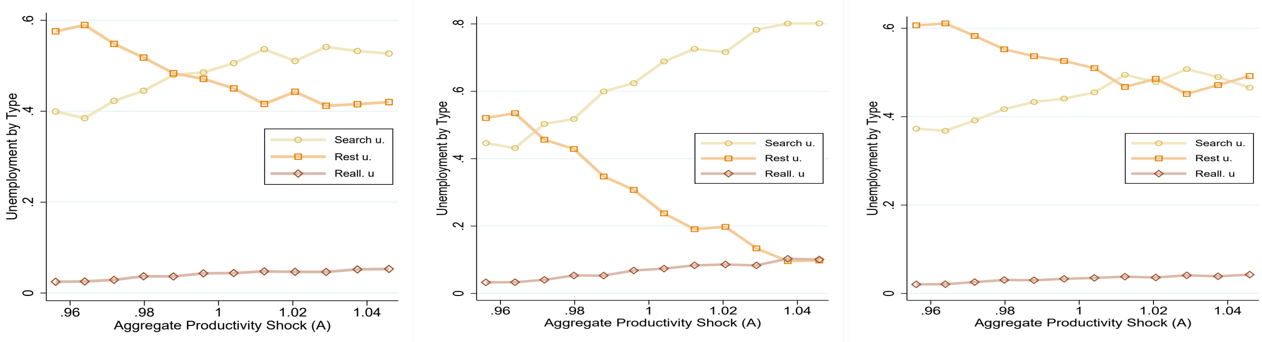


Figure 10: Unemployment decomposition - NUN spells

unemployment and job finding rates measures. Further, this version of the model still needs to accommodate short-term outflows as before and does so mostly through search unemployment episodes. As a result, the proportion of rest unemployment decreases at a slower rate with A. Even at the highest aggregate productivity levels rest unemployment is very prevalent, representing about 40% of all episodes during a non-employment spell, with a large role for prime-aged workers.

Overall we find that a version of the excess mobility model that considers NUN spells exhibits a higher non-employment rate but a lower cyclicality than in our benchmark model. This is consistent with the data, where we observe a lower cyclicality among the non-employment than among the unemployment.

C.3 The Importance of Occupational Mobility

To demonstrate that in our framework occupational mobility is key to *simultaneously* replicate the cyclical behaviour of the unemployment duration distribution and the aggregate unemployment rate, we re-estimate the model by shutting down the possibility of occupational mobility. This is done by exogenously setting c to a prohibiting level. We present two calibrations with no occupational mobility. Model I targets the same moments as in the full model with the exception of those pertaining to occupational mobility. We evaluate its fit and the implied cyclical patterns, finding that this model

Table 9: Targeted Moments. No Occupational Mobility I

Moments	Model	Data	Moments	Model	Data	Moments	Model	Data
Aggregate Productivity			**U Survival w. Age**			**Returns to Human Capital**		
outpw	1.005	1.000	Young 2 months	0.678	0.697	5 years (OLS)	0.151	0.154
ρ_{outpw}	0.787	0.753	Young 4 months	0.347	0.381	10 years (OLS)	0.240	0.232
σ_{outpw}	0.0092	0.0094	Young 8 months	0.133	0.156			
Aggregate Matching Function			Young 12 months	0.069	0.073	**Empirical Separation moments**		
$\hat{\eta}$	0.390	0.500	Young 16 months	0.041	0.038	rel. sep rate young/prime	2.125	2.004
Unemployment Rate			Young 20 months	0.026	0.020	prob u within 3yrs for emp.	0.181	0.124
u	0.0358	0.0355				rel sep rate recent hire/all	3.023	4.945
U. Survival all workers			Prime 2 months	0.758	0.777			
2 months	0.735	0.758	Prime 4 months	0.481	0.485			
4 months	0.442	0.457	Prime 8 months	0.246	0.234			
8 months	0.213	0.208	Prime 12 months	0.144	0.137			
12 months	0.123	0.120	Prime 16 months	0.089	0.090			
16 months	0.075	0.076	Prime 20 months	0.057	0.061			
20 months	0.048	0.048						

replicates well the long-tun targets but misses on the cyclical patterns of the unemployment, job finding and separation rates.[5] To gain further insights into the working of the no occupational mobility case, Model 2 is chosen to achieve a higher cyclical volatility in the aggregate unemployment rate but is more permissive of deviations from the targets.

Model I Table 9 presents all the targeted moments and shows that the fit is largely comparable along nearly all corresponding dimensions to the full and excess mobility models. The parameter estimates in this calibration remain largely sensible. In this case we obtain that $k = 195.58$, $b = 0.608$, $\eta = 0.290$, $\delta_L = 0.0092$, $\delta_H = 0.0014$, $\underline{z}_{corr} = 0.258$, $\rho_A = 0.9983$, $\sigma_A = 0.0021$, $\rho_z = 0.9923$, $\sigma_z = 0.0300$, $x^2 = 1.184$, $x^3 = 1.387$ and $\gamma_d = 0.00244$. Note, however, that we now have a higher role for search frictions as the model estimates a higher value k. Further, the z-productivity process is now less persistent and exhibits a much larger variance in the stationary distribution, generating a perhaps too large Mm ratio of 2.28.[6] Although the higher volatility of the z process may have created some difficulty in hitting the ratio of separations of recently hired workers to all workers, overall we find that the long-run moments are matched well. This is in contrast to its cyclical patterns.

Table 10 under "No Occupational Mobility - Model I" shows that a model that does not allow for occupational mobility, but reproduces well almost all the moments in Table 9 cannot generate enough cyclical volatility on all the relevant labor market variables. The unemployment, job finding and separation rates exhibit below half the volatility relative to their counterparts in the models with occupational mobility. It also generates a much weaker negative correlation between unemployment

[5]To make the estimation of Model I as comparable as possible with the previous ones, we continue targeting the returns to occupational mobility to inform the human capital levels, x^2 and x^3. Under no occupational mobility, human capital could also be interpreted as general and not occupation specific, depending on the aim of the exercise. For this exercise it would be more appropriate to target the returns to general experience. However, a comparison between the OLS returns to general experience and the OLS returns to occupational human capital estimated by Kambourov and Manovskii (2009) from the PSID (see their Table 3 comparing columns 1 and 3 or 6 and 8), suggests that this bias should be moderate. Using their estimates, the 5 year return to general experience is about 0.19, while the 10 years returns is about 0.38.

[6]In this context the z-productivity process can be interpreted as an idiosyncratic productivity shock affecting a worker's overall productivity, rather than a worker's idiosyncratic productivity within an occupation.

Table 10: Logged and HP-filtered Business Cycle Statistics

	No Occupational Mobility - Model I						No Occupational Mobility - Model II					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.04	0.02	0.06	0.03	0.03	0.01	0.10	0.03	0.12	0.08	0.05	0.01
ρ_{t-1}	0.94	0.84	0.93	0.85	0.86	0.94	0.95	0.83	0.94	0.90	0.89	0.94
	Correlation Matrix						**Correlation Matrix**					
u	1.00	-0.32	-0.92	0.72	-0.72	-0.85	1.000	-0.54	-0.98	0.84	-0.77	-0.97
v		1.000	0.67	-0.18	0.48	0.51		1.00	0.69	-0.55	0.69	0.61
θ			1.00	-0.63	0.77	0.88			1.00	-0.85	0.82	0.97
s				1.00	-0.48	-0.73				1.00	-0.84	-0.90
f					1.00	0.65					1.00	0.83
$outpw$						1.00						1.00

Note: Each model's aggregate time series arise from the distributions of employed and unemployed workers across all labor markets, combined with agents' decisions. Times series are centered 5Q-MA series of quarterly data to smooth out the discreteness in the relatively flat cutoffs (relative to the grid). The cyclical components of the (log) of these time series are obtained by using an HP filter with parameter 1600.

and vacancies.

Table 11: Incomplete Unemployment Duration Distribution Behavior

Panel A: Incomplete Unemployment Distribution (1-18 months)												
	All workers				Young workers				Prime-aged workers			
Unemp. Duration	Occ Model	No Occ. Model I	No Occ. Model II	Data	Occ. Model	No Occ. Model I	No Occ. Model II	Data	Occ. Model	No Occ. Model I	No Occ. Model II	Data
1-2 m	0.43	0.36	0.35	0.43	0.53	0.44	0.35	0.47	0.40	0.34	0.35	0.41
1-4 m	0.65	0.57	0.55	0.67	0.75	0.65	0.54	0.71	0.62	0.54	0.55	0.65
5-8 m	0.20	0.22	0.22	0.20	0.17	0.19	0.22	0.19	0.22	0.23	0.23	0.21
9-12 m	0.09	0.12	0.12	0.08	0.05	0.09	0.13	0.07	0.10	0.13	0.12	0.09
13-18m	0.06	0.09	0.10	0.05	0.03	0.07	0.11	0.03	0.07	0.10	0.10	0.06

Panel B: Cyclical Changes of the Incomplete Unemployment Distribution (1-18 months)								
	Elasticity wrt u				HP-filtered Semi-elasticity wrt u			
Unemp. Duration	Occ Model	No Occ. Model I	No Occ. Model II	Data	Occ Model	No Occ. Model I	No Occ. Model II	Data
1-2 m	-0.432	-0.323	-0.260	-0.464	-0.168	-0.108	-0.093	-0.169
1-4 m	-0.314	-0.237	-0.183	-0.363	-0.178	-0.115	-0.101	-0.186
5-8 m	0.374	0.145	0.119	0.320	0.074	0.043	0.038	0.077
9-12 m	1.083	0.408	0.295	0.864	0.061	0.040	0.037	0.072
>13 m	1.787	0.734	0.484	1.375	0.044	0.031	0.026	0.044

Moreover, Model I is not able to reproduce the observed average quarterly unemployment duration distribution at short or long durations, nor does it capture the cyclical behavior of this distribution. While Model I and the occupational mobility models replicate the same unemployment survival functions, they generate different incomplete duration distributions. This occurs because the survival functions are computed pooling the entire sample, while the distribution of incomplete spells between 1 and 18 months is calculated for each quarter and then averaged across quarters. Panel A of Table 11 shows that Model I generates about 50% more long-term unemployment (9-12 months) relative to the data. When considering durations between 13 and 18 months this discrepancy is even stronger, about 80%. At the same time, Panel B shows that the cyclical responses of the unemployment duration distribution generated by Model I are too small. It misses the semi-elasticity with respect to the unemployment rate by an average of about 40% across the entire distribution. This stands in contrast with the performance of the full occupational mobility model. Overall, Model I matches the

Table 12: Targeted Moments. No Occupational Mobility II

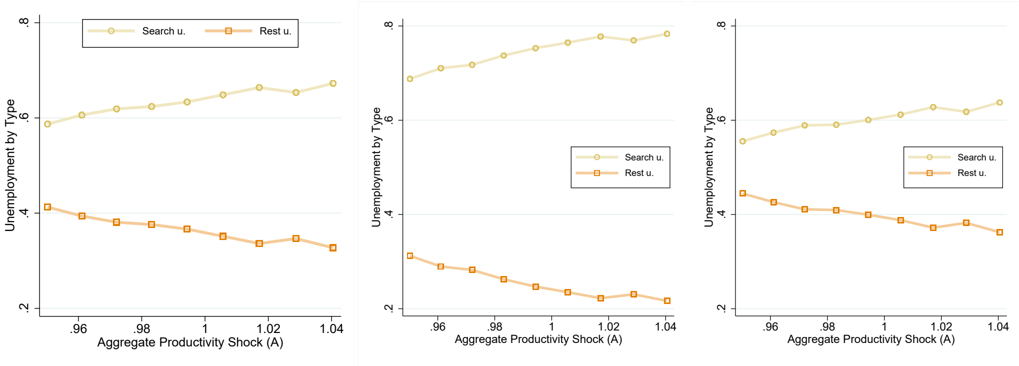
Moments	Model	Data	Moments	Model	Data	Moments	Model	Data
Aggregate Productivity			**U Survival w. Age**			**Returns to Human Capital**		
outpw	1.011	1.000	Young 2 months	0.710	0.697	5 years (OLS)	0.152	0.154
ρ_{outpw}	0.783	0.753	Young 4 months	0.421	0.381	10 years (OLS)	0.213	0.232
σ_{outpw}	0.0093	0.0094	Young 8 months	0.211	0.156			
Aggregate Matching Function			Young 12 months	0.128	0.073	**Empirical Separation moments**		
$\hat{\eta}$	0.341	0.500	Young 16 months	0.086	0.038	rel. sep rate young/prime	1.735	2.004
Unemployment Rate			Young 20 months	0.059	0.020	prob u within 3yrs for emp.	0.160	0.124
u	0.0335	0.0355				rel sep rate recent hire/all	4.167	4.945
U. Survival all workers			Prime 2 months	0.728	0.777			
agg. 2 months	0.724	0.758	Prime 4 months	0.445	0.485			
agg. 4 months	0.440	0.457	Prime 8 months	0.223	0.234			
agg. 8 months	0.220	0.208	Prime 12 months	0.132	0.137			
agg. 12 months	0.131	0.120	Prime 16 months	0.082	0.090			
agg. 16 months	0.082	0.076	Prime 20 months	0.053	0.061			
agg. 20 months	0.054	0.048						

unemployment survival functions by creating too dispersed unemployment durations within a typical period, in particular too many long spells, but its distribution then responds too little to the cycle.

Model II If one is willing to compromise on replicating the aggregate and age-group survival functions, however, the model without occupational mobility is able to generate larger cyclical volatilities. To show this we re-estimated the model by de-emphasising these survival functions. The estimated parameter values are now $k = 102.019$, $b = 0.840$, $\eta = 0.245$, $\delta_L = 0.0047$, $\delta_H = 0.0016$, $\underline{z}_{corr} = 0.201$, $\rho_A = 0.997$, $\sigma_A = 0.0018$, $\rho_z = 0.993$, $\sigma_z = 0.0132$, $x^2 = 1.272$, $x^3 = 1.302$ and $\gamma_d = 0.0043$. In this case Model II exhibits a lower degree of search frictions as it estimates a lower value of k. Further, the z process is also more persistent and its overall dispersion is now much lower than in Model I, and lower in the stationary distribution even than the occupational mobility models.

Table 12 shows that the unemployment survival functions of young and prime-aged workers are no longer well matched. In particular, Model II misses the distribution at longer durations for young workers and at shorter durations for prime-aged workers, such that age differences in job finding hazards have nearly disappeared. In contrast, we observe that the separation rate of young versus prime-aged workers is still significantly higher, though it remains below the targeted value. This version also displays a better persistence of workers' separation risk: recent hires have a 4 times higher separation rates than the average (vs. 5 in the data). The right panel of Table 8 shows that the main improvement of this version is that creates more cyclical volatility in the unemployment, job finding and separations rates as well as a stronger Beveridge curve.

Panel A of Table 11 - No Occ. Model II shows that although this model increases its cyclical performance, it still creates too much long-term unemployment (13-18 months) in the average quarter, where the proportion of long-term unemployed (among those with spells between 1-18 months) is missed by a large margin for all, young and prime-aged workers. Further, Panel B of Table 11 shows that this feature is also reflected in a muted cyclical response of the unemployment duration distribution. Here we also find that Model II misses the semi-elasticity with respect to the unemployment rate



(a) All workers (b) Young workers (c) Prime-aged workers

Figure 11: Unemployment decomposition - No occupational mobility, Model I

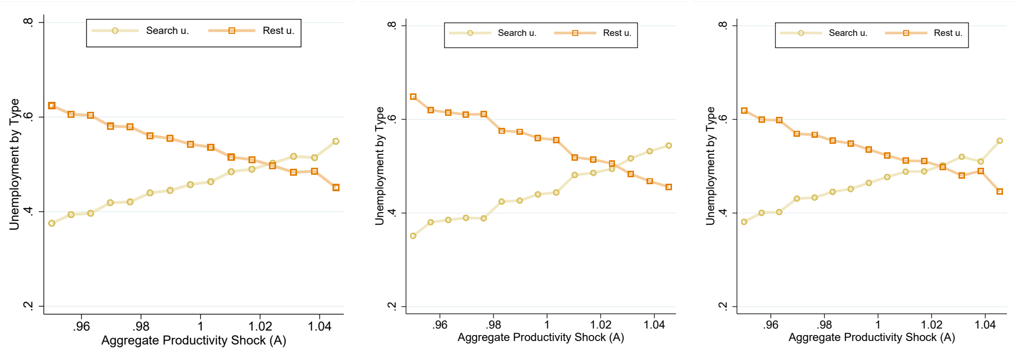
by an average of about 40% across the duration distribution.[7]

Discussion These calibrations show that without the z^r cutoff versions of our model with no occupational mobility cannot resolve the tension between individual unemployment outcomes and aggregate unemployment volatility. This arises as without the possibility of occupational mobility the new area of inaction is defined by the set of z-productivities that lie below the z^s cutoff down to the lowest value of the z-productivities. The cyclical response of this area now solely depends on $\partial z^s/\partial A$.

In the case of Model I, a less persistent and much more volatile z process creates enough heterogeneity in unemployment durations that allows it to match the empirical unemployment survival functions at the aggregate and across age groups. However, it also increases the heterogeneity in z-productivities relative to the cyclical range of A. This dampens the model's cyclical performance as it implies less responsive z^s cutoffs relative to the workers' z distribution, weakening the cyclical responses of job separations and the rate at which workers leave the area of inaction. Moreover, with a larger vacancy posting cost, Figure 11 shows that search unemployment is now more prominent than rest unemployment at any point of the cycle. Larger search frictions imply larger surpluses and therefore further reducing the cyclical responsiveness of the model.

The increased cyclical performance of Model II arises as its estimated z process becomes more persistent and less volatile, creating more responsive z^s cutoffs leading to stronger cyclical responses in job separations, as well as much more episodes of rest unemployment over all values of A. Figure 12 shows that rest unemployment episodes are now more prominent than search unemployment episodes even during economic recoveries. It is only for the highest values of A that search unemployment is more prominent, but only by a relatively small margin. With more responsive z^s cutoffs, an aggregate shock can now move somewhat larger masses of workers from rest into search unemployment episodes creating more amplification. This result is in line with Chassamboulli (2013), who extends the Mortensen and Pissarides (1994) model by adding permanent productivity differences among workers and shows that this feature allows that model to increase it cyclical performance rel-

[7] In these versions of the model the behavior of spells with durations beyond 18 months might also impact the overall unemployment rate more than empirically warranted, especially as persistence can create a "first-in last-out pattern" when entering a recession in the form of very long unemployment spells for those who lost their job early on in the recession. We focus on the distribution of spells up to 18 months because censoring issues in the SIPP restrict how accurately we can investigate the behavior of very long spells over the cycle.



(a) All workers (b) Young workers (c) Prime-aged workers

Figure 12: Unemployment decomposition - No occupational mobility, Model II

ative to the data. However, Table 11 demonstrates that this comes at the cost of not being able to match the distribution of unemployment durations nor the dynamic behavior of this distribution over the cycle.[8] Thus, in Model II the average unemployment rate responds more to the cycle as aggregate productivity takes on a more prominent role in shaping the amount of rest unemployment, but the individual unemployment outcomes that underlie these dynamics become counterfactual.

The possibility of occupational mobility would have given workers in rest unemployment episodes another margin through which they can escape the area of inaction and get re-employed faster. As a result, the individual-level unemployment duration dependence (given an aggregate state) is not only affected by z^s but also by the distance to z^r. Further, since the z^r cutoff is at different distances from the z^s across the cycle, it creates a more cyclically sensitive area of inaction. That is, occupational mobility creates a more responsive area of inaction with respect to both worker heterogeneity and the business cycle that resolves the tensions discussed above.

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[8] An extrapolation from the above discussion appears to suggest a model with permanent heterogeneity, where all moves in and out of rest unemployment would be because of aggregate productivity changes, cannot resolve the tension between cyclical performance and fitting the unemployment duration distribution moments. In principle our estimation allows and has evaluated in its procedure parameter tuples with a near-permanent z-productivity process (i.e. a persistence approximating 1). However, such parameter tuples yield stronger deviations from the individual-level unemployment outcomes we targeted compared to Model II.