Econometrica, Vol. 91, No. 3 (May, 2023), 1119–1153

UNEMPLOYMENT AND ENDOGENOUS REALLOCATION OVER THE BUSINESS CYCLE

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This paper studies the extent to which the cyclicality of occupational mobility shapes that of aggregate unemployment and its duration distribution. 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 multisector 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 many others. Our analysis shows that occupational mobility due to workers' changing career prospects, and not occupation-wide differences, interacts with aggregate conditions to drive the fluctuations of the unemployment duration distribution, and the aggregate unemployment rate.

KEYWORDS: Unemployment, business cycle, rest, search, occupational mobility.

1. INTRODUCTION

OCCUPATIONAL MOBILITY IS AN IMPORTANT PART of unemployed workers' job finding process. On average, 44% of workers who went through a spell of unemployment in the US changed "major occupational groups" (MOGs) at reemployment.[1] These occupation movers also take longer to find a job and contribute to the cyclical changes in long-term unemployment. When in downturns, the average unemployment duration for occupation stayers increases, for occupation movers the increase is around 35% larger. 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 behavior of the unemployment duration distribution and the aggregate unemployment rate.

We propose and quantitatively assess a multisector, 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

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We would like to thank Melvyn G. Coles, Leo Kaas, David Wiczer, and many other colleagues in workshops and seminars whose comments and suggestions helped improved the paper. We also thank Rahel Felder and Junko Iwagami who provided excellent research assistance with the data analysis. The authors acknowledge financial support from the UK Economic and Social Research Council (ESRC), award reference ES/V016970/1. Ludo Visschers further acknowledges financial support from the ESRC, award reference ES/L009633/1 (MacCaLM project at the University of Edinburgh) and Fundación BBVA (Ayudas a Equipos de Investigación Científica Sars-Cov-2 y Covid-19). The usual disclaimer applies.

[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.

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 characterized by simple reservation (idiosyncratic) productivity cutoffs that respond to aggregate and occupational-wide productivities.

A key success of the framework is that it can generate a wide range of cross-sectional occupational mobility and unemployment duration patterns, as well as the observed cyclical fluctuations of aggregate unemployment, its duration distribution, and a strongly downward-sloping Beveridge curve. The cyclical responses of the model's aggregate job separation and job finding rates are also in line with the data (see Shimer (2005)). 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); and Chodorow-Reich and Wieland (2020)).

Our approach provides a novel insight. It is the interaction between workers' idiosyncratic career productivities and aggregate conditions, and not occupation-wide differences, that drive cyclical unemployment. The main mechanism is as follows. The estimation yields within each occupation a job separation cutoff that is above the reallocation cutoff. This captures that with uncertain career prospects 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 currently no jobs they could fill. The higher option value of waiting drives up (long-term) unemployment more for occupation movers than stayers and helps create the observed cyclical amplification and persistence in the aforementioned aggregate labor market variables.

The importance of idiosyncratic career productivities in the model's mechanism reflects the prominence of *excess* mobility, that is, moves that cancel each other out at the occupation level, in driving key occupation 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 idiosyncratic career shocks. The estimated process then shapes workers' incentive to wait. This waiting motive is evidenced by the observation that even after a year in unemployment about 45% of workers still regain employment in their previous occupations. As the incentive to wait changes over the cycle, the model generates procyclical excess and gross mobility, inline with the data.

A prominent literature of multisector models in the spirit of Lucas and Prescott (1974) "islands" framework typically emphasizes countercyclical net reallocation of unemployed workers across sectors as the main underlying force behind unemployment fluctuations (see Lilien (1982); Rogerson (1987)). Countercyclical unemployment can arise when in recessions more workers engage in time consuming switches from hard hit sectors to those which offer relatively higher job finding prospects. To capture the role of occupation heterogeneity, we use an imperfect directed search approach to model search across occupations over the business cycle (see also Cheremukhin, Restrepo-Echevarria, and Tutino (2020) and Wu (2020)). Nevertheless, as gross flows are an order of magnitude greater than net flows, adding this dimension does not change the importance of workers' career shocks over occupation-wide productivities in explaining labor market fluctuations or the procyclical nature of gross occupational mobility. This occurs because the option value of waiting remains important within (cyclically) declining and expanding occupations. We show that 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 occupation (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 Kambourov and Manovskii (2008) and Moscarini and Thomsson (2007) among others). There is no reason, a priori, to conclude that the mobility patterns uncovered by these studies apply to the unemployed. We use data from the Survey of Income and Programme Participation (SIPP) between 1983–2014 to document relevant patterns linking individuals' occupational mobility with their unemployment duration outcomes. We use the Panel Survey for Income Dynamics (PSID) and the Current Population Survey (CPS) to corroborate our results.

We calibrate our model using simulated method of moments. The calibration finds that the nature of unemployment changes over the cycle. Rest/wait unemployment becomes relative more prominent in recession and search unemployment in expansions. Alvarez and Shimer (2011) also study the relative importance of rest and search unemployment using a multisector model, but in an aggregate steady state. Their analysis implies that transitions between work, rest, and search are not determined. In contrast, the dynamics of workers' idiosyncratic career shocks in our framework determines the transitions between employment and the different types of unemployment. This enables the joint analysis of unemployment duration and occupational mobility, 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 multisector business cycle models as useful frameworks to investigate cyclical unemployment. Like our paper, Pilossoph (2014) finds a muted effect of net reallocation on aggregate unemployment. Chodorow-Reich and Wieland (2020) build on this work and find that net reallocation comoves with unemployment most strongly during the recession-to-recovery phase of the cycle. In these papers, gross mobility is constant or countercyclical, which is at odds with the data.[2] These papers also do not focus on the relation between individuals' unemployment duration and their occupational mobility, how this relation changes over the cycle or results in cyclical shifts of the unemployment duration distribution, where the rise of long-term unemployment is shared across occupations (see Kroft, Lange, Notowidigdo, and Katz (2016)).[3]

The rest of the paper proceeds as follows. Section 2 presents the empirical evidence motivating our paper. Section 3 presents the model and its main implications. Sections 4 and 5 provide its quantitative analysis. Section 6 concludes. All proofs, additional data and quantitative analysis, and extensive robustness exercises are relegated to the Online

[2]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 remains far from the data (see his Table 9).

[3]Closer to our analysis is Wiczer (2015). An important difference is that in our framework workers take into account the potential recovery of their idiosyncratic productivities when making job separations and reallocation decisions. This feature is crucial for the cyclical properties of our model.

Supplementary Material (Carrillo-Tudela and Visschers (2023a)) and several further Supplementary Appendices.[4]

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, the armed forces, or agricultural occupations.[5] In our main analysis, we consider workers who have been unemployed throughout their jobless spells, but show that our results hold when using mixed unemployment/out-of-labor-force spells. To minimize the effects of censoring due to the SIPP structure, we consider *EUE* spells for which re-employment occurs as from month 16 since the start of the corresponding panel and impose that workers at the moment of reemployment have at least 14 months of continuous labor market history within their panel. In Supplementary Appendix B.7, we provide further details of the data construction and analyze the implications of these restrictions.

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.[6] After dropping all observations with imputed occupations, we compare reported occupations before and after the jobless 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 task-based occupational categories (see Autor, Levy, and Murnane (2003)). In the SIPP, however, the occupation information of employer movers is collected under independent interviewing, which is known to inflate the importance of occupational mobility. We address this issue by developing a novel classification error model that corrects for coding errors in the flows between particular occupations, and thereby capture more accurately coding errors for those occupations that weigh more among the unemployed.

[4]These Supplementary Appendices can be found in Carrillo-Tudela and Visschers (2023b). To distinguish these from the Online Supplementary Material (Carrillo-Tudela and Visschers (2023a), we refer to the latter as the Online Appendix.

[5]The self-employed are not included as they might face a very different frictional environment, one were vacancies are not needed to gain employment. These differences also seem to persist over time. We find that 50% of those who transited from self-employment to unemployment in the SIPP went back to self-employment. This suggests that self-employment begets self-employment, a feature not captured in our model. On the other hand, 96% of those who transited from paid employment into unemployment returned to paid employment and are captured in our model. Not including individuals that at some point during a SIPP panel were self-employed implies dropping 11% of person-month observations from our data.

[6]Fujita and Moscarini (2017) find that the unemployed consist of "temporary laid-off workers" and "permanent separators." In the latter group are those who lost their job with no indication of recall. Similarly, Hornstein (2013) and Ahn and Hamilton (2020) consider two groups among the unemployed: those with high and those with low job finding rates. Excluding those "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" and to Hornstein's and Ahn and Hamilton's "low job finding rate" workers. In Supplementary Appendix B.4.4, we discuss this issue further.

2.1. *Correcting for Coding Errors in Occupation Mobility*

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 $i = 1, 2, \dots, O$ is coded as occupation $j = 1, 2, \dots, O$, 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 degarble $\mathbf{M}$ as $\mathbf{\Gamma^{-1}}'\mathbf{M^I}\mathbf{\Gamma^{-1}}$.

Online Appendix A describes this correction methodology formally. Supplementary Appendix A provides all the proofs and detailed discussion. There we prove that $\mathbf{\Gamma}$ can be identified and estimated 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 miscode it. In Supplementary Appendix A, we use SIPP, PSID, and CPS data to evaluate the plausibility of these assumptions, investigate the implications of the error correction model and verify that the resulting patterns hold under alternative correction methods (see also Supplementary Appendix B).

We implement our method using the change from independent to dependent interviewing that occurred between the 1985 and 1986 SIPP panels. This shows that at reemployment true occupational stayers have on average about a 20% chance of appearing as occupational movers, based on the 2000 SOC. Further, different occupations have very different propensities to be miscoded and, given a true occupation, some mistakes are much more likely than others. This matters for measuring net mobility (defined below), where we find a sizeable *relative increase* in net mobility after correction.

2.2. *Gross Occupational Mobility and Unemployment Duration*

Figure 1 presents a key empirical pattern for our analysis: the mobility-duration profile. It shows the degree of attachment workers have to their pre-separation occupation in relation to their unemployment duration. Each profile shows, for duration x, the proportion of workers who changed occupations at reemployment among all workers who had unemployment spells that lasted at least x months.

Figure 1a shows that 44.5% of workers who had at least one month in unemployment changed occupation at reemployment, while 54.6% of workers who had at least 9 months in unemployment changed occupation at reemployment. This evidence thus shows that gross occupational mobility at reemployment is *high* and *increases moderately* with unemployment duration. The moderate increase implies that a large proportion of long-term unemployed, over 40%, still return to their previous occupation at reemployment.[7] The

[7]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. Supplementary Appendices A and B.5 relate in more detail our analysis to theirs.

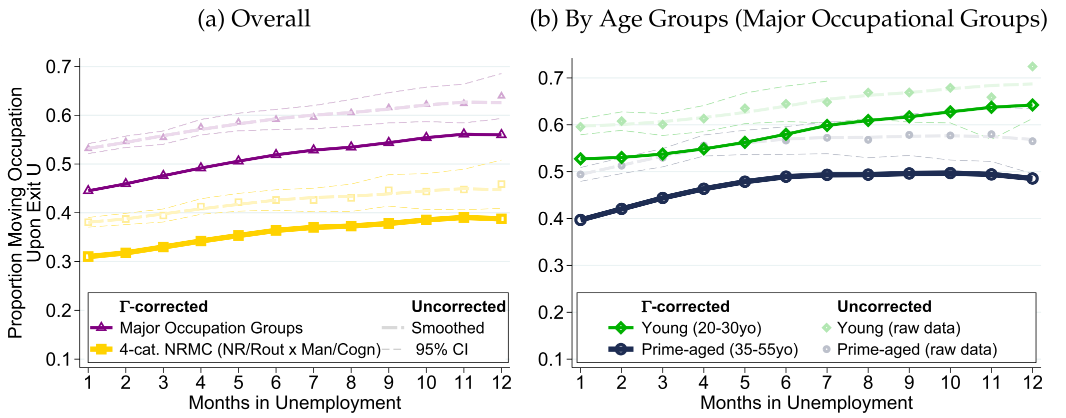

FIGURE 1.—Extent of Occupational Mobility by Unemployment Duration. **Notes:** Each mobility-duration profile shows for a given unemployment duration x, the proportion of workers who changed occupations at reemployment among all workers who had unemployment spells which lasted at least x months.

figure shows that a similar pattern arises when using the task-based occupational categories: nonroutine cognitive (*NRC*), routine cognitive (*RC*), nonroutine manual (*NRM*), and routine manual (*RM*) occupations. Supplementary Appendix B.1 shows this pattern also holds when using nonemployment spells, simultaneous industry/occupation mobility or self-reported duration of occupational tenure.

Demographics

Supplementary Appendix B.1 shows the same patterns across gender, education, and race groups. The level of gross mobility, however, decreases substantially with age, from 52.6% when young (20–30yo) to 39.7% when prime-aged (35–55yo). Figure 1b shows that the profile of prime-aged workers is below that of the young by about 9–13 percentage points but has a very similar slope. Thus, prime-aged workers display more attachment to their occupation but lose it in a similar way with duration as young workers.

Mobility by Occupation

Figure 2 shows that most occupations share high mobility rates. Occupation i gross mobility rate (height of each light-shaded bar) is defined as E_iUE_{-i}/E_iUE, where the numerator denotes the *EUE* spells of workers previously employed in i finding employment in a different occupation and the denominator captures all *EUE* spells that originate from occupation i.[8] Occupations with 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 rate of about 25%. Further, the slope of the mobility-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 (see Supplementary Appendix B.1 for details).

[8]We define our measures of gross, excess, and net occupational mobility based on *EUE* spells as the longitudinal dimension of the SIPP implies that a worker may have more than one *EUE* spell. We consider each spell separately when constructing these mobility measures.

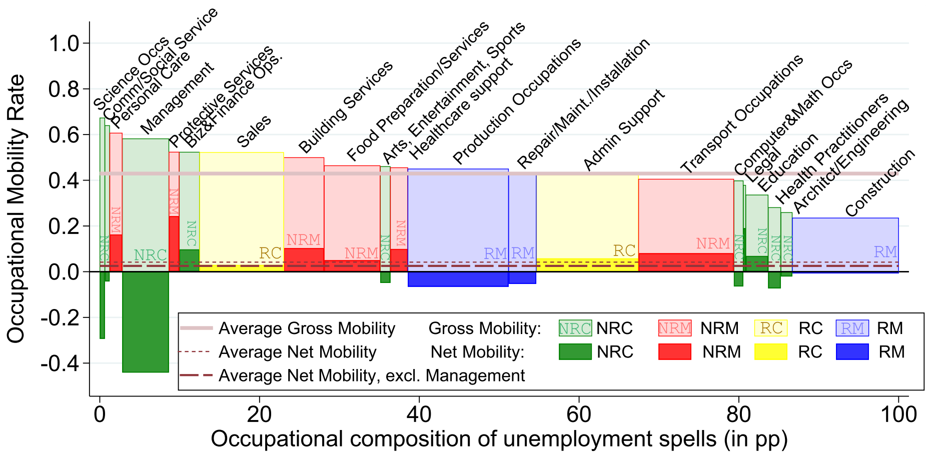

FIGURE 2.—Gross and Net Occupational Mobility per Occupation. **Notes:** *Gross mobility:* The height of each light-shaded bar measures the gross mobility. Occupations are sorted in decreasing order by their gross mobility. *Net mobility:* The height of each dark-shaded bar measures net mobility of occupation i. A positive value refers to net inflows, while a negative value to net outflows. The area of each of these bars gives the occupation-specific net flows. 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 are corrected for miscoding.

2.3. *Excess and Net Mobility*

To assess the importance of moves that result in certain occupations experiencing net inflows (outflows) through unemployment, we divide gross occupational mobility into net and excess mobility. The dark bars in Figure 2 depict the net mobility rate 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. It is evident that net flows are an order of magnitude smaller than gross flows 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 4.3% (uncorrected for miscoding, 3%).[9] Figure 2 also shows a clear directional pattern: net outflows from the *RM* occupations and net inflows into the *NRM* occupations.

Excess mobility is the most important component of occupational mobility, except for management. The average excess mobility rate $\sum \min\{E_{-i}UE_i, E_iUE_{-i}\}/EUE$ implies that 40.1% of all *EUE* spells represent excess mobility, about 90% of all gross mobility. In Supplementary Appendix B.2, we show that these results are robust to alternative occupational classifications and using nonemployment spells.

The increase of occupational mobility with duration documented in Figure 1 is also driven predominantly by excess mobility. We recompute the average net and excess mobility rates defined above on the subset of *EUE* spells of at least duration $x = 1, 2, 3, \dots, 12$. This shows that the rise of excess mobility with duration does not support the notion that long-term unemployment is primarily driven by a subset of occupations in which workers are particularly eager to leave for another set of occupations with better conditions (see Supplementary Appendix B.2).

[9]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. Kambourov and Manovskii (2008) have also highlighted the small relative importance of net mobility across occupations in pooled samples of employer movers and stayers.

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 workers who changed (did not change) occupations after an unemployment spell, will change occupation subsequently after a following unemployment spell. Here, we can also use the $\boldsymbol{\Gamma}$-correction to counteract coding errors in three-occupation histories (surrounding two unemployment spells).[10]

We find that of all those stayers who became unemployed once again, 63.4% remain in the same occupation after concluding their second unemployment spell. This percentage is higher for prime-aged workers, 65.6%, and lower for young workers, 61.7%. However, the loss of occupational attachment itself also persists. Among workers who reenter unemployment after changing occupations in the preceding unemployment spell, 54.4% move again. This is lower for prime-aged workers, 49.1%, and higher for the young, 64.5%. Supplementary Appendix B.5 shows a similar pattern in the PSID.

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 I investigates the cyclicality of occupational mobility by regressing the (log) gross mobility rate on the (log) unemployment rate. Columns (i) and (ii) relate the HP-filtered quarterly series of the $\boldsymbol{\Gamma}$-corrected and uncorrected occupational mobility rates obtained from the SIPP to HP-filtered series of the unemployment rate, with a filtering parameter of 1600. Because there are proportionally more stayers, and hence more spurious mobility in recessions, the $\boldsymbol{\Gamma}$-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 (see Supplementary Appendix B.5). We use the CPS as its quarterly mobility series does not suffer from gaps. We observe that the uncorrected SIPP and CPS series have nearly the same degree of procyclicality, suggesting that data gaps do not meaningfully affect our conclusion.[11]

Columns (iv)–(vii) present the results of regressing unfiltered occupational mobility series on the HP-filtered unemployment rate for further robustness. Again, both SIPP and CPS give a broadly similar procyclicality. The last column adds further individual-level controls and shows that these do not meaningfully change our results. The procyclicality

[10] Let the matrix $\mathbf{M}^{\mathbf{r}}$ (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 $\mathbf{M}^{\mathbf{r},\text{obs}}$ through $\mathbf{vec}(\mathbf{M}^{\mathbf{r}})' = \mathbf{vec}(\mathbf{M}^{\mathbf{r},\text{obs}})'(\boldsymbol{\Gamma} \otimes \boldsymbol{\Gamma} \otimes \boldsymbol{\Gamma})^{-1}$, where $\mathbf{vec}(\mathbf{M})$ is the vectorization of matrix $\mathbf{M}$, and $\otimes$ denotes the Kronecker product. Since $\boldsymbol{\Gamma}$ is invertible, $\boldsymbol{\Gamma} \otimes \boldsymbol{\Gamma} \otimes \boldsymbol{\Gamma}$ is also invertible. The repeat mobility statistics are then measured *within 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 modeling choices and quantitative analysis (by indirect inference).

[11] Restricting the CPS series to start after the 1994-redesign does not change our results; see Supplementary Appendix B.5. The SIPP series have data missing due to nonoverlapping 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 for interpolation, HP-filter the series, and then discard all quarters that were interpolated.

TABLE I

OCCUPATIONAL MOBILITY AND UNEMPLOYMENT DURATION OVER THE BUSINESS CYCLE.

	HP-filtered Qtrly Occ. Mobility			Unfiltered Occ Mobility			
	(i) SIPP Γ-corrected	(ii) SIPP uncorrected	(iii) CPS uncorrected	(iv) SIPP Γ-corrected	(v) SIPP uncorrected	(vi) CPS uncorrected	(vii) SIPP uncorrected
	Panel A: Mobility regression, not controlling for nonemployment duration						
HP U	−0.145	−0.088	−0.087	−0.122	−0.114	−0.077	−0.132
	(0.041)	(0.026)	(0.024)	(0.059)	(0.046)	(0.022)	(0.041)
Controls	–	–	–	T	T	T	D, T, C, S.O.
	Panel B: Mobility regression, controlling for nonemployment duration						
HP U	–	–	–	−0.171	−0.149	−0.112	−0.176
	–	–	–	(0.061)	(0.048)	(0.024)	(0.042)
Dur. coef	–	–	–	0.0126	0.0138	0.0116	0.0145
	–	–	–	(0.002)	(0.002)	(0.001)	(0.002)
Controls	–	–	–	T	T	T	D, T, C, S.O.

Note: 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 and shown in parenthesis. See Supplementary Appendix B.7 for details. CPS data described in Supplementary Appendix B.5. ***Controls***: D = demographic controls (gender, race, education, and a quartic in age); T = linear trend, C = dummies for the classification in which data was originally reported; S.O. = source occupation.

of occupational mobility is thus not the result of a compositional shift toward occupations or demographics characteristics that are associated with higher mobility during an expansion. In 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 procyclical occupational mobility using the PSID for the period 1968–1997.

Cyclicality of the Mobility-Duration Profile

Figure 3a depicts the cyclical shift of the mobility-duration profile. It plots the profile separately for those *EUE* spells that ended in times of high unemployment and those that ended in times of low unemployment. Times of high (low) unemployment are defined as periods in which the detrended (log) unemployment rate was within the bottom (top) third of the de-trended (log) unemployment distribution. Occupational mobility at any duration is lower in recessions, corroborating the procyclicality of gross occupational mobility. 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 in Table I similarly shows the vertical shift of the mobility-duration profile over the cycle and that this is robust to demographics and (origin) occupation controls.

The Cyclicality of Net Occupational Mobility

Figure 3b shows the cyclical behavior of the net mobility rate for each of the task-based categories. The net mobility rate is computed as $(E_{-i}UE_i - E_iUE_{-i})/EUE$, separately for periods of high and low unemployment.[12] Across all task-based categories the net mobil-

[12]Differently from Section 2.3, we normalize net flows in each task-based category by the total number of *EUE* spells observed in periods of either high or low unemployment. Here, we also exclude managers. Supplementary Appendix B.3 shows that this exclusion implies that *RC* occupations are now experiencing net outflows instead of net inflows as suggested by Figure 2.

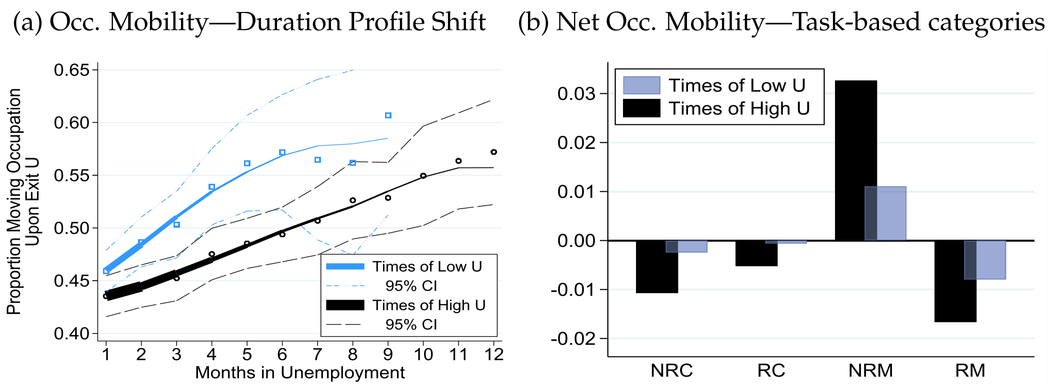

FIGURE 3.—Cyclicality of Occupational Mobility, 1985–2014. **Notes:** *Left panel:* The circular markers depict nonsmoothed data and the solid curves represent the smoothed mobility-duration profile. The thickness of the profiles indicates the amount of spells surviving at a given duration. *Right panel:* The net mobility rate for each task-based category is computed excluding managers, separately for periods of high and low unemployment. The version including managers can be found in the Supplementary Appendix B.3.

ity rate increases when unemployment is high, even though *EUE* also increases. In particular, *RM* occupations increase their net outflows in downturns relative to expansions, while *NRM* occupations increase their net inflows in downturns relative to expansions. The countercyclicality of net mobility therefore implies that the stronger procyclicality of excess mobility is the main driver of the procyclical behavior of gross mobility among unemployed workers.[13]

Comparing Unemployment Spells Between Movers and Stayers

The mobility-duration profile implies that occupational movers have on average longer spells than stayers. From an expansion to a recession, this difference grows from 0.4 to 0.9 months.[14] This increase does not result from cyclically different demographics of unemployed movers or because they are more likely to come from (move to) occupations with long unemployment durations in recessions (see Supplementary Appendix B.4). Although occupational mobility decreases in recessions, the lengthening of unemployment spells among movers is proportionally stronger. Occupational movers thus contribute meaningfully to the increase in aggregate unemployment, and especially to the increase in long-term unemployment.

3. THEORETICAL FRAMEWORK

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

[13]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.

[14]Averaging all spells in our sample, the difference is 0.7 month. This amount is economically significant, 40% of the difference between the average duration of unemployment spells in periods of high versus low unemployment.

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 $F(z_{t+1}|z_t)$.[15] Their realizations affect a worker both in employment and in unemployment and will drive excess occupational mobility. 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 unemployed. Conditional on the worker's employment status, his human capital x_t is assumed to evolve stochastically following a Markov chain with values $x_t \in \{x^1, \ldots, x^H\}$, $x^1 > 0$ 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 occupation 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 A_t. Both $p_{o,t}$ and A_t follow bounded first-order stationary Markov processes.

There is a large 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 an employed worker characterized by (z, x, o) in period t is given by the production function $y(A_t, p_{o,t}, z_t, x_t)$, which 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, unemployed, and 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 also if the worker and 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. An 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 equilibria, the value functions and decisions of workers and firms only depend on $\omega_t = \{z_t, x_t, o, A_t, p_t\}$ 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 (z, x) 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

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

costs k per period. Once an unemployed worker's z or x changes, his relevant labor market changes accordingly.[16]

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 redrawing their z-productivity. Workers rationally expect their initial career match in any occupation to be a draw from $F(.)$, the ergodic distribution associated with the Markov process $F(z_{t+1}|z_t)$. The i.i.d. nature of the redraws 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.

Differences in p_o imply that workers are not indifferent from which occupation the draw of z originates. To capture that in the data excess mobility is much larger than net mobility, and hence that workers not always specialize 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 choose how much effort to allocate to each one of these occupations to maximize the probability of 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 $\alpha(0; o) = 0$. The concavity creates a trade-off between concentrating search effort on desirable occupations and the total probability that the worker draws some z, given by $\sum_{\tilde{o}\in O^-} \alpha(s_{\tilde{o}}; o) \leq 1$. With probability $1 - \sum_{\tilde{o}\in O^-} \alpha(s_{\tilde{o}}; o)$, no z is received and 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.[17] 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.

3.2. *Agents' Decisions*

The timing of the events is summarized as follows. At the beginning of the period, the new values of A, p, z, and x are realized. The period is then subdivided into four stages: separation, reallocation, search and matching, and production. To reduce notation complexity, we leave implicit the time subscripts, denoting the following period with a prime.

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

[17]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 in the state space the histories of occupations ever visited by a worker.

Worker's Problem

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

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

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 the 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 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 (1). The term $R(\omega)$ denotes the expected net value of searching across occupations and is given by

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

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.

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

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

The second term describes the worker's option to quit into unemployment in the next period's separation stage. The job separation decision is summarized 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 submarket (z, x) in occupation o at the start of the search and matching stage. The expected value of a vacancy solves the entry equation

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

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 submarkets that yield a $\theta(\omega) > 0$, and $V(\omega) \leq 0$ for all those submarkets 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 (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

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

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 characterized by (z, x, o) such that it generates a positive surplus. Nash bargaining implies that the wage, $w(\omega)$, solves

$$(1 - \zeta)\big(W^E(\omega) - W^U(\omega)\big) = \zeta\big(J(\omega) - V(\omega)\big), \tag{6}$$

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 submarket (z, x). In our framework, this will guarantee firms post the efficient number of vacancies within submarkets and the constraint efficiency of our decentralized economy (see Supplementary Appendix C).

3.3. *Equilibrium and Characterization*

In a BRE, outcomes can be derived in two steps. Decision rules are first solved using (1)–(5). We then 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) 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 $\{M(\omega), W^U(\omega), R(\omega)\}$ from the appropriate functional space into itself, with a fixed point that implies a BRE. The key step to proof efficiency 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*.

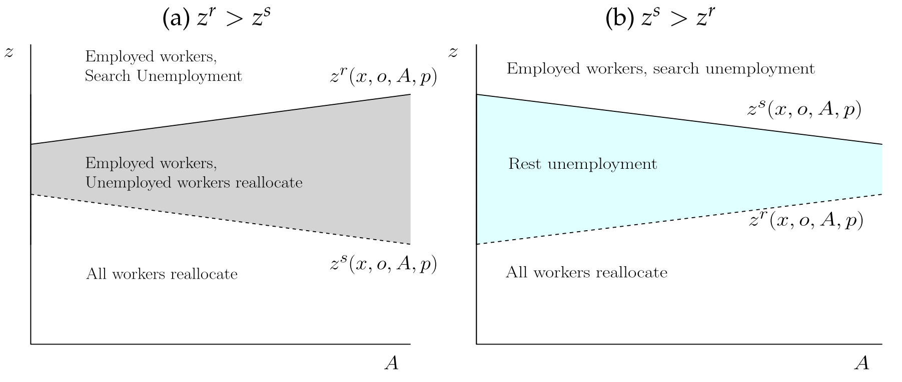

FIGURE 4.—Relative Positions of the Reservation Productivities.

Characterization

The decision to separate from a job and the decision to search across occupations can be characterized by z-productivity cutoffs, which are themselves functions of A, p, o, and x. The job separation cutoff function, $z^s(.)$ is obtained when the match surplus becomes zero, $M(\omega) - W^U(\omega) = 0$. In contrast to Mortensen and Pissarides (1994), z refers to the worker's idiosyncratic productivity in an occupation and not 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 reentering 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. This occurs if and only if $z < z^r(.)$, where the reallocation cutoff function $z^r(.)$ solves $R(\omega) = W^U(\omega)$.

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 4a 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 $z \in [z^s, z^r)$, the match surplus is enough to keep him attached to his occupation. For an unemployed worker with a 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 as in the canonical DMP model.

Figure 4b instead shows the case in which $z^s > z^r$ for all A. Workers who endogenously separate into unemployment, at least initially, do not search across occupations, while firms do not create vacancies in submarkets 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 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 across occupations. For values of $z \geq z^s$, the associated sub-markets function as in the DMP model.

An unemployed worker is 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 toward 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 4 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 $z^s > z^r$ one obtains 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 $z^s - z^r > 0$ is sufficiently large, job separations decisions mainly reflect whether or not an employed worker should wait unemployed in his current occupation for potential improvements in his z. As occupational mobility is uncertain and only a potential future outcome, it is discounted. Thus rest unemployment moderates the feedback of procyclical occupational mobility decisions on the cyclicality of job separation decisions.

4. QUANTITATIVE ANALYSIS

As the relative position and the 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.

4.1. *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 is chosen such that β matches an annual real interest rate of 4%. We target data based on major occupational groups and task-based categories as done in Section 2. Our classification error model 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 cyclical loading. 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.[18] 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, 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 the employment weighted average of $\overline{p}_o$ and of ϵ_o across $o \in O$ to one.

Worker Heterogeneity Within Occupations

The logarithm of the worker's idiosyncratic productivity, $\ln z_t$, is also modeled as an AR(1) process with persistence and dispersion parameters ρ_z and σ_z. The normalization parameter $\underline{z}_{\text{norm}}$ 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 5 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 exogenous job separation probability between low (x^1) and high human capital (x^2, x^3) workers: δ_L and δ_H. The matching function within each submarket (z, x) is given by $m(\theta) = \theta^\eta$.

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

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 and $s_{\tilde{o}} \in [0, 1]$. The parameter $\nu \in [0, 1]$ governs the responsiveness of the direction of search across occupations due 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 task-based category o has access to job opportunities in another 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 concavity 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,

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

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.[19] Note that $\overline{\alpha}_{o,\tilde{o}}$ appears inside the closed form and can freely shape *bilateral* flows between occupations. This leaves ν free to capture the responsiveness 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.[20]

Since our data analysis covers three decades, we need to distinguish the observed long-run changes in the employment-size distribution from their cyclical changes. For this, we first externally calibrate the initial size distribution to match the one observed in the

[19]To derive this result, note that for each $s_{\tilde{o};o}$ equation (2) yields the first-order condition $s_{\tilde{o}}^*(\omega) = [\frac{\nu\overline{\alpha}_{o,\tilde{o}}^{(1-\nu)}}{\mu} \int_{\underline{z}}^{\overline{z}} W^U(\tilde{z}, x_1, \tilde{o}, A, p)\,dF(\tilde{z}) - \hat{W}^U(\omega)]^{1/(1-\nu)}$, where μ 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, Visschers, and Wiczer (2022) for a detailed discussion.

[20]Many multisector 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 decision involves $\max_{o\in O}\{U_o(.) + \epsilon_o\}$, where $U_o(.)$ 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 through $\overline{\alpha}_{o,\tilde{o}}$ 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 fitting 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).

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. This size distribution then changes over time due to unemployed workers' mobility decisions. Let ψ_o denote the exogenous probability that a new entrant 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.

Simulated Method of Moments

In the above parametrization, $[c, \rho_z, \sigma_z, \underline{z}_{\text{norm}}]$ govern 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 minimizing 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.

Figures 5a–5e and Table II 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

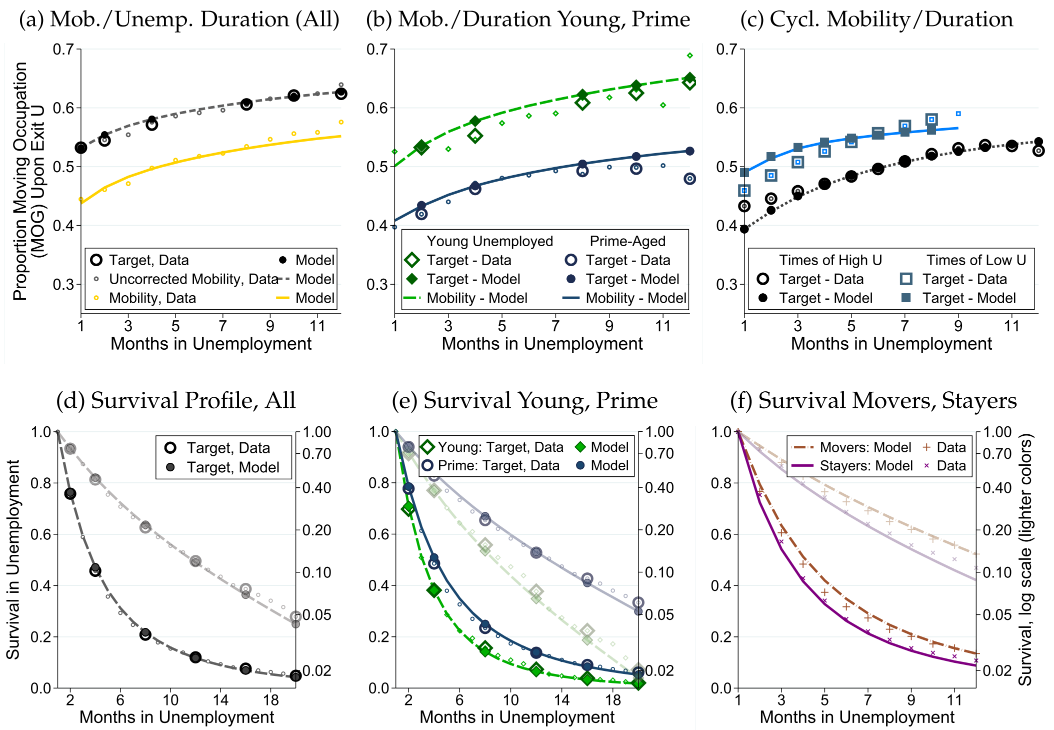

FIGURE 5.—Data and Model Comparison (including Targeted Moments).

TABLE II

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	2.002	1.994
Agg. output per worker persistence, ρ_{outpw}	0.764	0.753	Rel. separation rate recent hire/all	5.169	4.944
Agg. output per worker st. dev., σ_{outpw}	0.009	0.009	Prob (unemp. within 3 yr for empl.)	0.151	0.122
Mean unemployment	0.036	0.035	Empirical elasticity matching function	0.532	0.500
Task-based gross occ. mobility rate	0.280	0.289	5-year OLS return to occ. tenure	0.143	0.154
Repeat mobility: occ. stay after stay	0.598	0.634	10-year OLS return to occ. tenure	0.219	0.232
Occ. mobility young/prime-aged	1.173	1.163	Average u. duration movers/stayers	1.184	1.139
Occ. mobility-duration profiles	Fig. 5a, b, c		U. survival profiles	Fig. 5d, e	

Panel B: Occupation-Specific Moments, Long-run

	Proportion empl. size o_{2014}		Net mobility *Mean*		Transition Matrix							
					Model				Data			
	Model	Data	Model	Data	NRC	RC	NRM	RM	NRC	RC	NRM	RM
NRC	0.337	0.328	0.008	0.006	0.763	0.163	0.055	0.018	0.721	0.167	0.084	0.028
RC	0.246	0.258	0.007	0.000	0.175	0.681	0.108	0.036	0.078	0.680	0.168	0.074
NRM	0.260	0.260	−0.027	−0.021	0.034	0.064	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	0.246	0.647	0.013	0.066	0.188	0.733

Panel C: Occupation-Specific Moments, Cyclical

	Net mobility						$\Delta_{\text{exp}-\text{rec}}$ (inflow o/all flows)		$\varepsilon_{UD_o,u}/\varepsilon_{UD_{\text{avg}},u}$	
	Recessions		*Expansions*		*Rec-Exp*					
	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data
NRC	−0.008	−0.011	−0.009	−0.002	0.002	−0.008	−0.003	−0.010	0.988	1.096
RC	−0.009	−0.005	−0.005	−0.001	−0.003	−0.005	0.004	0.003	1.055	1.026
NRM	0.033	0.033	0.020	0.011	0.013	0.022	−0.028	−0.054	0.890	0.759
RM	−0.017	−0.017	−0.006	−0.008	−0.011	−0.009	0.026	0.060	1.072	1.119

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.[21] The net mobility patterns inform the occupation-specific productivities, occupation distribution for new entrants, and the imperfect direct search technology. 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 differences observed

[21]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, with a filtering parameter of 1600. 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.

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 5a and 5b (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. A lower ρ_z increases the relative number of unemployed workers deciding to reallocate 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 Figure 5a.

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 5b shows that the model is able to resolve this tension very well. The model also 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 (see Figure 3a, Online Appendix B.1).

The parameters x^2 and x^3 are informed by the observed 5 and 10-year returns to occupational experience. As it is difficult to accurately estimate the later with the SIPP, we use the OLS estimates for 1-digit occupations reported in Kambourov and Manovskii (2009) from the PSID and estimate the same OLS regression in simulated data.[22]

Calibrations with or without occupational human capital depreciation yield very similar long-run moments (see Online Appendix B.2). This occurs as the gradual loss of occupational attachment with unemployment duration underlying the mobility-duration profile can be generated by human capital depreciation or the z process. To differentiate these two forces, we use the cyclical shift of the mobility-duration profile. During recessions longer unemployment spells imply that expected 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 5c.

The unemployment survival function depicted in Figure 5d additionally inform 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

[22]We use the OLS estimates because occupation selection occurs both in the model and in the data, where selection arises as measured returns are a result of two opposing forces: human capital acquisition and z-productivity mean reversion.

duration 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 B.1). The model captures that duration dependence is different across 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 with duration. In addition, the model replicates the (untargeted) 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 B.1). Finally, we target the ratio between the average unemployment durations of occupational movers and stayers.

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 the standard value of 0.5 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. Larger search frictions push down the z^s cutoff relative to z^r, reducing the extent of endogenous separations.[23] Therefore, to inform k (and the relative position of z^s and z^r), we use 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 3 years 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. Although not shown here, the model is also consistent with the probability that an occupational mover remains a mover in the next unemployment spell, as documented in Section 2.4.

Given the job-finding moments, the overall job 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

[23]Intuitively, note that with $z^s < z^r$ and a persistent z-process, workers who endogenously separate will immediately change occupation (see Figure 4). 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 separated and managed to become reemployed in the same occupation 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. 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, 0.037, 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.

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 B.1 and Supplementary Appendix B.7 for details), consistent with the results of Hornstein (2013), Fujita and Moscarini (2017), and Ahn and Hamilton (2020).

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 5e inform δ_L, δ_H, and b. 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 relative to the average of these workers' productivities.

4.4. *Net Occupational Mobility*

Variation over the business cycle can naturally inform the loading parameters ϵ_o. We target the level 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, $\varepsilon_{UD_o,u}/\varepsilon_{UD_{\text{avg}},u}$ (see Online Appendix B.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*").

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, $\Delta_{\exp-\text{rec}}$ (inflow o/all flows). To recover $\overline{\alpha}_{o,\tilde{o}}$, we target the observed task-based occupation transition matrix. To recover ψ_o, we use the employment-size distribution of task-based categories observed in 2014, the end of our sample period. We target the average gross mobility rate across task-based categories so that the model remains consistent with gross mobility at this level of aggregation.

4.5. *Estimated Parameters*

Table III reports the resulting parameter values implied by the calibration. The estimated value of b represents about 80% of total average output, y. 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 all submarkets across occupations.[24]

[24]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

TABLE III

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	$\underline{z}_{\text{norm}}$	ν	
		7.604	0.9983	0.0072	0.354	0.04	
Occupation-specific	$\overline{p}_o$	ϵ_o	ψ_o	$\overline{\alpha}_{o,NRC}$	$\overline{\alpha}_{o,RC}$	$\overline{\alpha}_{o,NRM}$	$\overline{\alpha}_{o,RM}$
Nonroutine Cognitive	1.019	1.081	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
Nonroutine Manual	1.004	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

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 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.[25]

The z process has a broadly similar persistence (at a weekly basis) as the aggregate shock process. Its larger variance implies there is much more dispersion across workers' z-productivities than there is across values of A. They are also 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, Krusell, and Violante (2011) Mm ratio. These authors find an Mm between 1.46 and 1.90 using the PSID, while the estimated z-dispersion yields 1.41.

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. The value of ν also implies workers significantly

rate. It can be shown that this creates a wedge between η and $\hat{\eta} = 0.5$ that is governed by $\frac{0.5-\eta}{1-\eta}\varepsilon_{\hat{\theta},A} = \varepsilon_{u^s/u,A}$, where $\varepsilon_{\hat{\theta},A}$ and $\varepsilon_{u^s/u,A}$ denote the cyclical elasticity of aggregate labor market tightness, $\hat{\theta}$, and the proportion of search unemployment over total unemployment, u^s/u, 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.

[25]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.

adjust their direction of search as a response to cyclical differences in p_o. 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 II. Taken together, these estimates show a high degree of directedness when workers search across task-based categories.

5. CYCLICAL UNEMPLOYMENT OUTCOMES

We now evaluate the cyclicality of aggregate unemployment and its duration distribution in the model, noting that these were not targeted in the estimation procedure. Our aim is to evaluate the importance of excess and net mobility in generating these patterns. We first present the implications of the full model as estimated above. Then we discuss the implications of a reestimated version where we shut down the heterogeneity in occupation-wide productivities.[26] 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. Online Appendix B.2 presents the estimation results of this model.

Aggregate Unemployment

Table IV shows the cyclical properties of the aggregate unemployment, vacancy, job finding, job separation, and gross occupational mobility rates, computed from the data and the simulations. 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 IV also shows that the cyclical volatilities and persistence of all these rates are very close to the data.

This aggregate behavior is not driven by a higher cyclicality of young workers' unemployment rate. In Online Appendix B.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 toward high human-capital, prime-aged workers during recessions, a feature noted by Mueller (2017).

The model also generates a strongly negatively-sloped Beveridge curve. The latter stands in contrast with the canonical DMP model, where it is known that endogenous separations hamper it from achieving a Beveridge curve consistent with the data. Because all p_o comove with A and the loadings ϵ_o only create relative productivity differences, it also stands in contrasts with many multisector models that predict an upward sloping Beveridge curve. In these models, unemployment fluctuations arise from the time-consuming reallocation of workers from sectors that experienced a negative shock to the ones that experienced a positive shock and lead to more vacancies created in the latter sector (see Chodorow-Reich and Wieland (2020) for a recent exception).

Unemployment Duration Distribution

Panel A in Table V 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

[26]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.

TABLE IV

BUSINESS CYCLE STATISTICS. DATA (1983–2014) AND MODEL.

	Volatility and Persistence								Correlations With u and Output per Worker						
	u	v	θ	s	f	*outpw*	*occm*		u	v	θ	s	f	*outpw*	*occm*
				Data								**Data**			
σ	0.15	0.11	0.25	0.10	0.09	0.01	0.03	u	1.00	−0.95	−0.99	0.83	−0.86	−0.50	−0.56
ρ_{t-1}	0.98	0.99	0.99	0.94	0.93	0.92	0.94	*outpw*		0.61	0.55	−0.43	0.40	1.00	0.46
				Full Model								**Full Model**			
σ	0.14	0.04	0.17	0.07	0.09	0.01	0.04	u	1.00	−0.66	−0.97	0.79	−0.89	−0.94	−0.85
ρ_{t-1}	0.93	0.91	0.92	0.88	0.93	0.88	0.94	*outpw*		0.81	0.97	−0.91	0.94	1.00	0.85
				Excess Mobility Model								**Excess Mobility Model**			
σ	0.14	0.05	0.17	0.06	0.10	0.01	0.04	u	1.00	−0.72	−0.98	0.80	−0.89	−0.95	−0.87
ρ_{t-1}	0.95	0.91	0.94	0.89	0.94	0.94	0.93	*outpw*		0.85	0.97	−0.90	0.95	1.00	0.89

Note: All variables are obtained from the SIPP, except output per worker, obtained from the BLS, and the vacancy rate where we use the composite help-wanted index developed by Barnichon and Nekarda (2012). All times series are centered 5Q-MA series of quarterly data, smoothing out the discreteness in the relatively flat cutoffs (relative to the grid) and noisy observation of especially occupational mobility. The cyclical components of the (log) of these time series are obtained by using an HP filter with parameter 1600. See Online Appendix B.1 for more details and results without the 5Q-MA smoothing.

TABLE V

CYCLICALITY OF DURATION DISTRIBUTION

Panel A: Cyclicality of Duration Distribution						
	Elasticity wrt u			HP-filt. semi-el. wrt u		
Unemp. Duration	Full Model	Excess Model	Data	Full Model	Excess Model	Data
1–2 m	−0.451	−0.449	−0.464	−0.155	−0.169	−0.167
1–4 m	−0.321	−0.330	−0.363	−0.168	−0.184	−0.184
5–8 m	0.415	0.346	0.320	0.067	0.071	0.076
9–12 m	1.10	1.000	0.864	0.058	0.063	0.072
>13 m	1.817	1.742	1.375	0.044	0.050	0.043

Panel B: Semi-Elasticity Duration wrt u, by Occupational Mobility						
	HP-filtered			Log u linearly detrended		
	Full Model	Excess Model	Data	Full Model	Excess Model	Data
Movers	2.8	3.0	3.2	2.2	2.3	2.0
Stayers	1.3	1.5	2.5	1.2	1.2	1.7

Note: The elasticities are constructed using the cyclical components (after HP filtering or linear detrending) of the shares of unemployed workers by duration category and the aggregate unemployment rate.

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 semielasticity, 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 V 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 that of stayers, an increase that is consistent with the data. Stayers' durations respond somewhat less relative to the data, between 56% (relative to log HP-filtered unemployment) and 71% (relative to linearly detrended unemployment). 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 6 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 versus Net Mobility

A key insight from Tables IV and V is that the aforementioned cyclical patterns are nearly identical to the ones generated by the excess mobility model. Online Appendix B.2 shows that this model also fits very well the economy-wide targets described in Table II

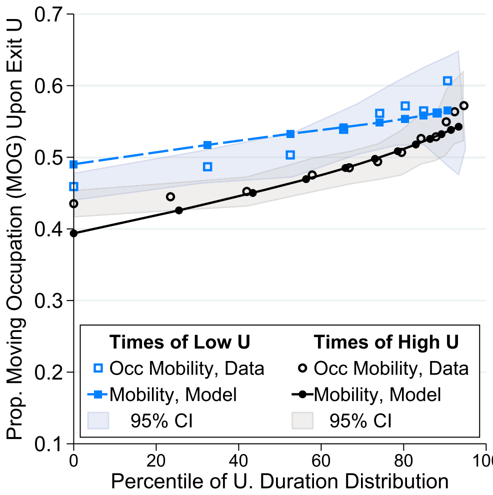

FIGURE 6.—Cyclical Shift of the U. Duration Distribution.

and the estimated values of the corresponding parameters are nearly identical to those in the full model. We further show that this conclusion holds when considering nonemployment spells. This comparison demonstrates that allowing workers to chose in which occupations to search due to difference in p_o is not the reason why the model is able to replicate the cyclicality of unemployment or its duration distribution. Instead, it highlights the importance of workers' idiosyncratic career shocks and its interaction with A.

The two versions are successful in these dimensions because they yield similar implications for search, rest, and reallocation unemployment. Section 5.1 first demonstrates this claim using the excess mobility model. This shows in more detail the importance of having a persistent z process for the cyclical performance of the model. Section 5.2 shows that the same forces occur within each o, 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 help determine the long-run and cyclical implications of our model.

Relative Position of z^s and z^r

Figure 7a depicts the cutoff functions generated by the excess mobility 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 $h = 1, 2, 3$.[27] This implies that periods of rest unemployment can occur together with periods of search and reallocation unemployment within the same unemployment spell as A and z evolve. Thus our calibration shows that

[27]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.

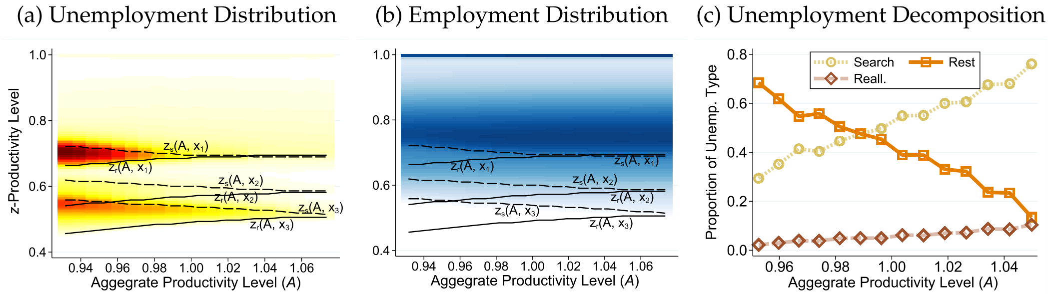

FIGURE 7.—Cutoffs, Unemployment Distribution and Decomposition.

the option value of waiting (as opposed to immediate reallocation) is important to explain the data. The importance of rest unemployment is grounded empirically in the mobility-duration profile and the unemployment survival functions.

The moderate increase of occupational mobility with unemployment duration implies that even though overall mobility is high, there is still a sizeable proportion of unemployed workers that regain employment in their pre-separation occupations after 12 months. The model rationalizes this feature with a z process that, while persistent, has still meaningful uncertainty. An occupational stayer, even after a long time unemployed, is interpreted as the realization of the worker's earlier "hope" for the recovery of his z-productivity.

The presence of rest unemployment also rationalizes the moderate duration dependence observed in our unemployment sample and the relatively stronger duration dependence among occupational stayers. To illustrate this, consider a set of workers with the same x who just endogenously separated. Given $z^s \geq z^r$ and a persistent z process, 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 reemployed, 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.

Slope of z^s and z^r

As discussed in Section 3.3, the presence of rest unemployment makes it more likely for the model to generate countercyclical job separation decisions and procyclical occupational mobility decisions. Figures 7a, b shows that in the calibration this is indeed the case, that is, $\partial z^s/\partial A < 0$ 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 7c illustrate this last feature by showing the proportion of workers facing search, rest, or reallocation unemployment for a given value of A. Although both rest and search unemployment are countercyclical, 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 position and slopes of the cutoffs reveal a cyclical area of inaction, $[z^r(A; x), z^s(A; x)]$ for each x. The cyclical change of the areas of inaction is important for it captures that workers' option value of waiting unemployed in their pre-separation occupations is higher in recessions than expansions, and is a key determinant of the cyclical performance of unemployment and vacancies in our model. The negative slope of the z^s cutoffs together with the large mass of workers right above them (see Figure 7b) imply that a decrease in A leads to a large increase in the inflow of workers into rest unemployment. 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 7a). 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 z^r or above z^s.[28] 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, reflecting the changes in the areas of inaction, imply that aggregate unemployment also becomes highly responsive to A.[29] Online Appendix B.2 shows that these patterns occur across all human capital levels, explaining why we obtain unemployment, job finding, and separation rates across age groups with similar cyclical responses.

The widening of the area of inaction during recessions also helps capture the cyclical behavior of the duration distribution. In recessions, long-term rest unemployed workers typically require a sequence of more and larger good z shocks before becoming search unemployed in their pre-separation occupation. They would typically also require a sequence of more and larger bad shocks before deciding to reallocate. 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 it is for the long-term unemployed. Hence, over the cycle we observe that the outflow rate of long-term unemployed workers responds more to changes in A 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 V, stronger than the one predicted based on the decline of f alone. The widening of the area of inaction in recessions implies that the expected time spent in rest unemployment increases for (ex post) occupations stayers as well as for (ex post) movers, but more so for the latter. 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

Online Appendix B.2 shows that human capital depreciation is important in determining these dynamics as it affects the cyclical changes in the areas of inaction. As discussed in Section 4.2, without it the model generates aggregate unemployment, job finding, and occupational mobility rates that are too volatile. This occurs as a potential loss of x during unemployment decreases the option value of waiting in the occupation and flattens the z^r cutoff. It also flattens the z^s cutoff as it increases the option value of staying employed.

[28]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 A.

[29]Episodes of reallocation unemployment 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 occupation.

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 process. To show this, we reestimate the model not allowing workers to change occupations. Online Appendix B.3 shows that this version of our model appears unable to reconcile the observe cyclical fluctuations of the unemployment duration distribution with those of the aggregate unemployment rate. This occurs as it cannot resolve a key trade-off. In the absence of the z^r cutoff, the estimated z process is less persistent and exhibits a larger standard deviation, which creates enough heterogeneity in unemployment durations to allow it to match the empirical unemployment survival functions. However, this z process also increases the heterogeneity of z relative to the cyclical range of A. This makes the z^s cutoffs less responsive and weakens the cyclical responses of job separations and the rate at which workers leave the new area of inaction, $[\underline{z}, z^s(A; x)]$, where $\underline{z}$ denotes the lowest value of z.

5.2. *Occupation Heterogeneity and Cyclical Unemployment*

The same mechanism described above also holds within each task-based category but its 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 VI 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 (column 3–column 1). 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 VI 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. 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 8 illustrates the mechanism. Figure 8a 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 8b, 8c, 8e, 8f 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

TABLE VI

ROLE UNEMPLOYMENT IN THE CHANGING SIZE OF OCCUPATIONS.

Task-Based	Distributions			Model Decomposition of Distribution Change			
	Initial	End Distribution		Entrants	Endogenous Occ. Mob in Unemployment		
Occupational Categories	Distribution	Data	Model	All Qtrs	All Qtrs	Qtrs $u < u^{\text{median}}$	Qtrs $u \geq u^{\text{median}}$
Nonroutine Cognitive	0.224	0.329	0.337	0.125	−0.011	−0.006	−0.005
Routine Cognitive	0.292	0.258	0.246	−0.012	−0.034	−0.012	−0.023
Nonroutine Manual	0.226	0.260	0.260	−0.054	0.088	0.031	0.057
Routine Manual	0.258	0.154	0.157	−0.062	−0.039	−0.009	−0.030

Note: Columns 1 to 3 show the initial and end distributions of workers across tasked-based occupations. Column 4 shows the contribution of the exogenous entry process in changing the initial distribution, while column 5 shows the contribution of unemployed workers switching occupations. The sum of columns 4 and 5 is equal to the difference of columns 3 and 1. The last two columns show the contributions of occupation switchers in times when cyclical unemployment is above or below its median.

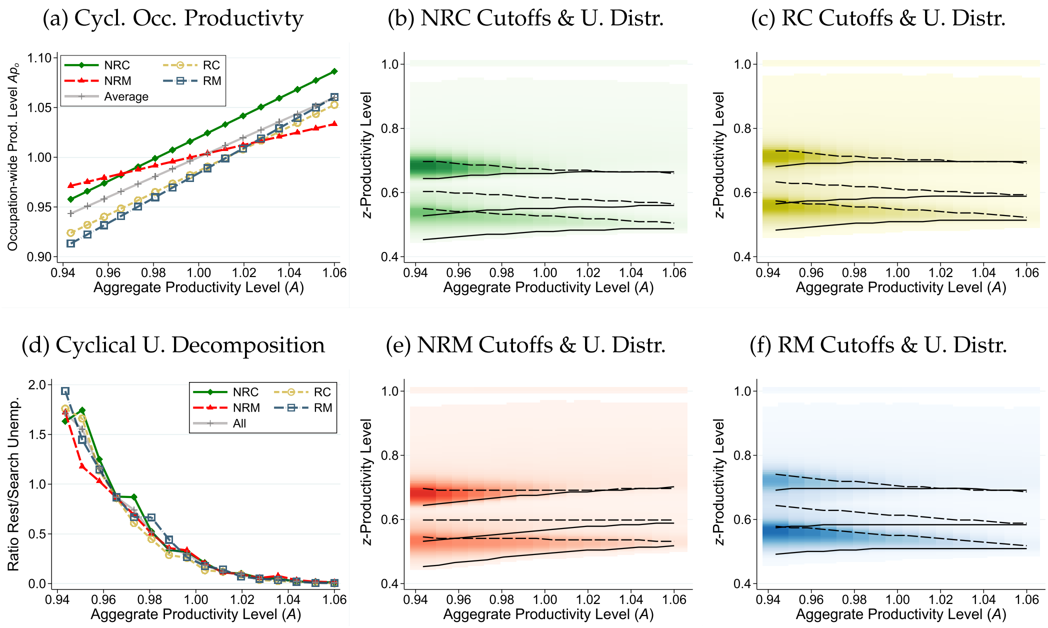

FIGURE 8.—Heterogeneity across Occupations over the Business Cycle.

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 8d 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 p_o 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 II shows that the model is also able to reproduce the shift in the inflow distribution toward *RM* and away from *NRM* occupations that occurs in recessions.

6. CONCLUSIONS

We have argued that workers' option value of remaining attached to their careers (occupations) while unemployed is relatively larger in recessions than in expansions. The cyclical variation in this option value creates more wait/rest unemployment episodes than search unemployment episodes in recessions, and it can jointly explain many features of cyclical unemployment, its duration distribution, and occupational mobility. While idiosyncratic uncertainty regarding a worker's career is the main force shaping this option value, the latter is also affected by occupation-wide differences that create net mobility across occupations. We find no tension between the cyclical behavior of individual unemployment outcomes, procyclical gross occupational mobility, and countercyclical net mobility through unemployment, where *EUE* transitions play a meaningful role in shaping the changing size of *RM*, *RC*, and *NRM* occupations. The potential responsiveness of this option value (or its relative importance in job search, separation, and reallocation decisions) to policy opens the door for normative investigations.

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Co-editor Guido Imbens handled this manuscript.

Manuscript received 12 May, 2014; final version accepted 5 February, 2023; available online 13 February, 2023.