Online Appendix

A Correcting for Occupational Coding Errors

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

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

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

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

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

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

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

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

Let $\mathbf{M_m}$ denote the matrix that contains the *true* occupational transition *flows* of employer/activity changers in this population. The diagonal of $\mathbf{M_m}$ describes the distribution of true occupational stayers across occupations among employer/activity changers.

The off-diagonal elements contain the flows of all true occupational movers. Under independent interviewing $\mathbf{M^I_m} = \mathbf{\Gamma}'\mathbf{M_m}\mathbf{\Gamma}$. Once again $\mathbf{M_m}$ is pre-multiplied by $\mathbf{\Gamma}'$ and post-multiplied by $\mathbf{\Gamma}$ as the observed occupations of origin and destination would be subject to coding error.

Letting $\mathbf{M^I} = \mathbf{M^I_m} + \mathbf{M^I_s}$ denote the matrix that contains the aggregate occupational transition flows across two interview dates under independent interviewing, it follows that $\mathbf{M^I_s} = \mathbf{M^I} - \mathbf{M^I_m} = \mathbf{\Gamma}'\mathbf{M_s}\mathbf{\Gamma}$. By virtue of the symmetry of $\mathbf{M_s}$ and assumption *A2*, $\mathbf{M_s}\mathbf{\Gamma} = \mathbf{\Gamma}'\mathbf{M_s}' = \mathbf{\Gamma}'\mathbf{M_s}$. Substituting back yields $\mathbf{M^I_s} = \mathbf{M_s}\mathbf{\Gamma}\mathbf{\Gamma}$. Next note that $\mathbf{M^I_s} = \mathbf{M_s}\mathbf{T^I_s}$, where $\mathbf{T^I_s}$ is the occupational transition probability matrix of the employer/activity stayers in this population *observed* under independent interviewing. Substitution yields $\mathbf{M_s}\mathbf{T^I_s} = \mathbf{M_s}\mathbf{\Gamma}\mathbf{\Gamma}$. Multiply both sides by $\mathbf{M_s^{-1}}$, which exists as long as all the diagonal elements of $\mathbf{M_s}$ are non-zero, yields the key relationship we exploit to estimate $\mathbf{\Gamma}$,

$$\mathbf{T^I_s} = \mathbf{\Gamma}\mathbf{\Gamma}. \tag{1}$$

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

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

In general one cannot guarantee the uniqueness, or even existence, of a transition matrix that is the (nth) root of another transition matrix. Here, however, existence is obtained by construction: $\mathbf{T_s}$ is constructed from $\mathbf{\Gamma}$, and in reverse, we can find its roots. The next result shows that $\mathbf{T_s}$ has a unique root satisfying assumptions *A2* and *A3*.

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

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

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

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

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

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

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

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

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

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

The intuition behind this result is that by comparing aggregate occupational transition flows under dependent and independent interviewing, it is unclear how many workers are 'responsible' for the change in occupational mobility between $\mathbf{M^D}$ and $\mathbf{M^I}$. Only when the diagonal of $\mathbf{M_m}$ contains exclusively zeros, identification could be resolved and one can recover $\mathbf{M_s}$, $\mathbf{\Gamma}$ and $\mathbf{M_m}$ as the number of equations equals the number of unknowns.[1]

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

An implication of the above corollary is that interrupted time-series analysis that is based on the difference in occupational mobility at the time of a switch from independent to dependent interviewing, does not identify the precise extent of the average coding error, but provides a downwards biased estimate.

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

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

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

B Quantitative Analysis

This Appendix is divided into three parts that complement Sections 4 and 5 of the paper. The first part provides further details of the full model calibration done in Section 4. The second part presents the calibration results from the "excess mobility model", where we analyse its ability to reproduce the long-run and cyclical patterns of several labor market variables.

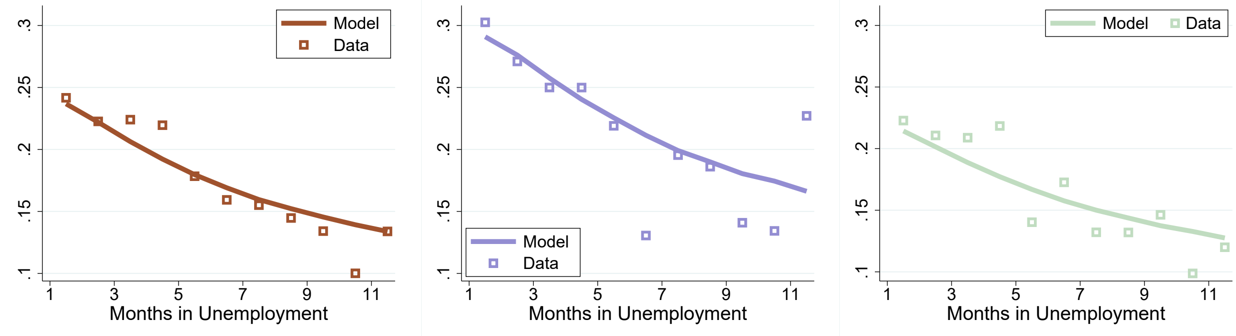
B.1 Full Model: Gross and Net Mobility

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

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

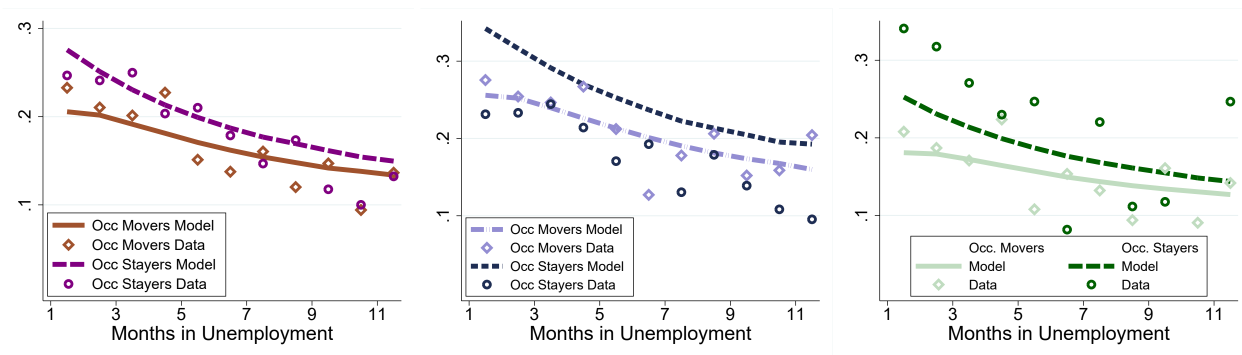
Unemployment duration moments Figure 1 shows the aggregate and age-specific unemployment hazard functions, comparing the model to the data. The observed duration dependence patterns are captured very well, where the young exhibit stronger negative duration duration dependence than the prime-aged. In our sample (and in the calibration) the degree of duration dependence in the unemployment hazard is relatively weak as we have tried to minimise the presence of unemployed workers who were in temporary layoff and/or returned to their previous employers (see Supplementary Appendix B.4 for a further discussion of this issue).

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



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

Figure 1: Hazard Functions. Data and Model Comparison



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

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

The unemployment duration distribution is also well matched. Table 1 shows it reproduces very well both the proportion of short and long durations spells across the distribution. This fit is achieved when pooling together all workers and when separating them between young and prime-aged workers. Crucially, the fit of the duration distribution is not implied by targeting the empirical unemployment survival functions. The reported duration distribution is constructed by averaging duration distributions across quarters, while the survival functions are derived from pooling all observations. For example, the observed long-term unemployment in the pooled survival functions occur mainly in recessions and these observations get down-weighted when averaging across quarters (instead of counting each observation equally). Indeed, we show below that matching the survival functions does not imply also matching the duration distribution.

Supplementary Appendix B (Figures 9 and 10) shows that both excess and net mobility increase with unemployment duration and that the former is the main driver of the

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

	All workers			Young workers			Prime-aged workers		
Unemp. Duration	Full Model	Excess Model	Data	Full Model	Excess Model	Data	Full Model	Excess Model	Data
1-2 m	0.43	0.42	0.43	0.53	0.52	0.47	0.41	0.39	0.41
1-4 m	0.65	0.64	0.67	0.76	0.75	0.71	0.63	0.61	0.65
5-8 m	0.20	0.21	0.20	0.16	0.17	0.19	0.21	0.22	0.21
9-12 m	0.09	0.09	0.08	0.05	0.05	0.07	0.10	0.10	0.09
13-18m	0.06	0.06	0.05	0.03	0.03	0.03	0.07	0.07	0.06

Table 2: Task-based Unemployment Duration Elasticities

	NRC	RC	NRM	RM
$\varepsilon^{Data}_{UD_o,u}$	0.410	0.384	0.284	0.418
(s.e.)	(0.068)	(0.050)	(0.045)	(0.053)
$\varepsilon^{Model}_{UD_o,u}$	*0.390*	*0.413*	*0.342*	*0.423*
$\varepsilon^{Data}_{UD_o,u}/\varepsilon^{Data}_{UD_{avg},u}$ (targeted)	1.096	1.026	0.759	1.119
(s.e.)	(0.183)	(0.132)	(0.119)	(0.141)
$\varepsilon^{Model}_{UD_o,u}/\varepsilon^{Model}_{UD_{avg},u}$	*0.988*	*1.055*	*0.890*	*1.072*

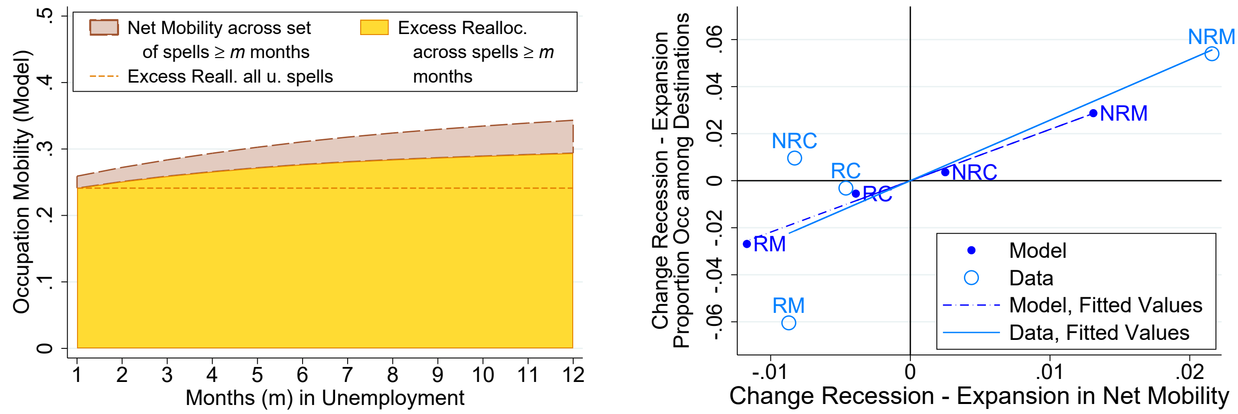
overall increase in the mobility-duration profile. Figure 3a (below) depicts the model's equivalent decomposition using task-based categories and without considering the "management" occupation. In the model both excess and net mobility increase with unemployment duration. Given the countercyclicality of net mobility, the latter occurs as net mobility is more prominent in recessions where workers' unemployment durations are typically longer. As in the data, excess mobility is the main driver of the mobility-duration profile.

Task-based occupational categories over the cycle The cyclical productivity loadings ϵ_o are the only four cyclical parameters that explicitly differ across task-based categories $o \in \{NRC, RC, NRM, RM\}$. Together with the elasticity of the cross-occupation search, ν, these parameters shape the differential cyclical response of each category o along three dimensions, summarised by 12 moments in the main text. (i) The cyclical response of net mobility for each task-based category, (ii) the cyclical change in the proportion of occupational movers that choose an occupation category o, and (iii) the strength of each category's unemployment durations response relative to the economy-wide average response to the aggregate unemployment rate.

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

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

As Figure 3b and Table 2 show, the model captures well the co-movement along di-



(a) Decomposition of the mobility-duration profile

(b) Cyclical Shifts across Occupation Categories in Net-flows vs Inflows

Figure 3: Task-Based Occupational Mobility

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

Economy-wide cyclical outcomes In terms of the cyclical properties of the unemployment, vacancies, job finding and separation rates, Table 3 show the full set of correlations for the model and data. The model's aggregate time series arise from the distributions of employed and unemployed workers across all labor markets, combined with agents' decisions. The top panel compares the data and model using centered 5Q-MA time series of quarterly data. The cyclical components of the (log) of these time series are obtained by using an HP filter with parameter 1600. It shows that the model matches the data very well. The bottom panel compares the data and model without using this smoothing procedure. The version now yields vacancy and job separation rates that are much less persistent than their data counterparts. This happens because we have used a relative coarse grid for the simulated productivity process, as making the productivity grid finer will make the computational time of the calibration unmanageable. This implies that the discreteness of the z^s and z^r cutoffs functions (relative to the productivity grid) makes the vacancy and job separation rates change value too often. Using a centered 5Q-MA on

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

Smoothed data: centred 5Q MA time series of quarterly data												
	Data (1983-2014)						**Full Model**					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.15	0.11	0.25	0.10	0.09	0.01	0.14	0.04	0.17	0.07	0.09	0.01
ρ_{t-1}	0.98	0.99	0.99	0.94	0.93	0.92	0.93	0.91	0.92	0.88	0.93	0.88
	Correlation Matrix											
u	1.00	-0.95	-0.99	0.83	-0.86	-0.50	1.00	-0.66	-0.97	0.79	-0.89	-0.94
v		1.00	0.98	-0.79	0.81	0.61		1.00	0.80	-0.83	0.90	0.81
θ			1.00	-0.82	0.85	0.55			1.00	-0.84	0.96	0.97
s				1.00	-0.71	-0.43				1.00	-0.87	-0.91
f					1.00	0.40					1.00	0.94
$outpw$						1.00						1.00
Un-smoothed data												
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.16	0.11	0.26	0.12	0.13	0.01	0.16	0.07	0.20	0.11	0.12	0.01
ρ_{t-1}	0.85	0.96	0.94	0.58	0.33	0.75	0.88	0.54	0.83	0.39	0.78	0.76
	Correlation Matrix											
u	1.00	-0.86	-0.98	0.69	-0.65	-0.38	1.00	-0.54	-0.96	0.52	-0.80	-0.89
v		1.00	0.95	-0.75	0.59	0.50		1.00	0.75	-0.74	0.85	0.78
θ			1.00	-0.74	0.65	0.44			1.00	-0.65	0.90	0.95
s				1.00	-0.57	-0.32				1.00	-0.79	-0.79
f					1.00	0.26					1.00	0.91
$outpw$						1.00						1.00

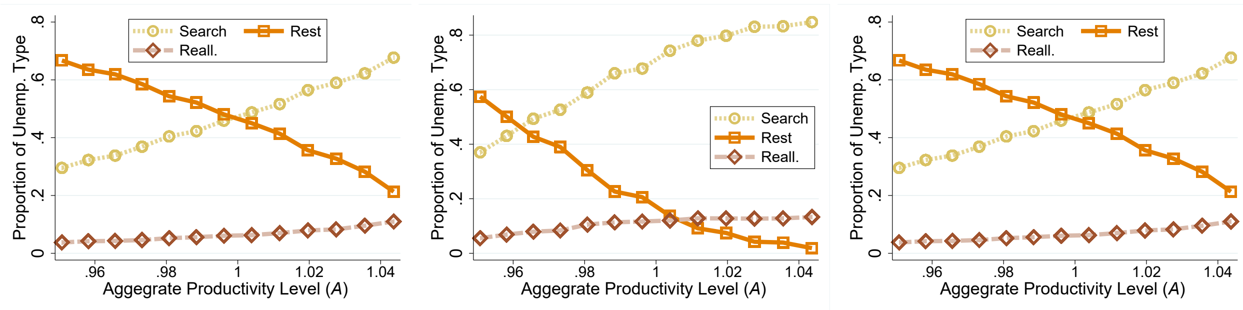
quarterly data alleviates this feature without further compromising on computation time. Note, however, that this comes at the cost of reducing the volatility of the vacancy rate (and labor market tightness) in the model from 0.07 to 0.05 (0.21 to 0.17), while in the data they remain stable. Similarly on the data side, the job finding rate, measured in a consistent way with the model while taking into account censoring in the SIPP, is somewhat noisy at quarterly frequency. Smoothing this time-series using the 5Q-MA helps diminish this noise.

As argued in main text (and in Supplementary Appendix B.7) we consider the unemployment rate of those workers who are unemployed between jobs (EUE), so that the occupational mobility of these workers can be straightforwardly measured. The resulting EUE unemployment rate $(EUE/(EUE+E))$, under the definitions and restrictions we explained in the main text, is significantly lower than the BLS at 3.5% (vs 6.3%), but drives much of its changes. In particular, for every one percentage point change in the BLS unemployment rate, we find that about 0.75 percentage points originate from the response of the EUE unemployment rate. This means that the relative cyclical response of the EUE unemployment rate is much stronger than the relative response of the BLS unemployment rate. Indeed, the volatility of the HP-filtered logged quarterly EUE unemployment rate is 0.16 while the corresponding BLS unemployment measure (which includes inflows from non-participation) over the same period is 0.11. For the 5Q-MA smoothed time series, the difference is from 0.15 (EUE) to 0.10 (BLS). The above also means that the focus on EUE unemployment raises the bar further to achieve sufficient amplification. Nevertheless, Table 3 shows that our model performs well.

In the model we also can calculate a measure of unemployment that includes unemployment following first entry into the labor market. Relative to the BLS measure, this measure still excludes unemployment associated with workers who re-enter the labor market during their working life or who subsequently leave the labor force but not before spending time in unemployment. Including entrants in unemployment raises the average total unemployment rate to 5.2% in the model, exhibiting a lower volatility of 0.12 (5Q-MA smoothed). The latter arises as with this unemployment measure, roughly 60% of the way from the EUE to BLS unemployment measures, the volatility gets closer to that of the BLS measure. Cross-correlation and autocorrelation statistics of this alternative unemployment measure are very similar to the EUE unemployment measure.

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

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



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

Figure 4: Unemployment decomposition - Full model

B.2 Excess Mobility and Cyclical Unemployment

To show the importance of idiosyncratic occupation-worker (z) productivity shocks in allowing the full model to replicate the cyclical behavior of many labor market variables, we re-estimate the model by shutting down occupation-wide heterogeneity (level and business cycle loadings), effectively setting $p_{o,t} = 1$ at all t. In this case, a worker's productivity at time t in an occupation o is completely described by aggregate productivity A, worker-occupation match productivity z and occupation-specific human capital x. Workers do not (and do not want to) prefer a new occupation over another before knowing their z. Note that although we label this model as the "excess mobility model", it can easily be made consistent with the observed average net flows by imposing an exogenous transition matrix that governs the probabilities with which a worker in occupation o observes a z in a different occupation o'.[2] This is in contrast to our full model, where occupational productivities $p_o, p_{o'}$ differ and change relative to one another over the cycle and in response workers change the direction of their cross-occupation search. As such the full model can be considered as the "endogenous net mobility" model, while the excess mobility model as the "exogenous net mobility" model.

B.2.1 Benchmark Excess Mobility Model

This version of the model corresponds to the excess mobility model in the main text. Except for occupation-wide productivity differences and a cross-occupation search decisions, everything else remains as described in Section 3 of the main text. We use the same functional forms as done to calibrate the full model in Section 4 of the main text. This

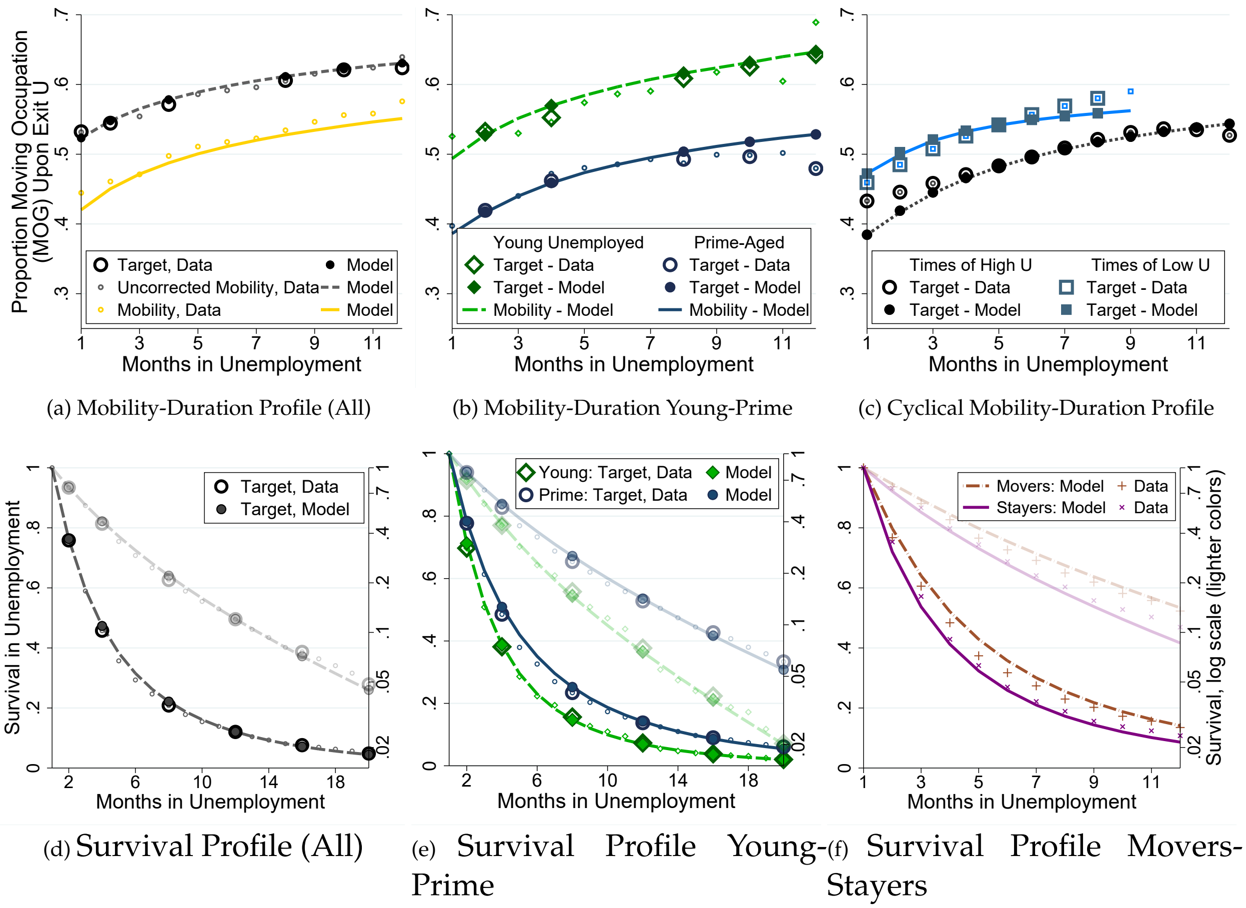
[2]With a cyclically varying exogenous transition matrix, we would also be able to match the observed cyclical net flows.

Table 4: Targeted Moments. Excess Mobility Calibration

Moments	Model	Data	Moments	Model	Data	Moments	Model	Data
Aggregate Productivity			**U Survival w. Age**			**Returns to Human Capital**		
outpw	1.005	1.000	Young 2 months	0.713	0.697	5 years (OLS)	0.150	0.154
ρ_{outpw}	0.761	0.753	Young 4 months	0.387	0.381	10 years (OLS)	0.230	0.232
σ_{outpw}	0.0094	0.0094	Young 8 months	0.147	0.156			
Aggregate Matching Function			Young 12 months	0.069	0.073	**Empirical Separation moments**		
$\hat{\eta}$	0.522	0.500	Young 16 months	0.036	0.038	rel. sep rate young/prime	2.134	1.994
Unemployment Rate			Young 20 months	0.020	0.020	prob (u within 3yrs for empl.)	0.148	0.122
u	0.0355	0.0355				rel sep rate recent hire/all	5.230	4.944
U. Survival all workers			Prime 2 months	0.783	0.777			
2 months	0.763	0.758	Prime 4 months	0.509	0.485	**Cyclical Mobility-Duration Profile Shift**		
4 months	0.473	0.457	Prime 8 months	0.252	0.234	Times High U. - 1 month	0.418	0.459
8 months	0.221	0.208	Prime 12 months	0.142	0.138	Times High U. - 2 months	0.503	0.484
12 months	0.121	0.120	Prime 16 months	0.086	0.090	Times High U. - 3 months	0.521	0.507
16 months	0.072	0.076	Prime 20 months	0.055	0.061	Times High U. - 4 months	0.528	0.526
20 months	0.045	0.048				Times High U. - 5 months	0.542	0.542
						Times High U. - 6 months	0.549	0.557
Occ. Mobility-Duration Profile All			**Occ. Mobility-Duration Profile w. Age**			Times High U. - 7 months	0.555	0.569
1 month	0.523	0.532	Young 2 months	0.528	0.539	Times High U. - 8 months	0.559	0.580
2 months	0.548	0.546	Young 4 months	0.570	0.546			
4 months	0.579	0.576	Young 8 months	0.616	0.617	Times Low U. -1 month	0.385	0.433
8 months	0.612	0.605	Young 10 months	0.632	0.631	Times Low U. -2 months	0.419	0.446
10 months	0.621	0.622	Young 12 months	0.647	0.689	Times Low U. -3 months	0.445	0.458
12 months	0.627	0.639				Times Low U. -4 months	0.466	0.471
			Prime 2 months	0.418	0.419	Times Low U. -5 months	0.483	0.483
			Prime 4 months	0.459	0.472	Times Low U. -6 months	0.496	0.496
			Prime 8 months	0.504	0.487	Times Low U. -7 months	0.508	0.509
			Prime 10 months	0.518	0.499	Times Low U. -8 months	0.517	0.521
			Prime 12 months	0.528	0.480	Times Low U. -9 months	0.525	0.531
						Times Low U. -10 months	0.532	0.537
						Times Low U. -11 months	0.538	0.535
						Times Low U. -12 months	0.544	0.527

implies that to capture economic choices and gross mobility outcomes, we now have a set of 14 parameters to recover, where $[c, \rho_z, \sigma_z, z_{norm}]$ governs occupational mobility due to idiosyncratic reasons (excess mobility); $\left[x^2, x^3, \gamma_d, \delta_L, \delta_H\right]$ governs differences in occupational human capital; and the remainder parameters $[k, b, \eta, \rho_A, \sigma_A]$ are shared with standard DMP calibrations. We jointly calibrate these parameters by matching the moments reported in Table 4 and Figure 5.

The excess mobility model matches very well the targeted occupational mobility moments as well as the job finding and job separation moments. The fit is comparable with the one of the full model. This model also matches well the untargeted moments pertaining to workers' gross occupational mobility and job finding hazards discussed in the previous section. The fit of other untargeted moments is not shown here to save space, but available upon request. The estimated parameter values in this calibration are also very similar to the ones obtained in the full model. These are $c = 7.549$, $k = 125.733$, $b = 0.843$, $\eta = 0.241$, $\delta_L = 0.0034$, $\delta_H = 0.0004$, $z_{corr} = 0.349$, $\rho_A = 0.998$, $\sigma_A = 0.00198$,



(a) Mobility-Duration Profile (All)

(b) Mobility-Duration Young-Prime

(c) Cyclical Mobility-Duration Profile

(d) Survival Profile (All)

(e) Survival Profile Young-Prime

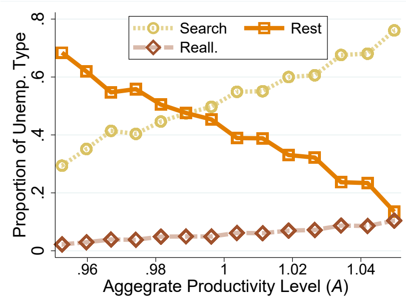
(f) Survival Profile Movers-Stayers

Figure 5: Targeted Moments. Data and Model Comparison

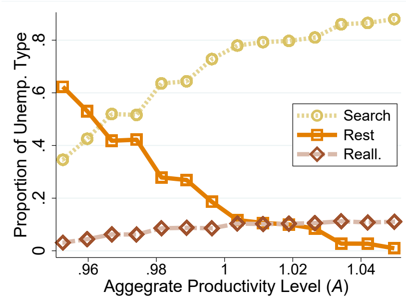
$\rho_z = 0.998$, $\sigma_z = 0.00707$, $x^2 = 1.181$, $x^3 = 1.474$ and $\gamma_h = 0.0039$.

As shown in the main text, the excess mobility calibration is also able to fit a wide range of cyclical features of the labor market. The left panel of Table 5 (below) shows the time series properties of the unemployment, vacancy, job finding and job separation rates and labor market tightness as well as the full set of correlations between them, obtained from the excess mobility calibration. Here we find that the cyclical implications of the excess mobility model are very similar to that of the full model, as shown and discussed in the main text.

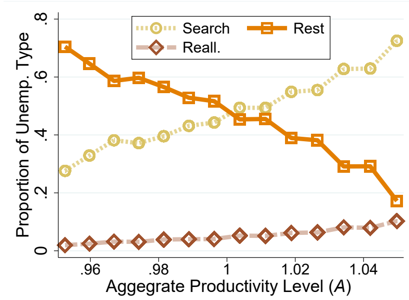
Age patterns Figure 6 shows that the occurrence of search, rest and reallocation unemployment episodes not only happens when pooling all workers together but also for each age group, as in the full model. Figure 7 shows these age group dynamics more clearly by depicting the distribution of unemployed and employed workers among young and prime-aged workers. It shows that during recessions unemployment among young work-



(a) All workers

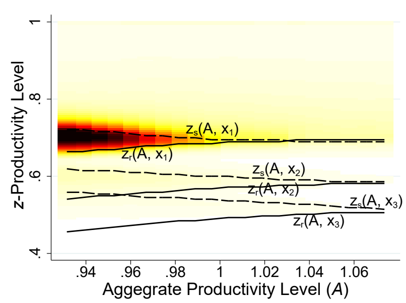


(b) Young Workers

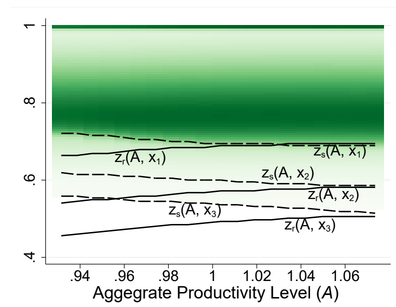


(c) Prime-aged Workers

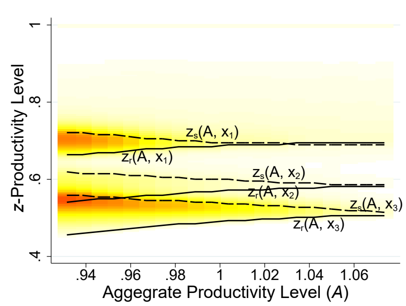
Figure 6: Unemployment decomposition - Excess mobility model



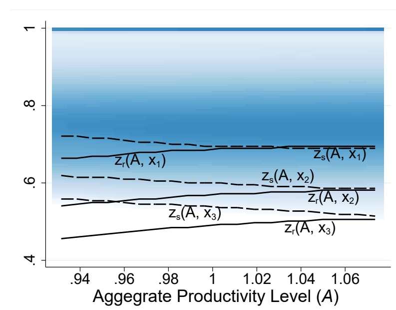
(a) Young Unemp. Dist.



(b) Young Empl. Dist.



(c) Prime Unemp. Dist.



(d) Prime Empl. Dist.

Figure 7: Unemployment decomposition and aggregate productivity by age groups

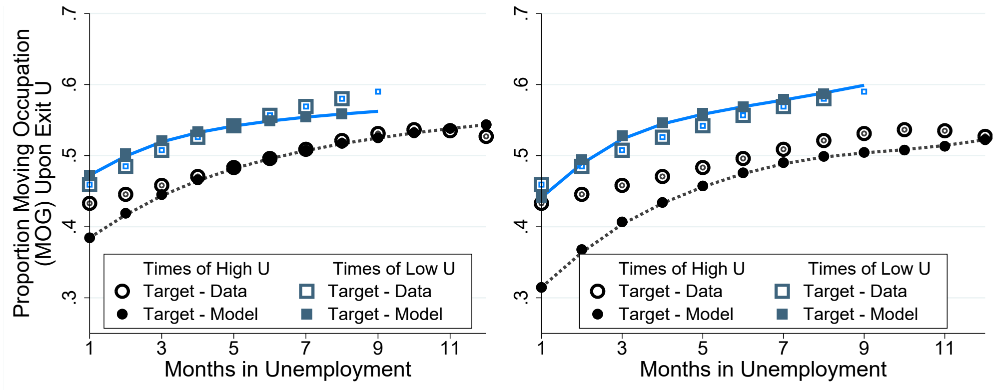
ers is concentrated slightly above $z^s(., x^1)$ and between $z^s(., x^1)$ and $z^r(., x^1)$. During expansions, however, unemployment is located above the $z^s(., x^1)$ cutoff. In the case of prime-aged workers, the concentration of unemployment during recessions and expansions occurs mostly above $z^s(., x^3)$ and between $z^s(., x^3)$ and $z^r(., x^3)$, but also between the $z^s(., x^1)$ and $z^r(., x^1)$ cutoffs. This difference implies that during expansion episodes of rest unemployment are still prevalent among prime-aged workers, while for young workers these episodes basically disappear (as shown in Figure 6) and are consistent with a lower occupational mobility rate among prime-aged workers.

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

Given that it is clear the excess mobility model is able to replicate on its own many critical features of the full model, in what follows we use it to perform two key exercises. The first one highlights the effect of human capital depreciation in attenuating the cyclical properties of the above labor market variables and motivates our use of the cyclical shift of the mobility-duration profile as a target. The second exercise investigates the quantitative implications of our model when considering that a worker's varying job finding prospects (due to the stochastic nature of the z-productivity process) during a jobless spell can be linked to observed transitions between the states of unemployment and non-participation (or marginally attached to the labor force) as defined in the SIPP. For this exercise we recompute all of the relevant empirical targets using non-employment spells that contain a mix of periods of unemployment and non-participation. To save space we refer the reader to our working paper Carrillo-Tudela and Visschers (2020) for the list of targeted moments, the fit and the estimated parameter values under both exercises.

B.2.2 The Importance of Human Capital Depreciation

To estimate the full and the excess mobility models we used the mobility-duration profiles at different durations during recessions and expansions. These patterns informed us about the rate of occupational human capital depreciation during spells of unemployment. In the main text, we argued that these profiles were crucial in helping us identify the depreciation parameter, γ_h. The reason for the latter is that a model which did not in-



(a) Model with HC Dep.

(b) Model without HC Dep.

Figure 8: Cyclical Mobility-Duration Profile

corporate human capital depreciation will generate very similar long-run moments as a model which did incorporate depreciation, but generate different cyclical predictions. To show this, we now discuss the result of the excess mobility model without human capital depreciation. To estimate the latter we target the same *long-run* moments as in the calibration described above, but do not target the cyclical behaviour of the mobility-duration profile.

We find that the fit is very good, similar to the models which incorporates human capital depreciation. It also does well in matching the same untargeted long-run moments described above. The estimated parameter values are also similar. Further, this calibration finds that periods of search, rest and reallocation unemployment can arise during a worker's jobless spell across all levels of occupational human capital.

Figure 8 shows the first key difference between the excess mobility model with and without occupational human capital depreciation. We plot the mobility-duration profile in times of expansions and recessions (low and high unemployment, respectively), where Figure 8a shows the mobility-duration profiles from the model with human capital depreciation and Figure 8b shows the ones for the model without human capital depreciation. The latter finds that the lack of human capital depreciation implies the model completely misses the profile at nearly all durations during recessions, particularly at low durations. Is precisely this lack of fit that motivated us to add the cyclical patterns of the mobility-duration profile as targets in order to help identify the rate of human capital depreciation.

Table 5 shows the second key difference. The model without depreciation generates

Table 5: Logged and HP-filtered Business Cycle Statistics

	Excess Mobility Model with HC dep.						**Excess Mobility Model with No HC dep.**					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.14	0.05	0.17	0.06	0.10	0.01	0.20	0.06	0.25	0.10	0.14	0.01
ρ_{t-1}	0.95	0.91	0.94	0.89	0.94	0.94	0.94	0.87	0.94	0.88	0.93	0.94
	Correlation Matrix						**Correlation Matrix**					
u	1.00	-0.72	-0.98	0.80	-0.89	-0.95	1.00	-0.62	-0.97	0.78	-0.89	-0.92
v		1.00	0.84	-0.81	0.94	0.85		1.00	0.76	-0.61	0.77	0.72
θ			1.00	-0.84	0.96	0.97			1.00	-0.78	0.94	0.93
s				1.00	-0.87	-0.90				1.00	-0.81	-0.84
f					1.00	0.95					1.00	0.89
$outpw$						1.00						1.00

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

a larger amount of cyclical volatility in the aggregate unemployment, job finding and job separation rates in relation to the model with human capital depreciation. Relative to the data, Table 3 shows an overshooting in the volatilities of the unemployment and job finding rates. This occurs as the area of inaction between z^r and z^s becomes too cyclical. Without human capital depreciation there is a sharp drop in the proportion of rest unemployment and a sharper rise in the proportions of search and reallocation unemployment as the economy improves. Human capital depreciation attenuates these effects, improving the model's fit.

B.2.3 The Unemployed and Marginally Attached

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

We do this by re-estimating the excess mobility model, recomputing the targets using non-employment spells in which workers transition between unemployment and non-participation as labelled in the SIPP. We consider non-employment spells with at least one period of unemployment, which we label 'NUN' spells. To avoid maternity and related

Table 6: Logged and HP-filtered Business Cycle Statistics

	Data (1983-2014) - NUN spells						Excess Mobility Model - NUN spells					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.11	0.11	0.21	0.10	0.08	0.01	0.09	0.03	0.11	0.04	0.07	0.01
ρ_{t-1}	0.97	0.99	0.94	0.99	0.94	0.93	0.95	0.85	0.94	0.87	0.93	0.94
	Correlation Matrix						**Correlation Matrix**					
u	1.00	-0.92	-0.98	0.79	-0.96	-0.51	1.00	-0.51	-0.96	0.65	-0.81	-0.89
v		1.00	0.98	-0.79	0.94	0.61		1.00	0.72	-0.50	0.75	0.65
θ			1.00	-0.80	0.96	0.57			1.00	-0.68	0.89	0.92
s				1.00	-0.87	-0.43				1.00	-0.64	-0.80
f					1.00	0.46					1.00	0.86
$outpw$						1.00						1.00

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

issues in non-participation we restrict the focus to men. We show that when considering NUN spells the model still reproduces the observed cyclical amplification in the non-employment rate.[3]

The fit is once again very good in this case even though the survival probability in NUN spells shifts up significantly at longer durations, compared to the corresponding patterns for unemployment spells, both for all workers and across age groups. The estimated parameter values are also broadly similar to the ones in the previous versions of the excess mobility model, changing in expected directions. The z process is now somewhat more volatile, but the higher reallocation cost implies that the area of inaction between z^s and z^r is (in relative terms) also larger. The latter leaves more scope for workers to get "trapped" for longer periods in rest unemployment episodes, thus creating an increase in the survival functions across all, young and prime-aged workers as observed in the data.

Table 6 shows the main takeaway of this exercise. The model remains able to generate cyclical movements of the non-employment, job finding and job separation rates as well as a relatively strong Beveridge curve. In particular, the cyclical volatilities of the non-employment and job finding rates are the same as in the data. As in the previous estimations, here we also find that the reason for the amplification of the non-employment rate is that the model generates period of search, rest and reallocation unemployment, whose relative importance changes over the cycle.

Including marginally attached workers in our analysis increases the overall impor-

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

tance of rest unemployment in normal times. This is consistent with the fact that in these times the non-employment rate is higher and the associated job finding rate lower, compared to our benchmark unemployment and job finding rates measures. Further, this version of the model still needs to accommodate short-term outflows as before and does so mostly through search unemployment episodes. As a result, the proportion of rest unemployment decreases at a slower rate with A. Even at the highest aggregate productivity levels rest unemployment is very prevalent, representing about 40% of all episodes during a non-employment spell, with a large role for prime-aged workers. Overall we find that a version of the excess mobility model that considers NUN spells exhibits a higher non-employment rate but a lower cyclicality than in our benchmark model. This is consistent with the data, where we observe a lower cyclicality among the non-employment than among the unemployment.

B.3 The Importance of Occupational Mobility

To demonstrate the importance of including the z^r cutoff to *simultaneously* replicate the cyclical behaviour of the unemployment duration distribution and the aggregate unemployment rate, we re-estimate the model by shutting down occupational mobility. This is done by exogenously setting c to a prohibiting level. We present two calibrations. Model I targets the same moments as in the full model with the exception of those pertaining to occupational mobility.[4] Model 2 is chosen to achieve a higher cyclical volatility in the aggregate unemployment rate but is more permissive of deviations from the targets.

Model I To save space our working paper, Carrillo-Tudela and Visschers (2020), shows the table of targeted moments and the fit as well as the estimated parameter values. The fit is largely comparable along nearly all corresponding dimensions to the full and excess mobility models. The estimated parameters are largely sensible. Two key features stand out: (i) there is now a higher role for search frictions as the model estimates a higher value $k = 195.58$; and (ii) the z process is now less persistent $\rho_z = 0.9923$ and exhibits a much

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

Table 7: Logged and HP-filtered Business Cycle Statistics

	No Occupational Mobility - Model I						No Occupational Mobility - Model II					
	u	v	θ	s	f	$outpw$	u	v	θ	s	f	$outpw$
σ	0.04	0.02	0.06	0.03	0.03	0.01	0.10	0.03	0.12	0.07	0.05	0.01
ρ_{t-1}	0.94	0.85	0.93	0.83	0.87	0.94	0.94	0.85	0.94	0.89	0.89	0.94
	Correlation Matrix						Correlation Matrix					
u	1.00	-0.42	-0.93	0.71	-0.77	-0.86	1.000	-0.57	-0.98	0.83	-0.79	-0.96
v		1.000	0.72	-0.26	0.58	0.60.		1.00	0.73	-0.60	0.72	0.66
θ			1.00	-0.65	0.82	0.90			1.00	-0.85	0.84	0.97
s				1.00	-0.52	-0.71				1.00	-0.85	-0.89
f					1.00	0.74					1.00	0.84
$outpw$						1.00						1.00

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

Table 8: Incomplete Unemployment Duration Distribution Behavior

Panel A: Incomplete Unemployment Distribution (1-18 months)

	All workers				Young workers				Prime-aged workers			
Unemp. Duration	Occ Model	No Occ. Model I	No Occ. Model II	Data	Occ. Model	No Occ. Model I	No Occ. Model II	Data	Occ. Model	No Occ. Model I	No Occ. Model II	Data
1-2 m	0.43	0.38	0.36	0.43	0.53	0.45	0.36	0.47	0.40	0.35	0.36	0.41
1-4 m	0.65	0.58	0.56	0.67	0.75	0.67	0.55	0.71	0.62	0.56	0.56	0.65
5-8 m	0.20	0.22	0.22	0.20	0.17	0.19	0.22	0.19	0.22	0.23	0.22	0.21
9-12 m	0.09	0.11	0.12	0.08	0.05	0.08	0.12	0.07	0.10	0.12	0.12	0.09
13-18m	0.06	0.09	0.10	0.05	0.03	0.06	0.11	0.03	0.07	0.09	0.09	0.06

Panel B: Cyclical Changes of the Incomplete Unemployment Distribution (1-18 months)

	Elasticity wrt u				HP-filtered Semi-elasticity wrt u			
Unemp. Duration	Occ Model	No Occ. Model I	No Occ. Model II	Data	Occ Model	No Occ. Model I	No Occ. Model II	Data
1-2 m	-0.432	-0.328	-0.265	-0.464	-0.168	-0.122	-0.099	-0.169
1-4 m	-0.314	-0.241	-0.186	-0.363	-0.178	-0.134	-0.107	-0.184
5-8 m	0.374	0.148	0.119	0.320	0.074	0.046	0.040	0.076
9-12 m	1.083	0.422	0.300	0.864	0.061	0.049	0.039	0.072
$>$13 m	1.787	0.752	0.504	1.375	0.044	0.039	0.029	0.043

larger variance $\sigma_z = 0.0300$ in the stationary distribution, generating a perhaps too large Mm ratio of 2.28.[5] Table 7 under "No Occupational Mobility - Model I", however, shows that this model cannot generate enough cyclical volatility on all the relevant labor market variables.

Table 8 further shows that Model I is not able to reproduce the observed average quarterly unemployment duration distribution at short or long durations (Panel A), nor does it capture the cyclical behavior of this distribution (Panel B). While Model I and the oc-

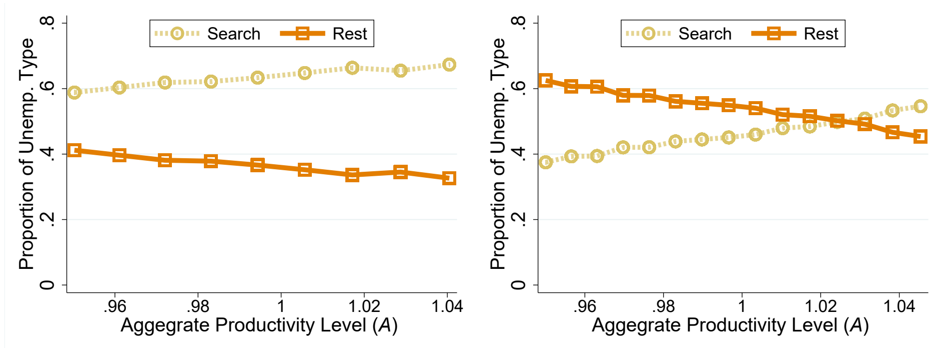
[5]In this context the z-productivity process can be interpreted as an idiosyncratic productivity shock affecting a worker's overall productivity, rather than a worker's idiosyncratic productivity within an occupation.

cupational mobility models replicate the same unemployment survival functions, they generate different incomplete duration distributions. This occurs because the survival functions are computed pooling the entire sample, while the distribution of incomplete spells between 1 and 18 months is calculated for each quarter and then averaged across quarters. Model I generates about 50% more long-term unemployment (9-12 months) relative to the data and the discrepancy is even stronger, about 80%, at longer durations. That is, this model matches the unemployment survival functions by creating too dispersed unemployment durations within a typical quarter, in particular too many long spells, but its distribution then responds too little to the cycle.

Model II If one is willing to compromise on replicating the aggregate and age-group survival functions, however, the model without occupational mobility is able to generate larger cyclical volatilities. To show this we re-estimated the model by de-emphasising these survival functions. Once again we refer to Carrillo-Tudela and Visschers (2020) for the fit of this model and the estimated parameter values. There we show that the unemployment survival functions of young and prime-aged workers are no longer well matched. This model misses the distribution at longer durations for young workers and at shorter durations for prime-aged workers, such that age differences in job finding hazards have nearly disappeared. However, there is now a lower degree of search frictions, $k = 102.019$ and the z process is more persistent, $\rho_z = 0.993$, and its overall dispersion is much lower than in Model I, $\sigma_z = 0.0132$. It is these last properties that allow Model II to create more cyclical volatility as shown in the right panel of Table 6.

Panel A of Table 8 - No Occ. Model II shows that this model still creates too much long-term unemployment (13-18 months) in the average quarter, where the proportion of long-term unemployed (among those with spells between 1-18 months) is missed by a large margin for all, young and prime-aged workers. Further, Panel B of Table 8 shows that this feature is also reflected in a muted cyclical response of the unemployment duration distribution. Here we also find that Model II misses the semi-elasticity with respect to the unemployment rate by an average of about 40% across the duration distribution.[6]

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



(a) All workers - Model I

(b) All workers - Model II

Figure 9: Unemployment decomposition - No occupational mobility

Discussion These calibrations show that without the z^r cutoff versions of our model with no occupational mobility cannot resolve the tension between individual unemployment outcomes and aggregate unemployment volatility. This arises as without the possibility of occupational mobility the new area of inaction is defined by the set of $z \in [\underline{z}, z^s]$, where $\underline{z}$ is the lowest value of z, and its cyclical response now solely depends on $\partial z^s/\partial A$.

In the case of Model I, a less persistent and much more volatile z process creates enough heterogeneity in unemployment durations that allows it to match the empirical unemployment survival functions at the aggregate and across age groups. However, it also increases the heterogeneity in z-productivities relative to the cyclical range of A. This dampens the model's cyclical performance as it implies less responsive z^s cutoffs relative to the workers' z distribution, weakening the cyclical responses of job separations and the rate at which workers leave the area of inaction. Moreover, with a larger vacancy posting cost, Figure 9.a shows that search unemployment is now more prominent than rest unemployment at any point of the cycle. Larger search frictions imply larger surpluses and therefore further reducing the cyclical responsiveness of the model.

The increased cyclical performance of Model II arises as its estimated z process becomes more persistent and less volatile, creating more responsive z^s cutoffs leading to stronger cyclical responses in job separations, as well as much more episodes of rest unemployment over all A. Figure 9.b shows that rest unemployment episodes are now more prominent than search unemployment episodes even during economic recoveries. It is only for the highest values of A that search unemployment is more prominent, but only by a relatively small margin. With more responsive z^s cutoffs, an aggregate shock can now move somewhat larger masses of workers from rest into search unemployment episodes creating more amplification. This result is in line with Chassamboulli (2013), who extends the DMP model by adding permanent productivity differences among workers and shows that this feature increases it cyclical performance relative to the data. Table 8 demonstrates, however, that this comes at the cost of not being able to match the distribution of unemployment durations nor the dynamic behavior of this distribution over the cycle.[7] Thus, in Model II the average unemployment rate responds more to the cycle as aggregate productivity takes on a more prominent role in shaping the amount of rest unemployment, but the individual unemployment outcomes that underlie these dynamics become counterfactual.

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

References

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[2] Chassamboulli, A. 2013. "Labor-Market Volatility in a Matching Model with Worker Heterogeneity and Endogenous Separations". *Labour Economics*, 24: 217-229.

[3] Kambourov, G. and I. Manovskii. 2009. "Occupational Specificity of Human Capital". *International Economic Review*, 50(1): 63-115.

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